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Predicting trail condition using random forest models in urban-proximate nature reserves

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ABSTRACT

Monitoring and managing the condition of recreational trails is a time- and resource- intensive process often requiring significant field data. We developed a method for predicting trail condition over 183 km of trails in three urban-proximate nature reserves in Orange County, California using field data from 118 km of trails and random forest (RF) models. Further, we use data from the fitness tracking application Strava to measure recreation use intensity, activity type, and spatial dimensions of visitor use. Our results indicate 30 km of trails in two nature reserves that are at risk of significant trail degradation. Additionally, trail grade, NDVI, and use-related factors such as activity type and use intensity were ranked among the most important variables for predicting trail condition. Variable importance measures produced by RF models can help inform site-specific trail management that takes environmental, managerial, and use-related factors into account. We argue that RF models, in combination with Strava data, are powerful tools for outdoor recreation monitoring and management.

1. Introduction

1.1. Modeling trail condition

Recreational trails serve many purposes. They facilitate the recreational use of landscapes by providing a transportation network through a given area (Leung and Marion, 1996) and specialized recreational opportunities, such as mountain biking or equestrian use through intentional design (Webber and IMBA, 2007). Additionally, they protect ecological and cultural resources by concentrating use on hardened surfaces (Hammitt et al., 2015).

Understanding the condition of recreational trails is an important consideration for protected area managers and outdoor recreationists alike. Protected area managers may want to know the condition of trails to provide site-specific maintenance or visitor education on trail use (Marion, 2023; Marion and Wimpey, 2017). Outdoor recreationists may prefer trails based on trail condition, surface type, width, grade, or amount of use (Korpilo et al., 2018; Lynn and Brown, 2003). However, mapping, monitoring, and communicating the condition of trails is often spatially and/or temporally restricted due to the time and effort required to collect and analyze trail data.

Data on trail condition are often collected by traveling the trail by foot and recording parameters of interest on a handheld GPS unit, tablet, or similar device. Parameters of trail condition may include trail width, depth, surface type, presence of roots or gullying, vegetation damage, and condition class (Hammitt et al., 2015; Olive and Marion, 2009). Trail condition class is a common method for documenting recreational impacts to trails, where classes range from 1 to 5 (see Table 1 in Supplemental Material). Generally, class 1 trails are least disturbed, while class 5 trails are most degraded, either because of poor design, improper type or amount of use, or environmental conditions. Class 4 and class 5 trails are more likely to exhibit 'trail degradation," a phenomenon by which the physical, ecological, and/or aesthetic qualities of trails are compromised (Leung and Marion, 1996). A large body of research uses this ranking system to classify and monitor recreational trails (Monz et al., 2010; Spernbauer et al., 2023).

Several studies have assessed trail condition by pairing field data with computational techniques, but most occur within a single protected area or trail (i.e., Olive and Marion 2009, Spernbauer et al. 2023, Tomczyk and Ewertowski 2015). There is also a growing interest among researchers and managers to map, monitor, and model trails through less field-intensive methods. One study used GIS to estimate conditions over

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1700 km of tracks (multi-use trails) in Tasmania, Australia; their results indicated 50 % prediction accuracy rates (Hawes et al., 2013). Rice et al. (2019) developed a low-cost method to identify undesignated trail use using heatmap data from the fitness tracking application Strava in three U.S. protected areas. Another study used drones to collect aerial imagery of trail degradation, including vegetation trampling, soil erosion, and changes in trail width and depth (Ancin-Murguzur et al., 2020).

Our study predicts trail condition class in three southern California urban-proximate nature reserves with a goal of identifying locations of potential trail degradation. We used a combination of GPS-collected field data and GIS data to predict the trail condition class of unmonitored trails using random forest (RF) modeling, where unmonitored trails represent 183 km of trails that were not mapped in-field. We integrate crowdsourced data from the fitness tracking application Strava to measure use intensity, activity type, and location of use. Further, we paid special attention to common challenges to using RF with spatial-ecological data such as spatial-autocorrelation and the careful section of predictor variables. Only one study (to date) has used RF to assess trail condition, it used relatively few sample points ($n = 200$) over one 24 km trail and did not include predictors related to visitor activity type or use intensity (Sahani and Ghosh, 2021). We further this discourse by using RF to predict trail conditions over 183 km of trail via 19 predictors related to the ecological, managerial, and social determinants of trail condition.

1.2. *Using random forest models on spatial-ecological data*

Random forest models have gained popularity for analyzing complex spatial-ecological data (Cutler et al., 2007; Lucas, 2020). RF can handle large, unstructured datasets (Breiman, 2001) and often outperforms traditional linear or logistic regression in both classification and regression in its predictive power (Cutler et al., 2007; Hengl et al., 2015). RF operates by constructing many individual decisions and deriving predictions through averaging (regression) or majority vote (classification). Although well-designed RF models yield high-accuracy predictions and valuable insights into variable importance, poorly designed models can produce overly optimistic or incoherent results (Gutzwiller and Serno, 2023; Wadoux et al., 2021).

An unresolved challenge in using RF on spatiotemporal data is autocorrelation (Tonini et al., 2020). Although RF is a non-parametric method and does not require independent observations, many scholars suggest that autocorrelation may impact RF results (Gutzwiller and Serno, 2023; Meyer et al., 2019; Ploton et al., 2020). Autocorrelation can be a particular problem in clustered data, such as spatially or temporally sequential observations made along trails. It can be assumed that two nearby locations on a trail will be more similar (ecologically, geologically, and recreation use-wise) than will two points that are farther apart.

Several techniques have been proposed to address spatial autocorrelation in RF models. One approach suggests including geolocated predictors, such as latitude, longitude, and distance to predetermined points to account for the spatial nature of the data (Hengl et al., 2018a). Alternatively, a comparative study on spatial autocorrelation in RF models found that using probabilistic sampling and design-based inference resulted in less bias in results compared to spatial cross-validation or buffered leave-one-out cross validation (Wadoux et al., 2021). We follow the recommendations of Wadoux et al. (2021) and used probabilistic sampling to collect data points used in the RF analysis.

1.3. *Selecting appropriate predictor variables for RF*

Increasing evidence suggests that RF models are affected by the character and structure of predictor variables (Baltensperger, 2018). Some research suggests that geolocated variables can improve RF model performance (Hengl et al., 2018b); others disagree (Meyer et al., 2019). In this work, we compare the performance of two models, one with and one without geolocated variables (latitude, longitude, and Euclidean distance to the center of the nature reserve) to explore this disagreement.

Baltensperger (2018) noted another challenge posed by RF models is their bias toward high-level categorical (HLC) variables, defined as those with greater than 20 classes. He found a decrease in overall accuracy when HLCs were included compared to when they were excluded; he argued that RF provides the least biased results when categorical predictors have 5 to 15 classes. Unfortunately, spatial-ecological data are often represented by HLCs, including soil, vegetation, or land cover type, all of which can be important determinants of trail condition. Best practices for using RF state that where appropriate, HLCs should be represented as continuous data or omitted altogether (Baltensperger, 2018). We integrated categorical and continuous variables for vegetation in place of a HLC dataset on vegetation type and omitted soil type because it is most commonly represented as a HLC variable.

