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Advancing Spatiotemporal Research of Visitor Travel Patterns Within Parks and Protected Areas

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ADVANCING SPATIOTEMPORAL RESEARCH OF VISITOR TRAVEL PATTERNS WITHIN PARKS AND PROTECTED AREAS

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ABSTRACT

Recent technological advances have made it possible to more accurately understand visitor travel patterns and their associated impacts. These advancements help to: accumulate voluminous data sets, collect alternative location data similar to GPS data, conduct spatiotemporal inferential statistics, and advance spatiotemporal visualizations. However, investigations of visitor travel patterns have not kept pace with recent technological advancements. Therefore, the purpose of this dissertation was to advance spatiotemporal research of visitor travel patterns within parks and protected areas by leveraging new technologies. The studies reported in this dissertation were designed to begin filling this gap, and include results from research conducted at: 1) Theodore Roosevelt National Park to identify which spatiotemporal variables are the most important to managers for understanding visitor travel patterns; 2) Hawai'i Volcanoes National Park to identify air tour travel patterns; and 3) the Bonneville Salt Flats to understand visitor travel patterns in a dispersed recreation setting that lacks organizational infrastructure.

These three independent but conceptually linked studies were designed to inform our understanding of visitor travel patterns within parks and protected areas. This information is important so that park managers: a) understand how space and time influence visitor routes; and b) have relevant information to continue to conserve the biophysical resource while providing opportunities for quality visitor experiences. Results from the study at Theodore Roosevelt National Park showed that managers identified three temporal variables as being the most important towards understanding visitor travel patterns. These variables were analyzed to determine time allocation and vehicle speed patterns. Results from the study at Hawai'i Volcanoes National Park determined air tour travel patterns and which terrestrial attraction areas were the most affected by air tours. The study at the Bonneville Salt Flats identified potential areas of conflict and designed areas recommended for monitoring. Overall, this dissertation contributes to further understanding of visitor travel patterns, which provides information for managers to continue conserving parks and protected areas for the benefit of society.

For my enduring family

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CHAPTER ONE

INTRODUCTION

Conserving the environment is inextricably connected to society, including the conservation of parks and protected areas (PPAs), which are important for many reasons, including leisure and recreation. The societal health benefits of leisure and recreation are well-documented (Godbey, 2009) and quality experiences in PPAs can foster conservation values and attitudes (McFarlane, Boxall, & Watson, 1998). Thus, these socially constructed and socially-valued areas require both environmental resource conservation and conservation of societal benefits to remain viable. Therefore, it is important to understand factors that contribute to quality visitor experiences.

Research has shown that visitor experiences in PPAs are a spatially-conditioned process (Beeco & Brown, 2013). This means that space (referred to as the spatial component) is a fundamental resource for visitors in PPAs (An et al., 2015). Space as a resource is not an exclusive entity; space is inherently connected to time (referred to as the temporal component), which is highlighted by the conceptual framework known as time-geography (Hägerstrand, 1970). Time-geography is a framework for the analysis of spatiotemporal behavior that identifies the inherent relationships between space and time. The guiding principle of the time-geography framework is that spatiotemporal investigations should analyze both the spatial and temporal components. The assumptions of the time-geography framework are that the individual is indivisible, space and time are inseparable, and space and time are limited resources (Pred, 1977). Therefore, visitor experiences in PPAs are spatiotemporally conditioned, because space and time are inherently linked and omnipresent.

Understanding how space and time influence the visitor experience is essential. Every moment of each visitor experience is influenced by space and time. Thus, data that includes information about space and time are important. Data that identifies a location with a timestamp is referred to as spatiotemporal data, which are important for managers of PPAs to understand visitor travel patterns. Understanding visitor travel patterns can help managers conserve the environmental resource while conserving quality visitor experiences.

Recent advancements in technology have enhanced research of visitor travel patterns. A valuable data collection tool is the GPS (Global Positioning System) data logger, which records timestamped locational data. The primary strength of GPS data loggers is the proven accuracy for collecting localized data (White, Brownlee, Furman, & Beeco, 2015). GPS data loggers are small, typically waterproof, record waypoints at regular intervals, and are intuitive to configure (Beeco & Hallo, 2014). However, methods of analyzing GPS data to understand visitor travel patterns can be improved by: a) incorporating site specific contextual information, b) conducting travel pattern analysis of wider ranges of visitor types, such as air tours, and c) analyzing visitor travel patterns in a dispersed PPA that lacks organizational infrastructure. Consequently, advancing spatiotemporal analyses of visitor travel patterns within PPAs is important to produce highly accurate information for managers to effectively conserve the environmental resource while providing opportunities for quality visitor experiences. Therefore, the purpose of this dissertation is to advance spatiotemporal research of visitor travel patterns within PPAs.

Accordingly, this dissertation features three empirical studies that advances understanding of visitor travel patterns. Each study occurred at a distinct type of park, and each study advanced spatiotemporal methods to understand visitor travel patterns. The research featured in Chapter 2 occurred at Theodore Roosevelt National Park in North Dakota and advanced spatiotemporal methods by using a management-centric approach to identify which spatiotemporal variables are most important to understand visitor travel patterns at the park. The managers identified spatiotemporal variables which were subsequently used by the researcher to segment visitors into travel groups, and these groups' travel patterns were compared. Additionally, this research advanced spatiotemporal visualizations and presents intuitive spatiotemporal displays.

The research featured in Chapter 3 occurred at Hawai'i Volcanoes National Park, which is located on the island of Hawai'i. This research used data that is conceptually similar to GPS data, known as Automatic Dependent Surveillance-Broadcast (ADS-B) Out, to analyze air tour travel patterns. These data were used to quantify air tour patterns and frequency across hours for weekdays, and weekends and holidays; and to spatiotemporally identify which terrestrial attraction areas are most affected by air tours. This research advanced spatiotemporal methods by using inferential statistics to analyze spatial variations of temporally-segmented air tour data to understand air tour travel patterns for an open system (air tours flying uninhibited above the park). Park managers can use the findings of this research to plan with air tour operators, the Federal Aviation Administration (FAA), and other entities.

The research featured in Chapter 4 occurred at the Bonneville Salt Flats in Utah. The Bonneville Salt Flats are a flat desert expanse comprised of a hard salt substrate that provides visitors with the opportunity to freely explore the vast landscape (Hogue, 2005). The Bonneville Salt Flats are popular for many reasons, but notably that there is no speed limit. Additionally, this park lacks organizational infrastructure (such as roads, trails, or signs), which is a challenging setting for understanding visitor travel patterns. This research advanced spatiotemporal methods by designing a digital grid to identify areas where potential conflict may occur and where there is high use and high vehicle speeds. Park managers can use the information produced by this research for monitoring purposes to reduce potential visitor conflict.

The purpose of this dissertation was to advance spatiotemporal research of visitor travel patterns within PPAs. This research was necessary because space and time are not well understood for visitors, and technological advancements provide opportunities for richer analytical depth. It is important for managers to understand visitors' use of space and time to understand where and when to allocate park resources. Additionally, this information is useful to understand how often to maintain resources, which is a function of time based on the location of park resources. The spatiotemporal methods documented in this dissertation advance analytical accuracy of understanding visitor travel patterns. This information can help managers understand visitor travel patterns to more effectively conserve the environmental resource while providing opportunities for quality visitor experiences.

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CHAPTER TWO

SPATIOTEMPORAL VARIABLES TO UNDERSTAND VISITOR TRAVEL PATTERNS: A MANAGEMENT-CENTRIC APPROACH

Abstract

Visitor travel patterns are affected by the unique context of each park and protected area. Consequently, researchers have used numerous options and associated methods to understand specific visitor travel patterns at individual parks. However, management input to identify the most important spatiotemporal variables used to understand travel patterns has not been fully taken into consideration during previous investigations. In this study, the researcher conducted semi-structured interviews and surveyed managers at Theodore Roosevelt National Park to determine which spatiotemporal variables were deemed the most important for understanding visitor travel patterns at the park. Next, these spatiotemporal variables identified by managers were used to cluster travel groups. These travel groups were compared to gain more understanding of visitor travel patterns. Lastly, 3D geovisualizations that are intuitive and easy to understand were created for management purposes. A significant finding produced by this research was that managers at Theodore Roosevelt National Park identified three temporal variables as being the most important for understanding visitor travel patterns: total time spent at attraction areas, total time spent at the visitor center, and total time spent in the park.

Introduction

No matter where humans visit, they travel along a route in which space and time are omnipresent. Accordingly, every human behavior and experience occurs at a specific location at a specific time because space and time are inherently linked (Hägerstrand, 1970). All human behaviors and experiences are spatiotemporally conditioned because a tripartite relationship exists between humans, space, and time. Although, spatiotemporal information provides meaningful information about human behavior, it is often overlooked because it is ubiquitous.

This fundamental tripartite relationship between humans, space, and time gained prominence from a research framework known as time-geography. According to the time-geography framework, all spatial behaviors should include a consideration of time because space and time are always linked (Hägerstrand, 1973). Consequently, budgeting of space and time by humans is constant. Therefore, human travel routes are comprised of a series of spatiotemporal-conditioned behaviors in which budgeting of space and time are regularly assessed (Grinberger & Shoval, 2019). These travel routes have implications for the management of parks and protected areas (PPAs), because as visitors move through these areas they spatiotemporally interact with biophysical resources and are influenced by other visitors' spatiotemporal behaviors (Beeco & Hallo, 2014). Information about visitor travel patterns, such as the locations they visit, times of visitation, and duration of visitation, can help managers of PPAs conserve the biophysical resource and provide opportunities for quality visitor experiences (D'Antonio & Monz, 2016). However, each PPA has a spatially unique context that influences visitor travel patterns, including geography, infrastructure, and locations of attraction areas. Therefore, it is important to include these site specific contexts into research of visitor travel patterns.

Tracking technologies, such as GPS (Global Positioning System), have made it possible to gather accurate and precise location data (D'Antonio & Monz, 2016). GIS (Geographic Information Systems) have made it possible to conduct geospatial mapping and statistics of location data (Shoval, Schvimer, & Tamir, 2018). These technological advances have provided an abundance of analytical possibilities, which make it difficult to determine which attributes to analyze regarding visitor travel patterns. Additionally, the unique spatial context of each PPA influences visitor travel patterns, and should be considered. Therefore, determining which travel pattern attributes to analyze needs to incorporate contextual information and contextual knowledge. Contextual knowledge is the capacity to navigate localized situations, and is important to incorporate into applied research (Aspers, 2006). Managers typically have the best contextual knowledge of the PPA they manage.

Applied research should also provide results that are intuitive and useful. However, most applied research of PPAs, that incorporates GPS and GIS, often constructs two-dimensional density displays that can be difficult to process (D'Antonio et al., 2010). These displays are difficult to understand the magnitude of the attribute analyzed, such as how long people visit a location (Beeco & Hallo, 2014). Applied spatiotemporal research could produce better displays in which the magnitude of attributes is easier to understand, such as three-dimensional (3D) displays, which are better at displaying magnitude than 2D density displays (Kwan & Lee, 2004). For example, 3D displays can be constructed to show time allocation and speed. Finally, 3D displays have been shown to avoid interpretative difficulties associated with other types of spatiotemporal displays (Kwan & Lee, 2004).

This study is valuable because it introduces an approach that includes contextual knowledge of the study site to understand visitor travel patterns, and produces intuitive visualizations that can help managers easily understand visitor travel patterns. The study site was Theodore Roosevelt National Park (THRO). The researcher interviewed and surveyed managers to understand which spatiotemporal variables are most important to understand visitor travel patterns. These variables were used to produce distinct travel pattern groups, and 3D geovisualizations were created. The resultant information advances science by introducing an approach that includes contextual spatiotemporal knowledge and provides managers with intuitive and useful results.

Literature Review

Travel Pattern Variables

Every visitor to a PPA travels a route comprised of numerous spatiotemporal intricacies known as travel patterns (Beeco & Hallo, 2014). Using GPS technology and GIS applications, it is possible to collect accurate, precise, and detailed travel pattern data and conduct several types of analyses (Riungu, Peterson, Beeco, & Brown, 2018). Using both GPS and GIS is valuable but hampered by a wide range of spatial, temporal, and spatiotemporal variables (An et al., 2015). This abundance allows for multiple analytical approaches but can result in challenges associated with determining which approaches and variables to assess. Therefore, identifying contextually important variables and operationalizing those variables is important.

The abundance of travel variables can make it difficult to identify which variables to analyze and how to include site specific context. Kidd et al. (2015) extracted 21 operationalized variables derived from GPS data to classify visitor vehicular behavior in a protected area. The researchers used an exploratory factor analysis as a data reduction technique to focus analytical efforts. Another strategy is to use the data to identify contextual characteristics of the study site (Beeco et al., 2013). Stamberger et al. (2018), noted that aspects of the study site's contextual characteristics are already naturally embedded in GPS data, and that GPS data can be used to identify visitor time allocation, visitor travel speed variations, use concentrations, and locations of visitation. However, contextual knowledge of the study site might be more effective to determine which travel variables to analyze, such as PPA managers' knowledge of study site. By combining both managers' knowledge and the study site's contextual characteristics, researchers can identify travel pattern variables to operationalize and analyze. Yet, such a contextualized approach has not been conducted in which both manager knowledge and unique park characteristics were used to understand visitor travel patterns.

Added to the challenge of abundant travel variables is the difficulty to operationalize travel patterns. Past research shows a variety of approaches. Beeco and Hallo (2014) examined factors that influenced visitor travel patterns in a complex trail system and operationalized travel patterns as total distance traveled, number of zones encountered, and distance from starting point. Ferrante, De Cantis, and Shoval (2016) analyzed cruise passengers' spatiotemporal behavior at a port destination with GPS tracking data, and operationalized travel patterns as total duration of tour, total length of tour, maximum distance from origin, average distance from origin, average speed, and 90th percentile of speed. The study conducted by Ferrante, De Cantis, and Shoval (2016) also brought attention to the difficulty of identifying a 'stop' at a tourist attraction area when analyzing GPS data. The authors determined that speed and duration can be used to operationalize a 'stop'. For example, a 'stop' could be identified when travel speed is below 2 mph for 2 minutes or longer. Past research demonstrates the challenges of operationalizing travel patterns, and the importance of including study site context.

Data Clustering

Technological advancements have resulted in efficient GPS data collection of voluminous datasets (Hagenauer & Helbich, 2013). GPS data includes a waypoint, timestamp, and an elevation (Hu & Wang, 2007). A waypoint is point location identified with a latitude and longitude (Niehöfer, Burda, Wietfeld, Bauer, & Lueert, 2009). One method to collect location data is by distributing GPS data loggers to a representative sample of PPA visitors (Riungu et al., 2018). However, when a sample population carries GPS data loggers this can result in large amounts of data (Shekhar, Gunturi, Evans, & Yang, 2012). For example, Beeco et al. (2013) conducted a study to analyze GPS tracks of different tourist typologies, which resulted in 1.5 million waypoints. The immensity of GPS data is also dependent on how often the devices record a waypoint, which are typically configured to record waypoints every 15 seconds (Beeco & Hallo, 2014). For example, if a sample of visitors (*n*=300) spent an average of five hours within a PPA, this would result in 360,000 waypoints. Studies have recognized that a 15-second interval is burdensome yet rich (Beeco et al., 2013).

These large datasets typically contain patterns that can be difficult to determine (Miller & Han, 2009). One method to overcome this challenge is clustering data with similar characteristics to facilitate further analyses (Peeters et al., 2015). These data groupings can be explored for patterns and tested for similarities and differences amongst cluster groupings (Hagenauer & Helbich, 2013). *K*-means clustering is one example of a clustering algorithm, which can be used to gain knowledge about visitor travel patterns in PPAs (Theodoridis, Pikrakis, Koutroumbas, & Cavouras, 2010).

K-means was developed by MacQueen (1967) and later improved by Hartigan and Wong (1979). The *k*-means clustering algorithm is an iterative process that divides observable continuous data into *k* clusters in which clusters maximize similarity within, and maximize differences between (Rendón, Abundez, Arizmendi, & Quiroz, 2011). A primary advantage of *k*-means is its simplicity and speed that makes it capable of processing large data sets, such as GPS data (Nath et al., 2010). Furthermore, clustering has proven to be a valid technique for understanding travel patterns (Grinberger, Shoval, & McKercher, 2014; Izakian, Pedrycz, & Jamal, 2012). *K*-means clustering has been used to identify spatial patterns of pedestrian-involved crashes (Kim & Yamashita, 2005), understand daily travel patterns of humans (Jiang, Ferreira, & González, 2012), and identify transit riders' travel patterns (Ma, Wu, Wang, Chen, & Liu, 2013). *K*-means clustering can also be used to cluster data using spatiotemporal variables of PPA visitors (Kidd et al., 2018).

A disadvantage of *k*-means clustering is that the number of clusters must be specified before the algorithm is applied, which is typically identified through an iterative process (Pham, Dimov, & Nguyen, 2005). *K*-means clustering is possible with spatiotemporal data, because they are not latent variables. Determining the appropriate number of clusters involves a combination of trial-and-error and data validation techniques (Pham et al., 2005). Within SPSS (Statistical Package for Social Sciences) the *k*-means output provides an analysis of variance *F* statistic to assess the subjective input (Kim & Yamashita, 2005). It is also recommended that internal validation indices be used when a pre-specified cluster cannot be initially identified. Dunn's index and Silhouette index can be used to check for internal validation, which assess inter-cluster distances and intra-cluster distances (Dunn, 1973). Lastly, it is recommended that *k*-means groupings should be checked by a team of experts who are familiar with the data by double-checking various cluster arrangements to validate optimal number of data groupings.

Geovisualizations

Geovisualizations are the display of geographically referenced spatiotemporal data (MacEachren, Wachowicz, Edsall, & Haug, 1999). Geovisualizations aid in the identification of spatiotemporal patterns and relationships within a geographic context (Kwan & Lee, 2004). Geovisualizations of visitor travel patterns within PPAs have been criticized for being limited to density displays (Beeco & Hallo, 2014). Density displays show where visitors concentrate (Riungu et al., 2018). However, it can be cumbersome to infer meaning from 'density' in these displays, which in geographic terms is equal to ‘parts per area’ (Downs, 2010). This can be problematic for applied research in PPAs because intuitive and useable information should be provided for managers.

3D geovisualizations are a powerful tool to help understand travel patterns because they are capable of showing important and intuitive spatiotemporal characteristics, such as time allocation patterns and driving speed patterns (Kwan & Lee, 2004). 3D geovisualizations allow for in-depth exploration of spatiotemporal data by the researcher because these displays are interactive (Herman, Popelka, & Hejlova, 2017). Kwan and Lee (2004) showed the utility of geovisualizations for understanding human activity patterns, and the authors noted that 3D geovisualizations provide a dynamic and interactive environment that include several useful navigational capabilities, such as 3D fly-throughs and dynamic rotations, which cannot be conducted with 2D density displays. Within ArcGIS, 3D geovisualizations can be constructed using the 3D viewing application known as ArcScene along with 3D Analyst (Herman et al., 2017). However, intuitive 3D geovisualizations of visitor travel patterns have not been widely produced for managers of PPAs.

Study Objectives

The purpose and research questions of this study were designed to address knowledge gaps in the literature: manager knowledge has not been systematically incorporated when investigating visitor travel patterns, this knowledge has not been used to cluster the data into groupings for further analyses, and geovisualizations have not been commonly constructed for transmission of intuitive information for PPA managers. Therefore, the purpose of this study is to advance understanding of visitor travel patterns using contextual knowledge and contextual information of a park setting. The study site for this research is Theodore Roosevelt National Park in North Dakota. The findings of this study can assist managers with further understanding of visitor travel patterns. Specifically, the following questions guided this research:

1.) What variables do managers identify as the most important to understand visitor travel patterns?
2.) How well do these variables produce distinct travel pattern clusters?
3.) How do travel patterns vary amongst cluster groups?
4.) How can visualizations be advanced for management and planning purposes?

Methods

Study Area

Theodore Roosevelt National Park (THRO) is located in western North Dakota, and is known for its unique badlands landscape, and abundance of wildlife. THRO is home to a variety of animals including: bison, mule deer, white-tailed deer, elk, feral horses, pronghorn, coyotes, bobcats, badgers, beavers, porcupines, prairie dogs, golden eagles, a variety of birds, and a variety of snakes (National Park Service, 2019). In 2019, THRO received 691,658 visitors (National Park Service, 2020).

THRO is comprised of three units totaling more than 70,000 acres: South Unit (46,158 acres), North Unit (24,070 acres), and Elkhorn Ranch Unit (218 acres) (National Park Service, 2019). The South Unit gets the most visitation because it is located adjacent to a major travel corridor (Interstate 94), and is situated next to the town of Medora which offers restaurants, museums, shops, and hotels (National Park Service, 2019). This research focused on the South Unit because of its popularity.

The South Unit features a 36 mile scenic loop drive, side roads to explore, hiking trails, National Park Service ranger-led activities, camping, a visitor center, and opportunities for wildlife viewing (National Park Service, 2019). The speed limit of the scenic loop drive is 35 mph. To enter the South Unit, visitors must drive through an entrance fee gate (visitors exit the same way they entered) where they receive a National Park Service map (Figure 1). The popular scenic loop can be driven in either direction; visitors can either turn right or left onto the scenic loop. Recently, THRO management has posed concerns about high visitation rates and visitors concentrating at the South Unit.

Procedure Overview

To address the research questions, the researcher distributed GPS data loggers to visitors of the South Unit, identified travel pattern variables most important to THRO managers, performed data clustering, conducted spatiotemporal analyses, and constructed geovisualizations.

