



Integrating existing data to assess the risk of an expanding land use change on mammals

Lindsey N. Rich · Ivan D. Medel · Sara Bangen · Greta M. Wengert ·
Matthew Toenies · Jody M. Tucker · Mourad W. Gabriel ·
Courtney L. Davis

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Abstract

Context Land-use change, including agricultural expansion, is one of the major drivers of biodiversity loss globally. Given the rapid pace of land-use change, data-driven, strategic, and dynamic conservation planning is imperative.

Objectives We present an exemplar application of using existing data to inform conservation planning. Specifically, we developed a systematic approach for identifying areas of conservation concern due to cannabis cultivation in California, USA.

Methods We used three existing datasets: (1) camera trap data from ten projects ($n=1186$); (2) the locations of cannabis cultivation sites eradicated by law enforcement ($n=834$); and (3) the locations of cultivation licenses ($n=4366$). We analyzed this data using multi-species occupancy models to estimate the

occupancy and richness of 30 species, and maximum entropy models to estimate the risk of unlicensed and trespass cultivation. We then identified areas of overlap and determined the percent of suitable habitat potentially impacted by cannabis cultivation.

Results Cannabis cultivation was estimated to overlap 39–74% of suitable habitat for special status species. Private land cultivation tended to have a larger influence on generalist species whereas trespass cultivation had the largest potential influence on fisher (*Pekania pennanti*), a special status species.

Conclusions Our results can be used to prioritize eradication, restoration, and remediation activities; to target mitigation efforts; and to guide the placement of new, licensed cultivation. Our approach demonstrates the utility of aggregating existing biological and socioeconomic data to inform conservation planning and is broadly applicable to other data sources and ecological stressors.

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L. N. Rich (✉) · S. Bangen · M. Toenies
California Department of Fish and Wildlife, 1010
Riverside Parkway, West Sacramento, CA 95605, USA
e-mail: lindsey.rich@wildlife.ca.gov

I. D. Medel · G. M. Wengert
Integral Ecology Research Center, 239 Railroad Ave,
Blue Lake, CA 95525, USA

J. M. Tucker
Rocky Mountain Research Station, USDA Forest Service,
800 E. Beckwith Ave, Missoula, MT 59801, USA

J. M. Tucker
Pacific Southwest Region, USDA Forest Service, 1323
Club Drive, Vallejo, CA 94592, USA

M. W. Gabriel
LEI Trespass Cultivation Ecology, Safety and Reclamation
Program, USDA Forest Service, 1700 Bayview St, Arcata,
CA 95521, USA

C. L. Davis
Cornell Lab of Ornithology, Cornell University, 159
Sapsucker Woods Road, Ithaca, NY 14850, USA

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Introduction

Land-use change resulting from habitat conversion, degradation, and fragmentation is one of the major drivers of biodiversity loss globally (Vitousek et al. 1997; Newbold et al. 2015). Agricultural expansion is the most prevalent type of land-use change and the leading cause of deforestation worldwide, with croplands and pastures now covering 38% of Earth's terrestrial surface (Fischer et al. 2006; Foley et al. 2011; FAOSTAT 2020). This agricultural expansion is accredited with the decline of many imperiled mammal species, as are other causes of land-use change like logging and urbanization (Tilman et al. 2017). Without proactive conservation planning that mitigates the potential impacts of land-use change, many terrestrial mammal species will continue experiencing population declines over the next century until they become extinct (Visconti et al. 2016; Powers and Jetz 2019).

Mammal species do not respond to land-use change similarly, but rather in complex and variable ways (Crooks and Soulé 1999; Swaddle et al. 2015; Tucker et al. 2018). Responses can be species- and community-specific; positive, negative, or negligible; and can vary depending on the intensity and spatial and temporal scales of the change (Fischer and Lindenmayer 2007; Chaplin-Kramer et al. 2015). Omnivorous species, for example, often benefit from increased resource availability in disturbed landscapes whereas carnivores, grazers, and range-restricted specialists tend to be more vulnerable to land disturbance because it limits their ability to access optimal habitat and move among all portions of their range (Laliberte and Ripple 2004; Crooks et al. 2017; Santini et al. 2019). These mixed responses often result in substantial restructuring of ecological communities in human-altered landscapes, which can have cascading impacts on overall ecosystem health and functioning (Newbold et al. 2020; Pineda-Munoz et al. 2021; Suraci et al. 2021).

Capitalizing on existing data to inform conservation planning and environmental policy is vital given the accelerating pace of land-use change, and the

variable ways in which species respond (Rich et al. 2016; Powers and Jetz 2019). Biodiversity datasets are available in greater spatial, temporal, and taxonomic resolution than ever before due to the widespread use of multi-species observation tools such as camera traps and acoustic recorders, and the growing engagement of citizen scientists (Blumstein et al. 2011; Steenweg et al. 2017; Fraisl et al. 2022). Further, biodiversity data are increasingly accessible given the scientific community and United Nation's push for open data, as well as the growing number of platforms for storing and/or processing data via artificial intelligence (e.g., The Global Biodiversity Information Facility, Wildlife Insights, Wildtrax, BirdNET; Lane and Edwards 2007; Pereira et al. 2013; Ahumada et al. 2020; Kahl et al. 2021). A wealth of socioeconomic and remote sensing data also exists and is regularly updated, thus enabling dynamic conservation planning and management (Pressey et al. 2007; Van Teeffelen et al. 2012).

Here, we present an exemplar application of using existing data to inform strategic and timely conservation planning via the development of a systematic approach for identifying areas of concern due to cannabis cultivation. Cannabis cultivation is expanding globally, with more than 40 countries having now legalized cannabis for medical and/or adult use. In the United States, recreational cannabis cultivation is legal in 22 states even though federally, it is still classified as a Schedule I controlled substance (US News 2023). The biggest cultivator of cannabis within the United States is California, with over half of U.S. cannabis being grown in the state (Wengert et al. 2018; DEA 2021). Despite recreational cannabis cultivation being legalized in California in 2016, illegal markets continue to thrive in the state, which has long been an epicenter for unlicensed cannabis production (Gabriel et al. 2012; Butsic et al. 2018; Wartenberg et al. 2021). The result is a mixed landscape of licensed cultivation, unlicensed cultivation on private lands, and trespass cultivation (i.e., unlicensed cultivation on any lands where the property owner is unaware).