Finally, RF may perform poorly on categorical data with uneven class distribution because classes with few samples may be entirely omitted from the training data (More and Rana, 2017). This problem can be reduced by ensuring that all values have an equal chance of being included in the training and predictor data through probabilistic sampling (Wadoux et al., 2021). When probabilistic sampling is used and a class imbalance remains, balanced accuracy should be reported and interpreted in addition to overall accuracy (Akosa, 2017). We follow these recommendations as our trail condition dataset has a class imbalance.

1.4. *Using the Strava Global Heatmap*

Research on visitor use management often requires data on use intensity, type of use, and location of use. Further, the condition of trails is partially determined by the amount of recreational use they receive. Trail use intensity is measured via self-counting at trailheads, direct-counting using observers, indirect counting through automatic counting devices, and more recently, crowdsourced methods. Each method requires varying investments in time, technology, and financial resources (D'Antonio et al., 2010; Norman and Pickering, 2017). Direct and indirect counting, while effective for measuring use intensity with high accuracy, capture a small spatial and/or temporal subset of users, and many protected areas lack large-scale data on spatial and temporal patterns of trail use. This is especially true of informal (visitor created) trails, which often lack data on visitor use altogether (Rice et al., 2019).

Recently, Strava has been used to measure and monitor trail use in protected areas (Rice et al., 2019; Venter et al., 2023). Strava is a fitness tracking application popular among runners and cyclists with over 120 million global users as of January 2024 (Strava Inc., 2024). The app, available via GPS-enabled devices, records information on recreational activities including a GPS track, average speed, distance traveled, and elevation gain and uploads this information to the web. Compared to other fitness tracking applications, Strava may pose the greatest potential for long-term visitor use monitoring due to its widespread availability, ease and cost of use, and ability to detect use on informal locations, particularly in urban-proximate or fitness-oriented locales (Norman and Pickering, 2017; Venter et al., 2023).

Our study uses a feature called the Strava Global Heatmap (SGH) to quantify visitor use intensity. The SGH depicts aggregated user data for various outdoor recreation activities from its inception in 2017 to date (Strava Inc., 2022). Publicly available as an interactive webpage, the SGH depicts areas of high intensity use as a more saturated hue (or a value 255 on the RGB hue scale) whereas areas of moderate to low use intensity show decreasing hue values (down to 0). The SGH makes visual the spatial distribution, use-intensity, and type of recreational activities that occur in a landscape at relatively fine spatial scales. It serves as a useful tool to monitor both formal and informal trail use in parks and protected areas.

Data from Strava have been used in several spatial-ecological recreation management studies (i.e., Rice et al. 2019, Jäger et al. 2020). Corradini et al. (2021) incorporated the SGH to create a Cumulative Outdoor Activity Index map to reveal where alpine brown bear (*Ursus arctos*) behavior was impacted by human presence in the Italian Alps. The authors validated SGH data with camera trap data on visitor use and found a positive, statistically significant correlation (Corradini et al., 2021). Creany et al. (2020) used Strava data to examine visitor use in the same network of southern California urban-proximate nature reserves we studied and found that Strava was the fitness tracking application with the highest reported use over the study area. Finally, Venter et al. (2023) found that Strava data capture spatial variation of recreational activity quite well ($r^2 = 0.9$) when compared to *in-situ* observations, but they found that Strava users were not representative of all outdoor recreationists. Representation poses a notable limitation when using Strava data to examine visitor demographics and preferences, but this concern is minimized when Strava is used to assess the spatial dimensions of recreation use. We use data from the SGH to incorporate use intensity, use location, and type of use into our RF model.

1.5. Study objectives

This study addresses several questions that serve both the recreation management and spatial-ecological data science communities.

1. Can RF models be used to predict trail condition in large nature reserves using a subset of field-mapped data?
2. Which variables are most influential in predicting trail degradation in Southern California urban-proximate nature reserves?
3. Can data from the Strava Global Heatmap be used to represent visitor use in RF models?
4. To what extent do geolocated variables affect RF model performance?

By addressing these questions, we contribute useful information to a growing body of knowledge on best practices for applying RF models and spatial-ecological data to recreation management.

2. Materials and methods

2.1. Study area

Our study occurs in three urban-proximate nature reserves in southern California: Alisoand Woods Canyon Regional Park (ALWO), Crystal Cove State Park (CCSP), and Whiting Ranch Wilderness Park (WHRA) (Fig. 1). ALWO, CCSP, and WHRA are part of a collaboratively managed network of protected areas called the Nature Reserve of Orange County (NROC). NROC consists of 22 open-space parks and preserves that provide critical habitat for coastal migratory birds and mammals as well as year-round outdoor recreation for 3.2 million residents of Orange County. Reserve units are managed under various designations, but a nonprofit organization, the Natural Communities Coalition (NCC) coordinates educational, managerial, and research efforts across the Reserve (Natural Communities Coalition, 2022).

ALWO, CCSP, and WHRA contain unimproved (dirt) trails, paved walkways, and gravel roads open to foot travel (hiking and running), cycling, and equestrian use, all referred to as “trails” hereafter. The official websites for ALWO, WHRA, and CCSP state that each location has 48, 48, and 29 km of official recreational trails, respectively (California State Parks, 2023; OC Parks, 2023a, 2023b). Many additional kilometers of informal trails were identified by reserve managers and the SGH (Strava Inc., 2022). This study used data from both the formal and

