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Recreation specialization: Resource selection functions as a predictive tool for protected area recreation management

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ABSTRACT

Widespread and ongoing increases in park and protected area (PPA) visitation presents managers with the imminent challenge of preserving ecological conditions while also maintaining accessibility in the open spaces that are fundamental to the health and wellness needs of society. In the field of recreation resource management, recreation specialization, the selective channeling of interests and abilities into a specific recreational activity, has contributed to a more comprehensive understanding of recreation behavior, site preference, management perceptions and conservation support. Contributing to historical understandings of specialization can inform recreation planning on the diversity of uses occurring in urban-proximate PPAs. In this study, survey and GPS data collected in urban and peri-urban parks in the Nature Reserve of Orange County, CA, USA, were used to classify recreationists into three specialization types based on empirically derived dimensions of involvement, commitment and skill. For each survey participant, thirteen spatio-temporal metrics (STM) were calculated. A principle component analysis (PCA) reduced STMs into 3 factors representing expressions of spatial behavior and a one-way analysis of variance indicated unique patterns between specialization types and time spent recreating, elevation gained, speed traveled and stopping behavior. Additionally, GPS point data were analyzed with an analytical approach adopted from the field of wildlife movement ecology; a resource selection function (RSF). The RSF assisted in quantifying spatial distribution patterns specific to each specialization type across activity types at four park locations and demonstrated a landscape-based statistical analysis of probability of use in relation to change in elevation, distance to starting points and park amenities. Committed hikers and mountain bikers largely demonstrated longer trip durations, more elevation gain, less overall stopping, faster overall speeds and farther total distances, while e-bikers in this study demonstrated unintuitive specialization dynamics; casual specialization types travelling farther from starting points and dispersing more across trail systems. Further spatial results revealed spatial behavior to be inherently complex and influenced by numerous confounding factors (i.e. activity type/bike type, starting points, park topography and trail design). This novel spatial examination of recreation specialization according to activity type and park location, is useful in understanding recreation behavior and park use in a spatial context. This ability is helpful in a predictive managerial context when reviewed in correspondence with historical evidence identifying behaviors with increased potential for ecological impact.

1. Introduction

Record increases in outdoor recreation participation (Outdoor Industry Association, 2022) and recreation related investment (The BEA Wire, 2022), continues to fuel the widespread growth of park and protected area visitation (Ferguson et al., 2022). With the increase in recreation demand and societies dependence on PPAs (Pröbstl-Haider et al., 2023) in the U.S., comes the elevated potential for recreation-related

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environmental impacts and crowding (Ciesielski et al., 2024; Manning, 2022). In response, managers are faced with the complex and multidisciplinary challenge of generalizing diverse expressions in recreation behaviors, preserving ecological conditions and maintaining accessibility in the open spaces that are a fundamental component to the health and wellness needs of society (Godbey et al., 2005). Research on social behavior has created a foundation for conceptual frameworks that inform contemporary outdoor recreation planning and management, through identifying the interrelationships between social and ecological factors (Manning, 2022).

Specialization theory, described as the selective channeling of interests and abilities into a specific activity, was initially applied to “man-environment research” from an environmental psychology perspective (Little, 1976). Introduced to the field of outdoor recreation by Bryan (1977), specialization, was examined through the case of trout fisherman, and a large body of research has since focused on specialization in the realm of recreational angling. The concept of recreation specialization has also been examined across activity types including birdwatchers (Scott et al., 2005), white water canoeists (Wellman et al., 1982), vehicle-based campers (McFarlane, 2004), backcountry hikers (Virden & Schreyer, 1988), rock climbers (Hollenhorst, 1987), scuba divers (Thapa et al., 2006), ultimate frisbee players (Kerins et al., 2007) and most frequently anglers (Beardmore et al., 2013; Bryan, 1977; Oh & Ditton, 2008; Salz & Loomis, 2005; Smith et al., 2023). Angler specialization levels have been crucial for developing realistic management applications such as harvest restrictions (Oh & Ditton, 2006), license fees and travel costs (Beardmore et al., 2013) and in establishing marine protected areas (Salz & Loomis, 2005). Beyond fishing, specialization has been perceived as a helpful conceptual tool for understanding how recreationists make decisions and process information about recreation opportunities (Bryan, 1979; Williams, 1985). Specialization has contributed to a more comprehensive understanding of recreation behavior (Bryan, 2000), site preference (Virden & Schreyer, 1988), conservation support (Oh & Ditton, 2006) and environmental attitudes (Dyck et al., 2003).

Existing research has suggested that casual or less specialized recreationists have weaker associations with concepts of resource use and dependency (Virden & Schreyer, 1988), conservation knowledge (Lessard et al., 2018), management perceptions/preferences (McIntyre & Pigram, 1992), recreation ecology attitudes (Oh & Ditton, 2008; Parsons, 2013) and Nature Reserve/park values (Dyck et al., 2003). Expanding on psychological and cognitive assessments, substantial differences have been observed between self-reported and actual movements of recreationists on the landscape (Manning, 2022; Stedman et al., 2004), and there is limited research exploring specialization and spatial distribution of visitors in parks and protected areas (PPA). Studies examining associations between recreation specialization and travel intention (De Salvo et al., 2020), length of approach (Merrill & Graefe, 1998) and environmental preferences (Virden & Schreyer, 1988), may suggest that specialized recreationists have a tendency to travel farther distances to less frequently visited park locations and exhibit longer trip durations, although these assumptions cannot be confirmed without the examination of spatio-temporal data. Activity style or activity type has been proven to be an effective measure of distance traveled (Lentnek et al., 1969), but when examining specialization within a specific activity, spatial analyses are nonexistent. Uncertainty pertaining to specialization’s influence on spatial behavior and distribution, becomes increasingly pertinent if reported behaviors, values, and attitudes of specialized recreationists contradict spatial and predictive evidence of low-impact behavior indicated by spatio-temporal metrics and probability of use across a park.

Numerous studies exist that track recreation movement and other social and demographic components of recreation (D’Antonio et al., 2010; 2020; Svajda et al., 2016; Svajda et al., 2018), however there are currently no published studies examining the effects of recreation specialization on spatial behavior and distribution through the use of location monitoring technologies. In the field of recreation resource management, GPS-based visitor tracking has been used to examine motivations and spatial behavior patterns, identify main user groups and use patterns, spatial distribution patterns, and preferred park settings and explore the social-ecological impact of recreation and tourism (Beeco et al., 2014; Kidd et al., 2015; Sisneros-Kidd et al., 2021; Stamberger et al., 2018; Zhai et al., 2018). An application of contemporary visitor tracking methods in specialization research can provide understanding on the ways in which involvement, commitment and skill, influence spatial behavior in a geographic context (Beeco & Brown, 2013). Acknowledging the pandemic influenced growth in outdoor recreation participation (Probstl-Haider et al., 2023), and indicated relationships between specialization and reported recreation behavior (Bryan, 2000; Dyck et al., 2003; Oh & Ditton, 2006; Virden & Schreyer, 1988), specialization theory may be especially useful for understanding emerging trends in recreation use, and will be essential for identifying potential ecological impact if specialists tend to disperse beyond confined recreation settings or to locations with little previous use. Specifically, this research addresses the following questions:

1. Can specialization be used to understand spatial behavior and spatial distribution on an activity type and park specific basis?
2. Can an identified relationship existing between specialization, spatial behavior and spatial distribution inform recreation resource management in a predictive capacity?