Cannabis cultivation is of environmental concern given it is frequently located in areas previously covered in old-growth and second-growth forests, far from developed roads, and near habitats for sensitive species like fishers (*Pekania pennanti*), northern spotted owls (*Strix occidentalis caurina*), and Coho salmon (*Oncorhynchus kisutch*; Thompson et al. 2013; Butsic et al. 2018;

Parker-Shames et al. 2022). Further, on trespass cultivation sites there has been widespread evidence of pesticide contamination, so much so that the risk from anticoagulant rodenticides at trespass cultivation sites was a contributing factor in the listing of the Southern Sierra Nevada Distinct Population Segment of fishers under the federal Endangered Species Act (Gabriel et al. 2012; USFWS 2020). Another potential concern is artificial nighttime lighting, which is often used in private cannabis cultivation to promote yield and for security (CDFA 2017), but likely influences species' activity and movement patterns, navigation, communication, phenology, and physiology, particularly in remote forests (Swaddle et al. 2015; Dominoni et al. 2020; Rich et al. 2020; Dittmer et al. 2021).

Seeing as many of the potential impacts of cannabis cultivation in California have already taken place, the next best solution is to develop conservation planning aimed at minimizing environmental impacts, effectively prioritizing management actions, and guiding future expansion of the crop within legal landscapes (Dillis et al. 2021; Wartenberg et al. 2021). Our systematic approach for identifying areas of high conservation concern capitalized on three existing datasets: (1) camera trap data aggregated across ten projects from 2019 to 2021; (2) the locations of cannabis cultivation sites eradicated by local, state, and federal law enforcement entities; and (3) the locations of cultivation licenses. These datasets enabled us to quantify and map suitable habitats for terrestrial mammal species and communities, the likelihood of unlicensed and trespass cannabis cultivation, and the distribution of licensed cultivation, which we then overlaid to identify areas of conservation concern (i.e., areas with high overlap between species and cultivation). We identified these areas at multiple spatial, taxonomic, and regulatory scales to help inform local to regional, species to community, and law enforcement to public outreach management decisions.

Methods

Study area

Our study was carried out in portions of the Northern Coast, Klamath Mountains, Southern Cascades (hereafter referred to as the northern region of California) and Sierra Nevada of California (Fig. 1),

encompassing close to 28% of the state (117,309 km²). The area was predominantly forested and included elevations ranging from 0 to 4414 m. Approximately 21% of the study area has been impacted by wildfires in the last five years and the entire area experiences periodic extreme droughts (Swain et al. 2018). It was a mixed-use landscape with 59% of the area privately owned and 41% publicly owned. We excluded more populated areas, which we defined as places with human population densities greater than 29 people/km², given we had a very small number of camera traps in these areas ($n=12$) and the drivers of unlicensed cultivation in populated areas likely differ from those in rural areas.

Camera trap surveys

As part of 10 projects, the California Department of Fish and Wildlife (CDFW) and United States Forest Service (USFS) deployed 1186 passive infrared camera traps for a minimum of 10 days between 16 March 2019 and 28 October 2021 (Online Resource 1). The number of trap days ranged from 12 to 574 (mean=65). The cameras, which were Reconyx, Bushnell, and Browning brand cameras, were programmed to take 1–3 photographs when triggered with a delay of 0–60 s between trigger events (Online Resource 1). Approximately half of the cameras were placed on trails, roads, or near a water source to increase the probability of photographing wildlife, while the remaining half were placed randomly or systematically without consideration of these landscape features. Projects' target wildlife included, for example, deer, bobcats, and entire mammal communities (Online Resource 1). Following projects' field seasons, all photographed wildlife were identified to species or the lowest taxonomic level possible either manually or within the online platform Wildlife Insights (Ahumada et al. 2020).

Occupancy modeling

We expected that wildlife distributions would be influenced by both environmental and anthropogenic factors. For the environment, we included covariates representing topography, water availability, wildfire activity, canopy cover, and precipitation (Sweitzer et al. 2016; Furnas et al. 2022). To represent anthropogenic activity, we included human population and land ownership covariates (Hobart et al. 2019; Nickel et al.