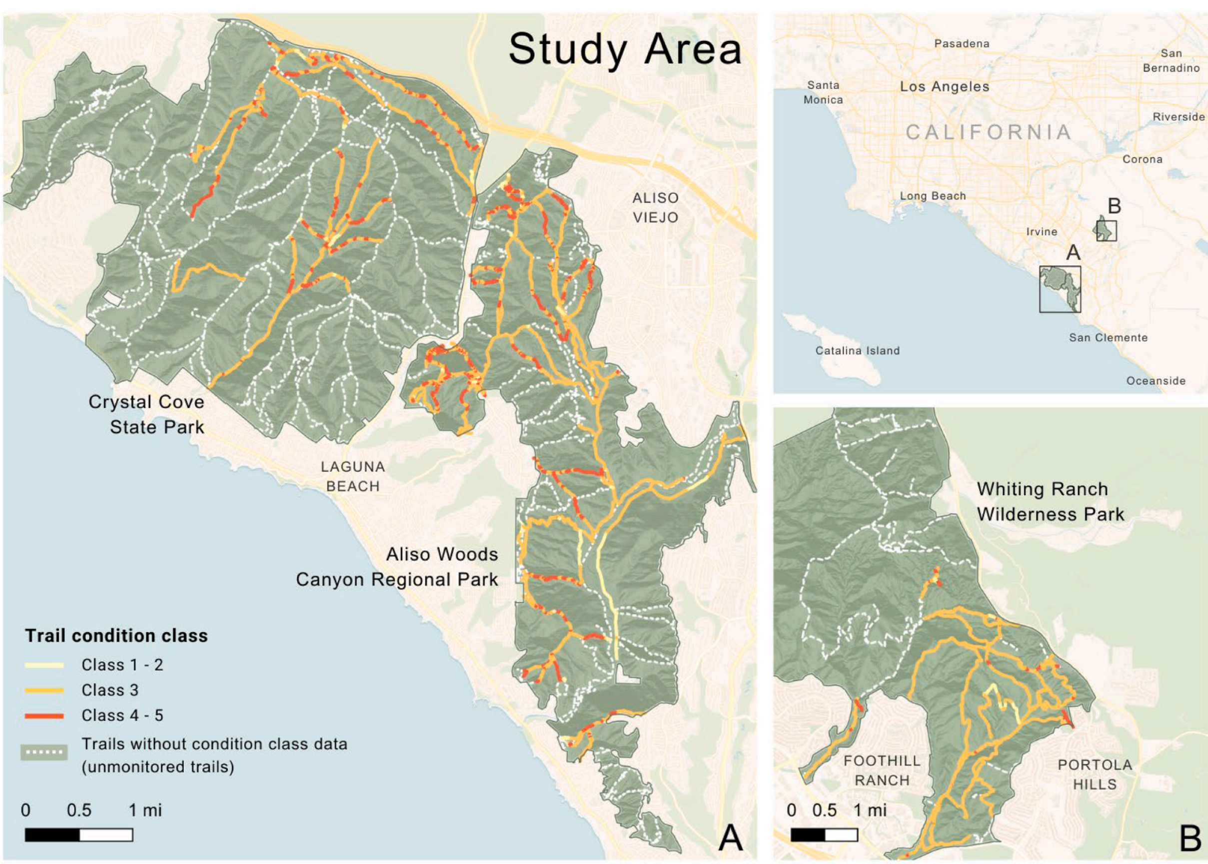

Fig. 1. The condition class of field-mapped trails and the locations of unmonitored trails in the three study sites. Table 1 describes the condition classes used in this study.

informal trails to predict condition class on unmonitored trails.

2.2. Model comparisons

To date, there is insufficient evidence on the effect of geolocated predictor variables (like latitude, longitude, and other spatially explicit measurements) on RF model performance. We compared two models to determine how geolocated variables (latitude, longitude, and the Euclidean distance to the center of the nature reserve) impacted model performance (Table 1).

2.3. Data resources

2.3.1. Response data

Field data on trail condition class were collected over 118 km (40 %) of informal and formal trails in the three study sites during summer 2019. Trained field technicians walked along the trail and recorded condition class on a scale of 1 to 5 on a Trimble Geo7x (Trimble, Inc., 2023). Approximately 183 km (60 %) of trails in the three study sites were not mapped in this effort (see Table 2 in Supplemental Material). We sought to predict the trail condition class on these unmonitored trails using a RF model trained on the field-collected data.

Only 4.15 % of the field-mapped trails were class 1 or 5 (0.67 km, or 0.57 % of the length of mapped trails and 2.24 km or 3.58 %, respectively.) Given that RF models can be impacted by uneven class sizes, we reclassified the data to improve the balance of the distributions (More and Rana, 2017). We combined class 1 and 2 trails into a “class 1–2″ category and class 4 and 5 became “class 4–5″ to produce a more evenly distributed dataset (Fig. 2 in Supplemental Material). For our purpose, the model need not differentiate between “very disturbed” (class 4) and “most disturbed” (class 5) trails.

2.3.2. Predictive data

Per the recommendations of Marion (2023), we assessed the relative influence of various managerial, environmental, and use-related factors on determining trail condition using RF models (Marion, 2023). Data on 21 predictive variables were initially identified as potential determinants of trail condition. However, highly correlated predictors can produce overoptimistic results and misguided variable importance measures in RF models and should be removed (Fig. 3 in Supplemental Material) (Nicodemus et al., 2010). We calculated Spearman’s rho for numeric predictors and removed those with $r_s > 0.80$ (Akoglu, 2018). After removing the correlated variables, 19 predictors remained (Table 2). In random forest models, dummy variables are used to represent categorical predictors; each level of a categorical predictor is represented as a binary variable. This increased the total number of predictors from 19 to 51 in model 1 (Wright and König, 2019).

We obtained the geolocated variables used in model 1 (latitude, longitude, and distance to center) in QGIS, version 3.16 Hannover (QGIS, 2024). Distance to center was calculated as the Euclidean distance from the sample point to the centroid of the reserve in which it was contained. Park was included to examine the influence of each unique reserve on trail condition. We calculated the Euclidean distance from the sampling point to the nearest identifiable trailhead or access point identified on Google maps and included this as the distance to trailhead predictor. Landform-related variables such as elevation, slope, and aspect have been shown to contribute to trail condition (Tomczyk and

Table 1
Descriptions of each model including type and quantity of predictors.

Model name	Predictors	Total predictors used
Model 1	Includes geolocated predictors latitude, longitude, and distance to center	19
Model 2	Geolocated predictors removed	16

Table 2
Descriptions of variables used in the analysis.

Elements	Data Type & Units	Description	Data Sources
Trail Condition Class	Ordinal	Less disturbed (Class 1-2) Disturbed (Class 3) Most disturbed (Class 4-5)	Field-mapped data from 2019
Latitude	Continuous (Decimal degrees)	UTM coordinates	Derived in GIS
Longitude	Continuous (Decimal degrees)	UTM coordinates	Derived in GIS
Distance to Center	Continuous (Meters)	Euclidean distance from sample point to center (centroid) of the reserve	Derived in GIS
Park	Nominal	Reserve name	Provided by NCC
Trail Grade (local)	Continuous (Percent)	Steepness of trail over 100 m trail segment	Derived in GIS
Trail Grade (trail-averaged)	Continuous (Percent)	Average steepness of entire unique trail	Derived in GIS
Trail Slope Alignment (TSA)	Continuous (Degrees)	Difference between azimuth of prevailing landform slope and the trail alignment angle (0: fall-line trails, 90: side-hill trails)	Derived in GIS from DEM
Distance to Trailhead	Continuous (Meters)	Euclidean distance from sample point to nearest trailhead identified on Google Maps	Derived in GIS
Designation	Nominal	Formal (0), known informal trail (1), or unknown informal trails identified on Strava (2)	Provided by NCC and the SGH
Pedestrian Use Intensity	Continuous	Pedestrian (foot travel) use intensity at sample point from the SGH rescaled to 0 (no use) to 100 (most use)	SGH
Bike Use Intensity	Continuous	Cycling use intensity at sample point from the SGH rescaled to 0 (no use) to 100 (most use)	SGH
Aspect	Nominal	Aspect at sample point; North, Northeast, East, Southeast, South, Southwest, West, Northwest	Derived from USGS DEM
Slope	Continuous (Degrees)	Slope at sample point	Derived from USGS DEM
Elevation	Continuous (Meters)	Elevation at sample point	Derived from USGS DEM
NDVI (at sample point)	Continuous (NDVI value from -1 to 1)	NDVI at sample point	Provided by NCC
NDVI (trail-averaged)	Continuous (NDVI value from -1 to 1)	NDVI averaged over the entire trail	Provided by NCC
Shrub Cover	Ordinal (0: No coverage, 9: Most coverage)	Cover of shrub vegetation at sample point	Provided by NCC
Herb Cover	Ordinal (0: No coverage, 9: Most coverage)	Cover of herbaceous plants including grasses, sedges and forbs at sample point	Provided by NCC
Riparian Cover	Ordinal (0: No coverage, 9: Most coverage)	Cover of riparian vegetation at sample point	Provided by NCC

Ewertowski, 2015). These data were extracted from USGS DEM datasets (U.S. Geological Survey, 2019).