2. Methodology

2.1. Study site

This study was carried out in four Parks of the Nature Reserve of Orange County, CA (the Reserve): Aliso and Wood Canyons Wilderness Park (ALWO), Peters Canyon Regional Park (PECA), Whiting Ranch Wilderness Park (WHRA) and Santiago Oaks Regional Park (SAOK) (Fig. 1). These specific parks were chosen out of the 22 management units that comprise the Reserve due to their geographic location across the county, diversity of user characteristics and moderate to high visitation rates, to obtain a robust and diverse sample of visitors. The Reserve is a 38,000-acre protected open space that aims to protect the wildlife and plants that define the uniqueness and diversity of the landscape (Natural Communities Coalition, 2023). The Reserve and the parks that lie within, are proximate to the City of Irvine, CA. Irvine has a population of 307,670 and is a major metropolitan area in Orange County which has a population of over 3.18 million (United States Census Bureau, 2020). The Reserve spans multiple jurisdictional boundaries and management agencies including; Orange County Parks, California State Parks, City of Irvine and the Irvine Ranch Conservancy. This analysis was conducted as part of a larger multi-year project (beginning in 2017), examining park usage and identifying social and ecological thresholds of acceptable and sustainable recreation conditions across the reserve’s park system (Natural Communities Coalition, Recreation Management, 2024).

2.2. Data collection and sampling

Visitor questionnaires were administered at two sample locations at each of the four parks and stratified by weekdays and weekends at park entrances, beginning when the park opened at either 6:00 a.m. or 7:00 a.m. until approximately 5:00 p.m. or 6:00 p.m. Visitors were intercepted at randomly selected minutes on the hour throughout the sampling period and as a visitor entered the park they were invited to participate in the study by carrying a *Garmin* eTrex 10 GPS unit (Garmin International Olathe, KS, USA) during their day-use of the park’s trail system. Visitors were then asked to complete a post-experience survey instrument, with scales designed to measure constructs associated with specialization. Technicians administered surveys via iPad handheld

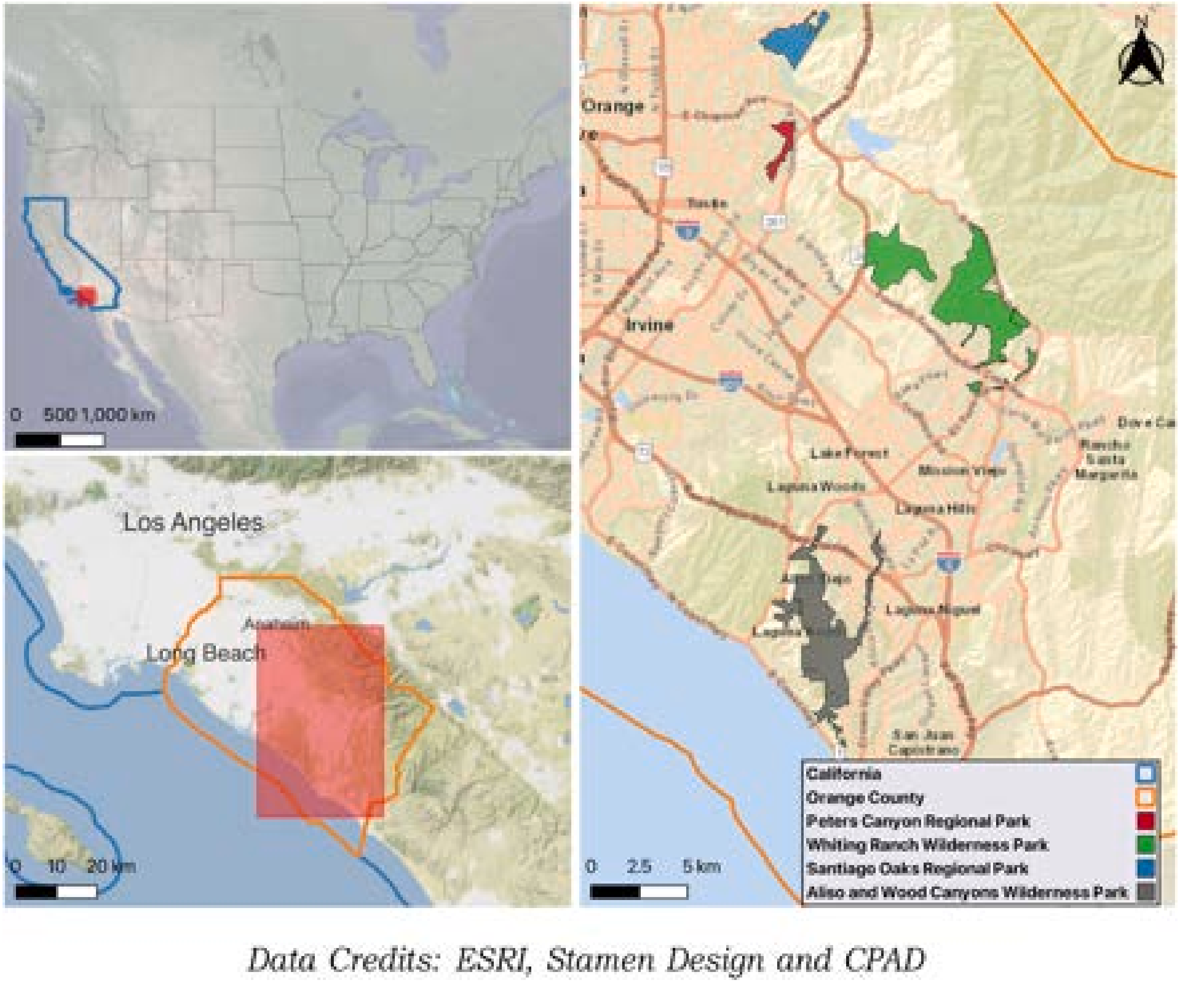

Fig. 1. Study area and parks of interest in the nature reserve of Orange county (California Protected Areas, 2018).

tablets, and orally administered surveys to respondents that had difficulty reading or seeing the written questions on the screen. Individual GPX files were downloaded from the *Garmin* eTrex 10 GPS units on a daily basis and given an identifier to correspond with the participant's associated survey.

The survey instrument was designed using Qualtrics Research Suite (Qualtrics Inter-national, Inc., Provo, UT, USA) and the conceptual orientation of the administered survey is summarized (Appendix A). The survey employed five to seven-point Likert scales, with some opportunities for open-ended answers when assessing respondents on descriptive items such as activity type (available options consisted of hiking/walking, biking, running, horse-back riding or other). Survey participants whose primary activity type was cycling were prompted to specify the type of bicycle (i.e., mountain bike, road bike, e-bike, hybrid bike, gravel bike or other), they were riding at the time the survey was administered. Additional descriptive items addressed in the survey consisted of demographic information (birth year, gender, zip code/nationality and highest-level of education) and GPS bias. Qualtrics's “display logic” feature was used to auto-populate the selected activity type and park location chosen by participants throughout various questions in the survey. Dependent and independent variables addressed in the survey are furthermore broken down by respective response items and scales (Survey Instrument and Tables A.2 and A.1 in Appendix A).

2.3. Data analysis

2.3.1. Survey

Survey scale items measuring 19 response items representing nine categories of specialization, were summarized using SPSS Statistical software (v.29,SPSS, Inc. Chicago, IL, USA) and a maximum likelihood exploratory factor analysis (EFA) with varimax rotation was performed, resulting in four latent components corresponding with specific dimensions of specialization. Factor scores from the EFA were saved, missing values were replaced with means, and each latent component group was named according to the interpretation of the factor scores greater than 0.4 for the categories of specialization indicators and dimensions (Costello & Osborne, 2005). Factor scores from the maximum likelihood EFA were used in a hierarchical cluster analysis procedure using Ward's method and squared Euclidean distance to evenly classify cases in the dataset into three cluster groups, each representing a unique composition of scaled specialization indicators. Generated clusters were associated with their respective specialization type (casual, active, committed), based on the results of a confirmatory one-way analysis of variance (ANOVA) completed to determine significant differences between the three specialization types and latent specialization components. The multivariate methods employed in this study have been used before in effort to reduce large survey datasets and identify latent variables (Leung & Marion, 1999; Sisneros-Kidd et al., 2021) and have been used to classify recreationists based on dimensions of specialization (Bricker & Kersetter, 2000; McIntyre & Pigram, 1992; Scott & Shafer, 2001).