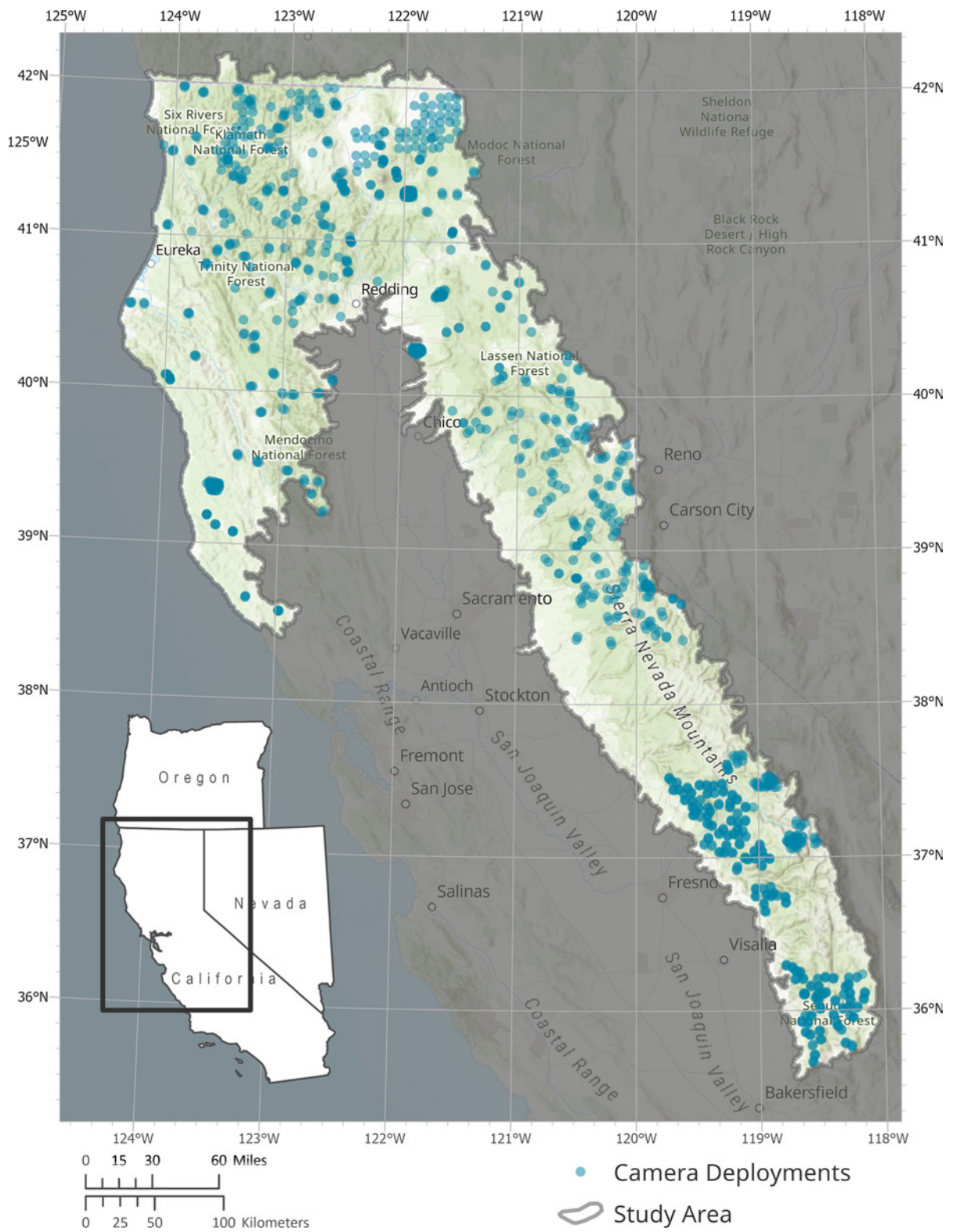


Fig. 1 Study area showing modeled extent and camera trap locations from 2019–2021, California, USA

2020). We calculated distance to the closest fire (km), year since the closest fire, distance to the nearest water source (km), and land ownership at the camera xy location. Elevation (m), slope ($^{\circ}$), canopy cover (%), mean annual precipitation (mm), and population density (per km^2) were calculated as the mean value within a 1-km diameter square buffer centered on the camera location. A 1-km buffer size provides information on the overall conditions surrounding the survey location (Rich et al. 2016). A full list of covariates included, and the respective references, can be found in Online Resource 2. All continuous covariates were assessed for correlation using the Pearson correlation method (Online Resource 2) and z-standardized prior to analysis.

We used a hierarchical multi-species occupancy model to estimate species-specific occurrence probabilities for all native species and one non-native species (Virginia opossum, *Didelphis virginiana*) detected at a minimum of five camera locations while accounting for imperfect detection (i.e., instances when a species was present but not photographed at a camera station; Dorazio and Royle 2005). For our study, occupancy represents suitable habitat. We treated each trap day as a repeat survey at a camera station and simplified daily detection histories into the number of 24-hour time periods during which species i was photographed at camera station j , $y_{i,j}$, to speed up computation (Kéry et al. 2010). That is, we estimated the probability of photographing species i at camera station j , $p_{i,j}$, conditional on the species being truly present as $y_{i,j} \sim \text{Binomial}(p_{i,j} \times z_{i,j}, N_j)$. Here, $z_{i,j}$ is the latent occurrence state where $z_{i,j} = 1$ if camera station j was used by species i and 0 otherwise, and N_j is the total number of possible trap days at camera station j . Latent occurrence was modeled as a Bernoulli random variable, $z_{i,j} \sim \text{Bernoulli}(\psi_{i,j})$, where $\psi_{i,j}$ is the probability that species i occurred at camera station j (MacKenzie et al. 2002).

We used a generalized linear mixed modeling approach to incorporate site-level (i.e., camera station-specific) covariates on species-specific occupancy and detection probabilities. The occupancy probability, $\psi_{i,j}$, of species i at camera station j , was specified as:

$$\begin{aligned} \log \text{it}(\psi_{i,j}) = & \beta 0_i + \beta 1_i \times \text{ownership}_j + \beta 2_i \times \text{elevation}_j + \beta 3_i \times \text{slope}_j \\ & + \beta 4_i \times \text{precipitation}_j + \beta 5_i \times \text{canopy cover}_j + \beta 6_i \times \text{population density}_j \\ & + \beta 7_i \times \text{distance to water}_j + \beta 8_i \times \text{fire year}_j + \beta 9_i \times \text{distance to fire}_j \end{aligned}$$

Here, the inverse logit of 0 corresponds to the occupancy probability for species i at a camera station located on public land (the reference category for land ownership) with average values for all other covariates. Coefficient $\beta 0$ corresponds to the effect of private land ownership, and all remaining coefficients ($\beta 2 - \beta 9$) represent the effect of a one standard deviation increase in the covariate value for species i . The detection probability, $p_{i,j}$, of species i at camera station j was similarly specified as:

$$\log \text{it}(p_{i,j}) = \alpha 0_i + \alpha 1_i \times \text{bait type}_j + \alpha 2_i \times \text{location}_j$$

where the inverse logit of $\alpha 0$ corresponds to the detection probability of species i at a non-baited camera station located on a trail, road or near a water source (the reference categories for bait type and location, respectively). Coefficients $\alpha 1$ and $\alpha 2$ correspond to the effects of baiting and randomly locating the camera, respectively, on the probability species i is photographed.

We linked species-specific models by assuming that coefficients (i.e., intercept and slope parameters) for detection and occupancy were random effects drawn from shared, community-level distributions (Dorazio and Royle 2005; Zipkin et al. 2010). For example, we assumed that the species-specific intercepts on occupancy, $\alpha 0_i$, were drawn from a normal distribution, $\alpha 0_i \sim \text{Normal}(\mu_{\alpha 0}, \text{var}_{\alpha 0})$ with a community-level mean $\mu_{\alpha 0}$ that describes the average expected occupancy across all species in the community, and variance $\text{var}_{\alpha 0}$ that describes the variation in expected occupancy across species. This random effects structure allows information to be shared across species within the community, which improves parameter identifiability for rare or elusive species and leads to increased precision in estimates of species-specific occupancy and detection probabilities (Zipkin et al. 2010). In addition, this structure provides a framework by which to estimate average covariate effects across the local community (via community-level hyperparameters; Iknayan et al. 2014).

We fit our model using JAGS (Plummer 2003) via the jagsUI package (Kellner 2021) in R (R Core Team

2022). We estimated posterior distributions of parameters using 3 chains of 80,000 iterations with a 50,000 burn-in period, thinned by 2. We used vague priors for all hyperparameters and other fixed effects. More specifically, we specified uniform priors between 0 and 1 on the logit-scale for all mean parameters (e.g., $\mu.\alpha_0$), and uniform priors between 0 and 10 for variance parameters (e.g., $\text{var}.\alpha_0$). Model convergence was assessed using the Gelman-Rubin statistic ($R\text{-hat} < 1.1$; Gelman et al. 2004).