Significant research shows that trail designation influences trail condition (Spernbauer et al., 2023; Wimpey and Marion, 2011). Formal trails are often intentionally designed, guided by specific rules and regulations, and maintained more regularly than informal (visitor created) trails (Marion, 2023a; Webber and IMBA, 2007). We included a three-class categorical variable "designation" to distinguish formal trails from two types of informal trails: those that were included in the dataset provided by managers and those identified via the Strava Global Heatmap (presumably unknown to managers).

We incorporate two aspects of trail construction that are thought to influence trail condition: trail grade and trail slope alignment (Leung and Marion, 1996; Olive and Marion, 2009). We calculated the maximum trail grade along 100 m segments of trail (as opposed to the entire trail) to capture local differences and account for differences in trail length, similar to measurements by Hawes et al. (2013). We also included trail grade averaged over the entire individual trail. In QGIS, we calculated trail grade according to Eq. (1). We calculated trail slope alignment (TSA) by finding the difference between the line bearing and azimuth of each 100-meter trail segment. Then, we subtracted 90 from values over 90 to achieve final TSA values between 0 and 90 per Cakir (2005) and Spernbauer et al. (2023).

$$\textit{Trail Grade} = (\textit{Max}\ (\textit{segment elevation}) - \textit{Min}\ (\textit{segment elevation}))\ /\ \textit{Length}\ (\textit{segment}). \quad (1)$$

The amount of use a trail receives, as well as the type of use, is thought to impact trail condition (Olive and Marion, 2009; Pickering et al., 2010). We collected pedestrian-use intensity (foot travel including running and hiking) and bike-use intensity data from the SGH using the methods documented by Corradini et al. (2021) (Fig. 4 in the Supplemental Material). Use intensity data from the SGH were validated against TRAFx brand automatic trail counter data from six trails in ALWO and CCSP (TRAFx Research, Ltd, 2023). Spearman correlations showed that bike-use intensity was poorly correlated with trail counter data ($r_s = 0.543$); however, pedestrian-use intensity was strongly correlated with the counter data ($r_s = 0.943$). Jäger et al. (2020) reported similar issues related to correlation with Strava data, likely due to the mismatch of timeframes used to collect the data and the very small quantity of available trail counter data. However, a 2023 review showed that Strava data are generally representative of spatial dimensions of recreation use, especially in urban-proximate and/or fitness focused locations (Venter, 2023).We consider Strava an appropriate source for understanding where visitors are recreating in our study system, an urban-proximate system used by recreationists with fitness-focused motivations.

Vegetation type is thought to influence trail condition (Cole, 1983; Leung and Marion, 1996). Vegetation data were provided by project partner NCC; they commissioned a high-resolution aerial vegetation survey from 2016 to 2019 (Aerial Information Systems, Inc., 2015). These data included percent cover of shrubs, herbaceous plants (grasses, forbs, and sedges), and riparian vegetation communities. Coverage data were represented as an ordinal categorical variable where 0 corresponded to 0 % cover and 9 represented near 100 % coverage of the vegetation type (over the individual patch). We opted to use this coverage data (9 classes) instead of the vegetation community type (46 classes), given that RF models can produce incoherent results when HLC variables are used (Baltensperger, 2018). Vegetation condition was also reported through NDVI, where NDVI is a remote sensing measurement that captures vegetation greenness that ranges from -1 (water) to 1 (very green vegetation) (Bhandari et al., 2012; Sahani and Ghosh, 2021). NDVI data were collected during an aerial imaging survey in 2019 around the same time as field data on condition class. Both NDVI at the sample point and the trail-averaged NDVI were used in this study; the latter was computed as the average NDVI within a 5-meter buffer of the individual trail.

All raster data (elevation, slope, aspect, NDVI, distance to trailhead) were resampled to a resolution of 2.5 m using nearest neighbor resampling to achieve consistency with the coarsest grain data (from the SGH). This effort ensured that differences between model performance metrics and variable importance measures were due to actual phenomena and not scale discrepancies (Sinha et al., 2019).

2.3.3. *Sampling design*

We used systematic random sampling to collect points from the training/testing data and the unmonitored trails to predict. Trails were split into 100-meter segments and five points were randomly selected per 100-meter segment with a minimum distance of 20 m between points (Fig. 5 in Supplemental Material). This ensures that points do not fall within the same pixel, that all field-mapped trails were included, and that points were evenly dispersed throughout the length of each trail. A total of 3600 points were selected from 118 km of field-mapped trails for the training/testing dataset. The same approach was used to select 5160 points from 183 km of unmonitored trails. For each dataset, data from the predictor variables were extracted using vector and raster-based tools in QGIS.

2.3.4. *Random forest models*

The dataset including condition class information was loaded into RStudio Version 4.3.1 (RStudio Team, 2020) and randomly split: 75 % for training and 25 % for testing (Lantz, 2013). We performed hyperparameter tuning on the training data to optimize model performance via identifying the appropriate *mtry* and *ntree* values, where *mtry* is the number of variables to include in each split, and *ntree* is the number of individual trees grown in the model (Table 3 in Supplemental Material). *Mtry* values both lower and higher than the default value (square root of the number of predictors) were tested for both models (2, 4, 6, 8, and 10), and we used *ntree* values of 500, 1000, and 1500 (Probst and Boulesteix, 2019). We ran the models using standard 10-fold cross validation to obtain performance metrics the R package 'caret' (Kuhn, 2008).

We compared the two models' performances based on several metrics: out-of-bag (OOB) error, overall accuracy, balanced accuracy, sensitivity, and specificity. OOB error is an estimate of the model's accuracy. OOB error compares the condition class the model predicted to the known condition class values in the test data. Balanced accuracy considers the model's predictive power for each class individually and is calculated as the mean of sensitivity and specificity for each class. Sensitivity is a measure of the model's ability to distinguish true

Table 3
Performance metrics OOB error and overall accuracy for both models.

	Description	OOB Error	Accuracy
Model 1	Includes geolocated predictors latitude, longitude, and distance to center	16.33 %	86.54 %
Model 2	Without geolocated variables	15.48 %	86.65 %

positives and specificity is the ability to detect true negatives. Finally, we used the models to obtain condition class predictions on the unmonitored trails; results were visualized in QGIS (QGIS, 2024).

3. Results

3.1. Model performance

Both models reported similar performance metrics; model 2 (without geolocated variables) reported 0.11 % higher overall accuracy compared to model 1 (Table 3). Additionally, model 2 reported a lower out-of-bag (OOB) error rate.

