Ecological Outcomes of Cannabis Legalization: A multidisciplinary study of cannabis land use change, its social drivers, and environmental outcomes

By

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A dissertation submitted in partial satisfaction of the

requirements for the degree of

Doctor of Philosophy

in

Environmental Science, Policy, and Management

in the

Graduate Division

of the

University of California, Berkeley

Committee in charge:

Professor Justin Brashares, Chair
Professor Van Butsic
Professor Mary Power

Summer 2022

Abstract

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Recent state-level legalizations of recreational cannabis across the US have created a large-scale policy experiment that could alter land use patterns and shape wildlife communities. Cannabis legalization provides a rare opportunity to study the consequences of land use change in a rural agriculture frontier. This dissertation explores the ecological outcomes of cannabis legalization by approaching cannabis landscapes as social-ecological systems and combining multiple disciplinary approaches. My research takes an interdisciplinary approach to quantifying land use change and contributes to our context-specific understanding of wildlife responses to human development. Ultimately, this research provides results that are timely and may be useful for policy, management, and land use decision-making.

I begin with an introduction on cannabis landscapes as social-ecological systems. I outline a brief history of cannabis farming in the western US, as well as an explanation of my focus on small-scale legacy cannabis farming. Then, in Chapter 1, I produce baseline distribution data on cannabis land use in southern Oregon, and examine the overlap with sensitive ecological features. This chapter addresses the questions: How is cannabis production distributed? Where might we be concerned about its environmental impact? In Chapter 2, I use cannabis farmer interviews to generate model covariates which contextualize the cannabis land use data from the first chapter. Here, I ask: What drives cannabis land use over time? What is the socio-ecological context for these drivers? In Chapter 3, I use wildlife camera data to examine the outcomes of cannabis land use for animals on and surrounding cannabis farms. This chapter focuses on the question: How do wildlife respond to cannabis farming? In Chapter 4, I detail the methodology for field experiments that address specific mechanisms of wildlife response to cannabis cultivation, asking: What is the role of light and noise disturbance in multi-taxa wildlife response to cannabis? Finally, I conclude with a summary of the broad implications of this work, as well as future research and policy recommendations.

This dissertation is dedicated to my "niblings" An Lei, Ozzie, Hailan, and Iris. May you always stay curious and excited about the world around you.

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Acknowledgements

This dissertation is built on determined hard work, a true belief in the value of collaboration, and a deep respect for community. I am immensely grateful for the many, many hands that have shaped, guided, and supported this work. It would not have been possible to do this alone—nor would I have ever wanted to do so. Even while the latter years of my dissertation were impacted by the isolating and disrupting forces of the COVID-19 pandemic, there have been so many who kept me connected to the value of my science and to my communities.

First, I want to acknowledge that my choice of dissertation topic was both scientific and personal. My roots are tied to the places and communities from whence the modern cannabis industry arose. My parents, Heidi and Jim, lived on a commune in Southern Oregon for two decades, and those hippie gatherings are where my family grew and where my sense of community was born. When researchers describe the history of the cannabis movement, they are describing a piece of my own history. For example, Corva (2014) quoted activist Bernardine Dohrn on the philosophical origins of the outlaw counter-culture cannabis production in the 1960s and 70s: "We fight in many ways. Dope is one of our weapons. The laws against marijuana mean that millions of us are outlaws long before we actually split." It's still strange to me to read a quote from someone I grew up with as extended hippie family in an article for my dissertation. The outlaws Bernardine referred to were my neighbors, my family, my friends. This dissertation owes much to the legacy of cannabis farming in these counter-culture communities.

The inspiration for my dissertation extends to the present moment as well. I am grateful to my communities in southern Oregon for investing themselves emotionally in my work. I chose the topic of cannabis land use change because it deeply affects the places where I grew up. These are spaces where we continue to hold tensions between rural livelihoods, a tradition of cannabis cultivation, love of natural spaces, and rampant development.

It is with this background in mind that I give my deepest thanks to my family, and to my communities in Takilma and Ashland. I want to especially acknowledge my aunt Susan, who always believed in me, and my uncle Sitting Dog, who helped me understand the depth and importance of my work. I wish I could have shared this dissertation with you.

It was my family that inspired my work, but it was my academic community that helped get it done:

I am immensely grateful to my advisor Justin Brashares. Justin gave me space to explore my own research ideas, and the confidence that those ideas were worth exploring. He allowed me to bring my full self to the work that I do, and saw that as a strength.