We extrapolated model results to our entire area of interest at a 1 km² scale. We used a common 1 km² grid to ensure that all input and output surfaces were orthogonal (i.e., same resolution and centroids) and concurrent (i.e., orthogonal and same extent). We calculated covariate values within each 1 km² grid cell based on grid cell mean values for elevation, slope, precipitation, percent canopy cover, and distance to nearest water source; center point values for distance to nearest fire and year since corresponding fire; area weighted mean for population density; and majority ownership type for land ownership. Continuous covariates were z-standardized before analysis using the mean and standard deviation of values from camera trap locations. During each iteration of our occupancy model, the model produced estimates of intercept and community- and species-level beta values. We used the mean coefficient estimates and covariate values to generate species- and grid-specific probabilities across the entire area of interest, which represent the probability a particular grid cell contains suitable habitat for a given species. We then summed the predicted probabilities across species to generate grid-specific indices of suitability for the observed mammal community and special status mammals (CNDDB 2023), specifically.

Distribution of cannabis cultivation

We used cannabis cultivation license data from the Department of Cannabis Control (DCC), which issues cultivation licenses within California. We buffered the locations associated with mixed-light and outdoor cannabis cultivation licenses by 500 m, to better account for the actual footprint of cultivation, and identified which 1-km² grid cells contained licensed cultivation. We included provisional and annual licenses. The primary difference between the two license types is that with a provisional license,

compliance with the California Environmental Quality Act (CEQA) must be underway but licensees do not have to be fully compliant with CEQA prior to beginning their operation.

We used data from local, state, and federal law enforcement agencies on the locations of unlicensed cannabis cultivation sites from public, private, and tribal lands that were raided and eradicated in California forested regions between 2016 and 2022. That is, we had data on cultivation site presence but had no information on where law enforcement agents searched for, but did not find, cultivation sites. To estimate the likelihood of trespass cannabis cultivation, we developed separate models for the northern region of California (Model 1a) and the Sierra Nevada mountains of California (Model 1b), as we believed cultivators' site selection criteria varied between these two areas. We delineated the areas using the boundary between the Cascade and Sierra Nevada mountain ranges and included all public lands identified in the Protected Areas Database (USGS 2022) as well as private parcels with contiguous parcel sizes ≥ 600 acres, the smallest known parcel size associated with trespass cultivation, whether on public, tribal, or private land. We included 175 sites in Model 1a, which we visited and documented to exist, or were visible and matched vegetation characteristics of trespass cannabis cultivation when evaluated using high-resolution aerial imagery (Butsic and Brenner 2016). We accounted for lower site visitation rates for Model 1b ($n=256$ sites) by also including sites confirmed by local law enforcement partners, and sites deemed highly plausible given they were located in appropriate habitat types and were a minimum of 100 m from the nearest road.

To estimate the likelihood of unlicensed cannabis cultivation on private land (Model 2), we included 403 sites that were (1) on private parcels and (2) plausible for cannabis cultivation given the presence of cultivation infrastructure or nearby roads (as determined by aerial imagery). We visited very few of the private land locations due to access issues that we didn't face at public land sites, so were rarely able to use first-hand observations as a secondary vetting process for this dataset. The extent of Model 2 included private lands within the overall study area, including appropriate parcels on tribal lands and private lands with protected designations. Instead of using exact locations, we used binomial pixel occurrences (i.e.,

each 1-km² pixel was considered a single occurrence, even if multiple sites were present within the pixel) to avoid inflating the representation of sites that may have been part of the same cultivation complex.

For all distribution models, we used spatial covariates summarized at the same 1-km² resolution

as those in our occupancy analysis. These covariates included road density, distance to nearest law enforcement station, ownership boundaries, and a suite of variables derived from climate, terrain, and land cover data (Table 1; Online Resource 2). If the

Table 1 Spatial covariates, and their respective unit and upscaling statistic (min = minimum; max = maximum, SD = standard deviation), evaluated to estimate the likelihood of trespass and unlicensed cannabis cultivation, as well as the percent contribution (PC) and permutation importance (PI; how much the model depends on the covariate) of each covari-

ate included in the final models estimating the likelihood of trespass cannabis cultivation in the northern region (Model 1a) and the Sierra Nevada of California (Model 1b) and unlicensed cannabis cultivation on private lands in both regions (Model 2) Source information is provided in Online Resource 2

Covariate	Unit and upscaling statistic	Model 1a		Model 1b		Model 2	
		PC	PI	PC	PI	PC	PI
Aspect	Mean°						
Slope	Mean%	27.2	18.2	1.8	0.9	3.1	2.7
Slope	Min%			13.6	10.9		
Elevation	Mean m					12.2	9.4
Latitude	Cell center						
Longitude	Cell center						
Precipitation—annual	Mean mm	22.1	17.5	12.3	17.5		
Precipitation—driest month	Mean mm	8.3	14.3	41.7	54.5	0.9	9.4
Precipitation—wettest month	Mean mm						
Solar radiation April–October	Mean kJ/m ² /day						
Temperature April–October	Mean °C					0.6	2.2
Temperature—max	Mean °C						
Temperature—min in April–October	Mean °C						
Perennial, intermittent streams ^a	Mean m	11.4	30.1				
Springs and seeps ^a	m						
Canopy height	Mean m						
Canopy cover	Majority%						
Land cover change index 2001–2019	Majority	5.9	2.6				
Fire return interval	Majority yrs	14.5	4.3	23.3	2.8	3	3.6
Roads ^a	m						
Road density	km/km ²					5.2	12.9
Population centers ^a	m	10.6	13			9	9.4
Parcel size ^b	Mean acres					27	28.8
Parcel size ^b	SD acres					31.3	16.2
Trespass modeling extent ^{a, c}	m					7.7	5.3
Private modeling extent ^{a, b}	m			7.4	13.4		
Law enforcement stations ^a	m						
Licensed mixed-light and outdoor grows ^b	Count						
County licensing status ^b	Yes/no						

No value indicates the covariate was not included in the final model

^aMeasured as distance to the respective covariate

^bOnly used in the trespass cannabis cultivation model

^cOnly used in the unlicensed cannabis cultivation on private lands model

resolution of an environmental variable was $<1 \text{ km}^2$, then we upscaled it across the pixel (Table 1).