GPS Data Loggers

The researcher used a random probability sampling procedure to intercept day visitors for distributing GPS data loggers. This procedure was stratified across time of day, day of the week, and season (Vaske, 2008). The researcher distributed GPS data loggers to one visitor per travel party (e.g., a family) at the entrance gate of the South Unit. The GPS data logger used for this study was the Canmore GT-740FL Sport. White, Brownlee, Furman, and Beeco (2012) compared the Canmore GT-740FL to three other GPS data loggers, and determined the Canmore unit achieved the highest accuracy, durability, and ease of use compared to the other loggers tested (Garmin Oregon 600, GlobalSat DG-100, and GlobalSat DG-200). The Canmore GT-740FL has extended battery capabilities, is approximately 2.5 x 1.3 centimeters, and is equipped with a power button but no LCD interface, which prevents visitors from accidently tampering with the device. The GPS data loggers were configured to record a waypoint in decimal degrees and a timestamp at 15-second intervals. The 15-second interval has proven useful in past research tracking pedestrians (e.g., walkers, hikers, runners) (Beeco & Hallo, 2014). The Canmore GPS data loggers must be analyzed retroactively, preventing the researcher from evaluating visitor travel patterns in real-time. This was communicated to visitors at the intercept location as an assurance of privacy. Visitors returned the data loggers as they exited THRO at the gate.

The researcher imported raw GPS data from the data loggers into MS Excel to perform initial cleaning. The data was then imported into R version 3.4.3 for analytical configuration and to construct point shape files projected to Universal Transverse Mercator (UTM) Zone 13N. The point shapefiles were then uploaded, organized, and further cleaned in ArcGIS 10.6.1, and ArcCatalog was used for organization. Five primary cleaning considerations were implemented: 1) raw GPS data were inspected for 15-second intervals for all consecutive waypoints, 2) mapped waypoint data were visually inspected if consecutive waypoints appeared congruous with a 15-second interval, 3) visual identification to confirm that the waypoints were consistent with human behavior, 4) mapped line data were visually inspected for routes incongruous with human behavior, and 5) physical feasibility if humans would be at that location (Beeco, Hallo, English, & Giumetti, 2013).

Identification of Spatiotemporal Travel Pattern Variables

The spatiotemporal variables most important to THRO managers were identified in two steps: 1) semi-structured interviews with THRO managers, and 2) quantitative questionnaires with the same managers. The researcher used nonprobability purposive sampling to locate THRO managers for data collection. A script for the semi-structured interviews was developed for managers to identify important travel pattern variables. This script included numerous spatial, temporal, and spatiotemporal travel pattern variables identified by the literature. The script was reviewed by a team of researchers (n=3) familiar with the park context and visitor travel pattern research. This step ensured the script was effective for managers to identify important travel pattern variables. The researcher conducted semi-structured phone interviews during September of 2019 (n = 5; $M_{minutes}$ = 15). The interviews included all permanent managers who have multiyear experience at THRO. Interviews were concise to identify important travel pattern variables. They were audio-recorded and standard coding procedures outlined by Saldaña (2012) were used to identify common responses (Burla et al., 2008).

Using the results of the semi-structured interviews, the researcher constructed a quantitative questionnaire to understand the level of importance of the identified travel pattern variables. Variables were assessed using a five-point Likert-type scale (1 = ‘not important at all’; 5 = ‘extremely important’) and rank order of importance (i.e., most important, 2nd important). The quantitative questionnaires were distributed through email using Qualtrics Survey Software (Qualtrics, 2014). Scores on questionnaire items were aggregated to identify the spatiotemporal variables most important to THRO managers to understand visitor travel patterns. Managers identified three spatiotemporal variables: total time at attraction areas, total time spent at the visitor center, and total spent in the South Unit. The spatiotemporal variables identified by THRO managers were then calculated for each travel party, and correlations were conducted to check for relatedness of these variables.

Data Clustering

Data clustering of visitor-based GPS data was conducted in SPSS version 24.0 using the *k*-means clustering algorithm. The spatiotemporal variables identified by THRO managers to be the most important for understanding visitor travel patterns were calculated for each travel party and entered into the *k*-means algorithm. *K*-means clustering algorithm has been commonly used to segment large data sets and performs well with observable continuous variables (Bishop, 2009; Duda, Hart, & Stork, 2001; Wu et al., 2008). Validation techniques were used to identify the optimal number of clusters: iterative trial-and-error, statistical output, Dunn's index, Silhouette index, and validation by a team of experts. This phase identified a cluster membership for each travel party.

Spatiotemporal Analyses

Cluster membership was used to segment the point shapefiles into travel groups, and these were subsequently organized in ArcCatalog 10.6.1. Each travel group's point shapefiles were merged together in ArcMap 10.6.1. Next, the researcher assessed variations in each group's spatiotemporal travel patterns. Continuous spatiotemporal variables were compared amongst groups using a One-Way ANOVA with a Bonferroni Post Hoc test. Dichotomous, proportion-based, spatiotemporal variables were compared using a chi-square test.

In addition to the manager-identified variables, the researcher analyzed each groups' travel patterns to determine other spatiotemporal variables of interest within the context of the South Unit. The researcher determined that it was important to analyze trail-use because time at attraction areas statistically differed amongst groups. To understand these differences the researcher analyzed each groups' trail use, because most attraction areas have hiking trails. The researcher also chose to analyze visitor travel patterns along the scenic loop drive, because of its popularity. Characteristics of the scenic loop drive were analyzed by comparing the following dichotomous variables across cluster groups: percent of group members that drove the entire loop, percent of group members that turned right onto the scenic loop, and percent of group members that turned left onto the scenic loop.

Geovisualizations

To construct 3D geovisualizations for THRO managers, the researcher used ArcMap and ArcScene 10.6.1. In ArcMap a digital grid was constructed, which requires input of a THRO perimeter shapefile and a grid cell size. The researcher constructed the perimeter shapefile by using ArcMap's aerial imagery. An appropriate grid cell size was determined using the 'Calculate Distance Band from Neighbor Count' tool, which assesses proximity of all neighboring waypoints. The output of this tool provides three pieces of information: the furthest distance between neighboring waypoints, the least distance between neighboring waypoints, and the average distance between neighboring waypoints. The researcher calculated this for each travel group, and compared the furthest distance between neighboring waypoints. The smallest finding of this measure for the three groups was used for the grid cell size. The grid was then constructed using the 'Grid Index Features' tool in which the grid cell size was inputted along with a perimeter shapefile of THRO. The resulting grid was then spatially joined to the merged point shape files for each travel group, and three new shapefiles were produced. Next, the researcher used the 'Summarize' tool to aggregate attribute counts found within each grid cell, which was done for each of the travel groups. 3D features were then constructed using the 'Feature To 3D By Attribute' tool. The resulting shapefiles were then opened in ArcScene and geovisualizations were constructed.

Results

GPS data loggers were distributed to 265 travel parties, yielding a 93.97% response rate and achieving a 4.62% confidence interval. The researcher assessed GPS data for error using cleaning procedures stated in the methods, and found all GPS data fit for analysis. The sampling stratification procedures, high response rate, and low confidence interval suggest that the resulting sample is robust and appropriately represents the visiting population to the South Unit of THRO. On average, visitors traveled within the South Unit for 158.78 minutes (2 hours and 38.78 minutes). Approximately 42% of visitors stopped at the visitor center for 10.20 minutes or longer. Approximately 50% of visitors hiked 0.52 miles or further.

Travel Pattern Variables & Clustering – Research Questions 1 & 2

The researcher identified six important travel pattern variables by conducting semi-structured interviews with THRO managers: total time at attraction areas, total time spent at the visitor center, total time spent within the South Unit, time entered the South Unit, total time on roads vs. trails, and vehicle speed patterns. The quantitative questionnaires identified the variables that were the most important: total time at attraction areas, total time spent at the visitor center, and total time spent within the South Unit. Using a map directly adopted from the National Park Service (Figure 1), the researcher defined attraction areas as any location referenced on the map, such as Prairie Dog Town and Buck Hill. The researcher operationalized a stop (e.g., at attraction areas and the visitor center) when the visitors' speed dropped below 2mph (8.05 km/h), and the duration of time the speed was below 2mph spanned longer than 2 minutes (Ferrante et al., 2016).

The researcher then calculated total time at attraction areas, total time spent at the visitor center, and total time spent within the South Unit for all travel parties. Using SPSS, the researcher checked for variable relatedness with a correlation test, which showed correlations to range from 0.14-0.66. The highest correlation was between total time spent at the visitor center and total time spent within the South Unit.

The researcher segmented the sample population using *k*-means clustering. Total time at attraction areas, total time at the visitor center, and total time spent in the South Unit were entered into the *k*-means clustering algorithm. The clustering outcome was statistically significant, internal validity was checked, and the team of researchers agreed on cluster results. These results showed that the manager-identified variables produced distinct travel pattern clusters.

The *k*-means algorithm segmented the data into three groups. The three groups of data represented: a ‘Low’ group (*n*=154), a ‘Medium’ group (*n*=88), and a ‘High’ group (*n*=23). The ‘Low’ group totaled 133,684 waypoints (40.99% of the sample), the ‘Medium’ group totaled 140,147 waypoints (42.97% of the sample), and the ‘High’ group totaled 52,289 waypoints (16.03% of the sample). The number of waypoints for each group is dependent on the number of members per each group. The entire sample population resulted in 326,120 waypoints. The ‘Low’ group spent the least amount of time at attraction areas, at the visitor center, and within the South Unit. The ‘High’ group spent the most amount of time at these locations.

Spatiotemporal Analyses of Travel Patterns Groupings – Research Question 3

The *k*-means groups of Low, Medium, and High established by the manager identified variables showed similar trends of low, medium, and high magnitudes for the researcher identified variables in Table 1. The groups’ data were statistically compared and found to be different for all variables in Table 1. This reveals that a variety of spatiotemporal behaviors are exhibited at THRO, otherwise statistical differences would not have resulted. The data also showed that the Low group spends the least time at attraction areas (*M*=9.67 minutes), spends the least time hiking trails (*M*=5.92 minutes), and spends the least time at the visitor center (*M*=5.21 minutes). In contrast, the High group spends the most time at attraction areas (*M*=61.96 minutes), spends the most time hiking (*M*=90.17 minutes), and spends the most time at the visitor center (*M*=27.35

minutes). An interesting finding was that the High group spends the most time on trails, but doesn't hike far (*M*=2.2 miles).

Table 2 shows analysis of the scenic loop drive. The results revealed that that there was not a significant association between cluster group and: if the entire loop was driven, and what direction was turned onto the scenic loop. Most visitors drove the scenic loop (85.70%), and the majority of visitors turned right onto the scenic loop (70.10%). Therefore, group membership is not an indicator of scenic loop driving characteristics.

To further understand this data, the number of members per each group should be taken into consideration. The Low group had the most members (*n*=154). Therefore, the Low group could be used to characterize the typical visitor to the South Unit, and on average spends: 9.67 minutes at attraction areas, 5.21 minutes at the visitor center, 108.14 minutes within the South Unit, and 5.92 minutes on trails. The Medium group (*n*=88), which did not have as many members as the Low group, should also be noted to understand common travel pattern behaviors at THRO. The Medium group on average spent 28.15 minutes at attraction areas, 14.43 minutes at the visitor center, 200.41 minutes within the South Unit, and 35.42 minutes on trails. The High group (*n*=23) had the least amount of members, and thus the travel pattern behaviors exhibited by this group may depict atypical behaviors of visitors to the South Unit.

The results related to research question 3, "how do travel patterns vary amongst cluster groups?" showed that travel groups exhibited different travel patterns. The results also showed that the manager-identified variables formed distinct cluster groupings, and the results of clustering showed trends that were observed in other spatiotemporal variables. Therefore, the primary finding of this research question is that a variety of travel patterns are exhibited by visitors to the South Unit.

Geovisualizations – Research Question 4

To construct the geovisualizations a digital grid was constructed in which a grid cell size needed to be specified. A grid cell size of 61.42 meters^2 (0.93 acres) was determined using the 'Calculate Distance Band from Neighbor Count' tool. Using the grid, 3D geovisualizations were created for each group that displays time allocation (Figure 2), and average speed (Figure 3). These figures do not include a base map, because they are dynamic 3D geovisualizations that can be virtually rotated in all directions, but for manuscript purposes these maps are displayed as 2D. A geovisualization of speed was necessary because of the popularity of driving the scenic loop. These geovisualizations intuitively show areas where visitors spend most of their time, and areas where visitors are driving at high speeds. Within the South Unit the maximum speed limit is 35 mph (56.33 km/h). The average speed geovisualizations identify areas where visitors drove faster than the speed limit.

The geovisualizations provide intuitive information for managers. The height of the columns are proportional to the magnitude of the data for percent of time spent and average speed exhibited at the South Unit. The time allocation maps show that the following park locations are popular: the visitor center, Wind Canyon Trail, Buck Hill, Coal Vein Trail, and North Dakota Badlands Overlook. Is not surprising that visitors spent the highest percentage of their time at the visitor center.

The average speed maps show large variations in speed. These maps can be used to identify where visitors were hiking (i.e., speeds < 5.0mph), and areas where speeds exceeded the driving speed limit. The High group exceeds the driving speed limit the least.

The researcher conducted dynamic definition queries in ArcScene to understand areas where average speeds were greater than 35mph between: 10:00am – 11:00am, 11:00am – 12:00pm, 12:00pm – 1:00pm, and 1:00pm – 2:00pm (Figure 4). These maps serve as an example of the capability of these visualizations to further understand visitor travel patterns. Other definition queries are useful such as to understand where visitors are concentrated the most during peak visitation hours.

Discussion

The purpose of this study was to advance understanding of visitor travel patterns using a hybrid approach that included contextual knowledge and contextual information of the park setting. This was accomplished by identifying which spatiotemporal travel pattern variables were the most important to managers for understanding visitor travel patterns, determining how well management selected variables produce distinct clusters, determining how much travel patterns vary across cluster groupings, and advancing intuitive geovisualization displays. The South Unit of THRO proved to be a good study site for the purposes stated, because visitors exhibited a variety of travel patterns, the distribution and collection of GPS data loggers was easy at the entrance/exit gate, and managers were willing to participate in the interviews and questionnaires. Additionally, the methods demonstrated in this study are transferable to other PPAs.

The results revealed which variables managers at THRO thought were most important towards understanding visitor travel patterns: total time at attraction areas, total time at the visitor center, and total time spent in the South Unit. These variables produced distinct travel pattern groups in which the trends of those groups extended to other spatiotemporal variables identified for analysis by the researcher. This analysis showed that travel patterns vary greatly at the South Unit.

It is a significant finding that THRO managers determined three temporal variables as the most important for understanding visitor travel patterns. In a study that analyzed tourists' time-space consumption it was found that time was more valuable of a resource than space (Grinberger et al., 2014). In the state of knowledge review about understanding visitors' spatial behavior, Riungu et al. (2018) explicitly acknowledged that the temporal component has not received as much research attention in regards to visitor travel patterns. Additionally, Fennel (1996) found that the longer a group of tourists stay in an area, the greater the implications to that area. This study with THRO managers suggests that the temporal component might be particularly important to managers, which may illuminate how managers evaluate park resources. Managers know the location of park resources, but need to understand how often to maintain resources, which is a function of time.

The approach used in this study is a relevant research advancement because visitor travel patterns have largely been studied from the researcher perspective instead of incorporating contextual knowledge of managers. Any analysis of humans is innately complex, including human travel patterns. This complexity should not be underestimated, and to gain richer insight, contextual knowledge should be incorporated. To further advance research on human travel patterns it is necessary to incorporate multiple perspectives for a more robust approach, such as manager and researcher perspectives in conjunction with the exhibited travel pattern characteristics of visitors. Future research of visitor travel patterns could use multiple perspectives to gain a richer understanding, which can be used to understand how visitors budget limited resources of space and time.

A tripartite relationship exists between space, time, and visitor experiences. A similar tripartite relationship exists for managers. Managers regularly consider both space and time when making decisions regarding allocation of park resources. Thus decision-making of resource allocation is spatiotemporally-conditioned. Future research could aim to understand managers' valuation of the temporal and spatial components of visitor travel patterns, and how that information affects management decision-making. Furthermore, future research could investigate generalized trends of managers' perspectives of travel pattern variables, and how managers can use information about spatial variations of visitor travel patterns. This research used a digital grid analysis to understand spatial variation of visitor travel patterns. However, grid analysis requires simplification and a level of diminishment of actual events. Alternatives to understand spatial variations of visitor travel patterns may provide more effective information for managers.

An interesting finding of this study was that the majority of visitors turned right onto the scenic loop drive (70.10%). This has several management implications. The majority of visitors will be on the south side of the scenic loop earlier in the day, and later in the day the majority of visitors will be on the north side of the scenic loop. Managers may want to assess this further to determine educational strategies that will result in equal amounts of visitors turning both directions onto the scenic loop. This information can also help managers identify where to place future park amenities (e.g., restrooms). If more visitors are turning right, then it may be beneficial to put amenities on the north side of the loop for visitors who have been in the park for a longer duration. Future research could aim to understand why visitors choose to turn right or left onto the scenic loop.

Most visitors to the South Unit drove the scenic loop, stopped at attraction areas, and did a small amount of hiking. This could be the result of how the infrastructure is designed. Infrastructure influences visitor spatiotemporal behavior in national parks. Most likely travel patterns would be different if the infrastructure was different. Future research is needed to understand how infrastructure affects visitor travel patterns in PPAs. This information could help managers design infrastructure that maximize quality visitor experiences while conserving the biophysical resource. In the future, when infrastructure updates are needed, managers will understand relationships between visitor travel patterns and park infrastructure.

Limitations

Limitations of this study are that GPS data loggers possibly influenced visitor behavior, one GPS data logger was distributed to each travel party, and only five managers were interviewed and surveyed. Although the GPS data loggers were small, they could have potentially influenced behavior, because visitors were aware that they were participating in research. Additionally, only one GPS data logger was distributed to each travel party. This assumes that everyone within a travel party goes to the same locations. It is possible that individuals of the same travel party may separate within the park, such as to hike or relax at a vista. Lastly, the sample size of managers was small. This sample included all the managers who are permanent and have multiyear experience at THRO.

Conclusions

The managers at THRO identified three temporal variables as being the most important towards understanding visitor travel patterns: total time at attraction areas, total time at the visitor center, and total time within the South Unit. Three travel groups were found at THRO: Low, Medium, and High. Each group exhibited different travel patterns for total time at attraction areas, total time at the visitor center, total time at the visitor center, total distance hiked on trails, and total time spent on trails. This research also found that travel group membership did not influence driving characteristics of the scenic driving loop.

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Tables

Table 1. *Analysis of spatiotemporal variables.*

Spatiotemporal Variable	Low Group (n=154) M (SD)	Medium Group (n=88) M (SD)	High Group (n=23) M (SD)	All Groups (n=265) M (SD)	F
Manager Identified Variables					
Total time attraction areas (mins)	9.67 (11.21)	28.15 (19.85)	61.96 (48.46)	20.34 (25.22)	40.28**
Total time visitor center (mins)	5.21 (10.61)	14.43 (19.96)^{a}	27.35 (24.66)	10.20 (17.01)^{a}	15.17**
Total time South Unit (mins)	108.14 (32.53)	200.41 (33.88)	338.52 (56.62)	158.78 (78.40)	115.74**
Researcher Identified Variables					
Distance on trails (miles)	0.13 (0.33)	0.80 (1.26)^{a}	2.20 (2.27)	0.53 (1.17)^{a}	26.59**
Time spent on trails (mins)	5.92 (13.83)	35.42 (40.77)	90.17 (54.72)	23.03 (39.03)	44.33**

Note. Superscripts within a row indicate groups are not statistically different; F = F-value; $^{**}p < .001$.

Table 2. *Analysis of scenic driving loop.*

Variable	Low Group (n=154)	Medium Group (n=88)	High Group (n=23)	All (n=265)	χ^2, p
Percent that drove entire loop	81.20	93.20	87.00	85.70	6.61, 0.09
Percent that turned right onto loop	73.40	65.50	66.70	70.10	1.75, 0.63
Percent that turned left onto loop	26.60	34.50	33.30	29.90	1.75, 0.63

Note. Degrees of freedom = 3; χ^2 = chi-square.

Figures

Figure 1. Map of THRO South Unit adapted directly from the National Park Service (National Park Service, 2019)

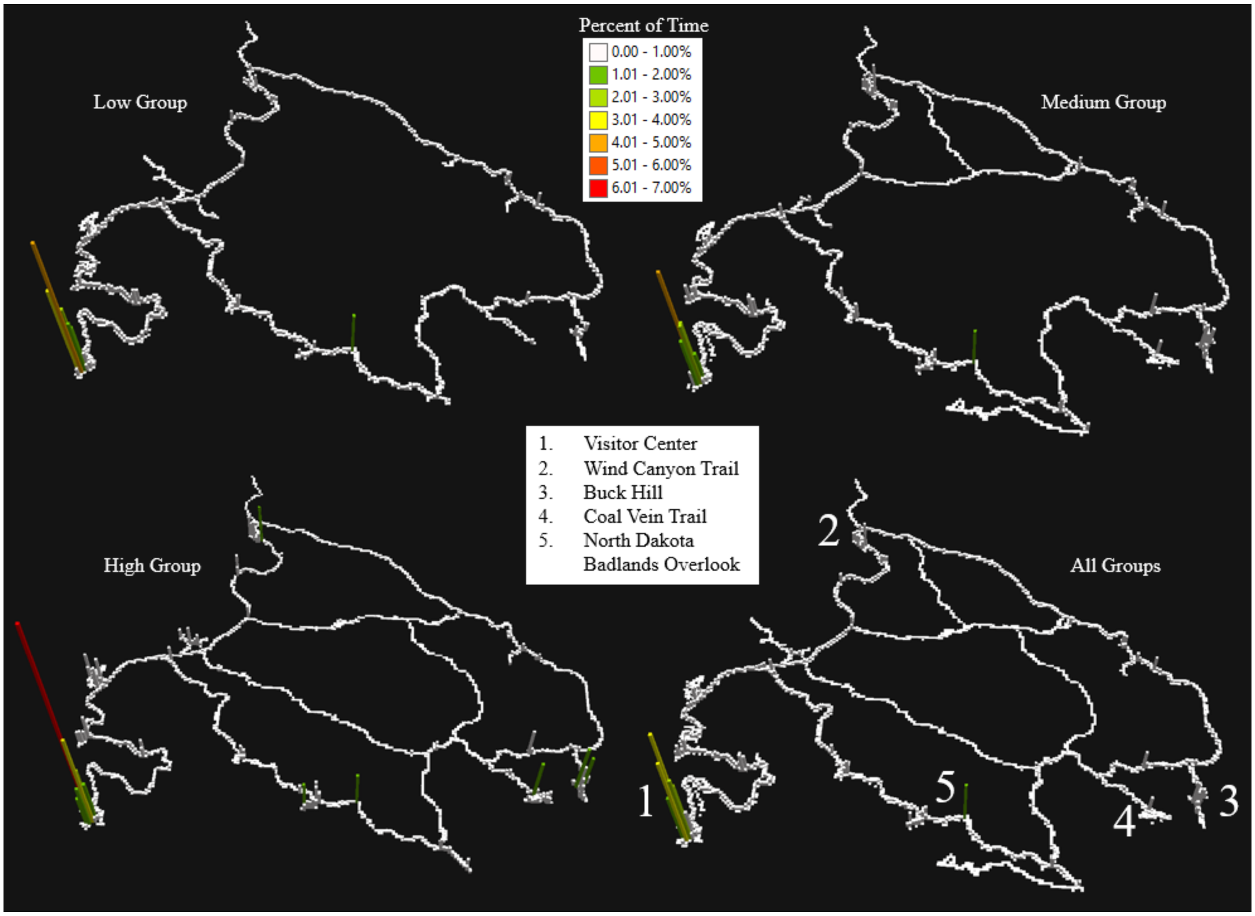

Figure 2. Geovisualization of each groups' percent time allocation.