I also want to thank the rest of my committee: Van Butsic and Mary Power. Van invited me into the world of cannabis research and opened new doors. Mary sparked my creativity and helped me think both more expansively and more precisely about my work. I am also grateful for my qualifying exam committee, who helped me shape my ideas into workable questions: Van Butsic, Mary Power, Adina Merenlender, and Arthur Middleton. Thank you for framing the qualifying exam as a unique opportunity—it was ultimately a highlight of my graduate experience.

I am so grateful to the members of the Brashares Lab: Kendall Calhoun, Amy Van Scoyoc, Millie Chapman, Mitch Serota, Jessie Moravek, Tyus Williams, Thomas Connor, Guada Verta, Janelle Dorcy, Christine Wilkinson, Katy Seto, Briana Abrahms, Tristen Nuñez, Lindsey Rich, Jennie Miller, Kaitlyn Gaynor, Alex McInturff, Mario Klip, Lauren Withey, and David Kurz. The Brashares lab has been my home base during graduate school, continuously providing me both intellectual and social support. Thank you for reading drafts, critiquing analyses, and providing feedback on research ideas, while also joining in sing-alongs, volleyball games, and zoom game nights.

In addition to my lab, I have found multiple other intellectual hubs that have inspired and supported my work. Thank you to the wildlife group within ESPM for providing social engagement as well as collaborative research opportunities. Thanks also to the short-lived but always memorable Conservation Community, and the informal space to share conservation ideas over a glass of wine. I am also grateful to the LUCLAB for helping me to better understand land system sciences and providing early support in the formation of my research questions. Finally, I have the deepest possible gratitude for the Cannabis Research Center at Berkeley (http://crc.berkeley.edu/), which helped me understand the depth and complexity of cannabis systems from multiple angles and disciplinary approaches. Chapter 2 would not have been possible without seeing the strengths of interdisciplinary approaches fostered by the CRC. It also provided invaluable opportunities to connect my work with stakeholders and the public. Thank you in particular to the CRC's Laura Herrera for keeping us organized and helping to center marginalized farmers in our work.

The Department of Environmental Science, Policy, and Management is a uniquely interdisciplinary community, and I grateful for the students, staff, and faculty that have put in the work to ensure that our department can be not only intellectually rigorous, but also expansive and supportive. Thank you to those who have helped the department function on the day-to-day, including Roxanne, Ryann, Bianca, and Nicole. My 2016 cohort was critical for finding my footing in Berkeley, and I am grateful to each of you. I found solidarity in the student groups pushing for positive change within the department, for example, the Graduate Student Association and the many members over the years, including Brian Klein, Juliet Lu, Dylan Beal, Sarah Hartman, and Robin Lopez. Thank you also to the Graduate Diversity Council, and in particular the Anti-Racism teaching team: Whitney Mgbara, Aidee Guzman, Kenzo Esquivel, Rosalie Fanshel, Natasha Shannon, Lorenzo Washington, and Damian Elias. May we always get into good trouble. Thank you to those who pushed me intellectually and engaged me socially, including Wenjing Xu, Ben Goldstein, Chelsea Andreozzi, Katherine Siegel, Emma Steigerwald, Vera Chang, Brian Whyte, Benji Kessler, Kristin Barker, and Avery Shawler.

There are many people who helped on specific components of my dissertation. For Chapter 1, I am grateful for my co-authors and their humble willingness to share data and expertise: Chris Choi, Van Butsic, David Green, Brent Barry, Katie Moriarty, Taal Levi, and Justin Brashares. It was particularly meaningful to me to get to lead a paper with David Green, who had mentored me in my first research position after undergrad with the Mara Hyena Project. Thank you to

Chris, as well as Aaron Howard and Jamie Trammel for helping me translate the data from this chapter into a publicly accessible storymap.

For Chapter 2, thank you to my co-authors Hekia Bodwitch, Justin Brashares, and Van Butsic. Thank you in particular to Hekia for helping me expand my way of thinking and visiting me in the field. Thank you to Ben Goldstein, Amy Van Scoyoc, Dylan Beal, and Thomas Connor for modeling advice. Thank you to the community of Takilma, Oregon for being a supportive home base during interview data collection, particularly the Magic Forest Farm and the Meadows. Finally, thank you to the farmers who agreed to be interviewed for this project.