We fit Models 1a, 1b, and 2 using the presence-only maximum entropy modeling framework (MaxEnt version 3.4.3, Phillips et al. 2006; Wengert et al. 2021). For background (availability) points, we used a random selection of 10,000 points across the modeling extent. For covariate selection, we used the MaxentVariableSelection package in R v3.6.2 (Jueterbock et al. 2016). We examined correlations among covariates and in cases when two variables were highly correlated ($r \geq 0.7$), retained the variable with the larger univariate effect size. We then used stepwise variable reduction to eliminate any covariates from the full model with a relative contribution score below 5% averaged from 10 model runs. We iterated the remaining covariates, identifying those causing the smallest decrease or largest increase in the Akaike information criterion corrected for small sample sizes (AICc), and selected the model with the lowest AICc and no correlated variables as our best-fit model. We only incorporated linear, quadratic, and hinge features and tested regularization parameters at 0.5 increments between 1 (default) and 5 to avoid overfitting using the selected model (Phillips et al. 2006). Through the automated variable selection process, we evaluated 59 (Model 1a), 44 (Model 1b), and 51 (Model 2) models for inclusion. We retrained the final model using the mean of 10 model runs with 80% of the cultivation site locations for model training, and 20% as test data.

Identifying areas and species of concern

We identified areas of greatest concern as those where cannabis cultivation activity overlapped with suitable habitat for the observed mammal community and for special status mammals, both individually and collectively. We overlaid species occupancy and richness layers with each of the three cannabis cultivation layers, and with an overall cultivation layer that captured the maximum likelihood of any cultivation activity occurring in each grid cell. We visualized areas of high versus low overlap using a bivariate mapping approach that classifies each layer into three equally-spaced quantiles and summarized these results by determining the percent cover of high overlap area within each HUC-12 watershed across the study extent. We used these summaries to identify the

ten HUC-12s of greatest concern for each special status species and our community metrics.

At the species level, we also estimated the percent of suitable habitat potentially impacted by cannabis cultivation. To do this, we first isolated areas with the highest occupancy for each species by thresholding at the 50th percentile, where probabilities greater than this percentile were set to 1 and 0 otherwise. We applied a similar threshold (50th percentile) to isolated areas with the greatest likelihood of unlicensed private and trespass cultivation. We then estimated the percent of grid cells with high species-specific occupancy and a high likelihood of unlicensed private, trespass or licensed cultivation. We also estimated the percentage of grid cells with high occupancy and a high likelihood of any type of cultivation, which we defined as the maximum value across the three cultivation layers.

Results

Camera trap surveys and occupancy models

We detected 30 species, including seven special status species (Table 2). Long-tailed weasels (*Mustela frenata*) and stoats (*Mustela erminea*) were detected the least, and American black bears (*Ursus americanus*) and mule deer (*Odocoileus hemionus*) the most (Table 2). At the community level, species tended to occupy public lands that were close to water with less steep slopes (Fig. 2; Online Resource 3). At the species level, elevation ($n=18$), slope ($n=13$), and canopy cover ($n=12$) had a significant influence on the occupancy of the greatest number of species (Online Resource 3).

Distribution of cannabis cultivation

There were 4,366 mixed-light or outdoor cannabis cultivation licenses within our study area (Fig. 3). Of these licenses, 830 were annual licenses and the remaining were provisional. Humboldt County had the greatest number of licenses ($n=2183$), followed by Mendocino County ($n=1012$) and then Trinity County ($n=515$).

Seven covariates were included in the final MaxEnt models representing the likelihood of trespass cannabis cultivation in the northern region (Model

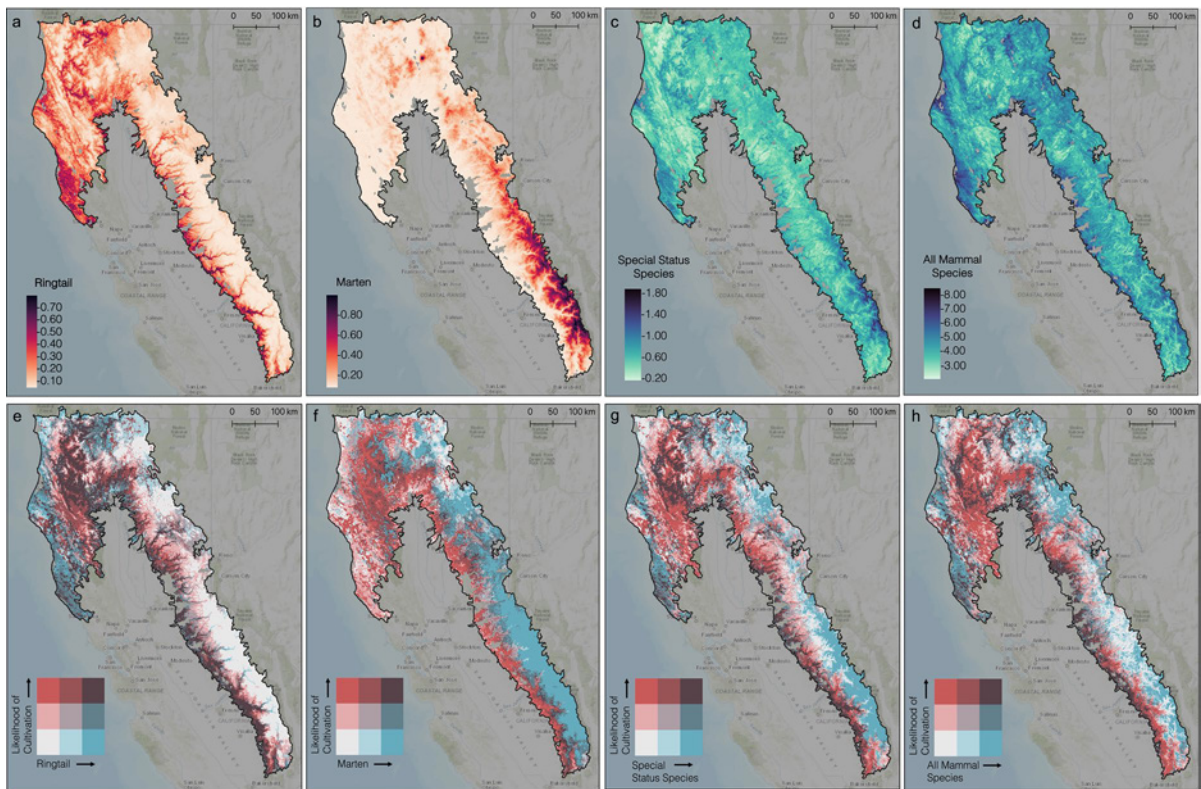


Fig. 2 Predicted suitable habitat for **a** ringtail and **b** Pacific marten, and for the community of observed **c** mammal species and **d** special status species, in the northern region and Sierra Nevada of California, 2019–2021. We also identify areas of

conservation concern **e–h**, defined as places with high overlap between suitable habitat and the likelihood of cannabis cultivation activity