2.3.2. Spatio-temporal metrics (STM)

Individual shapefiles of visitor GPS tracks were cleaned using QGIS (QGISDevelopment Team, 2023) where idle or stationary GPS points were removed from the starts and ends of the tracks. GeoPandas (Jordahl et al., 2020) and MovingPandas (Graser, 2019) packages in Python (Van Rossum & Drake Jr, 1995) were used to analyze the GPS data collected and calculate the thirteen STMs (spatio-temporal metrics) for each visitor's park experience (Table 1). Survey and GPS data were then merged using Pandas (McKinney, 2010; McKinney, 2010; Pandas Development Team, 2023) to create a composite dataset containing 765 unique observations, linking data from the survey response such as activity type, bike type, park location and specialization type with the thirteen predictor variables describing STMs.

To ensure the STMs were orthogonal and independent from one another, a principal components analysis (PCA) with varimax rotation was run on the 13 STMs. Cross-loading and freestanding items were removed from the initial PCA to achieve an interpretable and parsimonious model (Costello & Osborne, 2005). Factor scores from the PCA were saved, missing values were replaced with means, and each component produced in the PCA was named according to interpretation of the factor loadings (i.e., elevation gain and time, stopping behavior and speed). A one-way ANOVA was then conducted to examine significant differences among the three specialization types in the PCA components from Table 3. Data was sorted by specialization type, activity type and bike type (mountain bike, e-bike and an "other" category including gravel bikes, road bikes, hybrid bikes and street/cruiser bikes), and significant ANOVA results were examined with Tukey and Games-Howell post-hoc tests to determine where there were significant differences in spatial behavior between specialization types. The Tukey post-hoc test was employed when variances and sample sizes were equal and the Games-Howell post-hoc was used when there were violations of the assumption of homogeneity of variances (Field, 2013; Vaske, 2019).

Table 1
Spatio-temporal metrics calculated from GPS data.

Spatio-temporal Metrics	Description
Maximum Distance	Greatest planar distance traveled from starting point to the furthest recorded GPS point
Number of Stops	Total number of stops taken by a single recreator (periods of movement slower 5 m in 10 s were documented as one stop)
Maximum Speed	Fastest recorded speed for a single recreator (m/s) calculated by the greatest distance measured between two points (10 s fixed rate)
Mean Speed	Average recorded speed for a single recreator (m/s) calculated by dividing trip duration by total distance traveled
Median Speed	Median recorded speed for a single recreator (m/s), the middle was taken from a list containing speeds calculated for each data point
Total Distance	Total distance traveled for a single recreator (m), the sum of the measured distance between each data point
Elevation Gain	Total net increase in vertical distance traveled (m), the sum of each positive vertical distance recorded between data points
Trip Duration	Total time of a single recreators outing, the total elapsed time between the first and last recorded GPS points
Stop Duration	Total time spent not moving (hh:mm:ss), the sum of the elapsed time for each calculated stop
Moving Time	Total time spent moving (hh:mm:ss) the sum of the elapsed time not calculated as a stop
Stop Time Percent	Proportion of total time spent stopped (percent) in relation to trip duration
Mean Trail Difficulty	Average number of points to fall within easy, moderate or difficult trail buffers (buffers were created indicating trail difficulty for each trail "1 = easy, 2 = moderate, 3 = difficult")
Mean Trail Designation	Average number of points to fall within undesignated or designated trail buffers (buffers were created indicating trail designation for each trail "0 = informal/undesignated trail and 1 = formal/designated trail")

2.3.3. Resource selection function (RSF)

To further examine relationships between specialization and spatial distribution and account for variations in park topography and trail design, an exponential resource selection function (RSF) was used to estimate the probability of use of a pixel in relation to change in elevation and direct distance to starting points and park amenities. Data informing the RSF, was compiled by generating H3 hexagonal grids (200-m radius) (Venkat, 2021), over each sorted vector file using the GeoPandas package in python, and calculating the count of recreationists to pass through each hexagon at least once (unique count). Change in elevation and direct distance to starting points (situated at park entrances with public restrooms and potable water) and park amenities (i. e. viewpoints, picnic tables and shade structures) were calculated in relation to hexagon centroids, resulting in a data frame containing hexagon index numbers and unique-user presence counts (for each specialization and activity types). Although more frequently applied in ecological studies (Manly et al., 2002; Boyce & McDonald, 1999), RSFs have been used to understand potential and actual use of recreation resources (Zhao et al., 2021).

The probability of use of a hexagon as a function of covariates was estimated by fitting generalized additive models (GAMs). Separate models were fitted for each activity type (hikers, mountain bikers and e-bikers), excluding runners due to a small sample size. The GAMs were fit in R (V 4.2.2, R Foundation for Statistical Computing, Vienna, Austria), using the function 'gam()' from the package 'mgcv' (Wood, 2011). Parametric parabolas were fit (by including linear and quadratic terms) for each of our three covariates of interest: change in elevation, distance to amenities and distance to starting points. Interactions between specialization type (casual, active, committed) and the linear and quadratic terms were included for each covariate, to allow differently shaped parabolas for each specialization type. Although parametric terms were used for the covariates, using GAMs allowed for the incorporation of random effects and spatial autocorrelation into the model (Wood, 2017). Repeated measures from each starting point were accounted for in each park by including the corresponding park-start identifier as the random intercept. Spatial autocorrelation was accounted for with a Gaussian process estimation (i.e., kriging). The GAM used a binomial likelihood and a logit link function (i.e. logistic regression), with number of successes ($y_{i,j,k}$) given by the number of unique users of that activity type and specialization type recorded in each hexagon, and the number of trials given by the total number of tracked users of that activity type and specialization type for that park-start. Thus, the model for a particular user group can be written as:

$$logit\left(p_{i,j,k}\right) = \beta_0 + n_j + \omega_i + \sum_{m=1}^{3} f\left(x_{m,i}\right)$$

$$n_j \sim Norm\left(0, \sigma^2\right)$$

$$\omega \sim MVNORM\left(\mu, \sum\right)$$

$$y_{i,j,k} \sim Binomial\left(N_{j,k,p_{i,j,k}}\right)$$

Where i indexes each hexagonal cell, j indexes each park and starting location, and k indexes each specialization type. The three covariates, $x_{(1:3)}$, represent change in elevation, distance to amenities and distance to starting points. The function $f\ (x)$ is a second-degree polynomial expansion of the covariate x such that:

$$f\ (x) = \beta_{l,k}x + \beta_{q,k}x^2$$

Where $\beta_{l,k}$ is the estimated coefficient for the linear term, x, for the kth specialization type, and $\beta_{q,k}$ is the estimate coefficient for the quadratic term, x^2, for the kth specialization type. Note that a dummy encoding was used to represent the categorical variable for each specialization type. Thus, the model estimated $\beta_{l,k}$ and $\beta_{q,k}$ relative to a reference level ("active").

A random effect spline was used to fit the random intercept for park-start (8 knots). The Gaussian process term for every cell in space is assumed to come from a multivariate normal distribution, with a vector of means ($\boldsymbol{\mu}$) estimated from the data and variance-covariance matrix ($\boldsymbol{\Sigma}$) that varies as a function of the distance between two hexagonal cells. Note that it takes on a value for each cell in space (ω_i), but that the vector $\boldsymbol{\omega}$ is the random variable which is distributed multivariate normal. The Gaussian process was estimated using a reduced-rank Gaussian process smooth to estimate the spatial random effect (200 knots). A Matern covariance function was used for the Gaussian process, as suggested by Kammann and Wand (2003) and recommended by Wood (2017). The estimated relationships between each covariate and probability of use were visualized (Fig.3 and Fig C4 in Appendix C) by holding all other covariates at their global mean while varying the covariate of interest. Further detail demonstrating these complex methodological processes is displayed in Fig. 2.