Class-specific results are useful metrics for RF classification problems, particularly for unbalanced data. Both models reported high (>94 %) sensitivity scores for class 3, suggesting an ability to predict true positives for this condition class quite well (Table 4). Further, both models reported high specificity scores for class 1-2 and 4-5 (>98 % and >95 %, respectively), suggesting that the models predict true negatives for these condition classes with high accuracy. The lower sensitivity scores for class 1-2 and class 4-5 suggest that the models are not as capable of accurately predicting true positives for these classes, however, model 2 outperformed model 1 in its ability to predict true positives for class 4–5 (64.46 % and 59.64 %, respectively).

The distributions of condition class predictions differed somewhat (Fig. 6 in Supplemental Material). Model 2 predicted more class 4-5 points compared to model 1 (502 compared to 207). Model 1 predicted no class 1–2 points whereas model 2 predicted 54 class 1-2 points.

3.2. Variable importance

The variable importance measure used here was the area under the receiver operating characteristic curve (AUC hereafter). AUC is computed as *1 - Sensitivity* and is a meaningful representation of variable importance in classification problems (Hanley and McNeil, 1982; Ling et al., 2003). Importantly, AUC is more robust to data with class imbalance than other RF variable importance measures, particularly Mean Decrease Gini (Janitza et al., 2013; Strobl et al., 2007). Further, AUC reports class-specific variable importance, revealing which variables contribute most to our phenomena of interest: trail degradation (represented by class 4–5 predictions). Importance values for each predictor were scaled to 100 to interpret differences among models; the top 20 predictors (in descending order of importance for class 4-5 predictions) are shown in Fig. 2. See Figs. 7 and 8 in Supplemental Material for importance plots that include all predictors.

Both models identified trail grade (at the sample point) as the most important variable for predicting condition class 4-5. Trail grade (trail-averaged) was among the top 3 for both models. Trail-averaged NDVI was also among the top predictors for both models. In model 1, geolocated predictors longitude, latitude, and distance to center were ranked in the top quartile.

Pedestrian and bike-use intensity ranked consistently higher than all vegetation coverage variables and most landscape-related factors except elevation, which ranked among the top 10 for both models. Elevation ranked consistently higher than other landform-related variables (slope or aspect), neither of which ranked among the top 20 importance measures for either model.

Both NDVI measures (at the sample point and trail-averaged) ranked consistently higher than any of the vegetation coverage variables. However, dummy variables corresponding to shrub cover received consistently higher importance scores compared to other vegetation variables (herbaceous cover, riparian cover).

The dummy variable corresponding to WHRA ranked consistently higher than the other parks. Finally, the dummy variable associated with informal trails (identified by managers) ranked among the top quartile of importance measures for both models. The dummy variable associated with informal trails (identified on the SGH) only ranked in the top quartile for model 2.

Table 4
Sensitivity, specificity, and balanced accuracy (by class) for each model (model 1 includes geolocated predictors, model 2 does not).

	Class 1-2		Class 3		Class 4-5	
Value	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Sensitivity	52.83 %	56.60 %	95.74 %	94.41 %	59.64 %	64.46 %
Specificity	99.41 %	98.94 %	58.90 %	63.47 %	96.45 %	95.77 %
Balanced Accuracy	76.12 %	77.77 %	77.32 %	78.94 %	78.05 %	80.11 %

3.3. Visual comparison

Predictions were visualized in QGIS (Figs. 3 and 4). Condition classes were predicted at discrete points using RF; these points were joined to 25-meter trail segments to visualize the results linearly. Both models depict similar spatial distributions of predicted condition classes, particularly for class 3 and class 4-5 predictions (Fig. 5). There was some disagreement between models at WRHA; model 2 made 54 class 1-2 predictions and model 1 made no class 1-2 predictions.

Both models report similar results regarding the locations of highly disturbed trails, where more than 50 % of the length of the entire trail was predicted as condition class 4-5. These trails are potentially at risk of severe trail degradation (Fig. 6). ALWO and CCSP contained 21 and 5 highly disturbed trails, respectively. Similarly, ALWO and CCSP contain 20 and 6 moderately disturbed trails, where 25–50 % of the trail was categorized as class 4-5. WHRA contained no highly or moderately disturbed trails. In total, 14.2 km of highly disturbed trails and 16.2 km of moderately disturbed trails were identified in ALWO and CCSP, respectively.

4. Discussion

4.1. Significance of the findings

Our results demonstrate that RF models can be used to predict trail condition class with relatively high accuracy in our study areas, providing a less field-intensive method for monitoring trail condition in large nature reserves. Variable importance measures suggest that trail grade is the most significant determinant of trail condition and highlight additional site-specific factors that may influence trail condition in our study area. Specifically, activity type and use intensity may be more determinative of trail condition than some ecological and trail design parameters; this is in contrast to past work that suggests trail degradation is primarily a product of poor or improper design (Marion, 2023; Marion and Wimpey, 2017).

4.2. Model performance

We show that RF models can be used to predict trail condition on unmonitored trails using a subset of field data with moderately high accuracy (~86.5 %). Further, these models can be used to identify highly disturbed trails (class 4-5 predictions) with a relatively high balanced accuracy (80.1 %). Further, our results suggest that including latitude, longitude, and distance to center reduce model performance marginally, contradicting past work by Hengl et al. (2018b) and supporting the claim that geolocated variables may lead to overfitting (Meyer et al., 2019).

We used RF to model trail condition with a focus on identifying locations of potential trail degradation. We argue that continued use of these trails, without appropriate management intervention, may result in potentially irreversible degradation. This assumption is complicated