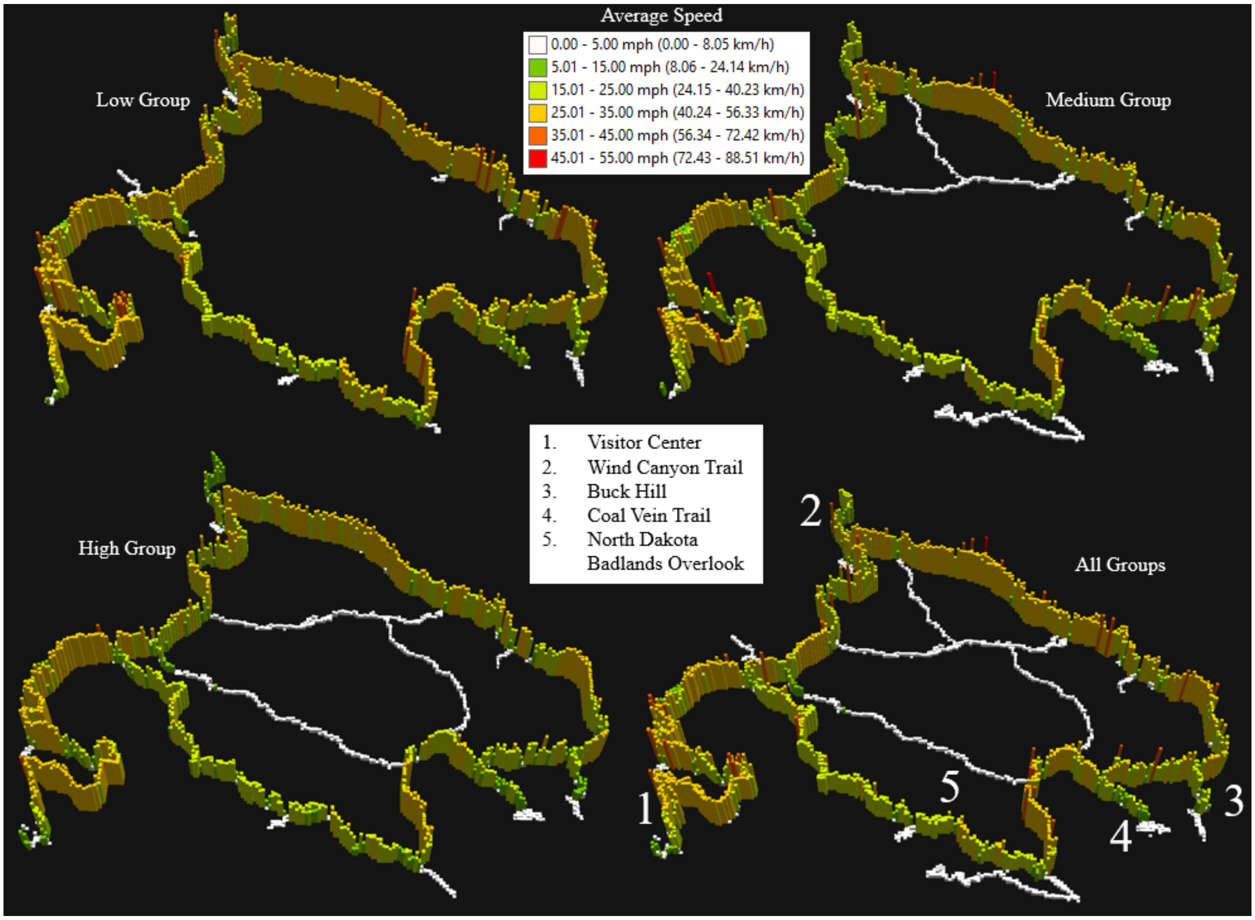

Figure 3. Geovisualization of each groups' average speed.

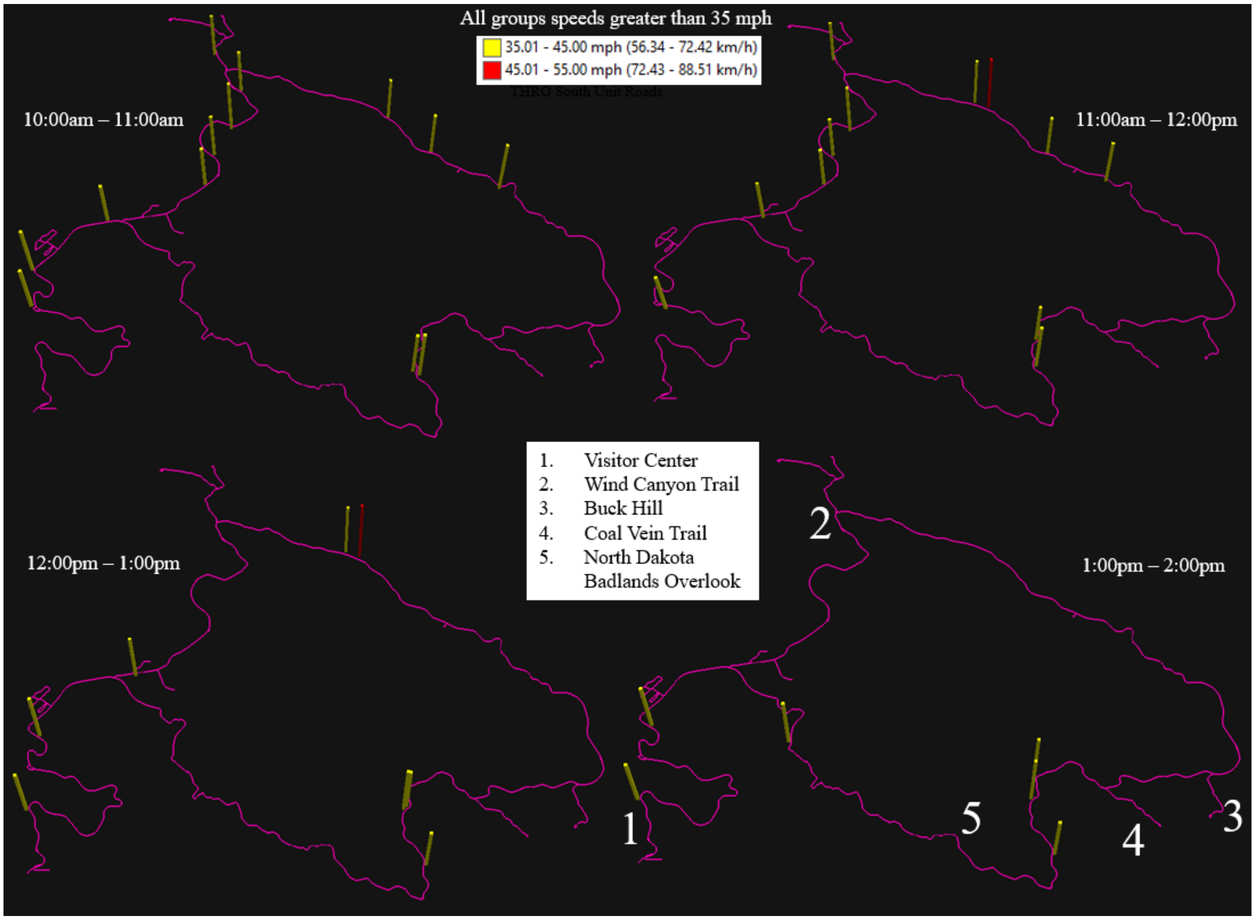

Figure 4. Hourly geovisualization of where all groups drive faster than 35mph.

CHAPTER THREE

SPATIOTEMPORAL ANALYSIS TO IDENTIFY AIR TOUR TRAVEL PATTERNS AT HAWAI’I VOLCANOES NATIONAL PARK

Abstract

Air tour travel patterns, such as sight-seeing helicopter experiences, above parks and protected areas have proven difficult to research and for managers to understand. Although recent technology makes it possible to collect accurate air tour data, researchers have generally not quantified air tour travel patterns across a protected area. This information is important for managers to plan with air tour operators to ensure visitor experiences are not being compromised. Therefore, the purpose of this study was to quantify air tour travel patterns at Hawai'i Volcanoes National Park using data derived from Automatic Dependent Surveillance-Broadcast (ADS-B). The researcher used this data to construct and analyze a digital grid while employing hot spot clustering to identify spaces with a high volume of air tours. Some of these spaces overlap with terrestrial visitor attraction locations, suggesting potential conflict between air tours and terrestrial visitors. Specifically, results indicate that Nāpau Trailhead and Nāpau Crater receive a high volume of air tours and that spatial clustering of tours varies across hours of the day. The described methods provide a useful foundation for future research.

Introduction

Understanding visitors' travel patterns in parks and protected areas (PPAs) is important for several reasons. First, travel patterns provide managers with critical information about visitors' behaviors (Hallo et al., 2012). Second, travel patterns are an omnipresent and inescapable aspect of the visitor experience because people always occupy a specific space at a specific time (Hägerstrand, 1970). Finally, since space (spatial component) and time (temporal component) are connected and ubiquitous, the visitor experience is a spatiotemporally-conditioned process. These basic tenets of travel patterns also apply to visitors experiencing PPAs via air tours.

Air tours refer to low flying air traffic, such as helicopters that are specifically touring above PPAs for sightseeing purposes. The National Parks Overflight Act of 1987 and the National Parks Air Tour Management Act of 2000 are evidence that the National Park Service is committed to managing air tours over NPS sites (Beeco & Joyce, 2019). This commitment is important because noise impacts (such as those from air tours) have shown to affect the quality of the visitor experience and ecological systems (Dumyahn & Pijanowski, 2011; Pilcher, Newman, & Manning, 2008). In the United States, laws and policies have recognized natural sounds as a resource that needs to be protected (Miller, 2008). Thus, understanding air tour travel patterns are important for managing visitor experiences that are free of anthropogenic sounds (Marin, Newman, Manning, Vaske, & Stack, 2011).

Air tour information can help managers make important decisions to ensure quality visitor experiences for both terrestrial visitors and air tour visitors (Newton, Newman, Taff, D'Antonio, & Monz, 2017). This information can help managers: collaborate with officials involved with transportation, wildlife, law enforcement, and adjacent communities; reduce visitor conflict within park boundaries; and understand when and where soundscapes are possibly being compromised due to air tour noise (Beeco & Joyce, 2019). However, understanding air tour travel patterns has proven difficult.

In the past it has been difficult for researchers to collect accurate and precise location data of air tours over PPAs. According to Beeco and Joyce (2019), prior studies have relied on mailed paper maps to air tour operators, and general observations by park staff to gain a better understanding of air tour travel patterns. A newer technology, Automatic Dependent Surveillance-Broadcast (ADS-B), provides exact information of air tours, including latitude, longitude, time stamp, and unique identification code (Beeco & Joyce, 2019). Using GIS (Geographic Information Systems), ADS-B data can be analyzed like GPS (Global Positioning System) data to determine air tour travel patterns. Information about air tour travel patterns can be used by managers for planning purposes, such as with the Federal Aviation Administration (FAA), and to understand where and when air tour noise may possibly be compromising the experience of terrestrial visitors (Beeco & Joyce, 2019).

However, managers lack information about air tour travel patterns (Beeco & Joyce, 2019). The purpose of this study is to address this gap by: a) quantifying hourly and daily air tours, b) determining areas of intense clustering of air tours, and c) identifying specific terrestrial attraction areas most affected by air tours. This study demonstrates analysis of air tours over Hawai'i Volcanoes National Park (HAVO) using ADS-B location data.

Literature Review

Air Tours

During 2018, the United States National Park Service (NPS) reported that 54 units received a total of 47,145 air tours (National Park Service, 2018). The United States Title 14 Code of Federal Regulations defines air tours as an airplane or helicopter used for sightseeing (Ballard, Beaty, & Baker, 2013). The NPS is legally required to manage air tours over parks, which first began with the National Parks Overflight Act of 1987 (Beeco, Joyce, & Anderson, article production in process, hereinafter referred to as 'Beeco et al., 2020'). Additionally, the NPS is charged with providing public enjoyment while preserving cultural and natural resources (Miller, Fefer, Kraja, Lash, & Freimund, 2017). Similar to visitors who drive or hike into a national park, visitors who take an air tour over a national park are also looking for a quality experience (McNicol & Rettie, 2018).

It is important for managers to understand relationships between air tours and quality experiences of terrestrial visitors (Mace, Bell, Loomis, & Haas, 2003). One reason is the noise of air tours can compromise the natural soundscape (Beeco et al., 2020). A compromised soundscape has been shown to have adverse effects on visitors (McDonald, Baumgarten, & Iachan, 1995). Additionally, air tours can affect terrestrial visitors in a variety of ways, including the sight of too many air tours (Miller, 2008).

In February of 2014, the NPS released an Environmental Assessment of HAVO (National Park Service, 2014). This document detailed an evaluation of HAVO's soundscape in terms of air tour noise (National Park Service, 2014). It was documented that visitors found it unacceptable to hear an air tour once every 15 minutes or more often (Lawson et al., 2007). Additionally, other aspects of air tours may affect experiences of terrestrial visitors, such as number of air tours seen at one time (Tarrant, Haas, & Manfredo, 1995). Air tours may also impact aspects of the biophysical resource, such as wildlife (Shannon et al., 2016). Therefore, it is important for managers to be familiar with precise and accurate air tour travel pattern information.

Until recently, managing air tours has been challenging because there has not been a valid method for collecting precise and accurate air tour data (Beeco & Joyce, 2019). Past studies have relied on mailing paper maps to air tour operators, and generalized information from park personnel (Beeco & Lignell, 2019). However, these techniques are not exact, and have been shown to vary by as much as several miles (Beeco & Joyce, 2019). Although these techniques were effective for managers to begin understanding air tour travel patterns, managers have not benefited from accurate and precise objective data. This information can help managers to understand relationships between terrestrial visitors and air tour visitors, and to provide quality visitor experiences.

Tracking Air Tours using ADS-B Data

A newer technology called ADS-B can be used for tracking air tours (Beeco et al., 2020). ADS-B is an air tour's signal that is broadcasted for monitoring purposes, which is intended to improve airspace safety and improve air traffic efficiency (FAA, 2018).

Broadcasted ADS-B data is unencrypted, publicly accessible, and can be gathered using a data logger that records ADS-B signals (Beeco & Joyce, 2019). ADS-B data loggers can record latitude, longitude, time stamp, and unique identification code. Beginning January 1st of 2020, the United States FAA requires all aircraft that enters designated airspace to have ADS-B technology (see 14 CFR § 91.225 and 14 CFR § 91.227).

ADS-B data can be collected via a radio signal, and therefore ADS-B data loggers should be located with an expansive skyward exposure. Data logger components include antennas, software, display screen, USB dongle, 5V AC-DC regulator, 50' AC power cable, thermal transfer pads, and a shielded aluminum enclosure (see Beeco & Joyce, 2019 for a review of these components). Research conducted by Beeco and Joyce (2019) validated that ADS-B data can be analyzed like GPS data, and is viable for understanding air tour travel patterns over national parks. One primary drawback of the ADS-B data logger is that it may not identify all air tours depending on geographic areas (Beeco & Joyce, 2019). The requirements for aircraft to be equipped with ADS-B depends on the airspace designation (see Beeco & Joyce, 2019 for a detailed description).

Visitor Travel Patterns

Space and time are limited resources, which affects how humans travel (Hägerstrand, 1970). Accordingly visitors must make decisions of where to visit, when, and for how long. Thus, visitation within PPAs is spatiotemporally-conditioned. The spatiotemporal characteristics of visitors' routes is referred to as visitor travel patterns (Beeco & Hallo, 2014). Understanding visitor travel patterns helps managers identify where and when visitor experiences are occurring. Additionally, managers can use this information to identify if travel patterns of different types of visitors are coinciding, and if this is potentially problematic. Therefore, it is important for managers to understand visitor travel patterns spatially and temporally of both terrestrial visitors and air tour visitors (Riungu et al., 2018).

Prior studies have analyzed visitor travel patterns using GPS data, and have documented many analytical strategies and techniques (Riungu et al., 2018). However, the spatial component of visitor travel patterns has received more research attention than the temporal component. One strategy to more fully incorporate the temporal component is to segment location data temporally for analytical purposes (Birenboim, Anton-Clavé, Russo, & Shoval, 2013). Spatial variations can then be analyzed using the temporally segmented data. For example, Kim et al. (2019) segmented visitor travel data hourly and seasonally to spatiotemporally understand activity hot spots. This information can help managers understand where visitors travel dependent on the temporal component (e.g., summer at 10:00am) (Kim et al., 2019). However, temporally segmented data has not been analyzed for air tour travel patterns using accurate and precise data, such as ADS-B data.

GIS

GIS is an extensive toolset that can be used to analyze geographic data, such as GPS and ADS-B data (Allen, 2016). ArcGIS is an example of a GIS software package, and includes ArcMap and ArcCatalog. ArcMap can be used to analyze geospatial data, while ArcCatalog can be used to organize data (Allen, 2016). ArcMap features a spatial statistics toolbox that has tools to conduct inferential statistics. One example is the Hot

Spot Analysis (Getis-Ord Gi*; hereinafter referred to as Gi*) tool, which identifies statistically significant clustering of point data (Getis & Ord 1992). This tool has been used: to identify locations of high-impact automobile accidents in Houston, Texas (Songchitruksa & Zeng, 2010); to determine ambulance standby points using historical emergency data in Minhang District of Shanghai in China (Yi, Xu, Song, & Wang, 2019); and to conduct spatiotemporal analysis of lightning distribution in Golden Gate Highlands National Park in South Africa (Mofokeng, Adelabu, Adepoju, & Adam, 2019). The Gi* tool is suitable to understand spatial variations of ADS-B data.

Another effective technique to analyze spatial variations is to construct a digital grid (Liu, Yan, Wang, Yang, & Wu, 2017). A grid can be used in conjunction with the Gi* tool to identify spatial variations of travel patterns. For example, Clevenger, Sinha, & Howe (2018) used a grid and the Gi* tool to assess physical activity of students during recess at an elementary school in Ohio. Additionally, Kim et al. (2018) showed that visitor travel patterns can be analyzed hourly and seasonally using a grid and the Gi* tool to understand spatiotemporal variations of visitors within Seoraksan National Park in South Korea. These studies validate that temporally segmented location data can be analyzed using a grid and the Gi* tool. Therefore, this type of analysis can be conducted using ADS-B data. However, ADS-B data has not been analyzed using a grid and the Gi* tool.

Study Objectives

The researcher conducted this study at Hawai'i Volcanoes National Park (HAVO).

The purpose and research questions of this study addressed knowledge gaps in the literature: air tour ADS-B data has not been analyzed for spatial variations of temporally segmented data, nor has this data been analyzed using a grid analysis and the Gi* tool, nor has this information been connected to terrestrial visitor attraction areas to determine which attraction areas are potentially affected the most by air tours. Therefore, the purpose of this study was threefold, to: 1) provide spatiotemporal information about air tour travel patterns across hour of the day and day of the week; 2) determine which terrestrial visitor attraction areas are potentially affected the most by air tours; and 3) assess if a spatial grid analysis advances understanding of air tour travel patterns. This study benefits managers by detailing air tour travel patterns, identifying when and where potential conflicts could occur between air tour visitors and terrestrial visitors, and reporting usable information that can be used for managing and planning of air tours. This study advanced research by using ADS-B data to conduct statistical analyses in which spatial variations of temporally segmented data were analyzed, and by statistically identifying terrestrial areas to monitor. Specifically, the following research questions guided this research:

At HAVO,

1. How do flight patterns differ across hour of the day, day of the week, and areas of the park?
2. What are the spatiotemporal relationships between flight patterns and terrestrial visitor attraction areas?

2. How does the process of spatial grid analysis advance our understanding of air tour travel patterns, and what are the drawbacks of the application?

Methods

Study Area

The study site, Hawai'i Volcanoes National Park (HAVO), is located on the island of Hawai'i (Figure 1). HAVO is comprised of 333,000 acres, has over 136 miles of hiking trails, and has two active volcanoes (Kīlauea and Mauna Loa) (Lawson et al., 2007). Kīlauea is located on the southeastern flank of Mauna Loa, and appears as a slight bulge at an elevation of 4,091ft. Kīlauea is its own volcano and last erupted in 2018 (National Park Service, 2019a). Mauna Loa rises 13,100ft above sea level and is the largest active volcano on the planet. Mauna Loa last erupted in 1984 (United States Geological Survey, 2019). The combination of adjacent volcanoes, and Kīlauea's recent eruption, makes HAVO a popular destination for air tours.