3. Results

3.1. Activity type, park location and demographics

The visitor-intercept survey had a total of 828 participants (including incomplete responses and 28 shortened non-response surveys). The response rate for this survey was 96.8 %. Of the complete survey responses, 235 were collected at ALWO, 232 were collected at PECA, 184 were collected at SAOK and 177 were collected at WHRA. Of the 800 complete survey responses, 492 respondents indicated their primary activity type to be hiking, 256 respondents indicated their primary activity to be biking (215 mountain bikes, 14 road bikes, 14 e-bikes, 8 hybrid bikes and 5 gravel bikes), 46 respondents indicated their primary activity type to be running, and 6 respondents indicated their primary activity to be other (open ended responses consisting of "looking at the view", "physical therapy", "writing", "identifying plants", "lunch" and "mountain unicycling"). Based on field observations, 19 additional e-bikes were recorded (reporting bike type as "mountain bike" rather than "e-bike") and their activity types were changed to "e-bike" in order to reduce error in the spatial analysis. Visitors to the four parks of interest were primarily male (62.9 %), middle-aged, college educated individuals (Table B1 in Appendix B). The majority of recreationists in this sample were highly educated, high earning individuals, having received at least a 4-year college degree (64.4 %) and earned over $100,000 USD a year (59.2 %). California residents comprised almost the entire portion of the sample (96.5 %) and non-California residents (3.5 %) were representing 16 different U.S. states. Additionally, GPS bias was assessed to minimize any possible priming effects GPS technology may have had on visitor behavior; 93.18 % of respondents indicated the GPS device did not influence their behavior.

3.1.1. Exploratory factor analysis, hierarchical cluster and associated specialization types

The exploratory factor analysis (EFA) resulted in a four-factor model containing ten specialization response items which explained 69.341 % of the variance in the dataset (Table B2 in Appendix B). This model required the removal of 9 of the 19 specialization response items: self-expression (enduring involvement), local and international club membership (centrality to lifestyle), general, county and state travel intent (travel intention), activity association (social investment), equipment costs (economic investment) and competitive history (achievement). The four factors produced in this model represent latent specialization components of Commitment-social investment, Skill-ability/knowledge, Involvement-centrality and Involvement-participation history (Table B2 in Appendix B). Items with factor loadings below an absolute value of 0.45, cross-loading items, and freestanding items were removed from the initial EFA (Costello & Osborne, 2005), and reliability analyses were performed for each component to confirm that their Cronbach's alphas were greater than 0.6, reflecting acceptable internal consistency.

A Ward's hierarchical cluster resulted in a three-cluster solution grouping the data based on EFA factor scores. The cluster analysis identified three distinct types of recreators across four parks and three

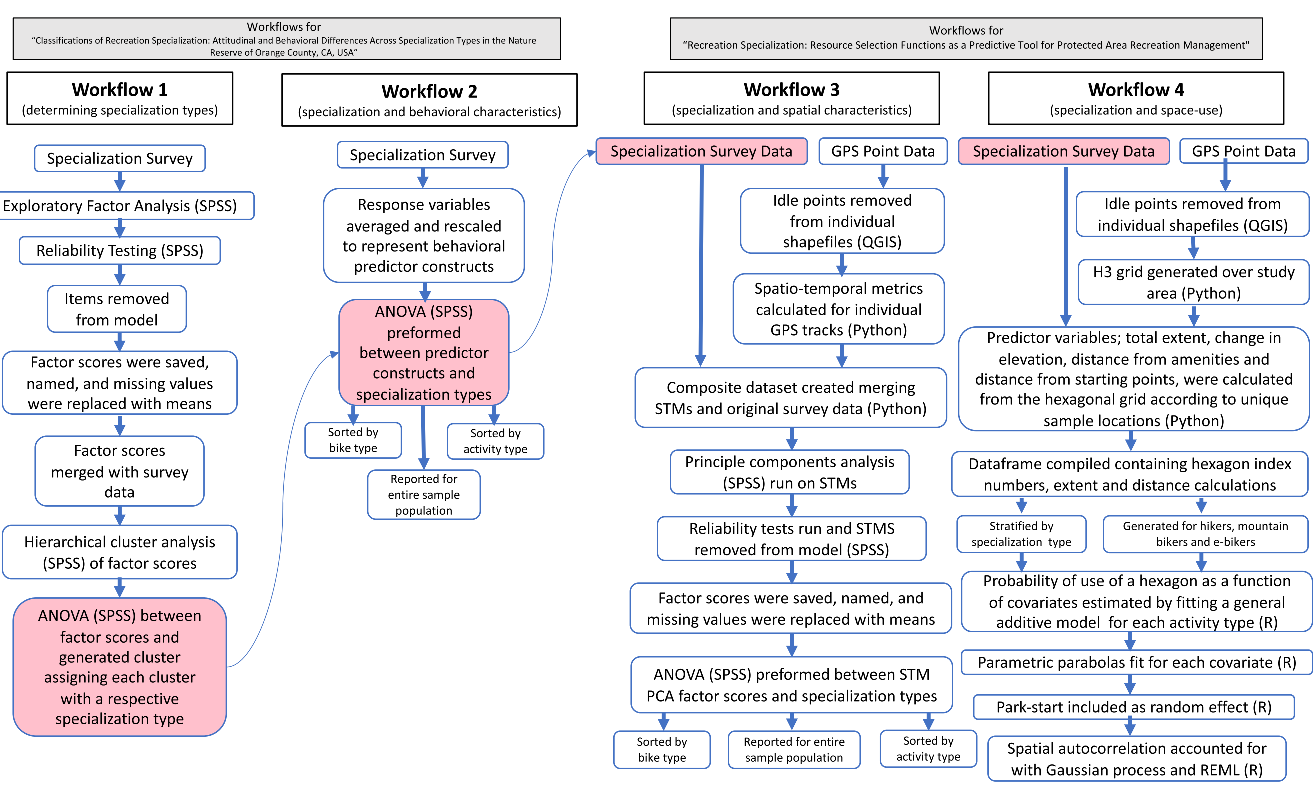

Fig. 2. Methodological workflows employed in Orange county specialization research.

primary activities, with unique survey responses and similarities in the 4 latent specialization components. A confirmatory one-way ANOVA comparing latent specialization components and the three generated clusters, assisted in associating the clusters with their representative specialization types (Table 2). Clustering the sample population based on social commonalities, made it possible to associate each cluster with an appropriate specialization type, in which the cluster 1 with the lowest mean values would be known as the casual (least specialized) type, cluster 2 with moderate mean values would be known as the active (moderately specialized) type, and cluster 3 with the highest mean values would be known as the committed (most specialized) type (Scott & Shafer, 2001).

3.1.2. Principal components analysis and resulting spatio-temporal metrics

The PCA on the spatio-temporal metrics, resulted in a three-factor model containing 9 of the original spatio-temporal metrics (Table 1) which explained 90.151 % of the variance among these metrics (Table 3), and satisfied assumptions of sample size with a Kaiser-Meyer-Olkin value of 0.610 and sphericity with a significant result from Bartlett's Test of Sphericity $p < 0.001$. To ensure response variables were orthogonal and independent from one another, the PCA required the removal of 4 out of 13 spatio-temporal metrics due to multicollinearity: maximum distance (from starting point), total distance, mean trail designation and mean trail difficulty. The three factors produced in this model represent spatial behaviors demonstrating a recreators expression of time and elevation, stopping behavior and speed. Total distance was included in future analyses and was examined separately from the PCA factors, recognizing its potential influence on other STMs.