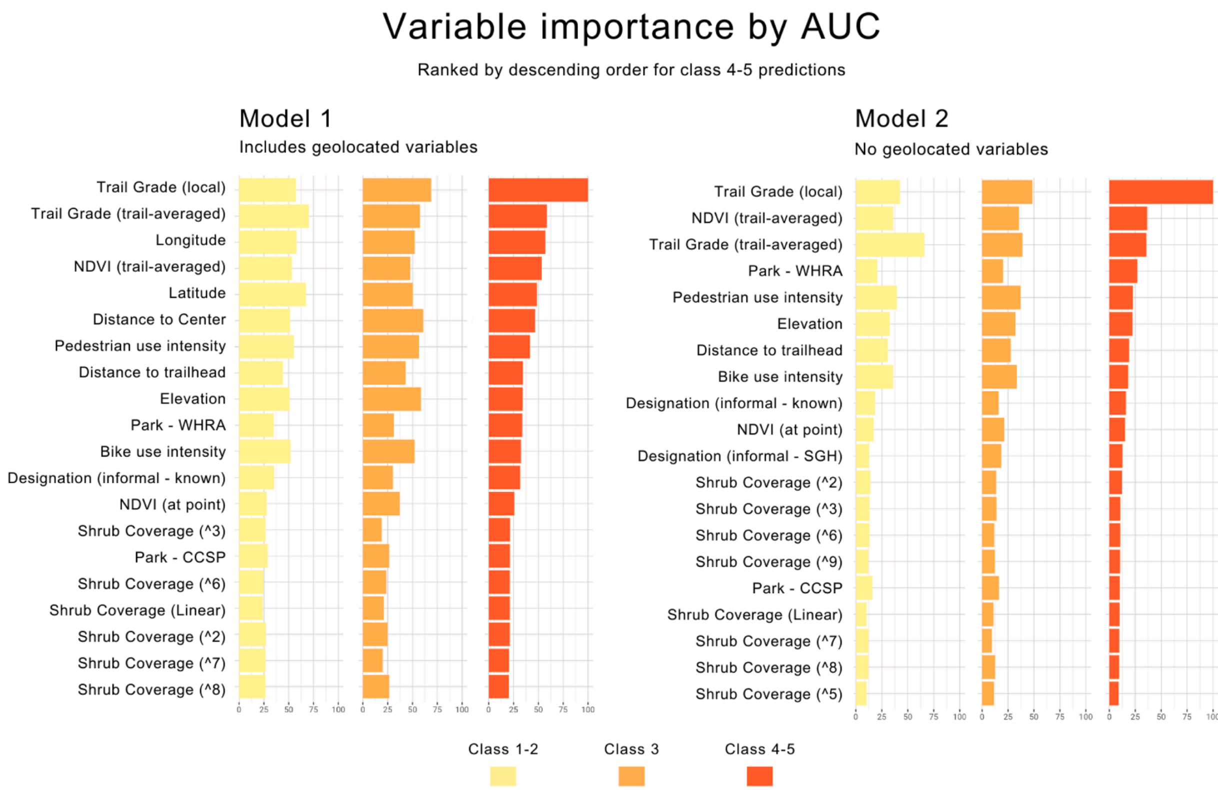

Fig. 2. The top 20 predictors of trail degradation (condition class 4-5) by AUC.

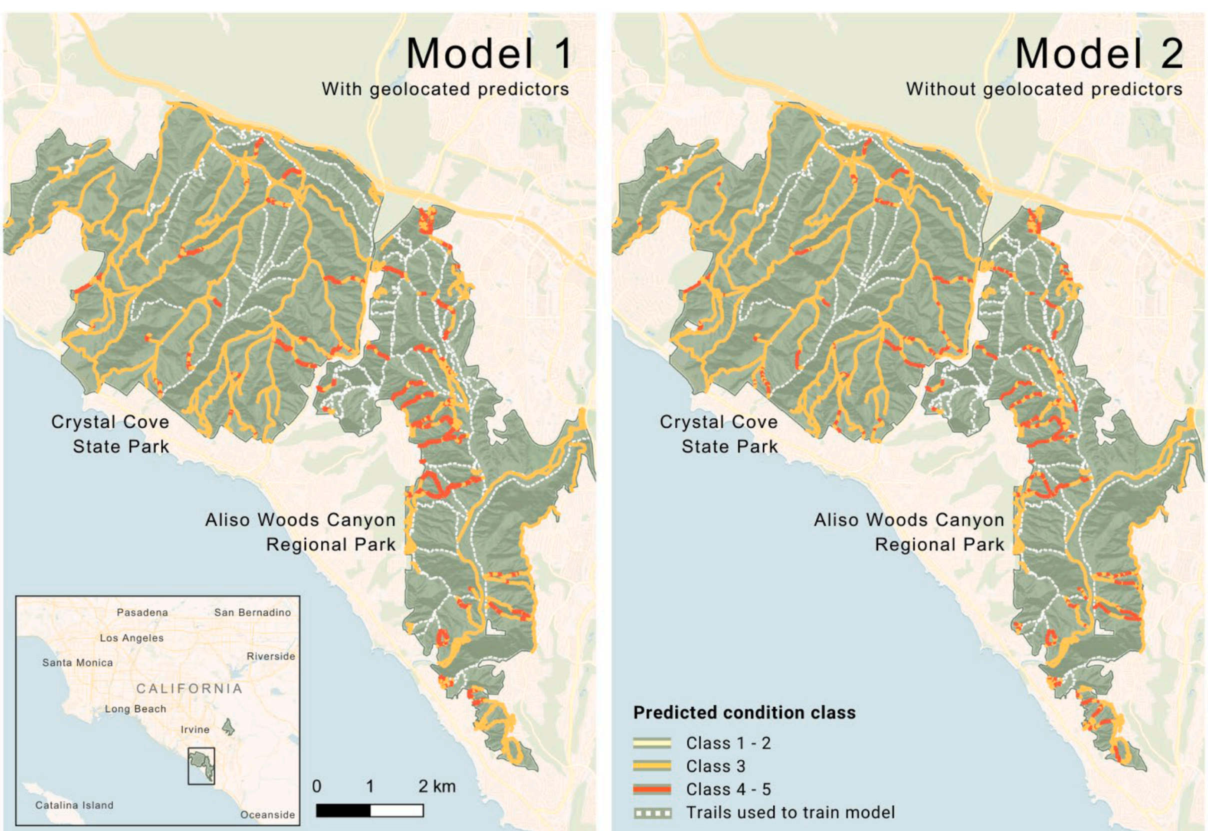

Fig. 3. Side-by-side comparison of predicted condition classes for CCSP and ALWO.