1a) and in the Sierra Nevada (Model 1b) of California (Table 1). Response curves indicated that trespass cultivation in the northern region tended to be in steeper sloped ($> 30\%$) areas with short fire return intervals (< 11 years) that were close to perennial or intermittent streams (< 1000 m) and far from population centers (~ 40 km; Table 1; Online Resource 4). Trespass cultivation in the Sierra Nevada, alternatively, tended to be in less sloped ($> 20\%$) areas with extremely short fire return intervals (~ 2 years) that had annual precipitation of > 500 mm and minimal rain during the driest month (Table 1; Online Resource 4). In model 1a, a beta multiplier of 3 produced the lowest AICc and prevented overfitting with mean minimum and 10% training omission rates of 0 and 0.94, respectively, and testing omission rates of 0.016 and 0.125, respectively. In model 1b, a beta multiplier of 5 produced the lowest AICc and prevented overfitting with mean minimum

and 10% training omission rates of 0 and 0.099, respectively, and testing omission rates of 0.013 and 0.135, respectively. Both models of trespass cultivation performed well with mean training area under the curve (AUC) scores of 0.879 (Model 1a) and 0.874 (Model 1b).

In our model representing the likelihood of unlicensed cannabis cultivation on private lands (Model 2), ten predictor variables were included (Table 1). Unlicensed, private land cultivation tended to occur on flatter (slope $< 30\%$), smaller sized parcels far from population centers (> 10 km), where neighboring parcels were similarly sized (Table 1; Online Resource 4). A beta multiplier of 3.5 produced the lowest AICc and prevented overfitting with mean minimum and 10% training omission rates of 0 and 0.96, respectively, and testing omission rates of 0 and 0.129, respectively. Our model of unlicensed

Table 2 Mammal species detected during camera trap surveys in the northern region and the Sierra Nevada of California, 2019–2021, including numbers of detections (det.), if it is a special status species within a portion of our study area (SS),

and the percent of each species' suitable habitat that could be influenced by cannabis cultivation, including licensed (lic.), unlicensed on private property (unlic), trespass, and in totality (Total)

Common name	Scientific name	Det.	SS	Lic.	Unlic.	Trespass	Total
American badger	<i>Taxidea taxus</i>	32	X	0.18	0.26	0.02	0.39
American black bear	<i>Ursus americanus</i>	2961		0.14	0.56	0.04	0.65
American pika	<i>Ochotona princeps</i>	117	X	0.02	0.39	0.00	0.40
Belding's ground squirrel	<i>Urocyon beldingi</i>	19		0.08	0.25	0.00	0.31
Bobcat	<i>Lynx rufus</i>	447		0.21	0.30	0.03	0.46
California ground squirrel	<i>Otospermophilus beecheyi</i>	447		0.20	0.31	0.04	0.46
Chipmunk species	<i>Neotamias species</i>	1060		0.05	0.34	0.01	0.37
Coyote	<i>Canis latrans</i>	1268		0.15	0.22	0.02	0.33
Douglas's squirrel	<i>Tamiasciurus douglasii</i>	1148		0.08	0.36	0.02	0.41
Elk	<i>Cervus canadensis</i>	37	X	0.26	0.32	0.06	0.51
Fisher	<i>Pekania pennanti</i>	158	X	0.14	0.57	0.04	0.65
Golden mantled ground squirrel	<i>Callospermophilus lateralis</i>	387		0.07	0.27	0.00	0.32
Grey fox	<i>Urocyon cinereoargenteus</i>	1398		0.26	0.50	0.06	0.69
Jackrabbit species	<i>Lepus species</i>	683		0.20	0.35	0.04	0.50
Long-tailed weasel	<i>Mustela frenata</i>	13	X	0.23	0.28	0.04	0.45
Mouse species	<i>Muridae species</i>	149		0.04	0.38	0.00	0.39
Mountain lion	<i>Puma concolor</i>	144		0.25	0.46	0.05	0.64
Mule deer	<i>Odocoileus hemionus</i>	5225		0.12	0.43	0.02	0.51
Northern flying squirrel	<i>Glaucomys sabrinus</i>	173		0.27	0.43	0.07	0.63
Northern raccoon	<i>Procyon lotor</i>	84		0.13	0.44	0.04	0.53
Pacific marten	<i>Martes caurina</i>	320	X	0.28	0.53	0.07	0.73
Ringtail	<i>Bassariscus astutus</i>	192	X	0.25	0.56	0.06	0.74
Stoat	<i>Mustela erminea</i>	13		0.03	0.36	0.00	0.38
Striped skunk	<i>Mephitis mephitis</i>	405		0.26	0.45	0.05	0.64
Rabbit species	<i>Sylvilagus species</i>	199		0.24	0.31	0.04	0.49
Virginia opossum	<i>Didelphis virginiana</i>	96		0.28	0.52	0.06	0.72
Western gray squirrel	<i>Sciurus griseus</i>	1575		0.25	0.57	0.07	0.74
Western spotted skunk	<i>Spilogale gracilis</i>	110		0.16	0.52	0.05	0.63
Woodrat species	<i>Neotoma species</i>	267		0.10	0.49	0.03	0.56
Yellow-bellied marmot	<i>Marmota flaviventris</i>	173		0.05	0.32	0.00	0.36

We only included areas with values above the 50th percentile when identifying suitable habitat and areas with high risk of unlicensed and trespass cultivation

cultivation performed satisfactorily with an AUC of 0.798.

Identifying areas and species of concern

Cannabis cultivation potentially influenced 39–74% of suitable habitat for special status species, with American badger (*Taxidea taxus*) having the smallest amount of overlap and ringtail (*Bassariscus astutus*) the greatest (Table 2). Private land cultivation,

both licensed and unlicensed, tended to have a larger potential influence on generalist species like mule deer, Virginia opossum, and northern raccoon (*Procyon lotor*) whereas the risk of trespass cultivation had the largest potential influence on fisher, a special status species, with 57% of suitable fisher habitat overlapping with areas that have a high risk of trespass cultivation (Table 2).