For Chapter 3, thank you to the farms that agreed to participate in this study; I know it took an inordinate amount of trust. Thank you also to all the landowners that agreed to let me set cameras on their properties. Thank you to my co-authors Ben Goldstein and Justin Brashares, and Ben in particular for his patient modeling advice. Thanks to Wenjing Xu and Lindsey Rich for co-authoring an earlier paper on a subset of the data. I am particularly grateful for my field assistants, Christy Dunn and Maelagh Baker who rescued me from boredom, feral dogs, and self-induced bear spray.

For Chapter 4, I am indebted to the staff at Hopland Research and Extension Center and Angelo Coast Range Reserve. This work would not have been possible without the tireless efforts of Alison Smith. Thank you also to Greg Solberg and Troy McWilliams for your fieldwork assistance, and my summer undergraduate assistants Cece Gonzalez and Jess Cronin. Thank you to Perry de Valpine for advice on experimental design; to Kendall Calhoun, Lindsey Rich, and Matt Toenies for advice on monitoring setups; and to the co-PIs on this research project: Justin Brashares, Mary Power, and Pete Oboyski. Thanks to Pete for helping me design the entomology protocols and pretend I understand something about insects.

Thank you to all the funders who have made this research possible: National Science Foundation Graduate Research Fellowship, the Department of Cannabis Control, the Carol Baird Award, Safari Club International, the SJ Hall Fellowship, and the Oliver Lyman Wildlife Award.

I am immensely grateful that throughout my years at Berkeley, I got to oversee and mentor a small legion of undergraduate research assistants: Alice Hua, Alyssa Perez, Anika Wikramanayake, Anna Mazur, Asher Thompson, Augie Clements, Brian Yang, Cece Gonzalez, Chloe Tilton, Elise Allen, Ellie Resendiz, Emily Ohman, Ethan Sheppy, Frances Bingham, Haina Jin, Hannah Liu, J'Hrenara Rios, Jamie German, Jasmin Elenes, Jess Cronin, Jessica Stubbs, Jordan Pulaski, Julianna Sams, Katrina Gonzales, Liam Jameson, Manuel Espinoza, Michael Xiao, Miranda Bustos, Parker Bohls, Sapphire Suzuki, Sara Soderberg, Sasha Kozlov, Summer Kang, Theo Snow, Tiffany Chen, and Varsha Madapoosi. Particularly during remote work lockdowns, my team of undergraduate researchers kept me motivated and grounded in a way I never anticipated. Thank you to the Geospatial Innovation Facility at UC Berkeley for providing computing space for the mapping assistants. Thank you to the Undergraduate Research Assistantship Program and Sponsored Projects for Undergraduate Research programs at UC Berkeley for providing student compensation. You are all worth more.

In addition to all those listed above, I want to extend my gratitude for the mentors who helped me make it to graduate school. Thank you to Marc Snyder, Brian Linkhart, Jim Ebersole, and Bernal Rodríguez-Herrera for introducing me to ecology and building my confidence. Thank you to Allen Fish for always calling me "Dr." even as an intern. And especially thank you to Kay Holekamp and the Mara Hyena Project—I measure my life pre- and post-hyenas because of how much I learned, and how much the experience shaped my research approach and goals.

I also had immense support from my friends outside of academia. Thank you to my COVID bubble buddies at HREC: Hannah, Will, Flora, and Rowan (and of course all your wonderful animals). You kept me buoyed at my lowest. Thank you to my Shattuck housemates Anna and Nick (and Monty), as well as our amazing neighbors Sarah, Tomás, and Susie. You made a hole-in-the-wall into a paradise. Thank you to Ada and Jo for proving that support can come from miles away. Thank you to my cat, Luna—I don't know how I made it before I got you.

Finally, I want to acknowledge that fieldwork for Chapters 2 and 3 were conducted in the ancestral home of the Cow Creek Umpqua, Tolowa Dee-ni`, Takelma, Karuk, and other Confederated Tribes of the Grand Ronde. Fieldwork for Chapter 4 was conducted in the ancestral and unceded lands of the Hopland people, and the Coast Yuki and Cahto peoples (https://native-land.ca/). UC Berkeley itself sits on the territory of the xučyun (Huichin), the ancestral and unceded land of the Chochenyo speaking Ohlone people, the successors of the sovereign Verona Band of Alameda County. I have benefitted from the use and occupation of this land, and by offering this Land Acknowledgement, I affirm Indigenous sovereignty.