3.1.3. Spatio-temporal metrics across specialization types

For the entire sample population, a one-way ANOVA revealed patterns between specialization, the 3 PCA factors examined and total distance (Table 4). Based on mean values, a positive relationship was found between specialization and PCA Factor 3 representing speed, in which the committed specialization type was found to travel at faster speeds than the active and casual specialization types $F\,(2, 799) = 7.597$, $p < 0.001$. Similarly, committed recreationists reported significantly greater mean values for total distance traveled in comparison to the active and casual specialization types (the active specialization type also reported a significantly greater mean total distance value in relation to the casual specialization type) $F\,(2, 764) = 6.494$, $p < 0.005$.

Additionally, a one-way ANOVA examining differences in PCA factors between specialization types for each activity type, demonstrated unique trends (Table B4 in Appendix B). For hikers, significant differences were reported between specialization and PCA Factor 2 representing stopping behavior and PCA Factor 3 representing speed. Casual hikers re-ported significantly higher mean values for stopping in relation to the active and committed hikers (the active specialization type also reported a significantly lower mean stopping value than the committed specialization type) $F\,(2, 489) = 3.756$, $p < 0.05$. A positive relationship was also demonstrated between hiker specialization and PCA Factor 3 representing speed $F\,(2, 489) = 2.973$, $p < 0.05$, in which the casual specialization type reported lower mean factor scores for speed than the active and committed specialization types.

The ANOVA results did not display any further significance between specialization types, the three PCA factors and total distance traveled, although it is demonstrated that committed recreationists generally reported more variability in factor scores for PCA Factors 1, 2 and 3 representing elevation/time, stopping behavior, and speed (in relation to active and casual recreationists) (Tables B3 and B4, and Figures B1 and B2 in Appendix B). The lack of significance among the cyclist, runner and specific bike type groups can likely be attributed to the low sample sizes collected in this study (255 total cyclists, 46 runners, 198 mountain bikers, 33 e-bikers and 24 ″other" bikers).

3.1.4. Resource selection function: probability of use in relation to change in elevation, distance to starting points and distance to park amenities

After examining relationships between specialization and spatio-temporal metrics, an RSF was implemented to examine spatial distribution of various specialization and activity types across the entire study area. This model reported significant differences between the probability of use of hiker, mountain biker and e-biker specialization types in relation to change in elevation, distance to starting points and distance to park amenities. When examining the probability of use of hikers in relation to elevation, all specialization types displayed higher a probability of use for negative changes in elevation, although the casual hikers demonstrated the highest probability of use values in areas of the park where change in elevation was closer to zero (Figure C.1 in Appendix C). In contrast, active and committed hikers reported lower probability of use values in these areas although still displaying decreasing probability of use values as change in elevation increased. Active and committed mountain bikers also reported higher probability of use values for negative changes in elevation, although probability of use values were even higher for mountain bikers then they were for hikers (Fig. 3). Casual mountain bikers, exhibited the highest probability of use values where there was little change in elevation and low probability of use values for increasingly negative and positive changes in elevation. For e-bikers, active and committed specialization types demonstrated similar relationships to casual mountain bikers (high probability of use values where there was little change in elevation), while casual e-bikers displayed an opposite relationship, reporting the low probability of use

Table 2
ANOVA: Comparison of latent specialization components across specialization types.

Latent Specialization Components	Specialization Type			F-ratio	P-value
	Cluster 1 [c]	*Cluster 2* [d]	*Cluster 3* [e]		
Commitment-Social Investment [a]	2.082^{a}	3.479^{b}	3.396^{b}	152.804	<0.001
Skill-Ability/ Knowledge [a]	2.503^{a}	2.98^{b}	3.092^{b}	26.66	<0.001
Involvement-Centrality [a]	1.075^{ab}	1.085^{a}	1.115^{b}	4.491	0.011
Involvement-Participation History [b]	2.186^{a}	2.17^{a}	3.725b	777.727	<0.001

[a] Groups with different subscripts are significantly different with Tukey procedure at .05 level of confidence.
[b] Groups with different subscripts are significantly different with Games-Howell procedure at .05 level of confidence.
[c] Cluster 1 contained 105 cases and was designated the 'casual' specialization type.
[d] Cluster 2 contained 302 cases and was designated the 'active' specialization type.
[e] Cluster 3 contained 393 cases and was designated the 'committed' specialization type.

Table 3
PCA reducing 13 STMs into 4 spatial factors.

Factors with Maximum Likelihood	Rotated Factor Loadings	Eigenvalue	% of Variation (Cumulative)
Factor 1			
Trip Duration	0.898		
Moving Time	0.974	3.970	44.109
Elevation Gain	0.892		
Factor 2			
Number of Stops	0.819		
Stop Time Percent	0.955	2.495	71.832
Stop Duration	0.908		
Factor 3			
Maximum Speed	0.870		
Mean Speed	0.955	1.649	**90.151**
Median Speed	0.889		

Table 4
ANOVA: Comparison of spatial factors and STMs across specialization type.

Latent Specialization Components	N	Specialization Type			F-ratio	P-value
		Casual	Active	Committed		
Elevation and Time (PCA Factor 1)[a]	797	−0.0858	−0.0627	0.0708	2.063	0.128
Stoppage (PCA Factor 2)[a]	797	0.1703	−0.0119	−0.0417	1.965	0.141
Speed (PCA Factor 3)[b]	797	−0.3035	−0.0309	0.1050	7.597	<0.001
Total Distance(m)[a]	762	6036.4541	7035.8150	7995.1378	6.494	0.002

[a] Groups with different subscripts are significantly different with Tukey procedure at .05 level of confidence.
[b] Groups with different subscripts are significantly different with Games-Howell procedure at .05 level of confidence.

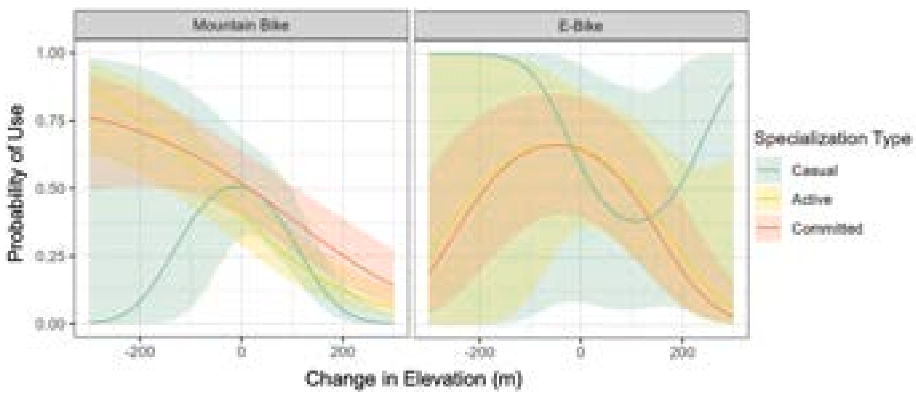

Fig. 3. Probability of use in relation to change in elevation for cyclists.

values where there was little change in elevation and high probability of use values for increasingly negative and positive changes in elevation.

Probability of use was also reviewed in relation to distance to starting points, in which hikers demonstrated decreasing probability of use values with increasing distance to starting points (Figure C.2 in Appendix C). Although all hiker specialization types exhibited very similar relationships, active and committed hikers demonstrated slightly higher probability of use values in areas farther from starting points, while probability of use for casual hikers tended to decrease faster as distance to starting points increased. For mountain bikers, the casual specialization type also demonstrated a decreasing relationship between probability of use and distance to starting points, while the active and committed specialization types displayed lower probability of use values at a mid-range distance to starting points and higher probability of use values at very low and very high distances to starting points (Fig. 4). For e-bikers, active and committed specialization types exhibited similar (but more dramatic) relationships in comparison to active and committed mountain bikers, while casual e-bikers exhibited high probability of use values at mid-range distance to starting points and decreasing probability of use values as distance to starting point increased (Fig. 4).