Four of the five watersheds with the greatest spatial overlap between suitable habitat for special

status species and trespass cannabis cultivation were in Trinity County, whereas those with the greatest overlap with unlicensed private cultivation were distributed across the study extent (e.g., Fresno, Amador, Shasta, and Mariposa counties; Online Resource 5). From a licensed cultivation standpoint, three watersheds in Humboldt County were identified as being of concern for the overall mammal community, elk (*Cervus canadensis*), fisher, and ringtail while one watershed in Nevada County and one in Mendocino County were identified as watersheds of concern for American badger, elk, long-tailed weasel, and ringtail (Online Resource 5).

Discussion

Our research demonstrates how existing biological and socioeconomic data can be integrated to inform strategic and timely conservation planning. We used camera trap, law enforcement, and agricultural license data to identify areas and species that may be of conservation concern due to a globally expanding land use, cannabis cultivation. Our approach enables resource managers, law enforcement officers, and scientists to quickly identify the potential footprint of three types of cultivation—private licensed, private unlicensed, and trespass—throughout the northern region and Sierra Nevada of California and its overlap with wildlife habitat. This information can be used by resource managers in their efforts to mitigate potential impacts of cannabis cultivation on threatened species, by law enforcement officers to prioritize where they search for and eradicate trespass cultivation, and by scientists to identify areas where restoration work would be most impactful. Further, given the distribution of licensed and unlicensed cannabis cultivation continually shifts as it responds to dynamic prices, policies, and social dynamics, our research could also be used to guide the placement of new, licensed sites (Bodwitch et al. 2021; Wartenberg et al. 2021). By directing cannabis away from environmentally sensitive areas and toward already disturbed landscapes that have access to roads and ample water resources, we could ensure the demand for licensed cultivation is met while simultaneously conserving ecosystems and California's diverse species (Chaplin-Kramer et al. 2015; Butsic and Brenner 2016).

The first dataset we capitalized on was camera trap data collected by the CDFW and USFS in 2019–2021. We used hierarchical multi-species occupancy models to integrate these data, which were collected as part of ten distinct projects, as this approach accounts for observation error and accommodates differences in project designs with random effects and detection covariates (Dorazio and Royle 2005; Zipkin et al. 2010). Our approach resulted in habitat suitability maps for 30 species across nearly one-third of California and demonstrates the tremendous utility of camera trap data. When researchers are willing to work collaboratively, and advanced analytical approaches are utilized, the door is opened to broad-scale assessments and management questions that are beyond the scope of what any project could achieve individually (Rich et al. 2017; Davis et al. 2018; Ahumada et al. 2020).

Another dataset we capitalized on were the locations of cannabis cultivation sites eradicated by local, state, and federal law enforcement entities. Using these data, we were able to apply a species distribution modeling technique, MaxEnt, to human choice, and predict the risk of trespass and unlicensed private land cannabis cultivation. Similar to our camera trap analysis, this work highlights the benefits of collaborations, specifically interdisciplinary collaborations. Trespass cannabis cultivation was predictably distributed throughout moderately sloped areas in the northern region and the Sierra Nevada of California, often in areas with recently disturbed vegetation (Fig. 3; Online Resource 4). Post-fire vegetation conditions likely provide more sunlight for cannabis growth and a rapidly growing understory for obscuring plots (Wengert et al. 2021). Private, unlicensed cultivation, alternatively, was more ubiquitous across environmental and socioeconomic spectra, as it can occur on any private parcel with open space, but appeared to be more prevalent on small parcels, clustered among other small parcels, and far from population centers. This supports previous research that found cannabis cultivation was often spatially clustered in more remote areas (Butsic et al. 2018; Parker-Shames et al. 2022), likely with unlicensed cultivators concealing themselves among those who are licensed. All cannabis risk models performed well, with AUC values ≥ 0.80 , but our data were limited to law enforcement reconnaissance and