Introduction

Land use change is one of the greatest threats to wildlife worldwide—globally, it can remove and alter habitat, or disrupt wildlife interactions (Driscoll et al., 2013; Ellis et al., 2013; Foley et al., 2005; Turner et al., 2001a). A major challenge for conservation involves navigating the negative environmental repercussions of land use change alongside the needs for human agriculture and development (Foley et al., 2011; Kremen & Merenlender, 2018). This means that studying land use change fundamentally engages the role of humans within ecological systems and processes (Crespin & Simonetti, 2019; Kremen & Merenlender, 2018). Research has increasingly focused on human impacts on surrounding ecosystems, revealing complex interactions and consequences (e.g., Alberti et al., 2020; Brashares, 2010; Estes et al., 2011; Prugh et al., 2009; Suraci et al., 2021). However, mechanistic understanding, universal rules, or consistent predictions are difficult to define, and more context-based research is needed, especially in systems early in the process of land use transition.

Cannabis agriculture (i.e., marijuana, *Cannabis indica*, or *C. sativa* cultivation) provides an ideal opportunity to study ecological outcomes of land use change in a rural and rapidly changing landscape. To understand why, it is important to start with the recent history of cannabis cultivation in the western US. For decades, cannabis was grown illegally in rural areas of California, Oregon, and Washington as part of the back-to-the-land movement (Corva, 2014). These were remote areas that allowed counter-culture communities to reinvent themselves, but which also happened to host some of the nation's highest biodiversity (e.g., D. Olson et al., 2012). The industry remained surreptitious and small-scale for many years, while ongoing law enforcement and the US "war on drugs" tried unsuccessfully to eliminate the practice (Corva, 2014). Then, the ground shifted with recreational legalization. Oregon passed recreational Adult Use cannabis legalization in the fall of 2015, and California followed suit a year later, riding a wave of recreational legalization measures that eventually passed across 19 states in the US. Very rapidly, this policy change initiated land use development for cannabis (see Chapters 1 and 2), first in areas with a history of cultivation, and later, into new regions. This shift in development was accompanied by subtle shifts in motives and philosophy behind cannabis cultivation – as one of the farmers I interviewed for Chapter 2 put it, "The quest for the all-mighty dollar got in the way of the spiritual cycle of the plant." Along with these rapid changes came calls of concern for potential environmental impacts (Carah et al., 2015) (see Chapters 3 and 4). However, the illicit history of cannabis meant that there was very little existing research on cannabis-environment interactions, and many gaps in baseline data (Carah et al., 2015; Short Gianotti et al., 2017).

To address this brewing conservation crisis, I focused my dissertation on the ecological outcomes of cannabis legalization. I was specifically interested in studying private land cannabis development in rural areas with a history of pre-legalization cultivation (so-called "legacy" areas) (Dillis, Biber, et al., 2021). In these regions, legalization has spurred major private land development for cannabis (both licit and illicit) alongside high biodiversity and few other crop-based agricultural land uses. The focus on small-scale outdoor private land cannabis cultivation sets my dissertation apart from other studies which have focused on public land production (e.g., Wengert et al., 2021), indoor cultivation (e.g., Mills, 2012), or large scale cannabis development in emerging regions (e.g., Dillis, Biber, et al., 2021). Each style of cultivation has its own ecological risks and social, economic, and ecological tradeoffs (Wartenberg et al., 2021). However, private-land outdoor cannabis production in rural legacy regions provides the best opportunity to study land use consequences for wildlife communities within a social-ecological context.

I approach legacy cannabis landscapes as an intertwined social-ecological system (Fig. 1). The history and context of cannabis, described in part above, influences the development of cannabis as land use drivers (Meyfroidt, 2015). These drivers in turn shape the ways in which the associated cannabis land use change affects local ecosystems. The ecological impacts can feed back into the land use drivers by way of social attitudes towards nature, or changes in regulation and enforcement. All these interactions are influenced by the shift in overarching policy brought by recreational legalization. Each of my chapters addresses different components in this system, going from a broad to fine scale.