Procedure Overview

To address the research questions, the researcher used a terrestrial data logger to collect ADS-B air tour signals, prepared and organized the data for analysis, conducted spatial descriptive analysis, constructed a grid, assessed spatial variations of temporally segmented data using the Gi* tool, and determined which terrestrial attraction areas were the most affected by air tours.

Data Collection and Preparation

The ADS-B data was collected using a terrestrial data logger that was located approximately one mile to the north of Kīlauea Caldera (latitude 19.421, longitude -155.288) and positioned with an unimpeded and expansive skyward exposure. The terrestrial data logger recorded the ADS-B signals as text files. The researcher imported the text files into ArcMap 10.6.1, and merged data into a single point shapefile. The researcher then projected the shapefile to Universal Transverse Mercator (UTM) Zone 5N. This resulted in nearly 2.3 million waypoints because the data logger recorded hundreds of waypoints per minute per air tour. Air tours were identified by their unique identification code.

The researcher then exported the point shapefile's attribute table and imported it into MS Excel. Using MS Excel, the researcher reduced the data so that each flight had one waypoint per minute for the purpose of assessing where air tours were hovering over HAVO. A similar technique was conducted by Beeco et al. (2013) to reduce 1.5 million waypoints using a five-minute interval for automobile GPS data. The researcher then imported the reduced data back into ArcMap, and data cleaning was conducted using similar techniques as Beeco & Joyce (2019), and Beeco, Hallo, English, & Giumetti (2013). To prevent inclusion of commercial air traffic, ADS-B data above 15,000 feet elevation were not included. Using ArcMap, the researcher assessed all flights for one waypoint within half a mile of the park boundary. If this inclusion criteria was met, then all waypoints were clipped that were beyond five miles of the park boundary. This resulted in 1,576 air tours analyzed.

Descriptive Statistics

The researcher used the single shapefile to conduct spatial descriptive analysis to determine mean center point, median center point, one standard deviational circle around the mean center point, and kernel density. The researcher then segmented the data into two groupings: 'Weekdays' and 'Weekends and Holidays', and determined the average number of hourly flights and associated standard deviations. Independent samples *t*-tests were conducted to compare hourly flights between Weekdays and Weekend and Holidays. Within each grouping of data, the research compared number of flights per hour using a One-Way ANOVA with a Bonferroni Post Hoc test.

Analysis for Research Question 1

To assess spatial variations of temporally segmented data, the researcher constructed a digital grid in ArcMap, and then conducted clustering analyses using the Gi* tool. (Nam, Hyun, Kim, Ahn, & Jayakrishnan, 2016). The researcher designated a grid cell size of 0.5mi^2 because this space was determined the distance that air tour noise likely affects conversation of terrestrial visitors. Speech interference between people (e.g., an interpretive terrestrial tour) begins at approximately 50dBA (Lam, Ng, Hui, & Chan, 2005). An EC130 helicopter (considered quiet technology) produces 58.7dBA at a distance of 2,000ft (0.38mi) in overflight mode (flying in a straight line). This means that a helicopter that doesn't have quiet technology will likely disrupt terrestrial conversations at a distance of approximately half a mile. Therefore, a half mile grid cell is valid to understand what areas in HAVO are possibly compromised by air tour noise.

The researcher constructed the grid in ArcMap using the 'Grid Index Features' tool. This tool requires designating a grid cell size and a perimeter polygon of the area to be analyzed. The researcher inputted a perimeter polygon of HAVO which was downloaded from a National Park Service geospatial data website (National Park Service, 2019c). The resulting grid was then spatially joined to two shapefiles: Weekday waypoints, and Weekend and Holidays waypoints. The spatially joined grids were then temporally segmented by hour producing several hourly grids for Weekdays and for Weekends and Holidays. The researcher then used the Gi* tool to identify grid cells that had statistically significant clustering for the temporally segmented data to determine areas most affected by air tours (Kim et al., 2019; Kim et al., 2018). The Gi* tool accounts for the spatial structure of the data, and assesses each grid cell's attribute value (i.e., number of waypoints) in relation to neighboring cells, and geographically displays areas of high and low clustering, along with associated *p*-values and *Z*-scores (Peeters et al., 2015). The *Z*-scores produced by the Gi* tool can be used to assess the intensity of data clustering (Kim & Choi, 2017). Higher values of *Z*-scores signify more intense clustering.

Analysis for Research Question 2

The researcher assessed areas that had statistically significant clustering for proximally located terrestrial attraction sites. GPS coordinates of attraction sites were determined from HAVO's website (National Park Service, 2019). Using ArcMap, the researcher constructed a half-mile buffer around each terrestrial attraction site. The results of the Gi* tool were overlaid with the buffers of the attraction sites to determine which attraction areas spatially intersected with grid cells that had statistically significant clustering. The researcher used *Z*-scores of the Gi* tool to assess clustering intensity of air tours by hour for Weekdays and Weekend and Holidays. Attraction areas that intersected with multiple statistically significant clustering grid cells, were designated an aggregate *Z*-score for all intersecting grid cells. This process was repeated for each hour of analysis for Weekdays and Weekends and Holidays. The researcher used this information to assess air tour clustering intensity over attraction areas.

Results

Descriptive Statistics

The data logger recorded air tour signals from June 25^{th}, 2019 to September10^{th}, 2019. The researcher analyzed a total of 33 Weekdays, and 22 days that were Weekends and Holidays (holidays being July 4^{th} and Labor Day). The data logger failed to record a unique air tour identifier for all flights for some of the dates. The researcher did not include these dates in analysis. On average, between the hours of 7:00am – 7:00pm, there were 33.97 air tours per day for Weekdays, and 31.45 air tours per day for Weekends and Holidays. The researcher conducted spatial descriptive analysis and determined that the mean center point of all waypoints was 19.40774, -155.241942 decimal degrees, and the median center point was 19.39462, -155.236274 decimal degrees. A kernel density display was constructed for all waypoints and shows high density of air tours near Nāpau Trailhead, Nāpau Crater, and Kīlauea Caldera (Figure 2, Figure 3).

Research Question 1

Research question 1 asked, how do flight patterns differ across hour of the day, day of the week, and areas of the park? Table 1 displays hourly data for Weekdays data. Table 2 displays hourly data for Weekend and Holidays. Hourly statistical comparisons were made using a One-Way ANOVA with a Bonferroni Post Hoc test. For Weekdays, air tours between 3:00pm - 4:00pm (M = 2.09) were the most similar to other hours, and air tours between 5:00pm – 6:00pm (M = 0.32) and 6:00pm – 7:00pm (M = 0.35) were the least similar to other hours (Table 1). For Weekends and Holidays, air tours between 2:00pm - 3:00pm (M = 3.09) were the most similar to other hours, and air tours between 6:00pm – 7:00pm (M = 0.14) were the least similar to other hours (Table 2). Table 3 shows the average number of hourly air tours. The researcher compared the number of hourly flights between Weekdays and Weekends and Holidays using independent samples t-tests. No differences were detected between the two groups for number of flights per hour.

To assess how flight patterns differed across areas of the park, the researcher used a grid and the Gi* tool to analyze clustering for each hour from 7:00am - 7:00pm for Weekdays, and Weekends and Holidays. The researcher included in this manuscript the results from the Gi* tool for: 1) 9:00am – 10:00am; 2) 10:00am – 11:00am; 3) 11:00am – 12:00pm; and 4) 12:00pm – 1:00pm. Figure 4 displays the results for Weekdays, and Figure 5 displays the results for Weekdays and Holidays. The two figures show grid cells highlighted in red and orange. Red grid cells represent statistical clustering at the 99% confidence level, and the orange grid cells represent statistical clustering at the 95% confidence level. Both figures document that air tours are primarily occurring over the west side of the park forming similarly looking arcs of hot spot clustering, regardless of the hour of day. These figures show where high intensity of clustering of air tours is occurring over HAVO.

Research Question 2

The purpose of Research Question 2 was to determine which visitor attraction areas have the highest clustering intensity of air tours (what are the spatiotemporal relationships between flight patterns and terrestrial visitor attraction areas?). To answer the question objectively, the researcher used the outputted *Z*-scores from the Gi* tool and aggregated them across the hours of 7:00am – 7:00pm (see Table 4). *Z*-scores were only assessed if statistically significant air tour clustering occurred over the attraction area. *Z*-scores are a measure of standard deviations and high *Z*-scores signify intense clustering of grid cells with similar levels of air tours (Prasannakumar, Vijith, Charutha, & Geetha, 2011). Two attraction areas had high clustering intensity of air tours: Nāpau Trailhead and Nāpau Crater. For Weekdays, Nāpau Trailhead had the highest clustering intensity from 12:00pm – 1:00pm, and Nāpau Crater had the highest clustering intensity from 4:00pm – 5:00pm. For Weekends and Holidays, Nāpau Trailhead had the highest clustering intensity from 9:00am – 10:00am, and Nāpau Crater had the highest clustering intensity from 6:00pm – 7:00pm. The researcher conducted further analysis to determine if the Kīlauea Caldera was attracting air tours because the volcano recently stopped erupting in 2018. It was found that the Kīlauea Caldera was indeed attracting air tours, however there are still park closures in this area due to the eruption events of 2018 (National Park Service, 2019a).

Research Question 3

Research Question 3 was: "How does the process of spatial grid analysis advance our understanding of air tour travel patterns, and what are the drawbacks of the application?” The grid enabled the researcher to conduct statistical analyses using the Gi* tool, which outputs *p*-values and *Z*-scores that can be used to understand clustering intensity of air tours. However, the grid analysis does have a drawback because it simplifies the data. In this analysis a grid cell size of 0.5mi^2 was used. This means that all waypoints that occur within that grid cell are counted, and it doesn’t matter if waypoints are homogeneously or heterogeneously spread within the grid cell. Therefore, determining the size of the grid cell is a significant methodological step.

Determining the appropriate grid cell size remains controversial because it is typically a decision that requires consideration of the context (Nam et al., 2016). The larger the grid cell, the more potential simplification, although a larger grid cell might be necessary to understand spatial variations depending on context. The researcher decided to use a 0.5mi^2 grid cell because air tour noise impacts typically occur within a half mile distance. Grid cell size can also be calculated using the data, such as calculating a distance measure of all neighboring waypoints. For the purposes of this research, the grid was effective because it enabled the researcher to draw the conclusion that the Nāpau Trailhead and Nāpau Crater attraction areas were receiving the highest clustering intensity of air tours.

Discussion

The purpose of this study was to spatiotemporally quantify air tour travel patterns, determine which areas of HAVO are the most affected by air tours, and to assess the effectiveness of grid analysis in regards to understanding air tour travel patterns. HAVO proved to be a good study site because of the recent eruption of Kīlauea attracted visitors to take air tours; there was no shortage of air tour data for this site. Additionally, the methods demonstrated in this study are transferable to other types of PPAs.

The researcher found that not all flights recorded by the data logger had an associated unique flight identification. Beginning January 1st of 2020 air tours that fly over HAVO are mandated to have ADS-B technology. The data used in this study were collected between June 25th, 2019 – September 10th, 2019. Therefore it is possible that some air tours over HAVO were not equipped with ADS-B technology. This possible lack of ADS-B technology may explain why some of the flights did not receive a unique identification number. However, the waypoints of these flights were still recorded, which likely means these air tours were using ADS-B to transmit location signals. Knowing that waypoints were recorded, but unique flight identifications were not recorded may mean there was a technological issue with the data logger.

The data logger is still in a state of infancy as identified by Beeco and Joyce (2019). The researcher chose to exclude flights that had no identification because it was impossible to objectively determine how many different air tours the non-identified data recorded. The data was voluminous enough that this did not affect the results.

A primary purpose of this research was to identify which terrestrial attraction areas were the most affected by air tours. This is important information because terrestrial visitors may have their experience compromised due to air tour noise and/or number of flights seen from the ground (Lawson et al., 2007). The identification of these areas is necessary for future research and can be used to assess noise and number of air tours seen. Lawson et al. (2007) identified an air tour threshold in which terrestrial visitors had a diminished experience when they saw more than one flight per fifteen minute interval. Future research should assess Nāpau Trailhead and Nāpau Crater for these data: soundscape recordings and number and frequency of air tours seen. Although it conceptually appears that the data used in this study could be used to understand how many flights terrestrial visitors see, this is not the case. This type of measurement should be taken from the ground because there could be terrestrial limitations to seeing the sky, such as vegetation and topography.

The grid analysis conducted by the researcher is transportable to other types of PPAs, particularly those that lack visitor travel infrastructure (e.g., roads), such as marine or wilderness settings. In the past, to understand travel patterns a unit of analysis was needed, such as a trail or a road. However, infrastructure is not always present, such as with air tours above HAVO. Thus, a grid analysis is suitable for those types of settings. Conversely, grid analysis can also be conducted at PPAs that do have visitor travel infrastructure. For example, a grid cell size can be constructed to the width of a road or a trail. A grid analysis can be used in a wide range of PPA settings to understand spatial variations of location data. Future research should be aware of the advantages and limitations of grid analysis.

Table 4 shows *Z*-scores from the Gi* analysis. An interesting finding was that for Weekends and Holidays at the Nāpau Crater the highest *Z*-score was for the hour of 6:00pm – 7:00pm. This may seem surprising because not many flights occur at that hour, yet there was still intense flight clustering. This finding highlights the difference between lots of flights and intense clustering of flights. Even if there are not a high number of flights, the terrestrial visitor experience can still be compromised by hovering air tours. Therefore it is important to understand intense clustering of air tours and the numbers of hourly flights.

Interestingly, air tours did not exhibit flight patterns over Mauna Loa (elevation of 13,100ft.). Mauna Loa is the largest volcano on Earth, has erupted 33 times since 1832, last erupted in 1984, and is within the bounds of HAVO (Trusdell & Lockwood, 2019). The high elevation of Muana Loa is probably not conducive for air tours, because of the density of air being too thin. Although air tours probably did not visit Mauna Loa because of the high elevation, the researcher double-checked the data. As stated in the methods, the researcher cleaned the data as outlined by Beeco and Joyce (2019), which included clipping out all waypoints above 15,000ft to prevent inclusion of commercial flights. The researcher revisited the data before the 15,000ft data clip was conducted, and found that air tours did not visit Mauna Loa. This means that air tours probably avoid Mauna Loa because of its high elevation.

Despite that air tours probably don't fly at high elevations, this research may have benefited from an analysis of air tour elevation. Air tours that hover at a higher elevation above terrestrial attraction sites may not be heard as loudly from the ground. However, the researcher chose not to do that type of analysis for two reasons. First, the primary purpose of this study was to quantify hourly air tours above HAVO to provide information for managers for planning purposes. Second, this research was not designed to understand the soundscape, but to provide information for future research that can be conducted by soundscape experts. Using an elevation analysis of air tours would not suffice to understand what noise levels are like on the ground. To understand noise levels on the ground, soundscape measurements would need to be taken. The information provided by this study identified which attraction sites future research should take noise measurements at.

Limitations

The primary limitations of this study occurred during research design conceptualization, data collection, and data management. The research design used a cautious approach to understand which terrestrial attraction sites were the most affected by air tours. This approach was devised as a beginning step towards understanding air tour travel patterns. Thus, the researcher did not consider air tour elevations for this study because this studied was designed to understand air tour travel patterns in relation to terrestrial attraction areas. The data logger was also a limitation. Beeco and Joyce (2019) tested the data logger, but it still may need revisions. For example, the researcher found that not all flights received a unique identification number.

Two limitations occurred with data management. The first being the ADS-B signals recorded by the data logger were reduced to a one-minute interval, which could have been too large of an interval. The other data management technique that is a limitation is the grid analysis. Designing the grid entails designating a grid cell size, which is a difficult decision because grid cell size is essentially an inclusion/exclusion criteria that is dependent on context of the study site. The researcher understands the influence this decision has on further analyses: too small of a grid cell size may risk exclusion of data, and too large a grid cell size may risk inclusion of too much data.

These difficult decisions are predicated on the research questions and the context of the study site.

Conclusions

The researcher used ADS-B data to understand air tour travel patterns. The analytical techniques demonstrated in this research have high transferability to other types of visitor travel pattern data and at other types of PPAs. Additionally, techniques featured in this study are beneficial because inferential statistics were conducted to understand where and when attraction areas are most affected by air tours. These results are usable by managers for future planning efforts, and the methods are usable by researchers to further understand visitor travel patterns within all types of PPAs. The information produced by this study serves as a resource for future research aiming to connect relationships between air tour visitors and terrestrial visitors. Lastly, these methods advanced techniques to further understand visitor travel patterns by assessing for spatial variations.

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Tables

Table 1. *Weekday ANOVA results comparing across hours.*

Hour	**Number of Flights** *M* **(SD)**	**Hour Identifier**	**Hour means statistically different (*p*>.05)**
7:00am - 8:00am	3.50(1.96)	1	10, 11, 12
8:00am - 9:00am	2.29(1.77)	2	3, 11, 12
9:00am - 10:00am	5.32(3.71)	3	2, 8, 9, 10, 11, 12
10:00am - 11:00am	3.97(3.05)	4	10, 11, 12
11:00am - 12:00pm	4.15(2.89)	5	9, 10, 11, 12
12:00pm - 1:00pm	3.74(2.67)	6	10, 11, 12
1:00pm - 2:00pm	3.74(2.85)	7	10, 11, 12
2:00pm - 3:00pm	3.26(2.39)	8	3, 10, 11, 12
3:00pm - 4:00pm	2.09(1.99)	9	3, 5
4:00pm - 5:00pm	1.24(1.35)	10	1, 3, 4, 5, 6, 7, 8
5:00pm - 6:00pm	0.32(0.68)	11	1, 2, 3, 4, 5, 6, 7, 8
6:00pm - 7:00pm	0.35(0.69)	12	1, 2, 3, 4, 5, 6, 7, 8

Table 2. *Weekends and Holidays ANOVA results comparing across hours.*

Hour	**Number of Flights** ***M* (SD)**	**Hour Identifier**	**Hour means statistically different (*p*>.05)**
7:00am - 8:00am	3.23(1.95)	1	10, 11, 12
8:00am - 9:00am	2.14(1.25)	2	3, 4, 12
9:00am - 10:00am	4.77(2.37)	3	2, 7, 9, 10, 11, 12
10:00am - 11:00am	4.68(2.36)	4	2, 7, 9, 10, 11, 12
11:00am - 12:00pm	3.77(2.22)	5	9, 10, 11, 12
12:00pm - 1:00pm	3.68(1.89)	6	9, 10, 11, 12
1:00pm - 2:00pm	2.59(1.89)	7	3, 4, 11, 12
2:00pm - 3:00pm	3.09(2.47)	8	11, 12
3:00pm - 4:00pm	1.77(1.74)	9	3, 4, 5, 6
4:00pm - 5:00pm	1.32(1.29)	10	1, 3, 4, 5, 6
5:00pm - 6:00pm	0.27(0.46)	11	1, 3, 4, 5, 6, 7, 8
6:00pm - 7:00pm	0.14(0.35)	12	1, 2, 3, 4, 5, 6, 7, 8

Table 3. *Hourly HAVO air tours.*

Hour	**Weekdays** *M*(SD)	**Weekends and Holidays** *M*(SD)	***t*-value**
7:00am - 8:00am	3.50(1.96)	3.23(1.95)	0.51
8:00am - 9:00am	2.29(1.77)	2.14(1.25)	0.36
9:00am - 10:00am	5.32(3.71)	4.77(2.37)	0.68
10:00am - 11:00am	3.97(3.05)	4.68(2.36)	-0.93
11:00am - 12:00pm	4.15(2.89)	3.77(2.22)	0.52
12:00pm - 1:00pm	3.74(2.67)	3.68(1.89)	0.09
1:00pm - 2:00pm	3.74(2.85)	2.59(1.89)	1.80
2:00pm - 3:00pm	3.26(2.39)	3.09(2.47)	0.26
3:00pm - 4:00pm	2.09(1.99)	1.77(1.74)	0.61
4:00pm - 5:00pm	1.24(1.35)	1.32(1.29)	-0.23
5:00pm - 6:00pm	0.32(0.68)	0.27(0.46)	0.31
6:00pm - 7:00pm	0.35(0.69)	0.14(0.35)	1.55

Note. Hour of the day for Weekdays and, Weekends and Holidays, were compared using independent sample *t*-tests; no statistical significance was found; all hourly groups are similar.

Table 4. *Z-score analysis of areas most affected by air tours.*

	Weekdays *Z*-scores			Weekends and Holidays *Z*-scores		
Hour	Nāpau Trailhead	Nāpau Crater	Kīlauea Volcano	Nāpau Trailhead	Nāpau Crater	Kīlauea Volcano
7:00am-8:00am	3.37	6.28	7.48	15.91	4.12	15.91
8:00am-9:00am	8.27	8.27	5.46	12.79	5.39	9.10
9:00am-10:00am	15.17	5.89	5.17	18.75	4.05	11.78
10:00am-11:00am	6.23	9.68	2.78	6.17	4.59	3.02
11:00am-12:00pm	3.52	6.64	3.01	7.76	6.00	4.25
12:00pm-1:00pm	15.81	4.96	7.53	15.69	4.03	9.06
1:00pm-2:00pm	5.10	6.83	p>.05	5.11	6.40	3.80
2:00pm-3:00pm	4.63	7.80	3.84	13.46	4.07	5.11
3:00pm-4:00pm	2.07	9.59	p>.05	8.78	5.83	p>.05
4:00pm-5:00pm	p>.05	15.37	p>.05	4.46	4.46	p>.05
5:00pm-6:00pm	5.73	5.73	5.73	10.06	p>.05	10.06
6:00pm-7:00pm	13.00	6.43	13.00	p>.05	12.15	p>.05
Total	82.90	93.47	54.00	118.94	61.09	72.09

Note. If p>.05, then the *Z*-score was not used.

Figures

Figure 1. Hawai'i Volcanoes National Park boundary (ESRI basemap, 2019).