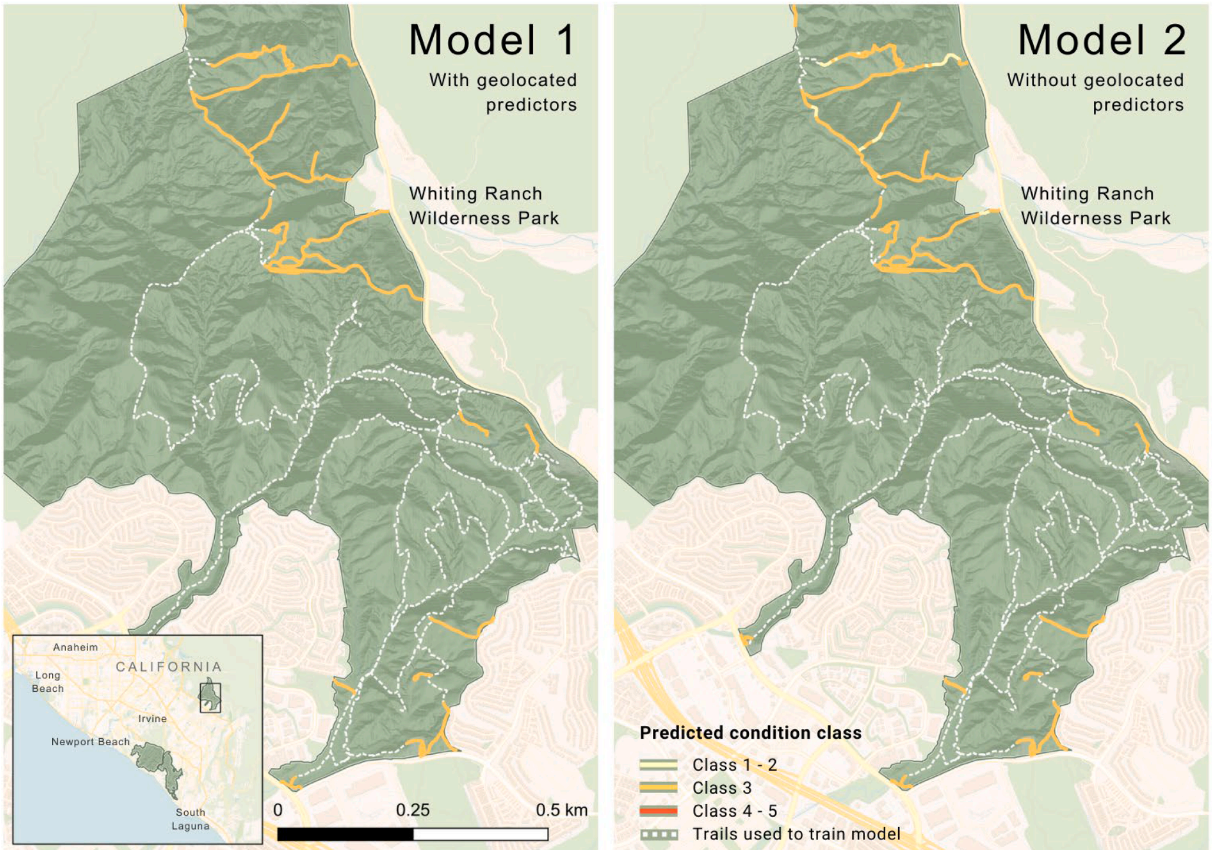

Fig. 4. Side-by-side comparison of predicted condition classes for WHRA.

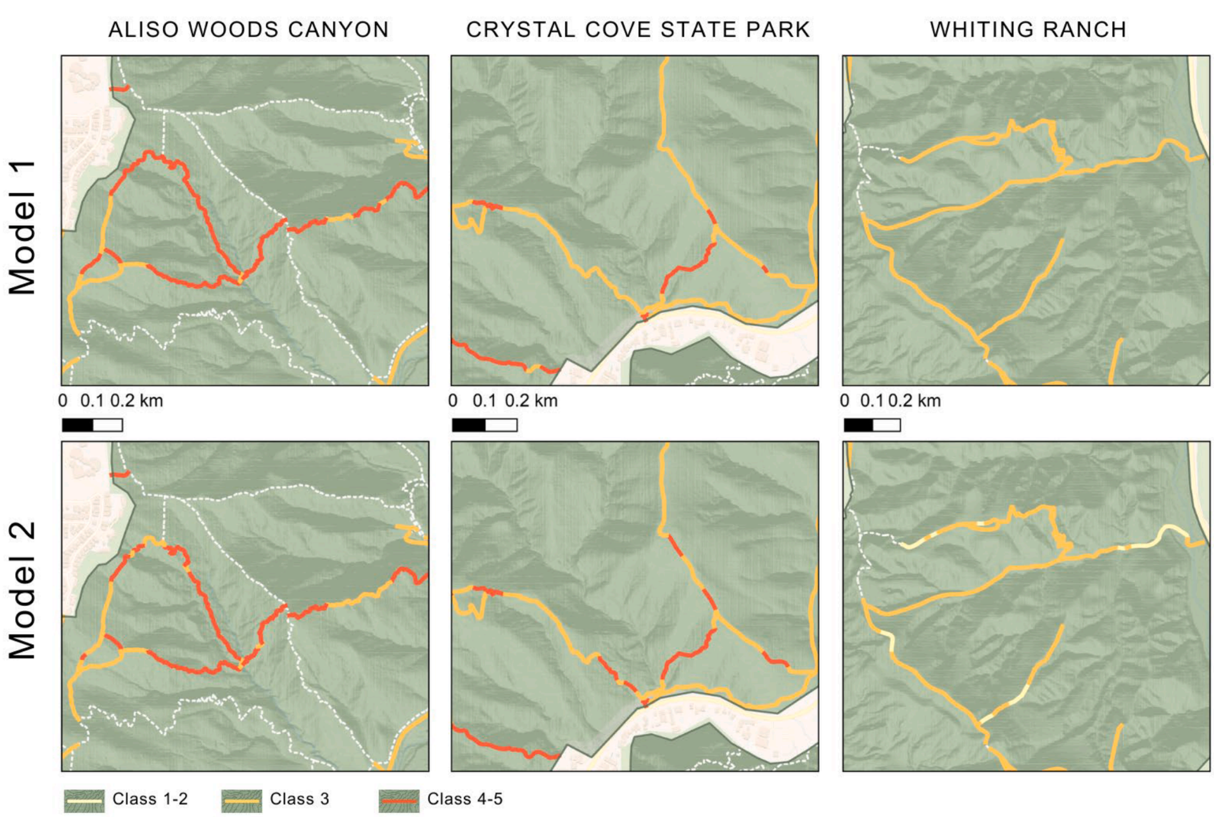

Fig. 5. Areas of disagreement between the models at each study site.