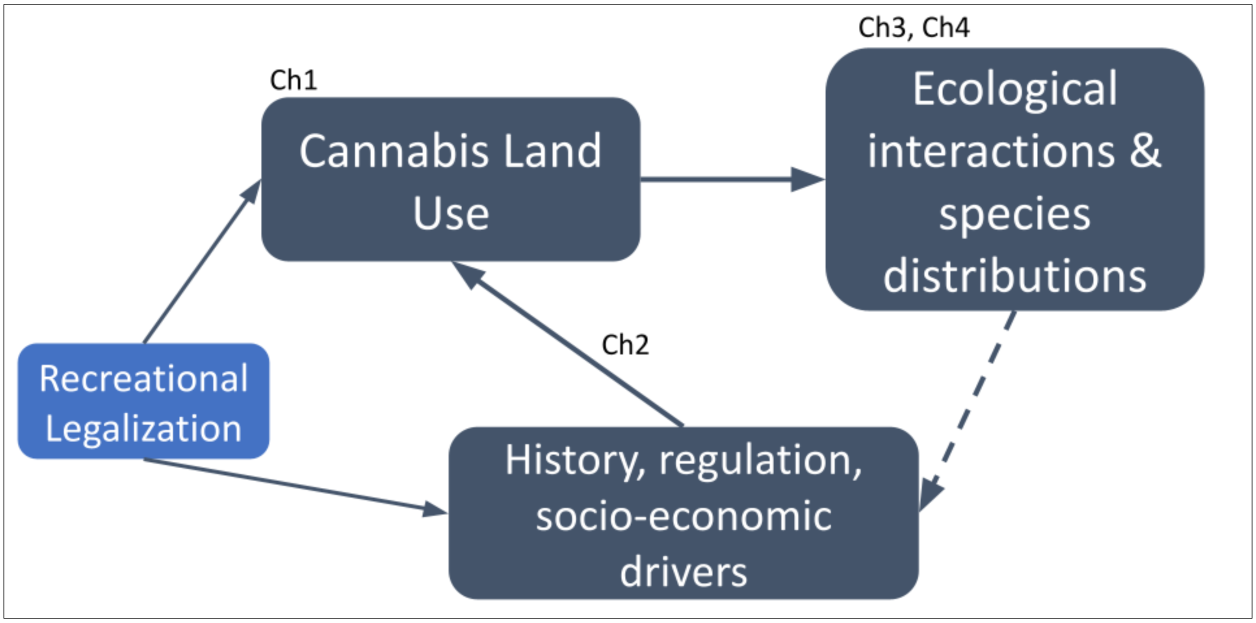


Figure 1. Conceptual diagram of socio-ecological cannabis systems.

My first chapter generates baseline descriptive data on cannabis land use and examines its broad scale overlap with wildlife habitat in southern Oregon (Ch1 in Fig. 1). I use publicly available satellite imagery to characterize the development patterns of outdoor and greenhouse cannabis land use in Josephine County, Oregon, during the first year of recreational legalization. I then examine the overlap of cannabis production with potentially sensitive ecological features, including predator distributions and salmonid habitat. This broad overview provides a baseline to understand patterns of cannabis development relative to all available private lands. It also identifies areas where overlap may create potential for wildlife impacts (recognizing that this broad scale overlap may not necessarily translate to overlap at a local scale, see Chapter 3).

My second chapter adds depth and context to the baseline data provided in the first chapter, by examining the drivers of cannabis land use change before and after legalization (Ch2 in Fig. 1). I use interview data with cannabis farmers to generate social and ecological covariates for models of cannabis land use and land use change. I interpret model results using the themes from the interviews and discuss possible conservation implications.

The third chapter moves to a finer spatial scale, investigating how the overlap presented in Chapter 1 affects wildlife on and surrounding cannabis farms in southern Oregon (Ch3 in Fig. 1). I use wildlife cameras to monitor animal space use and space use intensity as a function of distance to cannabis farms. I also identify general patterns of response by functional groups.

Finally, the fourth chapter (Ch4 in Fig. 1) presents a research design to investigate potential mechanisms for the wildlife responses observed in Chapter 3. I detail the methods for field experiments that measure the effects of light and noise on multi-taxa wildlife responses, mimicking conditions on active cannabis farms in a controlled setting. I present example data from field trials conducted in northern California.