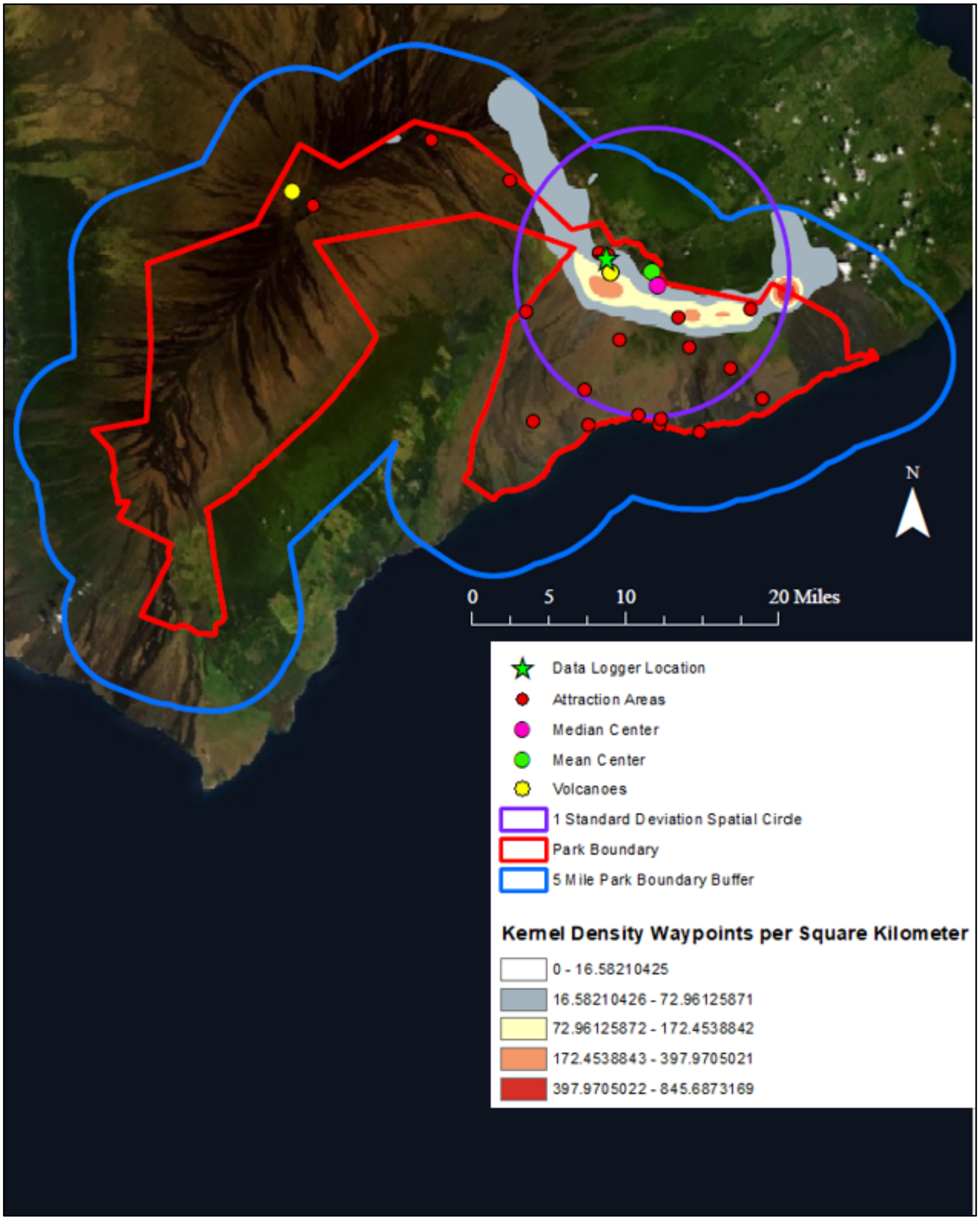

Figure 2. Spatial descriptives of air tours at HAVO (ESRI basemap, 2019).

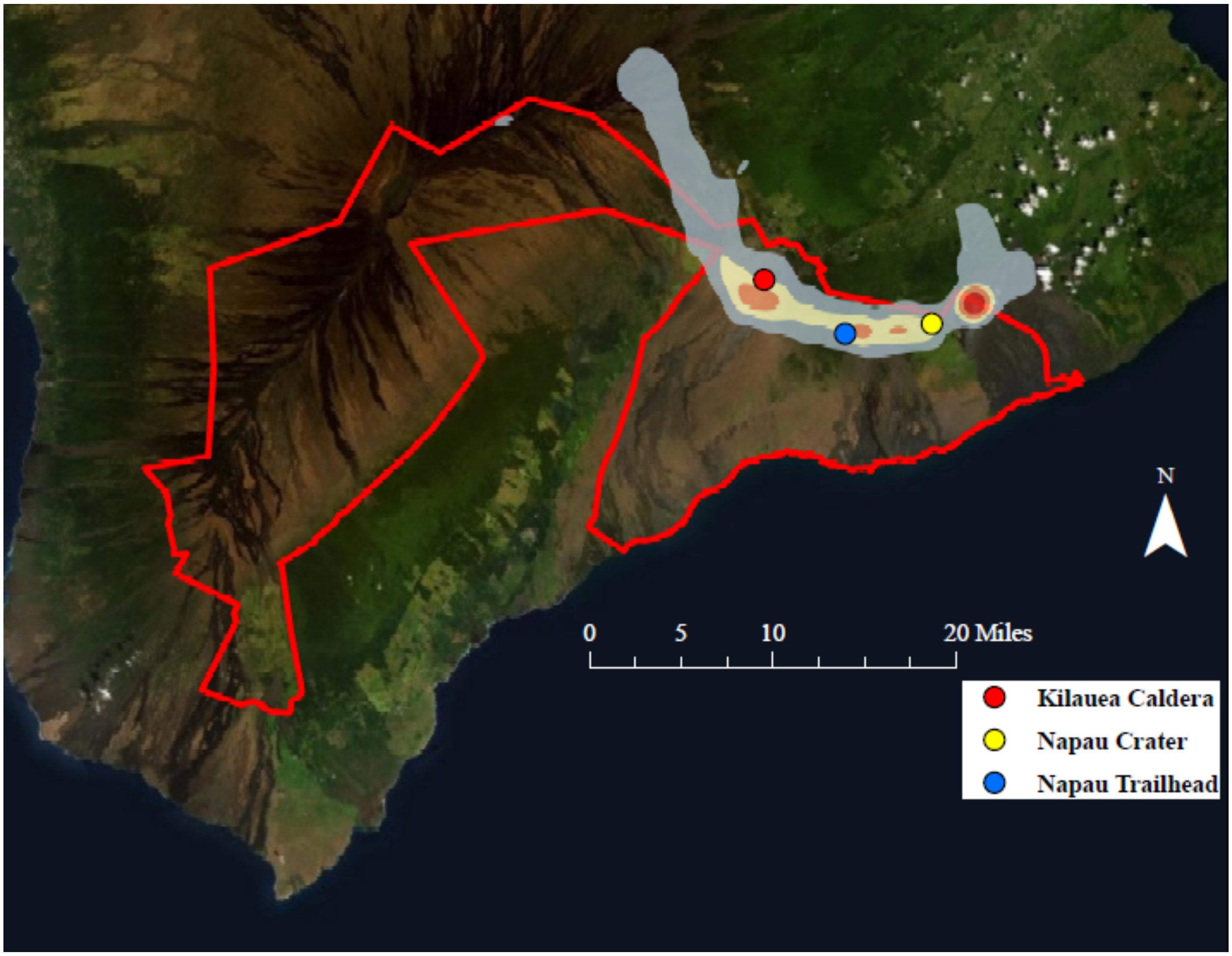

Figure 3. Locations of high clustering intensity of air tours (ESRI basemap, 2019).

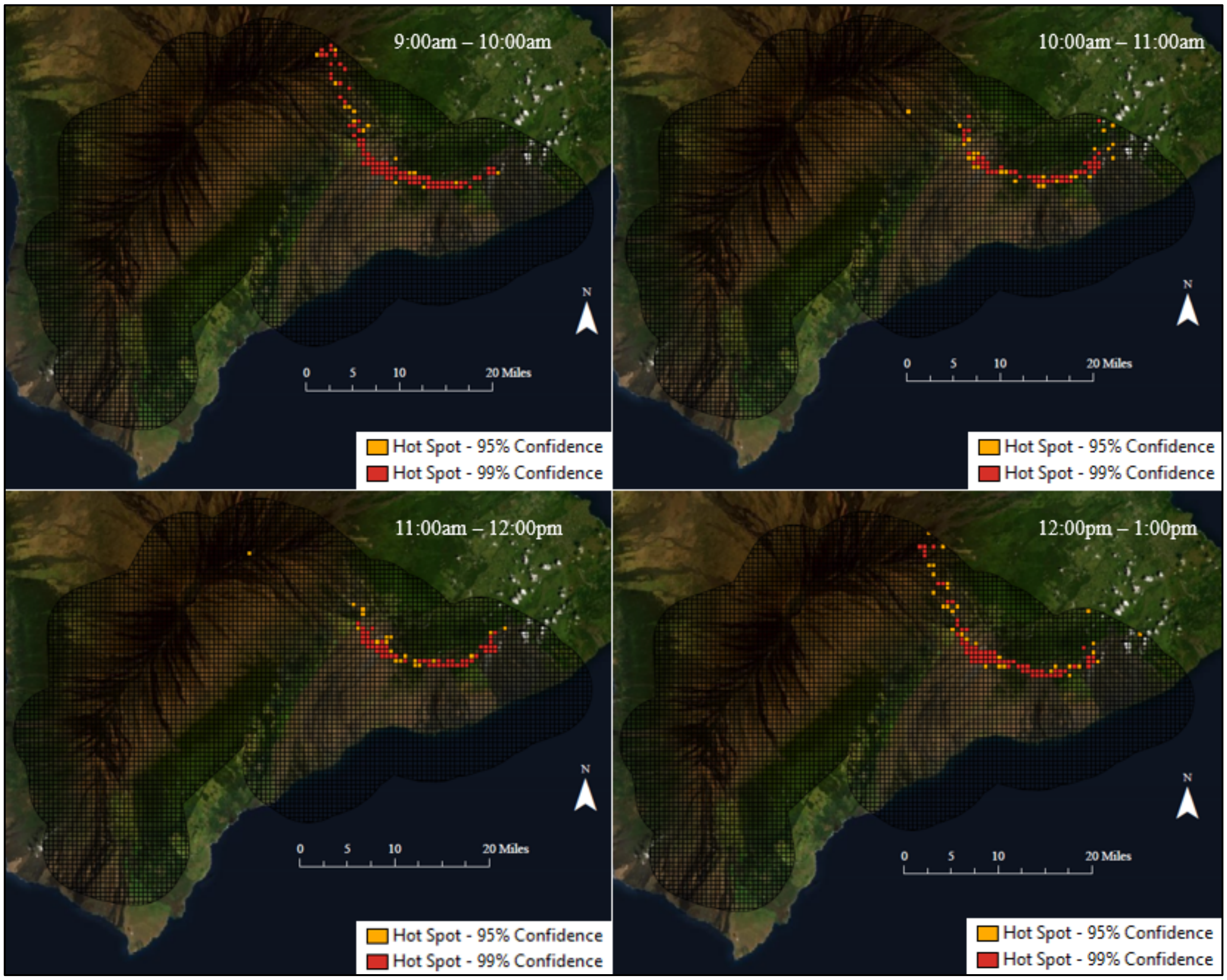

Figure 4. Gi* clustering analysis by hour for Weekdays (ESRI basemap, 2019).

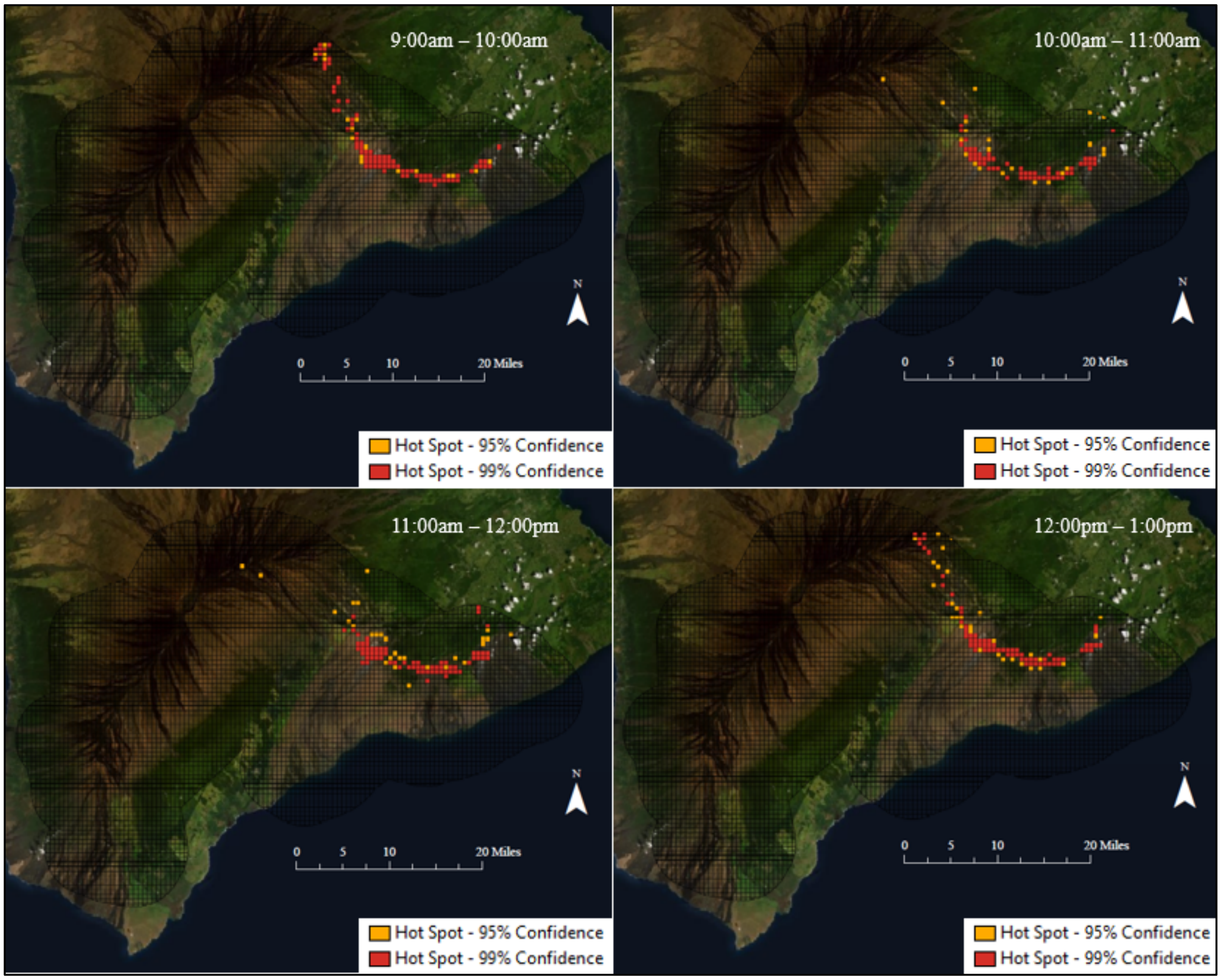

Figure 5. Gi* clustering analysis by hour for Weekends and Holidays (ESRI basemap, 2019).

CHAPTER FOUR

GRID ANALYSIS OF VISITOR TRAVEL PATTERNS IN A DISPERSED OUTDOOR RECREATION SETTING

Abstract

Understanding visitor travel patterns within parks and protected areas has continually been recognized as beneficial for managers. This information can identify high use areas and locations of potential conflicts. However, visitor travel patterns can be difficult to understand in parks and protected areas that lack organizational infrastructure, such as trails, roads, or signs (e.g., open deserts and marine environments). In this article, the author demonstrates a digital grid analysis of travel patterns at the Bonneville Salt Flats, which is a vast desert expanse where trails, roads, or wayfinding signs do not exist. Using Hot Spot Analysis, the researcher determined areas where high use and high vehicle speeds were coinciding, which informed a spatial grouping analysis to identify monitoring areas. The findings of this study demonstrate the utility of grid analysis for advancing understanding of visitor travel patterns and identifying areas to monitor in a dispersed recreation environment.

Introduction

Visitation to parks and protected areas continues to globally increase (Balmford et al., 2015). Visitation to the United States' National Parks was the highest it has ever been during the past four years (2016 = 330,971,689; 2017 = 330,882,751; 2018 = 318,211,833; 2019 = 327,516,619) (National Park Service, 2020). Others types of protected areas within the United States have also witnessed a substantial increase in visitation (Smith, Wilkins, & Leung, 2019). Although there are numerous positive benefits to this trend, problematic issues may arise, such as the diminishment of the visitor experience and potential conflict between visitors (Manning, 2011).

Visitor conflicts are potentially becoming more frequent because of increased demand for public resources within parks and protected areas (PPAs) (Stamberger, van Riper, Keller, Brownlee, & Rose, 2018). This places added pressure on public land managers to balance the conservation of biophysical resources and the visitor experience (Hammitt, Cole, & Monz, 2015). One type of conflict that could occur is visitor safety at high use areas, which could be mitigated by spatial zoning (Manning, 2011). For example, recreational lake boaters typically encounter low speed zones near the shore or in high traffic areas, which is intended to increase boater safety and reduce conflict.

The spatial element of visitor conflict is important because recreation in PPAs is a spatially conditioned process (Beeco & Brown, 2013). Space is an omnipresent aspect of the visitor experience and it continuously influences visitor travel patterns. Therefore, it is important for managers to understand how space affects the visitor experience (Stamberger et al., 2018). However, this is challenging when there are no organizing features at a PPA, such as roads, trails, wayfinding signs, or other visitor travel infrastructure.

Organizing infrastructure can help managers understand spatial variations of visitor travel patterns. However, open-dispersed recreation settings often lack organizing features, which provides challenges to understanding visitor travel patterns (Smallwood, Beckley, Moore, & Kobryn, 2011). An example is the Bonneville Salt Flats in Utah, which is a desert setting that has no roads, trails, wayfinding signs, or other infrastructure. At the Bonneville Salt Flats, visitors are permitted to freely explore with few managing limitations, including no vehicle speed limits. Additionally, the Salt Flats are comprised of a hard salt substrate that often prevents vehicle tracks from being visually apparent, and thus observing where other visitors explore is not easy. Consequently, it is difficult for managers to understand visitor travel patterns at the Salt Flats. The lack of infrastructure challenges managers' ability to objectively identify visitor use monitoring areas.

Using GPS (Global Positioning System) data and GIS (Geographic Information Systems) techniques it is possible to objectively identify areas to monitor, including PPAs that feature open-dispersed recreation that lack organizational infrastructure. GIS is an extensive toolset, including the automated ability to overlay data layers (e.g., topographic layers with GPS data), manipulate and manage spatial data, and conduct geospatial statistical analyses (Worboys & Duckham, 2004). GIS advancements have created a medium for researchers to combine multiple methods and techniques to efficiently gain a more comprehensive understanding of geospatial data (D'Antonio &

Monz, 2016). PPAs featuring open-dispersed recreation that lack organizational infrastructure can benefit from GIS analyses to objectively determine areas to monitor, such as areas where potential conflict could occur.

The study site for the investigation described in this paper was the Bonneville Salt Flats where the majority of visitors explore freely within cars. The management agency, Bureau of Land Management (BLM), dictates few rules and does not enforce a speed limit. Thus, visitors are at liberty to explore and drive as fast as they want. However, high use conditions sometimes exist and driving at high speeds may contribute to visitor conflict. Therefore, the purpose of this study was threefold, to: 1) analyze visitor travel patterns to identify potential areas of conflict between high use areas and areas where visitors are driving fast, 2) advance research methods associated with understanding visitor travel patterns, and 3) provide management recommendations for monitoring.

Literature Review

Visitor Travel Patterns

Traditionally, visitor travel patterns within PPAs are understood and influenced by organizing structures such as roads, trails, signs, or other infrastructure (Beeco, Hallo, English, & Giumetti, 2013). Organizing structures help managers and researchers understand visitor travel patterns. Dispersed recreation areas lack roads, trails, signs, and other infrastructure resulting in difficulty in understanding visitor travel patterns (Smallwood et al., 2011). An example of a dispersed recreation setting is large lakes where boating is common or vast desert expanses where vehicle use is unimpeded (Hunt, Morris, Drake, Buckley, & Johnson, 2019). Similar to other types of recreation environments, dispersed recreation settings have safety concerns, such as areas with high use and vehicles travelling fast. Yet, dispersed recreation settings have received less research attention regarding visitor travel patterns because it is more difficult to analyze travel patterns when there are no distinct spatial units of analysis, such as roads (Hunt et al., 2019). Therefore, a scarcity of knowledge exists about visitor travel patterns in PPAs that feature dispersed recreation and where there is limited organizational infrastructure.

Visitor Conflict

Preventing visitor conflict is an important task for managers (Wolf, Brown, Wohlfart, 2017). Conflict may potentially occur when there is goal interference between visitors (Manning, 2011). High use areas have shown more likelihood of conflict between visitors (Burns, Arnberger, & von Ruschkowski, 2014). Visitor conflict has also been found to increase in areas where visitors are driving at high speeds because perceptions of safety may be compromised (Hallo & Manning, 2009). Consequently, areas that have both high use and visitors driving at high speeds are important to identify for monitoring purposes.

One method for managing diverse recreational opportunities is by designing management zones in which certain recreation activities are assigned to specific areas (Manning, 2011). Zoning has proven to effectively mitigate visitor conflict (Cole & Hall, 2006). Zoning stems from the Recreation Opportunity Spectrum, which provides a framework for recreation opportunities where visitors can have various experiences within spatial zones, such as front-country versus backcountry settings (Clark & Stankey, 1979). Designing zones requires objective data and spatial data can help in this process (Beeco, Hallo, & Brownlee, 2014).

GPS and GIS

Advancements in GPS have enabled researchers to gather high-resolution and accurate data to better understand visitor travel patterns (D'Antonio & Monz, 2016). Furthermore GPS devices, such as GPS data loggers, have proven to be an effective tool for collecting spatial data in all types of recreational settings (D'Antonio et al., 2010). The primary strength of GPS data loggers is the proven accuracy for collecting localized data (Riungu et al., 2018). GPS data loggers are usually waterproof, record waypoints at regular intervals, and are easy to configure (Beeco & Hallo, 2014). GPS data loggers are small (about the size of a USB flash drive), automate GPS data collection, and these data can be used to gain insight into visitor travel patterns. Using GPS data loggers it is possible for researchers to understand where high use areas are located and understand spatial variations in speed (Bauder, 2015).