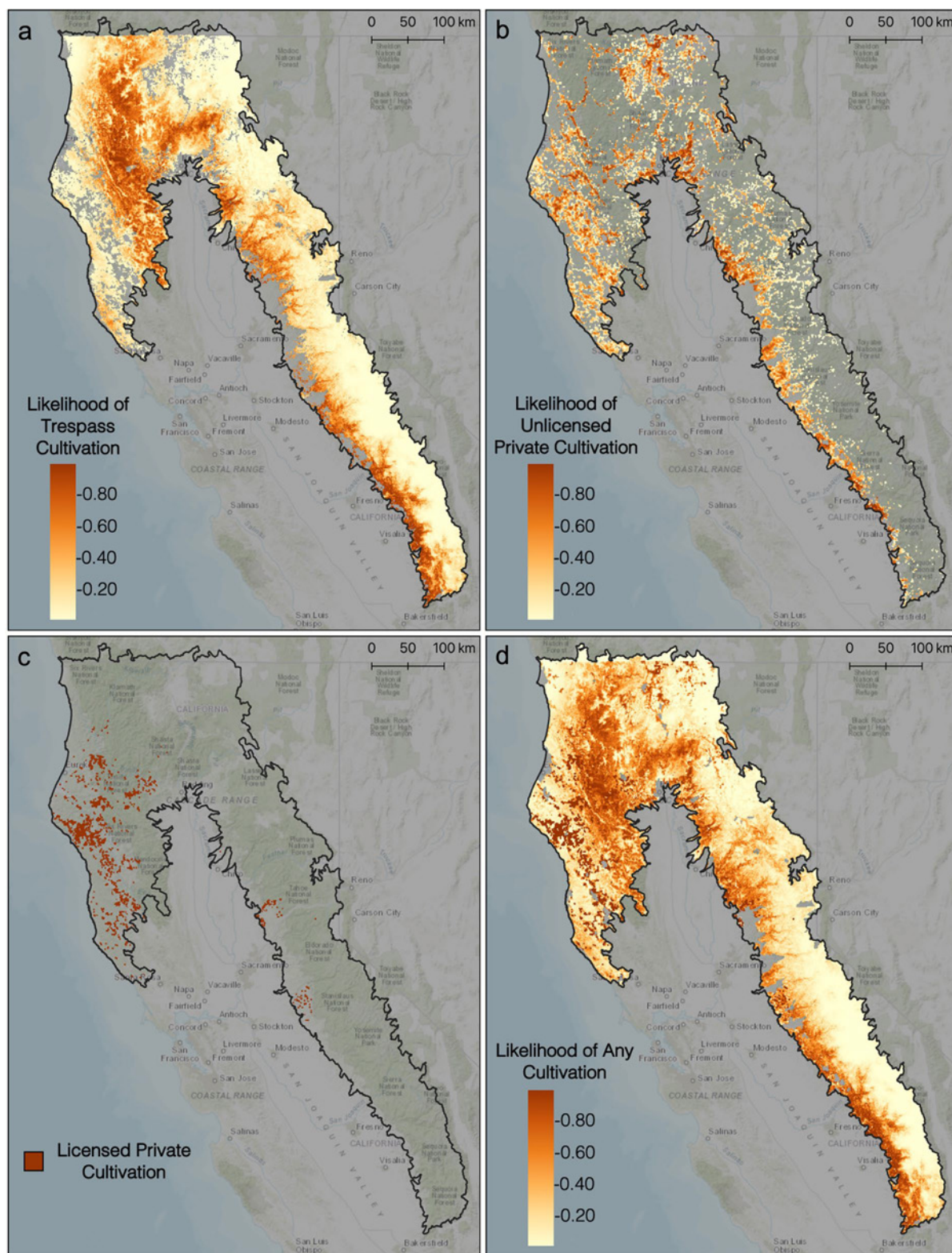


Fig. 3 Cannabis cultivation throughout the northern region and Sierra Nevada of California including the modeled likelihoods of unlicensed cannabis cultivation, which we estimated using a maximum entropy framework and the locations of eradicated cannabis cultivation, on **a** property where the owner was unaware (i.e., trespass cultivation) and **b** private property; as well as **c** the locations of mixed-light and outdoor cannabis cultivation licenses issued by the Department of Cannabis Control; and **d** the overall likelihood of any type of cultivation

eradication efforts and priorities. We acknowledge that our datasets only included a subset of all trespass and private unlicensed cultivation sites, and as such our risk maps are likely conservative.

Sixteen of the thirty observed species had over half of their suitable habitat potentially impacted by cannabis cultivation (Table 2). This included far-ranging species like mountain lion (*Puma concolor*) and elk, special status carnivores like fisher and Pacific marten (*Martes caurina*), and generalists like mule deer, northern raccoon, striped skunk (*Mephitis mephitis*), and Virginia opossum. If larger-bodied mammals avoid areas impacted by cannabis cultivation or if it restricts their movements throughout their range and beyond, it will impact everything from primary productivity and nutrient cycling to genetic connectivity and overall ecosystem health (Schmitz et al. 2018; Tucker et al. 2018; Dominoni et al. 2020). Alternatively, if the landscape mosaic created by small-scale cannabis cultivation benefits generalist species with faster reproductive strategies, then sensitive species that rely on intact, core habitat may experience the compounding impacts of habitat loss, competition, and predation (Crooks and Soulé 1999; Fischer and Lindenmayer 2007; Suraci et al. 2021). Understanding which species are at greatest risk and where, will enable managers to proactively work with cultivators in sensitive ecosystems, some of whom have voiced concern over a lack of education on how to cultivate cannabis while being a steward to the environment (Wartenberg et al. 2021; Parker-Shames et al. 2022).

A third of the watersheds of concern were located in northern California in Humboldt, Trinity, and Mendocino counties, which is known as the Emerald Triangle and often called the birthplace of cannabis production in the US (Butsic and Brenner 2016). This area encompassed 85% of licensed cultivation in our study extent, had a high risk of both trespass and unlicensed cultivation, and provided suitable habitat for species like fisher, ringtail, and the mammal

community overall (Fig. 3; Online Resource 4). While much of the land-use conversion and other impacts of cannabis cultivation have already taken place in this region, knowing where the hotspots of concern are located can help prioritize eradication and remediation efforts. This is vital given only a small fraction of trespass cultivation sites are found by law enforcement each year and of those, an even smaller number are remediated, meaning they continue to pose an environmental threat (Wengert et al. 2021).

Our approach for identifying areas of conservation concern by overlaying the footprint of a land-use change, cannabis cultivation, with that of terrestrial mammal habitat is an important first step in informing targeted management, enforcement, and outreach activities. Camera traps only collect information on a small portion of wild fauna, however, so we recommend expanding our approach to encompass a wider breadth of data sources. Data from acoustic recorders, for example, could be integrated as they provide information on vocalizing taxa like insects, fish, amphibians, reptiles, birds, and mammals and similar to camera traps, are increasingly available across broad spatial and temporal scales (Blumstein et al. 2011; Sugai and Llusia 2019). Environmental DNA, alternatively, continually advances as a tool for identifying the hyperdiversity of species found in water, soil, and on land (Deiner et al. 2021). The availability of these types of primary occurrence data will only grow over time as technology improves, thus enabling conservation planning aimed at entire ecosystems (Steenweg et al. 2017; Newbold et al. 2020; Fraisl et al. 2022).

While our research focused on cannabis cultivation, the approach we used could be applied to other ecological stressors such as logging, renewable energy development, megafires, increasing temperatures, or any combination thereof. Assessing these stressors individually and holistically enables both targeted management actions (e.g., how to expand agriculture in a way that minimizes impacts to biodiversity—Chaplin-Kramer et al. 2015) as well as broadscale conservation planning (e.g., an effort to protect 30% of nature in areas most important to biodiversity—Obura et al. 2021). Our approach could also be embedded in a dynamic framework, where the species, landscape, and socioeconomic inputs are updated regularly, which would facilitate management decisions that incorporate habitat change as well

as shifts in environmental policy and socioeconomics (Pressey et al. 2007; Van Teeffelen et al. 2012). Approaches like this that allow for data-driven, strategic, and dynamic management decisions are imperative to ecosystem and species conservation given the rapid pace at which landscapes are changing (Fischer et al. 2006; Foley et al. 2011; Crooks et al. 2017). We encourage broader application of this type of proactive conservation planning as only then will we be able to slow, or even reverse, global declines in biodiversity (Visconti et al. 2016; Powers and Jetz 2019).

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Data availability Our occupancy modeling code is publicly available on GitHub (github.com/CourtneyLDavis/California-Cannabis-Mammals).

Declarations

Competing interests The authors declare no competing interests.

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