Hikers displayed somewhat weak relationships between distance to amenities and probability of use for all specialization types, although there were slightly higher probability of use values apparent for all hikers at lesser distances to amenities (Figure C.3 in Appendix C). Mountain bikers demonstrated decreasing probability of use values with increasing distance to amenities, although probability of use values for the casual and active specialization types decreased more quickly than they did for the committed specialization type (Figure C.4 in Appendix C). Active and committed e-bikers also displayed high probability of use values at lesser distances to amenities, while probability of use quickly decreased with increasing distance from amenities. However, casual e-bikers demonstrated high probability of use values at mid-range distances to amenities, low probability of use values where distance to amenities is close to zero, and decreasing probability of use values with increasing distance to amenities (Figure C.4 in Appendix C).

3.1.5. Resource selection function: examining probability of use across specialization type and activity type on a park specific basis

Probability of use as modeled in the RSF, was also analyzed on a park

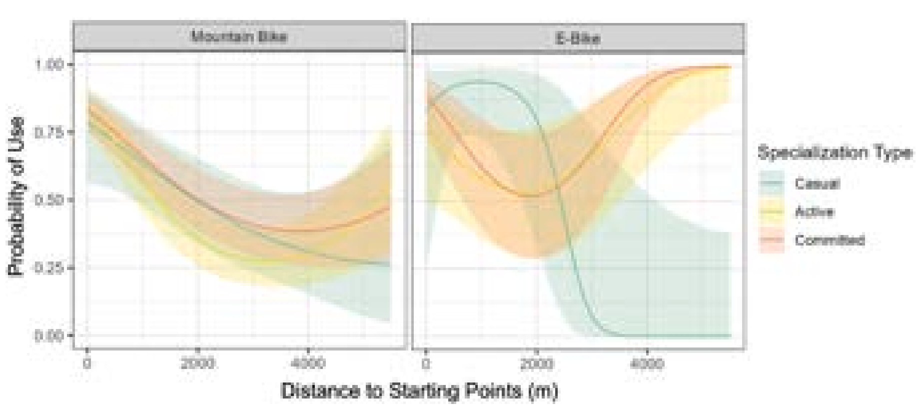

Fig. 4. Probability of use in relation to distance to starting points for cyclists.

specific basis (Figs. 5–7) and can be seen in relation to park boundaries, designated trails and the associated starting point. This projection of the RSF in space, demonstrates the probability of use (%) within each hexagon across a park's extent. In general, higher probabilities of use (80–100%) are displayed in hexagons proximate to starting points (park entrances), and on the designated trails leading from these starting points (typically trails with less change in elevation (Fig. 3). Although probability of use for hikers (Figure C.2 and C.5 and in Appendix B) and mountain bikers (Figs. 5 and 6) is generally lower in locations farther from starting points, the committed and active specialization types demonstrate higher probabilities of use in relation to the casual specialization types in areas farther from starting point (Figs. 5 and 6, and Figure C.6 in Appendix C). It is also evident that committed mountain bikers at ALWO display higher probabilities of use (~20%) in the hexagons on the western side of the park (the hexagons with higher elevation values) (Fig. 5), mirroring higher probabilities of use in relation to change in elevation (Fig. 3). Additionally, active and committed mountain bikers demonstrated high probability of use values (in the 40–60% range) in hexagons extending beyond park boundaries.

While examining probability of use of e-bikers across specialization types and parks, there were few observations collected at ALWO, PECA and WHRA, so the results demon-strated (Fig. 7) are solely representative of the sample of recreationists at SAOK. Casual e-bikers at SAOK demonstrated relatively high probabilities of use (over 20%) across most of the park's extent, indicating that the casual and active specialization types typically dispersed more than the committed specialization type. In relation to active and casual e-bikers, the committed e-bike population generally demonstrated lower probability of use values on trails farther from starting points. While committed mountain bikers were the only specialization type exhibiting probability of use values above 20% beyond the northern park boundary (Fig. 6), casual e-bikers also demonstrated this behavior and high probability of use values (above 40%) in many hexagons beyond the southern park boundary (Fig. 7).

3.1.6. Resource selection function: controlling for spatial autocorrelation

Because the RSF in this study applied the use of a 200m hexagonal grid to assess variability in spatial distribution across trail networks at four different parks, it was inherently likely that a degree of spatial variation was present due to the close proximity of each hexagonal cell to the nearest neighbor (i.e. a cell could report a high value because a recreationist passed through this cell on the way to nearby cell). However, the previous results demonstrating probabilities of use within hexagon cells across various park locations, accounted for spatial autocorrelation in the data due to the fitted spatial random effect in the model (i.e., the Gaussian process term). The estimated term can be seen across the Reserve (Fig. 8), and use values proximate to each park location were higher than the values beyond park boundaries. The spatial distribution relationships modeled by the RSF (Figs. 3–7) are those above and beyond the probability of use due to spatial autocorrelation (Fig. 8).

4. Discussion

There are currently no published studies examining the effects of recreation specialization on spatial behavior with the use of location monitoring technologies. However, existing literature examining specialization and reported recreation behavior contributes to the understanding of why individual recreationists may exhibit certain spatial patterns across a landscape. As indicated by the spatial analyses demonstrated in this study, there is evidence that classifying recreationists based on specialization indicators can be an effective method for identifying spatial patterns in recreation use. For instance, an association between recreation specialization and travel intention (De Salvo et al., 2020) and studies indicating specialists are less concerned with length of approach (Merrill & Graefe, 1998), may suggest that committed specialization types will travel further while recreating. Additionally, findings that indicate higher levels of specialization may be associated with preferences for more rugged, primitive environments, with fewer amenities and less social contact (Virden & Schreyer, 1988), could reflect that these recreationists may travel to less frequently visited park locations and exhibit longer trip durations. Although reporting on attitudes is common practice in recreation resource management (Dyck et al., 2003; Manning, 2022; Sisneros-Kidd et al., 2021), actual behaviors of specialized recreationists can not be entirely inferred and should be verified with spatio-temporal evidence on an activity type and park specific basis.

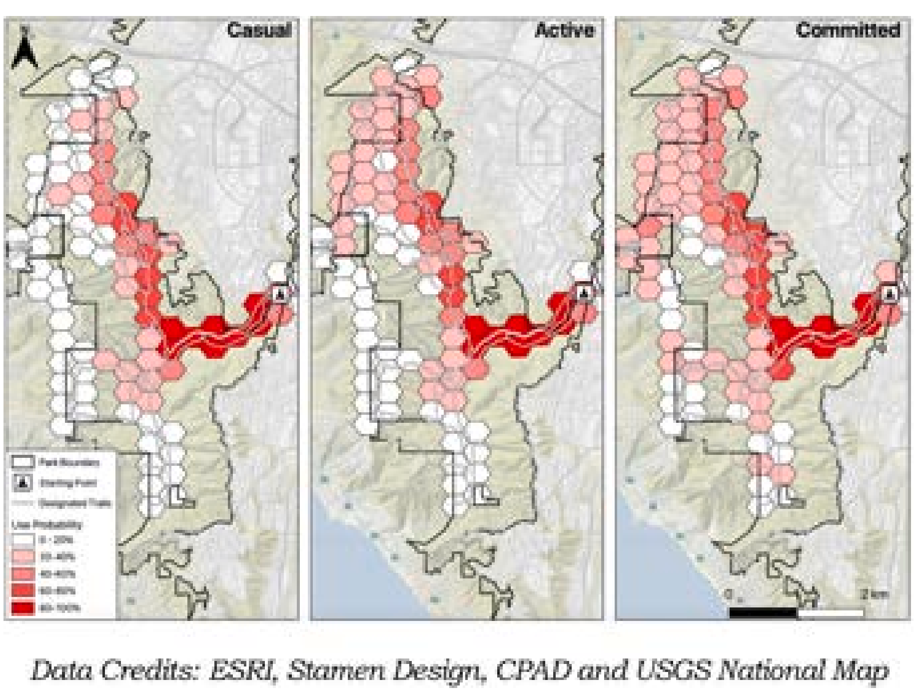

Fig. 5. Probability of mountain bike use at aliso and wood Canyons.