Advancements in geographic information systems (GIS) have resulted in improvements in analyzing GPS data (Beeco et al., 2013). GIS software packages (e.g., ArcGIS and R) have the ability to conduct descriptive calculations and also to conduct geospatial statistical analyses (Allen, 2016). GIS advancements allow for combining multiple methods and techniques to efficiently gain a comprehensive understanding of geospatial data (Kim et al., 2019). Using GPS data and GIS techniques, researchers can determine where specific conditions spatially overlap, such as high use areas and areas with high vehicle speeds. Additionally, combining GPS and GIS can be used to help managers accurately and precisely understand visitor travel patterns and identify monitoring areas.

Grid Analysis

Grid analysis has been used to understand spatial variations of travel patterns for a variety of research. For example, Kim et al. (2018) used a grid to understand seasonal and hourly visitor activity patterns at Seoraksan National Park in South Korea. Smallwood et al. (2011) used a grid to understand recreational use patterns in marine parks of Australia. Fjørtoft, Löfman, and Thorén (2010) used a grid to understand student activity during recess at a school in Norway. Grid analyses enable integrative and dynamic methods that are vital for understanding spatial variations and relationships (Zhao & Zhao, 2011). Using a GIS software package, such as ArcMap, a grid can be designed where each grid cell is characterized by conditions found within. Geospatial calculations can then be conducted for each grid cell (Clevenger et al., 2018).

For PPAs that lack organizational infrastructure, the grid cell can be used as the unit of analysis, along with the travel party, to gain insight into spatial variations of travel patterns (Dalton, Thompson, & Jin, 2010). Grid cells can be further analyzed using a tool that computes statistically significant clustering, such as the Getis-Ord Gi* tool. Kim et al. (2018) used a grid along with the Gi* tool to statistically understand seasonal and hourly visitor activity clustering. Additionally, results of clustering analysis can be inputted into spatial grouping analysis. This technique is valuable because multiple variables simultaneously can be assessed to identify areas of spatial overlap (Weerasinghe & Bandara, 2019). However, grid analysis has rarely been used for PPAs that lack organizational infrastructure. Therefore, using these techniques helps increase knowledge about spatial variations of visitor travel patterns and to identify areas to monitor.

Spatial Behavior

Spatial behavior refers to the behaviors visitors exhibit in PPAs, such as changing locations if high use is observed (Riungu et al., 2018). Technological advancements of GPS and GIS applications have increased knowledge about visitor spatial behavior in PPAs (Beeco & Brown, 2013). Using GPS and GIS applications, Taczanowska et al. (2014) found that a formal trail network has little influence on hikers' behavior; Kidd et al. (2015) found that different types of educational approaches to keep hikers on a trail had a range of effectiveness on behaviors; D'Antonio and Monz (2016) found that visitor dispersion may have an inverse relationship with concentration of visitor use in backcountry trail settings where the potential to distribute off-trail is available; and Korpilo, Virtanen, Saukkonen, and Lehvävirta (2018) found that activity type influences visitor spatial behavior when deciding to use formal trails or to explore off-trail. However, a literature gap exists regarding visitor spatial behavior in PPAs that lack organizational infrastructure.

Study Objectives

The purpose and research questions of this study were designed to address the knowledge gaps present in the research literature: little knowledge is known about visitor travel patterns in dispersed recreation settings, spatial grouping analysis has scarcely been used to identify monitoring areas, and visitor spatial behavior is not well understood in these types of settings.

Therefore, the purpose of this study is to understand spatial relationships of visitor travel patterns in a dispersed recreation setting that lacks organizational infrastructure. The study site for this research was the Bonneville Salt Flats (BSF) in Utah, which is a dispersed recreation PPA that lacks organizational infrastructure. This study can assist managers with information about zones to monitor and spatial behaviors exhibited by visitors. Specifically, the following research questions guided this research:

At BSF,

1.) What areas have intense clustering of waypoints?
2.) What areas have intense clustering of high vehicle speeds?
3.) How can this information be used to help managers design monitoring zones?
4.) What do the results reveal about visitors' spatial behavior in a PPA?

Methods

Study Area

The BSF, located at the western edge of Utah, is a dispersed recreation setting that lacks roads, trails, signs, or other infrastructure. It is managed by the Bureau of Land Management, and visitors are permitted to explore freely (Bowen et al., 2018). The BSF covers an area larger than $75km^2$ and is comprised of a perennial salt pan that is remnant of the Pleistocene Lake Bonneville (Bowen, Kipnis, & Pechmann, 2018). Visitors gain access into the BSF via a paved access road. Upon exiting the access road and entering the BSF, visitors find themselves in an expansive homogeneous flat landscape comprised of a hard salt substrate (Figure 1). The broad flatness of the landscape provides visitors an opportunity to see the curvature of the earth and to freely explore the vast landscape (Hogue, 2005). The primary type of recreation at the BSF is vehicular recreation.

The BSF is the location of the historic Bonneville Speedway that hosts annual events where enthusiasts attempt to set land-speed records in racing vehicles. The salt crust makes an ideal location to drive fast because vehicle tires stay cool on the salt and the flat terrain allows for linear driving without obstacles (Bowen et al., 2018). The racing events have witnessed vehicles travelling beyond 600mph (Red Bull, 2018).

The BSF is conducive for driving fast, not only for professional drivers, but also for visitors. There are no posted speed limits at the BSF. However, most of the year there is a shallow layer of water during which time vehicular recreation is not permitted. During summer months, surface water has typically evaporated, and visitors can drive fast while exploring the BSF. The research in this manuscript was part of a larger project that evaluated the rapidly changing biophysical resources and human uses of the BSF.

Procedure Overview

To address the stated research questions, the researcher conducted spatial analyses of data collected using GPS data loggers. A representative sample of BSF visitors was acquired using a stratified random probability sampling approach in which one person of at least 18 years of age from each travel party (i.e., a personal vehicle) was asked to carry a GPS data logger during their BSF visit. Sampling occurred in the summer of 2018 during peak visitation season with the exception that data was not collected during sanctioned vehicle racing events. Data collection was stratified by day of week, week of the season, and time of the day. This approach was conducive to capture typical visitation during non-racing peak season and to increase sample representativeness by ensuring all visitors had equal probability of being included in the study during the sampling period (Vaske, 2008).

GPS Data Loggers

GPS data loggers were distributed at an intercept location along the paved access road. The intercept location was intentionally positioned approximately three miles from the entrance to the BSF to decrease the potential of visitors altering their behavior due to direct observation by the researcher. At the intercept location, a research assistant distributed GPS data loggers, which were returned at the same site upon conclusion of the visit.

Numerous types of GPS data loggers have been used to collect spatiotemporal data of visitors to PPAs. The researcher chose to use the Canmore GT-740FL Sport because it achieved the highest accuracy, durability, and ease of use when compared to three other models (Garmin Oregon 600, GlobalSat DG-100, and GlobalSat DG-200) (White, Brownlee, Furman, & Beeco, 2012). Additionally, the Canmore GT-740FL has extended battery capabilities, lacks an LCD interface that could be accidentally engaged by research participants, and is relatively small (2.5 x 1.3 centimeters). These GPS data loggers have an internal memory that records data allowing for research analysis to occur retroactively; these units are not capable of real-time monitoring by the researcher. Like previous research, the GPS data loggers were configured to record a waypoint and time stamp at 15-second intervals (Beeco, Hallo, & Brownlee, 2014).

Data Cleaning and Configuring

The researcher exported data from the GPS data loggers and imported that data into

MS Excel for initial cleaning. The researcher then used R to configure files for analysis including designation of a speed attribute and to construct point shapefiles projected to Universal Transverse Mercator Zone 12N. The shapefiles were then uploaded, organized, and further cleaned in ArcGIS 10.6.1. The researcher used ArcMap to upload the shapefiles, and ArcCatalog for organizing shapefiles. Five primary cleaning considerations were implemented: 1) raw GPS data were inspected for 15-second intervals for all consecutive waypoints, 2) mapped waypoint data were visually inspected if consecutive waypoints appeared congruous with a 15-second interval, 3) visual identification to confirm that the waypoints were consistent with human behavior, 4) mapped line data were visually inspected for routes incongruous with human behavior and 5) physical feasibility if humans would be at that location (Beeco, Hallo, English, & Giumetti, 2013).

In ArcMap the researcher constructed a half mile buffer around the access road and subsequently clipped out all waypoints that were located within this buffer. At the end of the access road is a parking lot, and visitors often walk along the access road from the parking lot. It was necessary to keep the scope of the analysis focused on dispersed visitation and not on visitation occurring adjacent to the access road. The initial sample consisted of 257 travel parties, and subsequently was reduced to 130 after the data was clipped using the half mile road buffer.

Descriptive Analyses

In ArcMap spatial descriptive analysis was conducted for point and line data. The point data were combined into a single shapefile to determine the mean and median center point, and one standard deviation directional ellipse (D'Antonio & Monz, 2016). The median center point is typically viewed as a better measure of spatial central tendency than mean center point because it is less skewed by outliers (D'Antonio & Monz, 2016). The mean and median center point analyses produce coordinates that can be used by managers for navigational purposes. The one standard deviational ellipse displays the spatial dispersion and directional tendency of the data and produces an ellipse that can be used for visual inspection to identify directional trends (D'Antonio & Monz, 2016). The researcher then converted individual point shapefiles for each travel party vehicle to line features. The line data were used to determine the central line feature to identify the most geographically common track.

Grid Construction

To assess spatial variations of high use and vehicle speed the researcher constructed a grid (Nam, Hyun, Kim, Ahn, & Jayakrishnan, 2016). Although grid analysis is useful for study sites that lack organizational infrastructure, the ideal grid cell size remains controversial and is typically determined by site-specific information (Nam et al., 2016). For example, the distribution of waypoints could be used to determine grid cell size. This approach includes site-specific information because the distribution of waypoints is affected by the landscape. To include the contextual nature of the data, the researcher calculated a distance band from neighbor count using the 'Calculate Distance

Band from Neighbor Count' tool. This determined the furthest distance between two neighboring waypoints, which was determined to be 514.88 meters. The researcher rounded down to 500 meters and designated that distance as the grid cell size.

In ArcMap the researcher constructed a perimeter polygon of the BSF using aerial imagery. Using the 'Grid Index Features' tool the researcher constructed a digital grid by inputting a grid cell size of $500m^2$ and the BSF perimeter polygon. The resulting grid was then spatially joined to a shapefile of all waypoint data. The final grid used for analysis featured 1,116 grid cells (Figure 2). Lastly, the 'Summarize' tool was used to aggregate number of waypoints, maximum speed, and average speed for the data found within each grid cell. These attributes were used to conduct hot spot clustering for waypoints, maximum speed, and average speed.

Hot Spot Clustering Analysis – Research Questions 1 & 2

In ArcMap, the researcher used the 'Hot Spot Analysis (Getis-Ord Gi*)' tool to asses statistically significant clustering at the 99% and 95% confidence intervals for number of waypoints, maximum speed, and average speed (Kim, Thapa, & Jang, 2019). The Gi* is a univariate tool that accounts for the spatial structure of the data (Peeters et al., 2015). The Gi* tool assesses each cell's attribute value in relation to neighboring cells, geographically displays areas of high and low clustering, and calculates *p*-values and *Z*-scores. This analysis identified areas with intense clustering of waypoints, maximum speeds, and high average speeds.

Of specific interest was to determine if clustering of maximum speed and/or high average speeds spatially intersected with intense clustering of waypoints for the same grid cells. The findings of this step informed the analysis of the next step.

Spatial Grouping Analysis – Research Questions 3 & 4

The researcher visually inspected results of the Gi* tool for spatial intersection of intense clustering of high waypoints with either high maximum speeds and/or high average speeds. Spatial grouping analysis was conducted in ArcMap using the 'Grouping Analysis' tool, which spatially groups data using multiple inputted variables. This tool evaluates the optimal number of groups using a pseudo F-Statistic, which evaluates if variance within groups is low and variance between groups is high. The highest pseudo F-statistic identifies the optimal number of groups. The optimal number of groups is then inputted into the 'Grouping Analysis' tool. The output of this tool can be used to identify potential management monitoring areas. A schematic flow chart of complete analytical procedures is shown in Figure 3.

Results

Response Rate and Description of the Sample

The research assistant intercepted 327 travel parties and 285 elected to participate in the research, which yielded an 87% response rate. After cleaning for GPS error, the researcher elected to reduce the sample to 257, which generated a 6.03% confidence interval at the 95% confidence level. The larger study also collected survey data of the travel parties that included demographic data in which one person from a travel party completed a quantitative paper-based onsite questionnaire. Although the questionnaire data is not the focus of this paper, it is appropriate to share the demographic data to understand the visiting population at the BSF. This sample included 50% males, 33% females, and participants who chose to not identify their gender. Participants ranged in age from 18-79, with only 8% identifying between the ages of 18-25, and 10% identifying between the ages of 66 or older. The majority of participants identified as white/Caucasian (79%), Asian participants comprised 8%, and Hispanic or Latino/a comprised 6%. Approximately 63% of participants reported being residents of the United States, and the remainder of participants consisted of citizens from one of 23 different countries. Annual income was evenly distributed, and level of education trended towards completion of a four-year college degree or graduate degree (52%).

Descriptive Statistics

The researcher conducted descriptive statistics using all waypoint data merged into a single point shapefile, which consisted of 5,011 waypoints. The average speed was 51.82 km/h (32.20 mph). The maximum speed was 265 km/h (164.55 mph) and high speeds were common: 10.77% of visitors drove faster than 160.93 km/h (100 mph), 19.23% drove faster than 128.75 km/h (80 mph), and 50% drove faster than 96.56 km/h (60 mph).

The mean center point was 40.786, -113.855 decimal degrees, and the median center point was 40.777, -113.872 decimal degrees. These measures are displayed in Figure 4 along with a one standard deviation directional ellipse and the central line feature. The one standard deviation directional ellipse identifies where the majority of waypoints are located, and that the majority of travel parties traveled approximately in the northeast direction. The central line feature shows the approach from the access road and into the BSF. The central line feature extends 2.75 kilometers (1.71 miles) from the end of the access road.

Hot Spot Analyses – Research Questions 1 & 2

Hot spot clustering analysis illuminated that high intensity clustering of waypoints intersected with high intensity clustering of maximum speeds in three grid cells (Figure 5). These results show that in those grid cells there are both high use and high maximum speeds. These three grid cells are located near the end of the access road, suggesting that visitors are driving high speeds immediately after leaving the access road.

Figure 5 marks three grid cells where high intensity clustering of waypoints intersected with high intensity clustering of maximum speeds. Table 1 displays further analysis of these three cells. For Cell 1, 12.40% of visitors who travelled through that cell drove faster than 96.56 km/h (60 mph). For Cell 2, 7.81% of visitors who travelled through that cell drove faster than 96.56 km/h (60 mph). For Cell 3, 11.76% of visitors who travelled through the cell drove faster than 96.56 km/h (60 mph). Table 1 also shows that the average speed is low for these three cells, which confirms that the majority of visitors are not driving fast through these areas. Lastly, Table 1 displays the *p*-values and Z-scores of Cells 1, 2, and 3. The higher the *Z*-score, the higher intensity of clustering. Cell 1 had the highest *Z*-score for clustering intensity of waypoints and maximum speed.

Spatial Grouping Analysis – Research Questions 3 & 4

The previous analytical step identified that hot spot clustering of waypoints and hot spot clustering of maximum speed occurred in three of the same grid cells, therefore these two variables were entered into spatial grouping analysis. The researcher compared pseudo F-statistics for number of groups (number of spatial areas) ranging in from 2-15. The highest pseudo F-statistic calculated (922.92) was for six groups (Table 2), which was used to identify six areas for monitoring. Figure 6 displays the BSF divided into six areas. To understand the differences in these areas, the researcher included a parallel box plot that shows the differences in waypoints and maximum speeds for each area (Figure 7). The values in this figure are standardized for comparison sake.

Areas 1 and 5 exhibit high numbers of waypoints and high maximum speeds (Table 3), and thus should be monitored for potential conflict. Figure 6 shows that from the end of the access road to the northeast corner of Area 1 is a distance of 1.85 kilometers (1.15 miles), and the distance from the end of the access road to the northeast corner of Area 5 is 3.94 kilometers (2.45 miles). This allows for navigation to monitoring areas by using a vehicle's odometer once it leaves the access road, granted that the vehicle drives in a fairly linear trajectory. The researcher recommends that managers focus monitoring efforts on Areas 1 and 5, because these two areas are likely where high visitor use and high vehicle maximum speeds coincide. These two areas potentially could have visitor conflict.

Discussion

The purpose of this study was to identify specific areas of the BSF that have both high use and high vehicle speeds, and to provide relevant information for management. Since the BSF lack organizational infrastructure, the researcher conducted a grid analysis. The grid cell was used as the unit of analysis along with each travel party vehicle.

Identifying the areas with high use and high vehicle speeds can help managers understand if safety is possibly being compromised, and if potential visitor conflict could be occurring.

The results showed that high vehicle speeds occurred near the end of the access road, which coincides with areas of high use. These two variables were the drivers of spatial grouping analysis, which produced information for monitoring purposes. This study also produced other information that has functional utility for managers. The mean and median center points are expressed in decimal degrees that can be inputted into any smartphone, or GPS unit, for navigation. The clustering and grouping results answered research questions 1, 2, & 3.

The one standard deviational ellipse showed that most visitors traveled in the northeast direction. Visitors are most likely guided by the exit of the access road, which points visitors to the northeast. Furthermore, visitors mostly drove in linear trajectories, which could result from being in an area that does not have organizational infrastructure to disrupt a straight trajectory. Visitors also may have driven in linear trajectories to experience driving fast in a large area without a speed limit.

The researcher also conducted clustering analysis of average speed, which did not coincide with areas of high use. It may seem confusing that grid cells with high clustering intensity of average speeds did not spatially intersect with high way points, while maximum speeds did. The grid cells that had high maximum speeds also exhibited low speeds, which reduced the average speed. This suggests that most visitors are not demonstrating high maximum speeds. These types of differences were not apparent until the researcher conducted grid analysis.

The grid analysis was effective for two primary reasons. The first was that the grid is capable of analyzing spatial variations using inferential statistics. The results show spatial variations of the variables for 500 meter increments. Depending on the data and the research questions the grid cell size can be adjusted to analyze micro or macro spatial variations. Grid cell size highly influences the analysis. Instead of conceptually deciding on a grid cell size, the researcher used the data's context and calculated a distance band from neighbor count to determine the furthest distance between waypoints, which was 514.88 meters. Also, this distance conceptually made sense to use, because a 500 meter buffer is a safe distance to separate high use areas from areas with high vehicle speeds. Secondly, grid analysis produced results that have utility for managers. Without the grid it is difficult to statistically analyze spatial variations of waypoints and speed, and to conduct a spatial grouping analysis.

The final research question (#4) asked what was learned about spatial behavior. Weber & Bauder (2013) posit that 'spatial visitor behavior' is the connection between location-dependent actions and the broad structure of movement via a connecting element, such as mobility. Mobility is of interest because a decision must be made to move, moving involves choosing a route, and those decisions are predicated on a person's preconditions and aims. Two findings about spatial behavior are apparent from this study. The first was that visitors drove fast immediately after leaving the access road and entering the BSF, which has no speed limit. The excitement of driving in an area without a speed limit may have influenced visitors to drive fast immediately upon entering the BSF. Managers may want to put a speed limit near the access road for visitor safety. The other finding was that most visitors stayed nearby the access road. Stamberger et al. (2018) found similar results with backpackers in Denali where outdoor recreationists camped near the road despite being encouraged to disperse and camp away from the road. The findings from this study and Stamberger et al. (2018) could mean that recreationists stay within sight of a perceived safety outlet in case of an emergency. The BSF are a vast flat homogeneous landscape and once the access road isn't visible anymore visitors may feel uncomfortable. It has been documented that for an observer who has a height of 5 feet and 7 inches, and is standing on flat ground in standard atmospheric conditions, the horizon is at a distance of 5.00 km (3.1 miles) (Young, 2016), and this data showed that the majority of visitors to the BSF did not drive beyond 3.93 km (2.44 miles) of the access road. This also could explain why many travel parties were clipped out after the half-mile access road buffer was applied, and why there are not more waypoints extending into the far reaches of the BSF.

All GPS data is embedded with speed, yet park visitors' speed has been under-researched. Past research has mostly focused on distances traveled and when events occurred. As seen in this study, further understanding about visitor spatial behavior can be investigated with speed analyses. Analyzing where visitors stop and where visitors are moving quickly can help researchers identify attraction areas and areas that are not capturing the attention of visitors. This knowledge can help managers with more sophisticated decision-making and is essential towards developing visitor management strategies (Pettebone, Newman, & Lawson, 2010). For example, at the BSF managers can use this information to create educational signs at the end of the access road that state the distances out to Areas 1 and 5.

Besides conducting more research of visitor speeds in PPAs, this study showed several necessary areas for future research. Acceleration has not been studied for PPA visitors and this study could have benefited from an acceleration assessment to determine exact areas vehicles are increasing speed rapidly. Trajectory analysis has not been robustly conducted for PPA visitors either. In the R software package, it is possible to conduct acceleration and trajectory analyses to gain a more robust understanding of spatial behavior.

The grid can also be used to increase understanding of temporal patterns of visitors. As Tobler's First Law of Geography (1970) states, near entities are more similar than distant entities, and the same is true for temporal entities: more recent entities are more similar. Conducting a speed analysis in which the visitor trajectory is segmented temporally could help researchers and managers understand if visitors are travelling the same or differently throughout their experience (i.e., is a group always moving at high speeds).