Taken together, these chapters present multiple approaches to understanding the ecological outcomes of cannabis legalization. More generally, research on cannabis agriculture can provide insights on the intersections between rapid changes in human land use and wildlife communities, especially at rural-wildland interfaces. By taking a multi-scalar approach to understanding a unique industry at a critical moment in time, I hope this dissertation sheds light on land use change processes to help promote human-wildlife coexistence in an ever-changing world.

Chapter 1

The spatial overlap of small-scale cannabis farms with aquatic and terrestrial biodiversity

This chapter has been previously published (Parker-Shames et al., 2022) and is included here with permission from co-authors

Phoebe Parker-Shames, Christopher Choi, Van Butsic, David Green, Brent Barry, Katie Moriarty, Taal Levi, Justin S. Brashares

Abstract

The rapid expansion of cannabis agriculture in the Western United States provides a rare opportunity to study how an abrupt change in land-use policy affects local biodiversity. There is broad speculation that cannabis production on private land is expanding and having negative effects on aquatic and terrestrial ecosystems, yet there exists little empirical data to evaluate this concern. In this study, we mapped and characterized outdoor cannabis production during the first season of legal recreational production (2016) in a large legacy cannabis-producing region of Southern Oregon, Josephine County. We descriptively compared cannabis farms to all available private parcels based on proximity to rivers/streams and undeveloped land, and their overlap with carnivore richness. Using publicly available satellite imagery, we found approximately 1.34 km^2 (331 acres) of cannabis cultivation within Josephine County during the first season of legal recreational production. Most cannabis production areas were small (median size 414 m^2), spatially clustered at all observed scales, and recently established (67% were not visible in 2013-2014 pre-legalization). When compared with all available private parcels, cannabis was preferentially located in forested areas and in undeveloped land, and slightly closer to rivers. Within riparian areas, farms were slightly closer to rivers with predicted occurrence of coho salmon (*Oncorhynchus kisutch*). While projected carnivore richness was similar between cannabis and all private parcels, projected fisher (*Pekania pennanti*) occupancy was more than five times higher on cannabis farms, with a median occupancy of 0.69 (IQR 0.24-0.87). Our results establish a baseline for cannabis landcover at the time of early recreational legalization and rapid expansion, and can be used to predict future patterns or ecological consequences of cannabis development in other production areas. Understanding the potential ecological impact of cannabis is increasingly important as legalization expands, and may also offer insights into other rural land use change frontiers.

Introduction

Land use change is one of the oldest and most pervasive threats to global biodiversity (Ellis et al., 2013; Foley et al., 2005), yet it often occurs over time spans that obscure pattern (Turner, 2005; Turner et al., 2001b), or in tandem with multiple development drivers that are difficult to disentangle (Meyfroidt, 2015; Turner, 2005). An exception to this is when abrupt changes in law or regulation accelerate development, creating what is known as a “policy-induced rapid land use change frontier” (le Polain de Waroux et al., 2018). The acceleration of development at these frontiers enables researchers to assess how land-use change affects biodiversity or ecosystem function over short time periods (Turner, 2005). One such unique opportunity to study land use change frontiers has emerged recently in the western United States of America (U.S.) with the legalization of cannabis production and use (Butsic et al., 2018).

Over the past decade, 17 states and the District of Columbia in the U.S. have legalized recreational cannabis, or marijuana (*Cannabis sativa* or *C. indica*), and the rate of recreational legalization has increased over that time. This policy change has initiated rapid development of cannabis cultivation, particularly in areas with a history of illicit or medical cannabis farming (Butsic et al., 2018; Butsic & Brenner, 2016). Note that because of the complex policy background of cannabis and its quasi-legal status (Short Gianotti et al., 2017), this expansion occurs across types of cultivation including licensed and unlicensed producers. As with any development frontier, the rapid expansion of recreational cannabis is likely to come with ecological costs. Indeed, cannabis production has sparked considerable conservation concern for its potential effects on water, land, and wildlife (Carah et al., 2015; LaChance, 2019; Wartenberg et al., 2021). These effects may occur in part through (1) water withdrawals that lower freshwater availability (Bauer et al., 2015; Dillis et al., 2020; Zipper et al., 2019), (2) road construction or use of pesticides that lower freshwater quality (Carah et al., 2015; Portugal & Hwan, 2020), (3) clearing or fencing of undeveloped land that removes or degrades wildlife habitat (Butsic et al., 2018; Butsic & Brenner, 2016; I. Wang et al., 2017; Wengert et al., 2021), (4) toxicants or poaching that directly kill animals and pose particular risk to terrestrial carnivores like the fisher (*Pekania pennanti*) (Gabriel et al., 2012, 2015; Rich, McMillin, et al., 2020; Thompson et al., 2014), and (5) human disturbance (from increased human presence, use of security or grow lights, or noise from generators and equipment) that alters animal behavioral cues (Parker-Shames et al., 2020; Rich, Baker, et al., 2020; Rich, Ferguson, et al., 2020) (see Chapters 3 and 4). These five impact pathways likely vary depending on surrounding context, production practices, and license status, but provide a general guideline for potential ecological effects (Wartenberg et al., 2021).