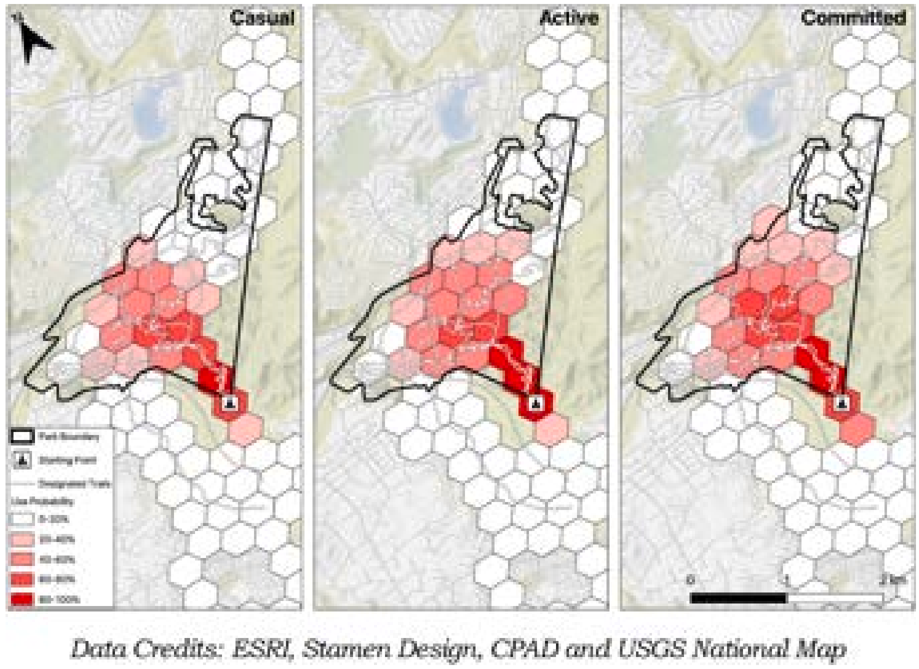

Fig. 6. Probability of mountain bike use at Santiago Oaks.

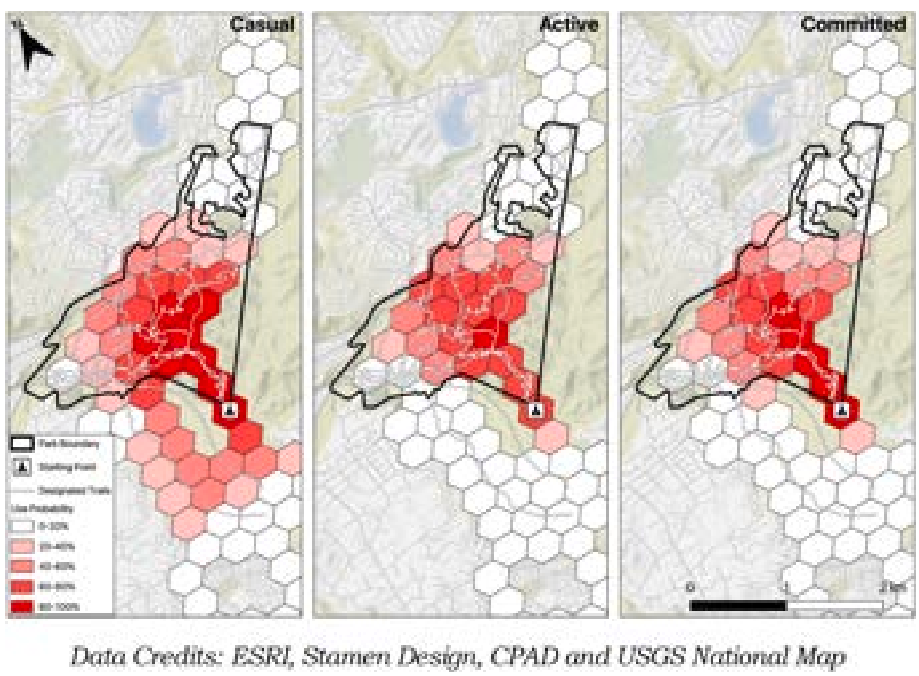

Fig. 7. Probability of E-bike use at Santiago Oaks.

When classifying recreationists into certain specialization types based on latent expressions of involvement, commitment and skill, it was assumed from historical specialization-behavior studies (McFarlane, 2004; Merrill & Graefe, 1998; Needham et al., 2009; Oh & Ditton, 2008; Virden & Schreyer, 1988), that specialization types with greater mean factor scores (committed types) would demonstrate movement patterns expressing higher levels of skill and expertise: longer trip durations, more elevation gain, less overall stopping, faster overall speeds and farther total distances. Although this assumption proved to be mostly true at a population level and for hikers, the assumption was based on solely behavioral and attitudinal research and therefore it was not surprising that findings from this study revealed spatial behavior to be inherently more complex and influenced by numerous confounding factors (activity type/bike type, starting points, park topography and trail design).

As hypothesized, the population ANOVA (Table 4) indicated that committed recreationists traveled at faster speeds and traveled farther distances in comparison to active and casual recreationists. When analyzed on an activity-specific basis, hikers also demonstrated anticipated results in which the casual specialization type traveled at slower speeds, stopped more frequently, and stopped for longer periods of time in relation to the active and committed specialization types. However,

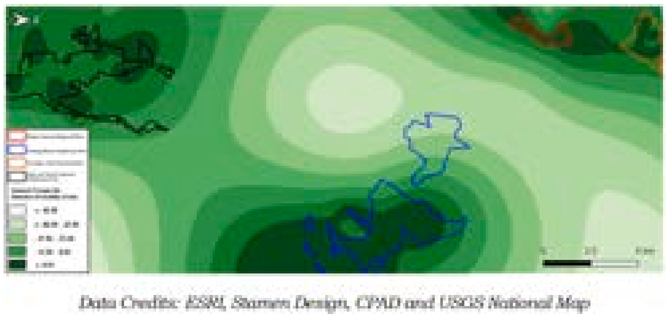

Fig. 8. Gaussian proccess estimation across the reserve.

when examining spatial patterns in runner and cyclist behavior, no significant differences were evident between specialization types and a high degree of variation was observed across factor scores. Because STMs were calculated from GPS tracks that were oriented in a linear fashion (along trail systems), it is possible that the weak trends in spatial behavior exhibited for cyclists were influenced by factors that affect spatial distribution: park specific change in elevation and distance to starting points and amenities.

To control for these factors and variations between parks, the RSF was performed on a park-specific basis, examining spatial distribution across varying landscapes and providing context to the distinct spatial behaviors identified among specialization types and activity types in the ANOVA. Modeling probability of use as a function of change in elevation, distance to starting points and distance to amenities, revealed unique spatial distribution characteristics for each specialization type and activity type. This model predicted that hikers typically traveled downhill from their starting points, while the casual specialization type indicated the strongest affinity to travel downhill in comparison to the active and casual specialization types. Hikers generally demonstrated a strong presence in areas close to starting points, but active and committed hikers showed a stronger presence than casual hikers in areas distant from starting points; indicating a willingness to travel farther from their point of origin. For mountain bikers mostly intuitive relationships were seen between probability of use and spatial distribution, in which casual specialization types indicated an affinity for travel on flat terrain, while active and committed mountain bikers displayed a strong affinity for downhill travel. Committed mountain bikers also demonstrated a willingness to travel farther from starting points and amenities that the casual mountain bikers did not. E-bikers on the other hand expressed somewhat unintuitive results, in which the committed and active specialization types preferred travel on flat terrain and the casual specialization type preferred travel uphill and downhill. Additionally, casual e-bikers expressed an affinity for travel moderately close to starting points and amenities, while committed and active e-bikers exhibited an affinity for travel farther from starting points and closer to amenities.