Lastly, the analysis presented in this paper could be enhanced when coupled with visitor surveys, which help gain information about complex social questions (e.g., 'why' do visitors exhibit spatial behaviors). Using survey data combined with GPS data it is possible to gain knowledge about why visitors make decisions to move, why visitors choose a specific route, and what visitor preconditions may contribute towards decision-making within a PPA. Surveys can also be used to validate where crowding conditions occur instead of using number of waypoints as a proxy. Crowding is a perception, so a high density of waypoints may not necessarily constitute feelings of being crowded.

The methods used in this study have far-reaching transferability. Obvious transferability is to other locations that have dispersed recreation with limited organizational infrastructure, such as lakes or wilderness areas devoid of trails. These methods can also be used at PPAs that have organizational infrastructure to understand spatial variations, such as speed variations along a scenic loop drive in a PPA. Beyond PPAs, these methods are also transferable to tourist settings. A grid can be constructed for any study site, and can be used to conduct inferential statistics, instead of relying on visual analysis, such as with density displays. This is also applicable to non-vehicular tourism settings that are rather homogeneous, such as beaches or battlefield sites.

Limitations

The use of GPS data loggers may have influenced visitor behaviors. GPS data loggers are intrusive, even if the GPS data logger is small. These are limitations of all studies using GPS data loggers. GPS data loggers are being used in research less frequently as technology continues to advance. Smart phone tracking applications and geotagged social media data are two examples of GPS data that are being used by researchers that are less intrusive (Hale, 2018). Another limitation of this study was the $500m^2$ grid cell size. Although this size was determined from the data, it is difficult to determine with certainty that it was the best grid cell size. Lastly, with any study researchers should be aware of simplification that may occur during analysis. Using a grid, although pragmatic, does simplify because data is aggregated for each cell even if data for a cell is not uniformly distributed.

Conclusions

The use of GPS technology and GIS techniques are helpful for conducting analysis of visitors in a dispersed PPA that lacks organizational infrastructure. This study also demonstrated the use of GPS data to help managers identify areas where safety potentially is compromised and areas of possible visitor conflict. The analysis and results are powerful because they produced statistical significance and did not exclusively rely on visual assessment of visitor travel patterns. The researcher hopes that this study will stimulate future studies to employ grid analysis to assess spatial variations to gain more understanding of visitor travel patterns in PPAs.

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Tables

Table 1. *Summary of Cells 1, 2, and 3.*

	Percent of Total Waypoints of Sample	Maximum Speed	Average Speed	Percentage of Visitors who Travelled through the Cell Faster than 96.56 km/h (60 mph)	Waypoint Clustering Z-score	Waypoint Clustering *p*-value	Maximum Speed Clustering Z-score	Maximum Speed Clustering *p*-value
Cell 1	14.97%	235 km/h (146.02 mph)	15.69 km/h (9.75 mph)	12.40%	8.15	<.001	2.77	0.006
Cell 2	4.59%	233 km/h (144.78 mph)	31.34 km/h (19.47 mph)	7.81%	2.30	0.02	2.73	0.006
Cell 3	3.45%	212 km/h (131.73 mph)	29.27 km/h (18.19 mph)	11.76%	4.61	<.001	2.32	0.02

Table 2. *Analysis of Pseudo F-statistic to determine optimal number of groups*.

Number of Groups	Pseudo F-Statistic
2	97.92
3	487.49
4	668.47
5	841.63
6	922.92*
7	910.60
8	879.41
9	869.77
10	845.42
11	837.16
12	813.49
13	798.49
14	791.18
15	793.27

Note. Six groupings received the high Pseudo F-statistic.

Table 3. *Descriptive statistics of grouping analysis; calculations are per grid cell.*

Area	Variable	Mean (SD)
1	Waypoints	744.00 (6.00)
2	Waypoints	4.57 (5.66)
3	Waypoints	1.22 (6.15)
4	Waypoints	0.49 (9.14)
5	Waypoints	128.17 (62.83)
6	Waypoints	17.04 (29.33)
1	Maximum Speed	202.00 km/h (33.00), 125.52 mph
2	Maximum Speed	100.68 km/h (32.13), 62.56 mph
3	Maximum Speed	3.76 km/h (13.15), 2.34 mph
4	Maximum Speed	2.68 km/h (14.13), 1.67 mph
5	Maximum Speed	162.42 km/h (35.87), 100.92 mph
6	Maximum Speed	99.95 km/h (51.33), 62.11 mph

Note. Areas 1 and 5 had the highest means for waypoints and maximum speed.

Figures

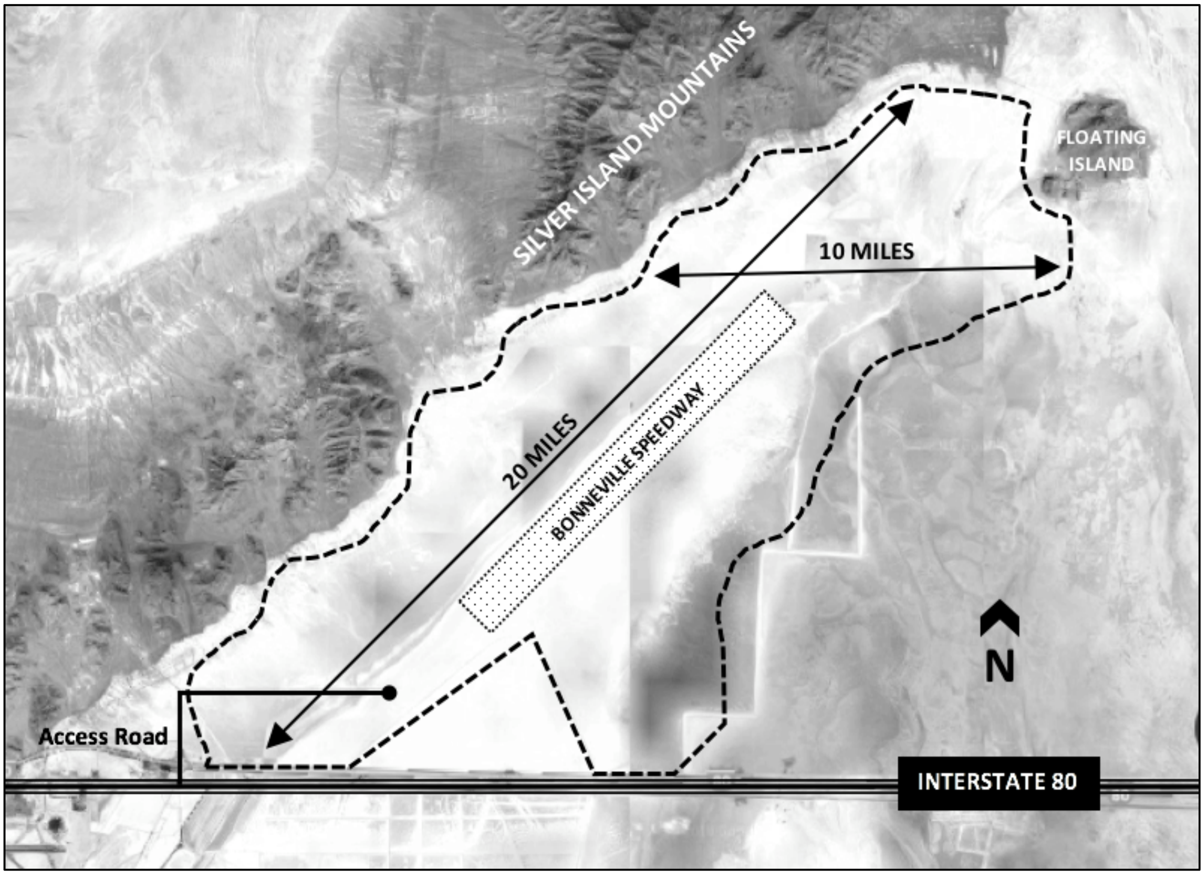

Figure 1. Map of the Bonneville Salt Flats.

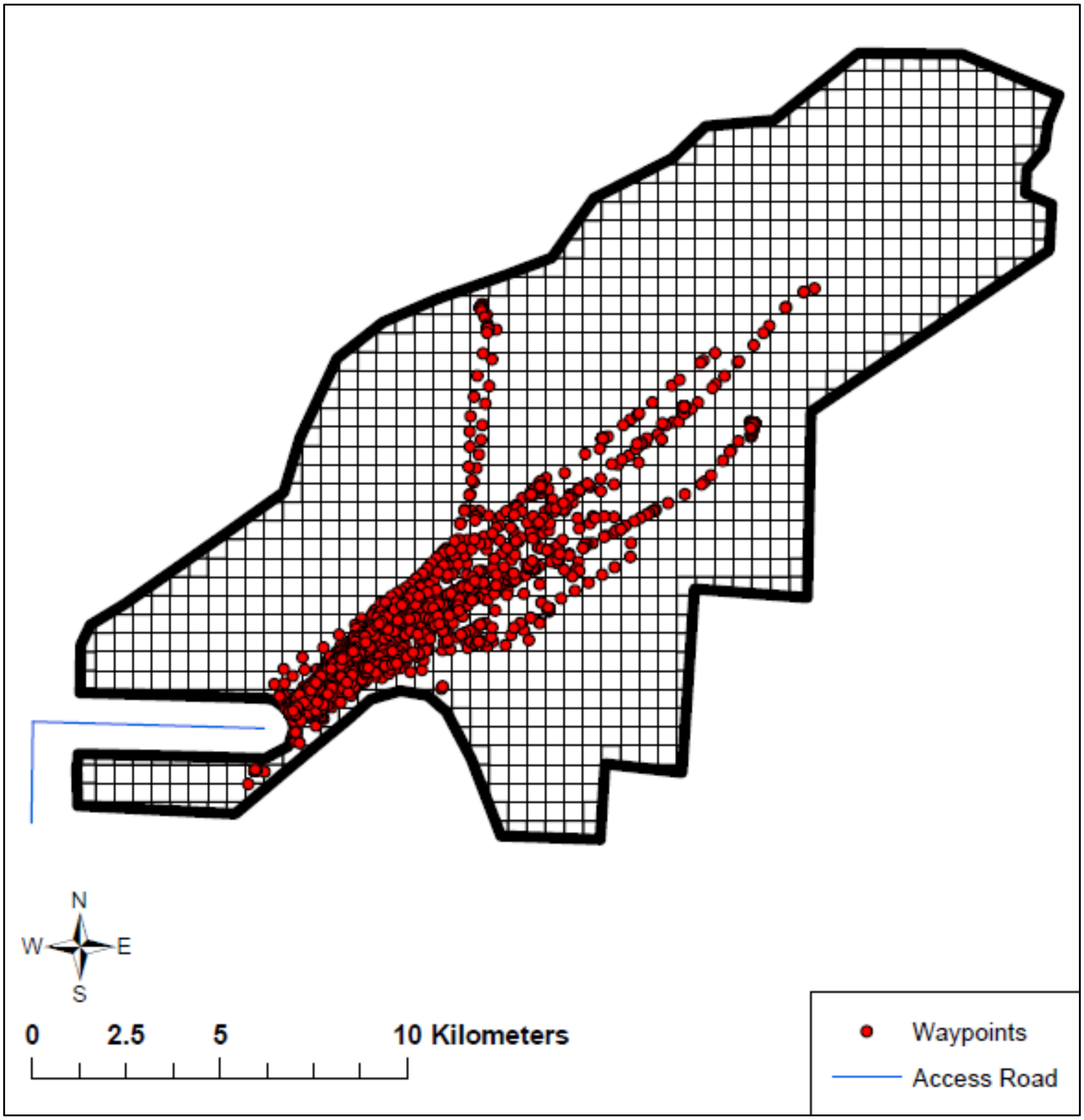

Figure 2. Waypoints and grid used in analysis of the Bonneville Salt Flats.

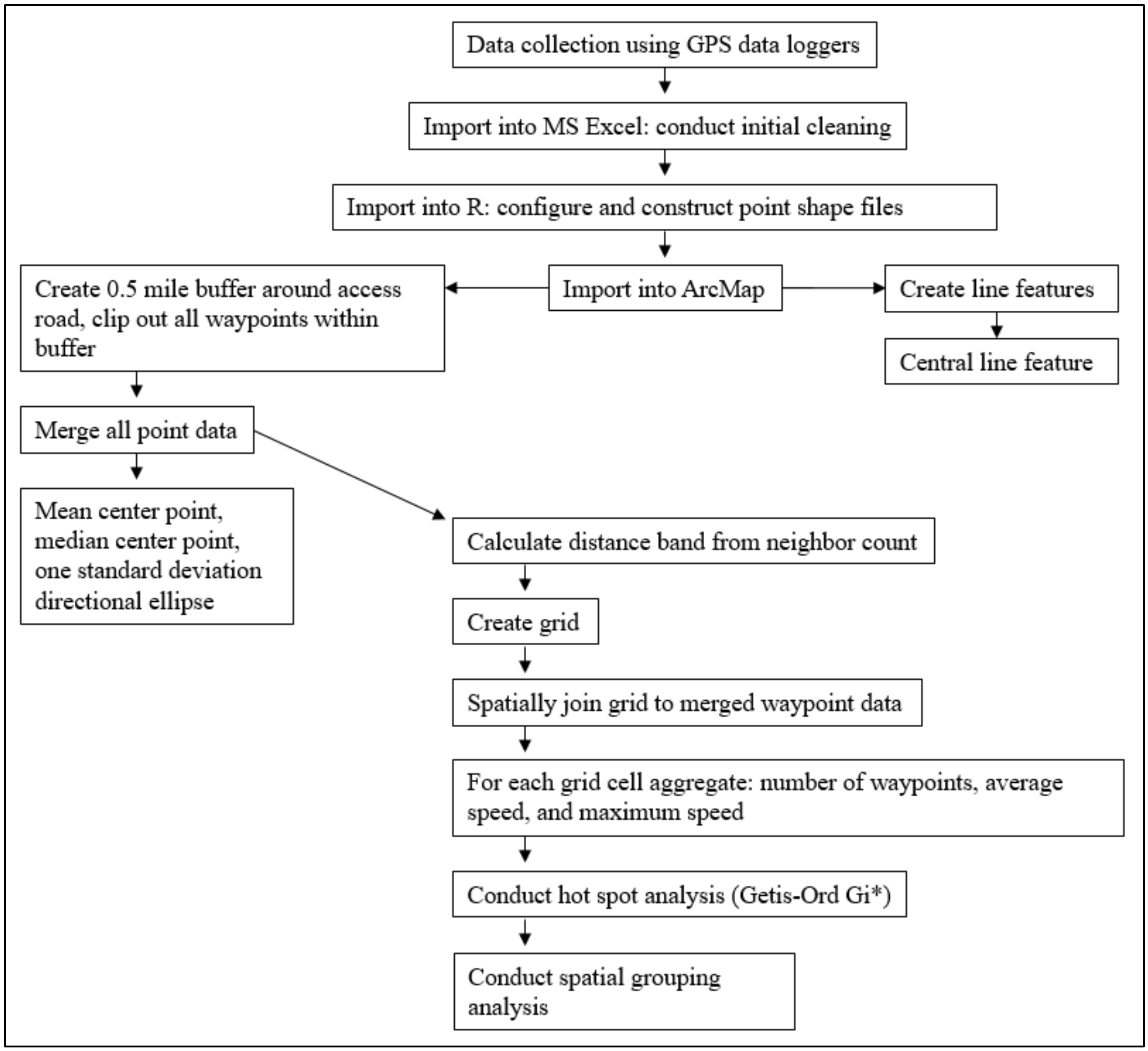

Figure 3. Schematic flow chart of methods.

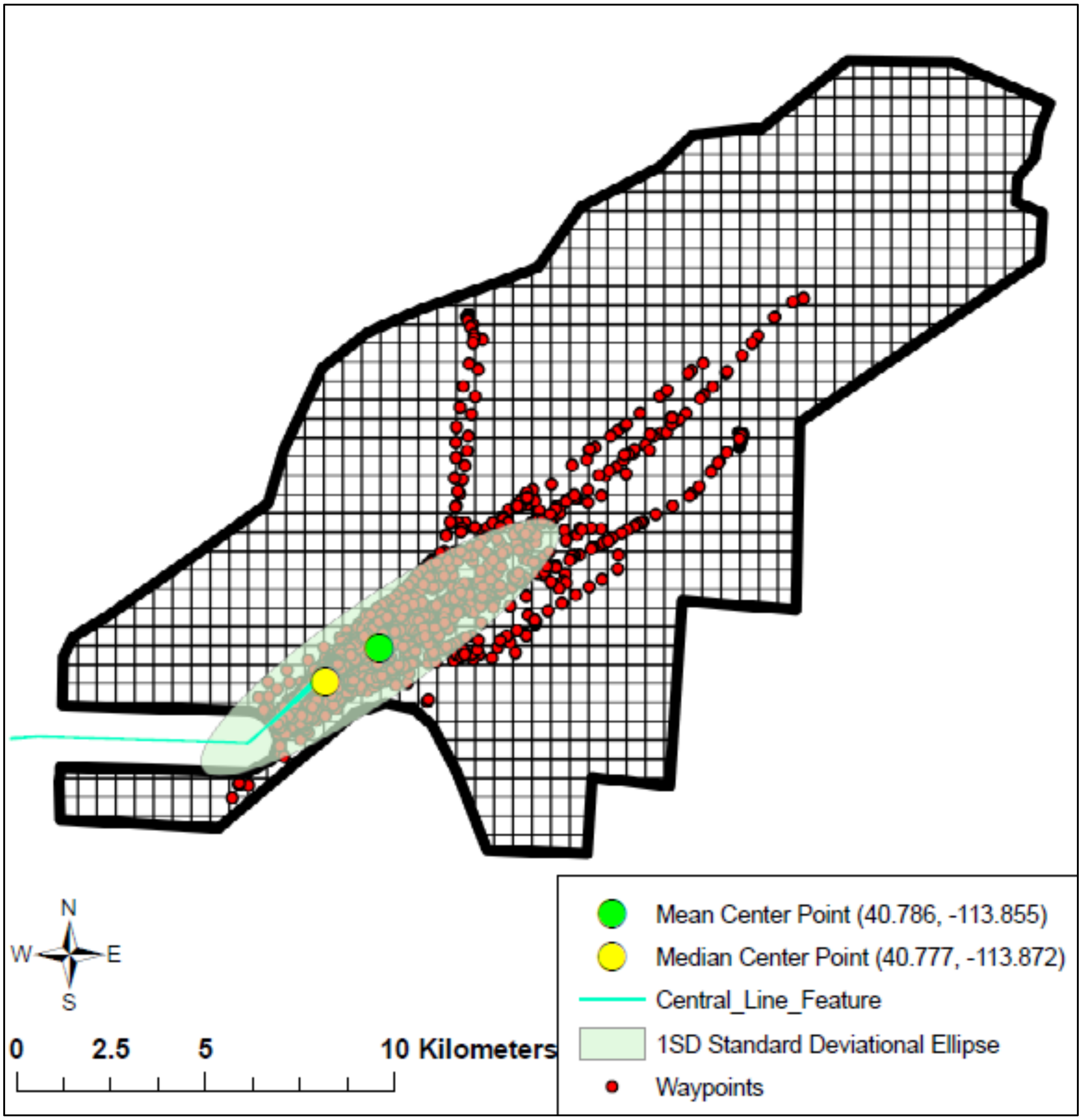

Figure 4. Map displaying mean center point, median center point, central line feature, a one standard deviation directional ellipse, and waypoints.

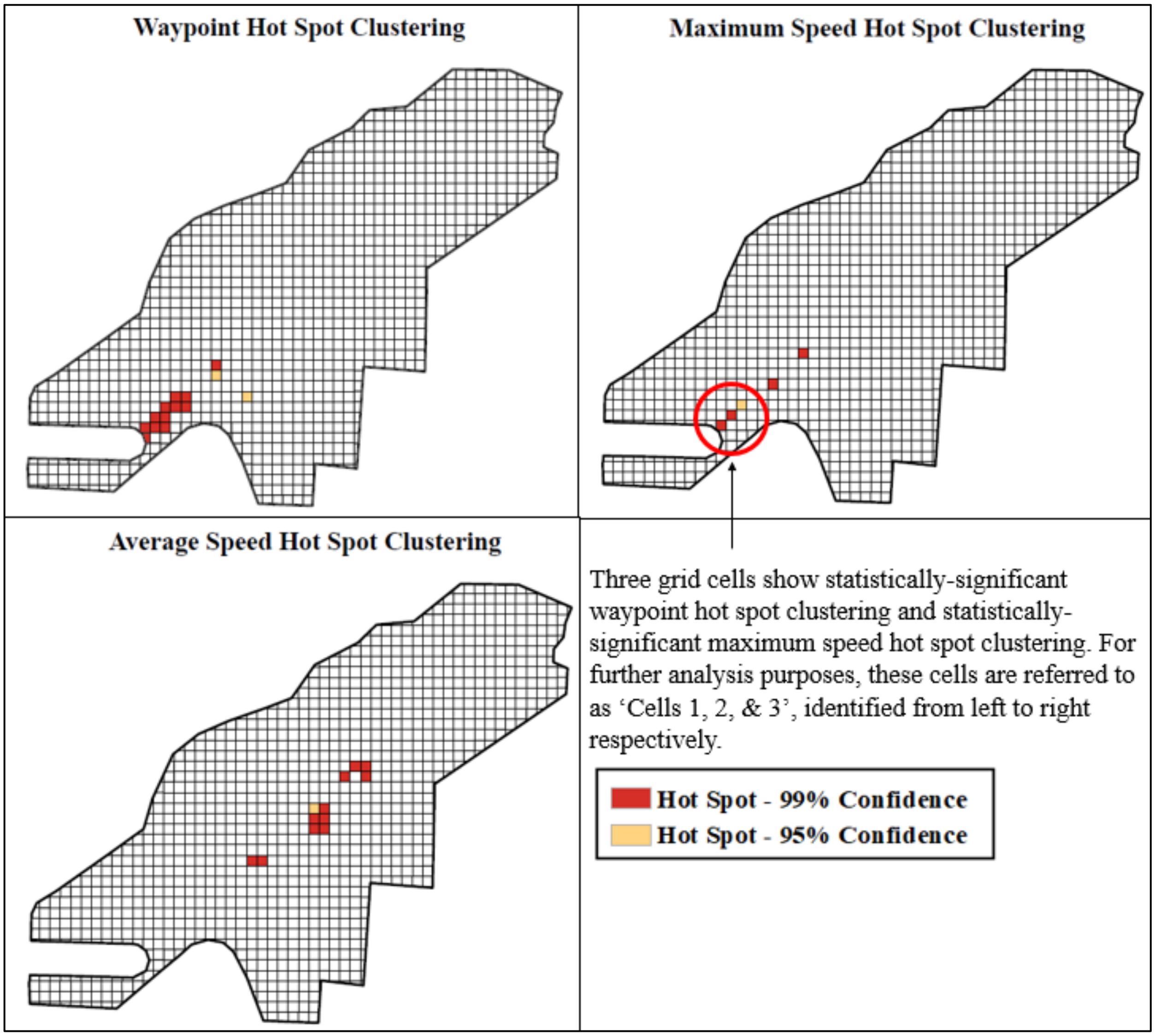

Figure 5. Hot spot (Getis-Ord Gi*) clustering results for: waypoints, maximum speed, and average speed.