Much of the existing research on ecological effects of cannabis has focused on illicit production on public lands (e.g., Carah et al., 2015; Gabriel et al., 2012; Levy, 2014). However, private land production is quickly becoming a dominant source of cannabis in the western U.S. while illegal public land production in the region either appears to be declining (Klassen & Anthony, 2019), shifting, or possibly increasing in some areas with increased enforcement (Wengert et al., 2021). Private land cannabis cultivation appears to generally follow one of two development trajectories (Dillis, Biber, et al., 2021). The first pathway consists of many, smaller farms in rural areas with a history of illicit or medical cultivation (i.e., “the legacy pathway”). The second path is dominated by fewer, larger farms in new areas more conducive to large-scale, industrial farming (i.e., “the industrial pathway”). Note that although the legacy pathway is characterized by historical growing practices, this form of production can also expand with emerging development frontiers. Research on these development trajectories in California suggests that, although both trajectories are expanding, the legacy pathway may require policy intervention if it is to fully transition to, and persist in, the legal industry (Bodwitch et al., 2019; Dillis, Biber, et al., 2021). Proponents often argue that smaller-scale styles of farming are more sustainable (Bodwitch et al., 2019), sometimes drawing parallels to industries such as craft vineyards (e.g., Hilty & Merenlender, 2004; Kremen & Merenlender, 2018). However, these farms are also often located in more rural, biodiverse watersheds close to protected wilderness and managed timberlands that could be at environmental risk from expanding development (Butsic et al., 2018; Carah et al., 2015). As land managers and policymakers decide where to prioritize cannabis farming, there is a growing need to contextualize the potential effects of the legacy pathway in ecologically sensitive regions.

In Josephine County, Oregon, the co-occurrence of cannabis agriculture within the highly biodiverse Klamath-Siskiyou Ecoregion has created a natural experiment to examine how the post-legalization expansion of small-scale, private land farms might affect freshwater and terrestrial biodiversity. In this study we ask: what was the development pattern of cannabis land use in Josephine County during the first year of recreational legalization, and how might cannabis production overlap with sensitive ecological features?

To address these questions, our objectives were to: (1) map and characterize the spatial configuration of cannabis farms in Josephine County, Oregon in an early stage of cannabis legalization, and (2) examine the proximity of cannabis production to undeveloped land cover, freshwater, sensitive fish species (e.g. coho salmon (*Oncorhynchus kisutch*), Chinook salmon (*Oncorhynchus tshawytscha*), and Steelhead (*Oncorhynchus mykiss*)), and terrestrial carnivore richness (e.g. fishers (*Pekania pennanti*), coastal marten (*Martes caurina humboldtensis*), ringtail (*Bassariscus astutus*), cougar (*Puma concolor*), bobcat (*Lynx rufus*), gray fox (*Urocyon cinereoargenteus*), and coyote (*Canis latrans*)). We anticipated that due to the cultural dominance of historical growing practices, cannabis production in this region would be comprised of relatively small-scale farms representative of the legacy industry pathway (Dillis, Biber, et al., 2021), but most farms would be new since legalization. Based on research from California pre-legalization (Butsic et al., 2018; Butsic & Brenner, 2016), we expected that cannabis in our study area would also be clustered at the subwatershed level. Concerning proximity to ecologically sensitive areas, we expected that cannabis agriculture would be located in more undeveloped lands, closer to freshwater streams or rivers, and closer to sensitive fish species compared with the surrounding context of all private land parcels. The proposed mechanisms behind these predictions are summarized in Table 1 and draw on the five hypothesized pathways of effect for cannabis on the surrounding environment listed earlier (Wartenberg et al., 2021). Finally, we quantified spatial overlap of cannabis farms with projected terrestrial carnivore distributions. We focused on carnivores because previous studies have described this group as particularly sensitive to cannabis cultivation (Carah et al., 2015; Gabriel et al., 2015; Parker-Shames et al., 2020; Rich, Baker, et al., 2020; Rich, Ferguson, et al., 2020; Rich, McMillin, et al., 2020; Thompson et al., 2014), and because this group includes species of regional conservation concern, such as the fisher.