With nuances in specialization and spatial distribution dynamics revealed across activity and bike type, it was crucial to examine probability of use visually on a park specific basis to identify specific locations where use is likely to occur. Mapping projections of the RSF in space portrays intuitive results, in which causal mountain bikers and hikers demon-strated concentrated use in areas near starting points with less change in elevation, and active and committed mountain bikers and hikers exhibited more dispersal across park trail systems. However, when examining probability of use in relation to e-bikers specialization, results differed from the hiker and mountain biker populations. Active and committed e-bikers dispersed less than casual e-bikers and demonstrated confined use near park starting points; results that were almost opposite of patterns demonstrated in hiker and mountain biker spatial distribution. Furthermore, the relationships displayed for each specialization and activity type in the RSF, suggest that spatial behavior is inherently complex and cannot be entirely understood without considering spatial distribution; park specific random effects (varying park-starts) and the possible interactions that may influence recreation movement through an interconnected trail network (spatial autocorrelation).

Trends in spatial behavior and distribution exhibited across specialization types largely reflect the few projections that exist in historical literature; which indicate boater specialization and activity type can be an effective measure of distance traveled (Lentnek et al., 1969) and that specialists have higher preferences for more challenging trails (Virden & Schreyer, 1988; Williams & Huffman, 1986). However, spatial patterns exhibited in the e-biker sample contradicted results demonstrated in the greater sample population in Orange County. The unique trends demonstrated between specialization and spatial behavior for the sample of e-bikers at the Reserve, can likely be attributed to the understanding that e-biking is an emerging activity, and it is largely possible that it has not existed long enough for participants to express typical specialization dynamics. Additionally it can be presumed that there is a substitution effect occurring between specialization type and modern advancements in outdoor recreation equipment; in which a recreationist may be able to compensate for lower skill levels by purchasing the newest available technology.

4.1. Ecological and managerial implications

With very few studies of a similar nature preceding this work, much of the methodological process for the spatial component of this study was drawn from recent analyses reviewing GPS data and spatio-temporal metrics (Baker et al., 2021; D'Antonio et al., 2020; Sisneros-Kidd et al., 2021; Stamberger et al., 2018), as well as wildlife ecology studies examining species resource selection, resource utilization distribution and spatial use on an individual and population level (Kertson & Marzluff, 2011; Kittle et al., 2015; Papworth et al., 2012). A robust GPS dataset (765 individuals with points collected at 10 s intervals), provided the opportunity for an exploratory spatial analysis, revealing results that can be applied in a predictive capacity or reviewed in tandem with ecological data containing information on the whereabouts of protected species or park locations of conservation concern. More generally, this study has identified the spatial behaviors unique to certain specialization and activity types, and identified park locations where recreation movement is likely to occur.

The identification of actual movement patterns of various recreation activities across four park trail systems in the Reserve has provided the necessary groundwork for identifying potential impact to park resources and ecological systems. Examining actual use patterns demonstrated by recreators has been a common aim in recreation studies examining the social-ecological impact of recreation and tourism (Beeco et al., 2014; Kidd et al., 2015; Stamberger et al., 2018) and the use of GPS data allows for statistical estimation of recreation use, providing the ability to predict small-scale visitor use patterns, use in-tensity, and visitor flows and densities (D'Antonio et al., 2010). Integrating GPS data from this study with data acquired from ecological assessments, and historical ecological knowledge of a curvilinear use-impact relationship (Monz et al., 2013), concentration theory (Marion et al., 2016), user-created trails (Baker et al., 2021), mechanical forces exerted by various recreation activities (Liddle, 1997) and use-patterns associated with degradation (Mitterwallner et al., 2021), can indicate behavioral tendencies likely to negatively affect ecological systems. For instance, hikers, runners, mountain bikers and e-bikers with the ability to travel far from their starting point, have an increased likelihood of reaching an area of a park with less use, therefore their impact may be proportionally greater then the recreationists confined to popular park areas with frequent use.

4.2. Limitations

In situations where park visitors were traveling in a group, only one group member was asked to participate in the study, which may have led to the collection of data that represents behavior of the group rather than behavior of the individual. Additionally, it should be noted that only 14 of the 33 of e-bikers in this study (42.4%), directly reported their bicycle type as an "e-bike", which suggests that a large portion of the e-bike population was hesitant to participate in this study. This hesitation may have been the result of a stigma that surrounds e-biking as a new and emerging activity, but also likely a result of e-bikes being prohibited in many park locations (as it was in the Nature Reserve of Orange County), which may have limited our ability to gather a more robust e-bike sample.

Understanding that specialization research can be limited by an existing tautology, it was important to avoid classifying specialization in terms similar to the variables it is anticipated to influence (Manning, 2022). However, identifying skill as a latent dimension of specialization in this study may have introduced somewhat obvious spatial results in which spatial results could be more heavily associated with individual indicators of specialization rather than the sum of all indicators. In future research a recommendation would be to cluster the study population based on spatial data and examine the social commonalities that exist within these clusters. Due to the linear expressions of spatial behavior common with recreationists using a designated trail system, there was expected to be a high degree of association occurring between the point data present in each hexagon and its nearest neighbor. For instance, high probability of use could have been reported in a certain location due to the fact that the given area is a popular pass-through zone. However, using Gaussian process and random effects terms in the GAM assisted in capturing these patterns and thus minimizing error in the estimation of the parametric terms. Discrepancies existing between the results produced in the RSF and the ANOVAs, can likely be attributed to the unique nature of spatial distribution across a trail system. Direct distances were used as inputs to this function which did not take into account the way in which trails meander, switchback, intersect and loop, which may have introduced interference when modeling probability of use in proximity to starting points and amenities. The possible simplification of trail networks in the RSF, could be further investigated through application of graph and network-based approaches have been applied to track spatial behavior and use across a functional network (Bielański et al., 2018; Taczanowska et al., 2014; Taczanowska et al., 2017).

5. Conclusion

In a predictive capacity, comprehending specialization as a social driver of spatial behavior and spatial distribution can be helpful when reviewing existing management objectives and identifying where increased visitation may cause issues due to limited carrying capacity (Manning, 2011). Understanding visitor use patterns through the collection of GPS data can be especially informative for identifying resource protection priorities, when coupled with survey instruments profiling different park visitors (Meijles et al., 2014). This study's propensity to identify trends in recreation movement based on the social similarities that exist between groups of recreators, is crucial for managing trail use and visitor experience on a spatial scale. Knowing why people use different portions of a park, or specific trails in a park can inform future planning by suggesting where trail designs would be preferred and where maintenance initiatives may be a priority. Alone, the novel application of an RSF in this study can be largely helpful in a park-specific management context, however overlapping this knowledge with social data and resource use knowledge will increase a manager's ability to respond to issues such as crowding and conflict by designating certain trails to specific uses and directions, implementing educational outdoor recreation programs, or even initiating reservation systems that temporally disperse use.

CRediT authorship contribution statement

Jake Van Deursen: Writing – review & editing, Writing – original draft, Visualization, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Noah Creany:** Writing – review & editing, Supervision, Software, Investigation, Formal analysis, Data curation, Conceptualization. **Brian Smith:** Writing – review & editing, Validation, Software, Resources, Methodology, Investigation, Data curation, Conceptualization. **Wayne Freimund:** Writing – review & editing, Visualization, Conceptualization. **Tal Avgar:** Writing – review & editing, Visualization, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **Christopher A. Monz:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization.

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Appendices

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