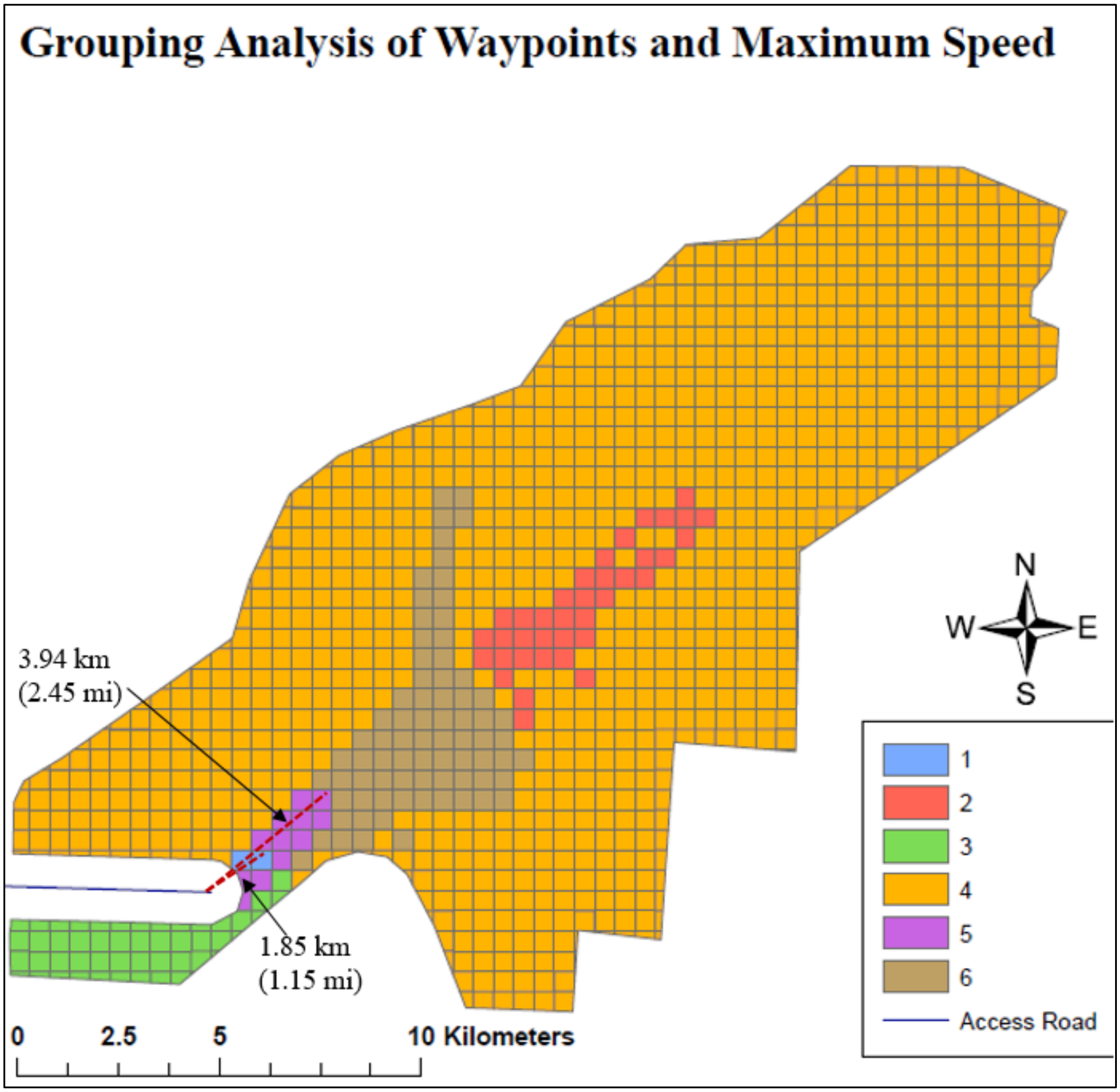

Figure 6. Spatial groupings of waypoints and maximum speed.

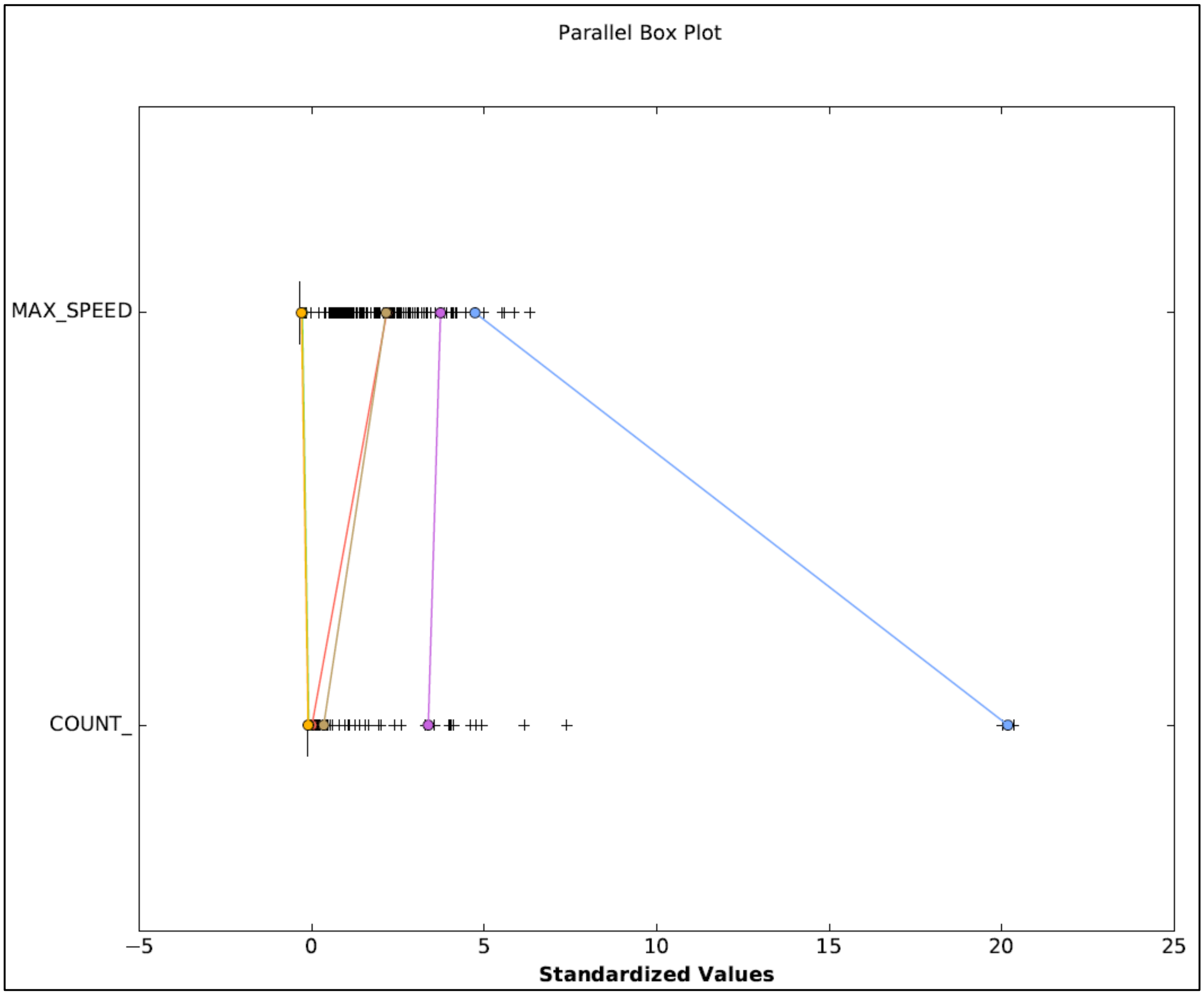

Figure 7. Parallel box plot of grouping analysis of maximum speed (MAX_SPEED) and waypoints (COUNT_).

CHAPTER FIVE

CONCLUSION

This dissertation features three independent empirical research studies that are conceptually linked by the time-geography framework (Hägerstrand, 1970). The purpose of this dissertation was to advance spatiotemporal research of visitor travel patterns within parks and protected areas (PPAs). This research is pertinent because space and time are omnipresent influencers of visitor travel patterns.

This concluding dissertation chapter discusses how this research advanced scholarship of visitor travel patterns, highlighted opportunities for future investigations, and provides information that could benefit society. This final chapter also includes reflections on management and theoretical implications. A noteworthy theme of this dissertation is the incorporation of contextualized information found at each unique study site: Theodore Roosevelt National Park, Hawai'i Volcanoes National Park, and the Bonneville Salt Flats.

Chapter 2 featured research at Theodore Roosevelt National Park (THRO) where a management-centric approach was used to understand visitor travel patterns. This approach is important methodologically because it included the contextual knowledge of managers to identify the spatiotemporal variables most important to understand visitor travel patterns. An important finding of this research was that managers identified three temporal variables as the most important to understand visitor travel patterns within the Park. This was an exciting discovery because a state of knowledge review about understanding visitors' spatial behavior (published in January of 2019) identified that the temporal component of visitor travel patterns was under-researched (Riungu, Peterson, Beeco, & Brown, 2018). The research conducted at THRO also determined spatial variations of visitor time allocation and visitor speed patterns. This information was used to produce 3D spatiotemporal visualizations that are more easily interpreted than traditional density visualizations. The spatiotemporal visualizations of this dissertation display intuitive quantitative results, unlike density displays that are difficult to quantitatively comprehend. Managers can use these intuitive visualizations to efficiently interpret information related to visitor travel patterns. Future research could assess which spatiotemporal variables are most important to managers at other PPAs, and determine the effectiveness of those variables for understanding travel patterns.

Chapter 3 featured research conducted at Hawai'i Volcanoes National Park (HAVO) where I used Automatic Dependent Surveillance-Broadcast (ADS-B) Out, which is conceptually similar to GPS data and can be analytically assessed similar to terrestrial GPS data (Beeco & Joyce, 2019). The ADS-B data were used to quantify visitor air tours across hours of the day and to determine the terrestrial attraction areas most affected by air tours. Collecting accurate and precise data of air tours has not been possible until recently and this study was the first to use accurate and precise locational data to understand air tour travel patterns over a PPA. This study advanced research by understanding spatial variations of temporally segmented data of air tours over HAVO. The analysis of air tours is considered an open system because air tours can enter the Park from any location, can freely fly around, and are uninhibited by entrance/exit gates, roads, trails, and other infrastructure. Open system settings have previously provided challenges related to analyzing travel patterns because open systems are complex. To overcome this challenge, this research demonstrated the effectiveness of a spatial grid analysis for investigating visitor travel patterns. A key finding of this research was determining the attraction areas most affected by air tours, which was made possible using a spatial grid analysis and inferential statistics. This research produced usable information for managers to coordinate with air tour operators, the Federal Aviation Administration (FAA), and other officials. Future research can use the information from Chapter 3 to conduct further analysis of the visitor experience at the terrestrial attraction areas potentially most influenced by air tours.

Chapter 4 featured research conducted at the Bonneville Salt Flats (BSF) where methods were designed to identify monitoring areas where there is both high visitor use and high vehicle speeds. Speed is a function of space and time but spatial variations of speed patterns within PPAs have received limited research attention. The research at the Bonneville Salt Flats analyzed spatial variations of waypoints and vehicle speed patterns to identify areas where both high use and high vehicle speeds coincided. However, because the Bonneville Salt Flats has no organizational infrastructure it is challenging to identify areas to monitor. This research overcame that challenge and reported monitoring information that is intuitive for navigation. Future research should include an analysis of spatial variations of acceleration patterns. This information would help managers understand where people are accelerating rapidly and if these areas coincide with high use and high speed areas.

All three of these research studies used a digital spatial grid analysis constructed using GIS software. The spatial grid is a worthy tool for understanding spatial variations, such as variations in visitor time allocation, temporally-segmented air tour data, or vehicle speed patterns. A spatial grid is exceptionally useful in open system settings that lack organizational infrastructure. Spatial grid analysis is useful because it creates and focuses a new unit of analysis – the grid cell. However, grid analysis is limited by aggregating data for each grid cell as if the data is homogeneous within the grid cell, which is rarely true. Therefore, the size of the grid cell is extremely important and highly influential in the analysis process.

Past research has identified that the question of the best grid cell size remains controversial (Nam, Hyun, Kim, Ahn, Jayakrishnan, 2016) because the context of the study site is relevant for determining the appropriate grid cell size. All three research studies featured in this dissertation used the context of the study site to determine the appropriate grid cell size. For the research conducted at THRO and the BSF, the Calculate Distance Band from Neighbor Count Tool was used to determine the appropriate grid cell size. Using this tool it is possible to include the contextualized nature of the data that results from the influence of the PPA setting. At HAVO, the spatial grid was designed using conceptual information about helicopter noise instead of using a spatial tool. As seen with the construction of the spatial grid, this dissertation incorporated relevant information contextual to each study site.

Constructing a spatial grid was also necessary to conduct inferential statistics. The research conducted at both HAVO and the BSF used inferential statistics to understand spatial variations of temporally-segmented air tour data (HAVO) and spatial variations of waypoints and speed patterns (BSF). Rarely has research used inferential statistics to more accurately understand travel patterns. Past research has typically relied on density displays that are descriptive in nature and do not provide statistical information to make conclusions about the data that can be reported to managers and planners.

There is a literature gap identifying how to determine spatiotemporal inclusion/exclusion criteria. The research conducted at THRO quantified data for attraction areas, which was a challenge because it is difficult to define the parameters constituting an attraction area. Thus, attraction areas needed to be operationalized for further analysis. One technique is to put a spatial buffer (e.g., half a mile) around the parking lot of an attraction area but this was not suitable for THRO. Instead, attraction areas were operationalized as areas where speed dropped below 2 mph, and the duration of time the speed was below 2 mph spanned longer than 2 minutes. This was suitable for THRO because there are several vehicle pull-outs along the scenic loop drive.

At HAVO, inclusion/exclusion criteria of an attraction area was operationalized differently. To understand which terrestrial attraction areas were most affected by air tours a buffer with a radius of one half mile was constructed around each attraction site. The half mile buffer was used because this was the distance helicopter noise would likely impact conversation of terrestrial visitors. For this research at HAVO, operationalized inclusion/exclusion criteria needed to be spatial to determine what terrestrial attraction areas were most affected by air tours. Similarly to constructing a spatial grid, the context of the study site is important towards determining inclusion/exclusion criteria.

The research conducted at HAVO demonstrated that other types of locational data other than traditional GPS loggers can be used to understand visitor travel patterns. As technological advancements continue, researchers will be able to use other types of locational data, such as mobile phone data. Other types of locational data could be effective for researching multiphasic visitor travel patterns to understand where visitors travel before and after visiting a PPA. Understanding multiphasic visitor travel patterns is important to gain insight into factors that influence visitor travel patterns within a PPA. Experiences that occur before visiting a PPA could affect travel patterns within a PPA, and perceptions of future events immediately after visiting the PPA could affect travel patterns during the PPA visit. For example, future events may constrain the amount of time a visitor can spend in a PPA. Similarly, events before visiting a PPA could result in a visitor having less time to explore a PPA.

This research was also the first to posit and document that every moment of every experience for visitors within a PPA is 'spatiotemporally-conditioned'. Past research provided the conceptual basis for this advancement by identifying that recreational experiences within PPAs are spatially-conditioned (Beeco & Brown, 2013). Using the time-geography framework, this research extended this concept to include the temporal component. Therefore, visitor travel patterns and visitor experiences are always affected by space and time because space and time are omnipresent, enduring, and inescapable for a PPA visitor. Consequently, these omnipresent influencers are valuable for managers to recognize when attempting to understand a visitor population.

A major challenge of this dissertation was operationalizing travel patterns, and specifically operationalizing spatiotemporal variables. Visitor travel pattern research is broad because travel patterns are comprised of many variables. For example, Kidd et al. (2015) extracted 21 operationalized variables derived from GPS data to classify visitor vehicular behavior in a PPA. Hence, it is difficult to determine which spatiotemporal variables to focus research efforts towards. This is why the research conducted at THRO was important because it demonstrated a management-centric focus that identified the spatiotemporal variables necessary to understand visitor travel patterns. In the future, multiple perspectives should be used to research travel patterns: management perspectives, researcher perspectives, and visitor perspectives to more holistically understand visitor travel patterns.

All visitor experiences are spatiotemporally-conditioned. This concept illuminates that space and time are constant influencers of the visitor experience. Therefore, it is important to understand how space and time affect the visitor experience. Consequently, management should take into consideration how space and time influence the visitor experience to more effectively and efficiently manage.

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APPENDIX A

THEODORE ROOSEVELT NATIONAL PARK EMAIL SCRIPT

Hello, my name is Brian Peterson. I am a graduate student at Clemson University in the department of Parks, Recreation, and Tourism Management. I am conducting research on visitor travel patterns in national parks, and I am inviting you to participate because you work at a national park. Participation in this research includes a telephone interview to discuss what spatiotemporal variables are most important towards your understanding of visitor travel patterns for the national park you work at. The interview will last approximately 15-30 minutes, and will be audio-recorded. After the interview has been conducted, I will follow up with an email to confirm your interview responses were recorded accurately. Your part in this study will inform which spatiotemporal variables to assess as a step in the study's analysis. The results of this study may be published in scientific journals, professional publications, or educational presentations. The information collected during this study will not be used or distributed for future research studies.

Participation in this research is completely voluntary, and your responses will remain anonymous. You may choose not to take part and you may choose to stop taking part at any time. You will not be punished in any way if you decide not to be in the study or to stop taking part in the study. Identifiable information collected during the interview will be removed and de-identified information will not be used or distributed for future research studies. Audio recordings will be retained until data analysis is complete, which will be completed by May of 2022. You can choose to be in the study or not.

If you have any questions or concerns about your rights in this research study, please contact the Clemson University Office of Research Compliance (ORC) at (864)656-0636 or irb@clemson.edu. If you are outside of the Upstate South Carolina area, please use the ORC's toll-free number: (866)297-3071. The Clemson IRB will not be able to answer some study-specific questions. However, you may contact the Clemson IRB if the research staff cannot be reached or if you wish to speak with someone other than the research staff.

By participating in this study, you indicate that you have read the information written above, been allowed to ask any questions, and you are voluntarily choosing to take part in this research. You do not give up any legal rights by taking part in this research study.

If you'd like to participate or have any questions about the study, please email me at bpeter6@clemson.edu. You may print a copy of this document for your records.

Thank you very much.

Sincerely,
Brian Peterson

APPENDIX B

THEODORE ROOSEVELT NATIONAL PARK INTERVIEW SCRIPT

1. Do you mind if I record the interview with you?
2. Did you read the consent form I emailed you?
3. Please describe components of visitor travel patterns that are most important to the visitor experience.
4. When you think of visitor travel patterns in your park, are there any specific characteristics that interest you?
5. Are there any issues in your park that could be resolved by analyzing GPS data?
6. What types of spatial characteristics do you want to know about visitors?
7. What types of temporal characteristics do you want to know about visitors?
8. What speed characteristics do you want to know about visitors?
9. Tell me about any specific locations in your park where space and time need to be researched.
10. Using GPS data – is there any research in your park that you'd be interested in?
11. Are you more interested in knowing about visitors': spatial patterns, temporal patterns, or speed patterns?
12. Are there any specific spatial variables, temporal variables, or speed variables you'd like to mention/discuss?
13. What spatial and temporal variables do you recommend to use to objectively designate management zones?

POSSIBLE VARIABLES

SPACE VARIABLES
Total distance traveled
Distance traveled on roads
Distance traveled on trails
Distance traveled on water (e.g., rivers & lakes)

TIME VARIABLES
Total time spent in park
Time entered park
Time exited park
Accumulated time spent on paved roads
Accumulated time spent on trails
Accumulated time spent at attraction sites

SPEED VARIABLES
Average speed
Maximum speed

APPENDIX C

THEODORE ROOSEVELT NATIONAL PARK QUESTIONNAIRE

DISTRIBUTED VIA QUALTRICS SURVEY SOFTWARE

Q1.

We want to know the level of importance of each item below in terms of - how important are they to understand visitor travel patterns at THRO? Please rate the six items listed below in terms of importance for THRO:

	Not important at all	Slightly important	Moderately important	Very important	Extremely important
Total time spent in THRO	○	○	○	○	○
Total time at attraction areas	○	○	○	○	○
Total time on roads vs. trails	○	○	○	○	○
Times when the is visitor center gets the highest usage	○	○	○	○	○
Time entered park	○	○	○	○	○
Vehicle speed patterns	○	○	○	○	○

Q2.

Please rank the six items below in terms of which is most important towards understanding visitor travel patterns at THRO. '1' = highest importance; '6' = lowest importance. Please give each item a rank order of 1-6:

- [ ] Total time spent in THRO
- [ ] Total time at attraction sites
- [ ] Total time on roads vs. trails
- [ ] Times when the visitor center gets the highest usage
- [ ] Time entered park
- [ ] Vehicle speed patterns