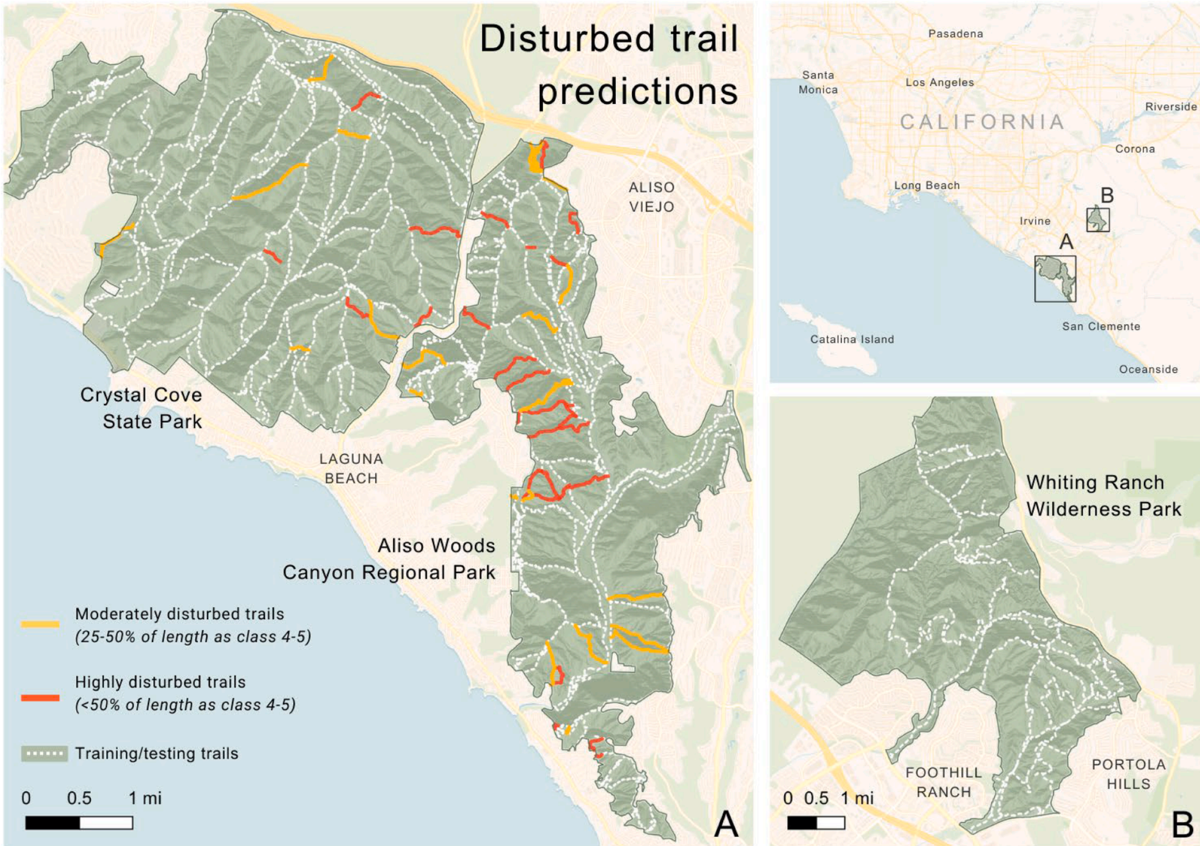

Fig. 6. A map of highly and moderately disturbed trails; defined by the proportion of class 4-5 predictions within an individual trail.

by the use-impact relationship in recreation ecology, which states that the relationship between visitor use and ecological disturbance generally follows a sigmoid curve (Monz et al., 2013). Per this relationship, the disturbed trails identified here may not experience further degradation, whereas class 2 and 3 trails may continue to degrade until class 4 or 5 status is reached. Continued trail monitoring will be necessary to confirm the condition of these trails.

4.3. Variable importance

Trail grade was ranked as the most important variable for determining trail condition in both models, concordant with past trail science research (Marion, 2023; Olive and Marion, 2009). Trade grade (local) was consistently ranked slightly higher than the trail-averaged grade, suggesting that the influence of trail grade on trail condition occurs at smaller spatial scales. Trail maintenance efforts should focus on ensuring that trail grades are within the recommended threshold of along the entire length of the trail (Marion and Wimpey, 2017).

Curiously, trail slope alignment (TSA) did not appear in the top 20 importance values for either model despite evidence and best practices that state that TSA does influence trail condition (Meadema et al., 2020; Webber and IMBA, 2007). Likely, TSA is an important determinant of trail condition in many locations, but our model did not identify it as such in this landscape, potentially due to discrepancies in the scale at which TSA was calculated and the scale at which this phenomenon influences trail degradation.

In both models, pedestrian- and bike-use intensity ranked in the top quartile in terms of importance values, with pedestrian-use intensity ranked higher than bike-use intensity. These results suggest that pedestrian-use intensity may be more determinative of trail condition than bike-use intensity. An alternative explanation for these results is the weak correlation between bike-use intensity and trail counter measurements; thus pedestrian-use intensity derived from the SGH may be a more valid estimate of use than bike-use intensity. Finally, use-related predictors scored higher than nearly all ecological predictors in both models, suggesting that use intensity may be more determinative of trail condition than previously thought (Marion, 2023; Olive and Marion, 2009). These results provide further justification for using the SGH to monitor trail use; particularly when the location of use, activity type, and use-intensity are of interest.

NDVI (at the sample point and trail-averaged) was the ecological parameter that received the highest importance values for class 4-5 predictions, suggesting that NDVI may be more determinative of trail condition than vegetation coverage and corroborates the results. Furthermore, NDVI (trail-averaged) reported a higher importance value compared to NDVI at the sampling point. This may provide evidence that the effect of vegetation on trail condition is more pronounced at the scale of an entire trail, not at a specific location. In addition, interactions between use intensity and NDVI (trail-averaged) may exist due to preferences for using shaded trails, especially during hot summer months. Recreation ecology has not yet explored multiscale and cross-scale interactions between ecological and use-related variables; future research could illuminate these associations.

Finally, latitude, longitude, and distance to center were ranked among the top 6 most important predictors in model 1. Given that model 2 (without these geolocated variables) slightly outperformed model 1, this provides further evidence that geolocated variables likely produce overfitting in random forest models (Meyer et al., 2019).

4.4. Recommendations for RF models in recreation management research

We recommend selecting continuous representations of environmental, managerial, and use-related variables when using RF models in recreation management research. Additionally, we recommend taking precautions to improve the balance of data distributions (where appropriate) and reporting class-specific performance metrics when imbalanced data are used in RF classification problems. These practices are vital for developing rigorous RF models that are minimally biased by the characteristics of predictor variables and data structure. Further, we find that including geolocated variables leads to overfitting and slightly reduces model performance; such variables should not be included in RF models. Finally, we promote the SGH as a source of visitor use data, particularly in urban-proximate and fitness-oriented locations or when existing visitor use data are insufficient or unavailable. When using SGH data, we recommend reporting correlations to ground-truthed data.

4.5. Management implications

Trail degradation is considered permanent and irreversible; therefore, early intervention is needed to mitigate or reduce disturbed trails. This study identified 30 km of trails in three urban-proximate nature reserves that are potentially vulnerable to degradation due to less sustainable design and/or levels or types of use incompatible with the design. By identifying potentially disturbed trail segments, managers can mitigate or reduce future trail degradation by modifying levels and locations of use, hardening the trails, modifying visitor behavior through education, and/or closing or rerouting certain trails (Marion, 2023). In many cases, proactive management and intervention are required to maintain sustainable trails for the benefit of outdoor recreationists, ecosystem components, and park managers alike. Using RF models to predict trail condition reduces the time and effort required to monitor recreational trails; identifying determinants of trail degradation using RF models may help inform intervention and maintenance that takes local environmental, managerial, and use-related factors into account. Monitoring the condition of recreational trails is a time-consuming process when done *in situ*; predictive modeling techniques significantly reduce the time and effort required to manage recreational trails.

5. Conclusion

We used RF models and field-mapped data on trail condition to predict trail degradation in three southern California urban-proximate nature reserves. The results identify 30 km of trails in two nature reserves that managers may want to consider remediating, rerouting, or closing altogether, depending on the extent of trail degradation. We discuss the importance of the intentional design, application, and interpretation of RF models in a recreation management context. We find the Strava Global Heatmap to be an appropriate source of data on visitor use location, acvitity type, and use intensity; these data are particularly useful in random forest models due to their numeric structure. This investigation contributes to an expanding body of literature on appropriate ways to use RF on spatial-ecological data in recreation management research, providing evidence for how predictive models may aid in managing and monitoring recreation resources.

CRediT authorship contribution statement

Kira Minehart: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ashley D' Antonio:** Writing – review & editing, Supervision, Resources, Conceptualization. **Noah Creany:** Writing – review & editing, Investigation, Conceptualization. **Chris Monz:** Writing – review & editing, Investigation. **Kevin Gutzwiller:** Writing – review & editing, Methodology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.envc.2024.100937.

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