Table 1. Summary of layers used for spatial analyses. Related pathways refers to the five hypothesized ecological effects of cannabis that could potentially affect the given layer (see text): 1) water availability from withdrawals, 2) water quality from contamination, 3) loss or degradation of habitat from clearing/fencing, 4) direct animal mortality from toxicants or poaching, and 5) behavioral shifts from human disturbance.

Layer	Used for	Related pathways	Source	Year	Resolution
Digital Elevation Model (DEM)	elevation	Loss/ degradation of habitat (3)	Oregon Department of Forestry	2008	10 m
Land cover	developed/ undeveloped classification	Loss/ degradation of habitat (3)	NLCD (Dewitz, 2019)	2013	30 m
Forest structure	canopy cover and stand age	Loss/ degradation of habitat (3)	GNN (LEMMA Team, 2020)	2016	30 m
Carnivore richness	average carnivore richness for fisher, marten, ringtail, cougar, bobcat, gray fox, and coyote combined	Loss/ degradation of habitat, direct mortality, behavioral shifts (3-5)	Barry (2018) and Moriarty et al., unpublished data (Appendix S5)	2016	3x3 km grid
Individual carnivore distributions	projected probability of occupancy for fisher, ringtail, cougar, bobcat, gray fox, and coyote individually	Loss/ degradation of habitat, direct mortality, behavioral shifts (3-5)	Barry (2018) and Moriarty et al., unpublished data (Appendix S5)	2016	3x3 km grid
Rivers/streams	proximity to freshwater	Freshwater availability/ quality (1, 2)	NHD (U.S. Geological Survey, 2018)	2018	Vector data
Fish habitat	proximity to coho, chinook, and steelhead habitat	Freshwater availability/ quality (1, 2)	OFHD (Bowers, 2020)	2020	Vector data

Methods

Study Area

Our study focused on Josephine County in Southern Oregon (4,250 km^2). Josephine county was an ideal location to measure cannabis dynamics of legacy areas and to gain broader insights on the ecological outcomes of cannabis legalization. Josephine County had a long history of illicit and medical cannabis cultivation, and an active presence in the growing legal industry in Oregon (Klassen & Anthony, 2019; V. Smith et al., 2019). In 2014, Oregon became one of the first U.S. states to legalize recreational cannabis. Southern Oregon has become known as a prime destination for outdoor cannabis production (V. Smith et al., 2019), and Josephine County had the highest number of applications for licensed producers relative to population size in the state (0.38 per 100 inhabitants) (Oregon Liquor Control Commission, 2019). Widespread cultivation of cannabis started in the region during the 1960s (Corva, 2014) and is now viewed as one of the county's main economic drivers (see Chapter 2).

Josephine County is also located in a biodiversity hotspot. The study area is part of the Klamath-Siskiyou Ecoregion, one of the most biodiverse temperate forest regions, and an area of increasing conservation focus (D. Olson et al., 2012; D. M. Olson et al., 2006). The Klamath-Siskiyou Ecoregion straddles the Oregon-California border and contains several regions identified as critical climate change refugia (D. Olson et al., 2012; D. M. Olson et al., 2006). The study area contains several protected areas including state and federal protected lands (68.8% of the county is state or federal land), and several federally threatened and endangered species including northern spotted owl (*Strix occidentalis caurina*) and coho salmon (*Oncorhynchus kisutch*), and state sensitive species such as fisher (*Pekania pennanti*).

Mapping cannabis farms

To characterize the spatial distribution of cannabis farming, we hand-digitized cannabis production sites across Josephine County using high spatial resolution Google Earth images taken after statewide legalization (Example Fig. 1D). We based our methods on those previously used to map cannabis production in regions of northern California (Butsic & Brenner, 2016; Butsic et al., 2018). We used publicly available satellite imagery for May or July 2016, the first year with a full growing season after recreational legalization went into effect in July 2015.

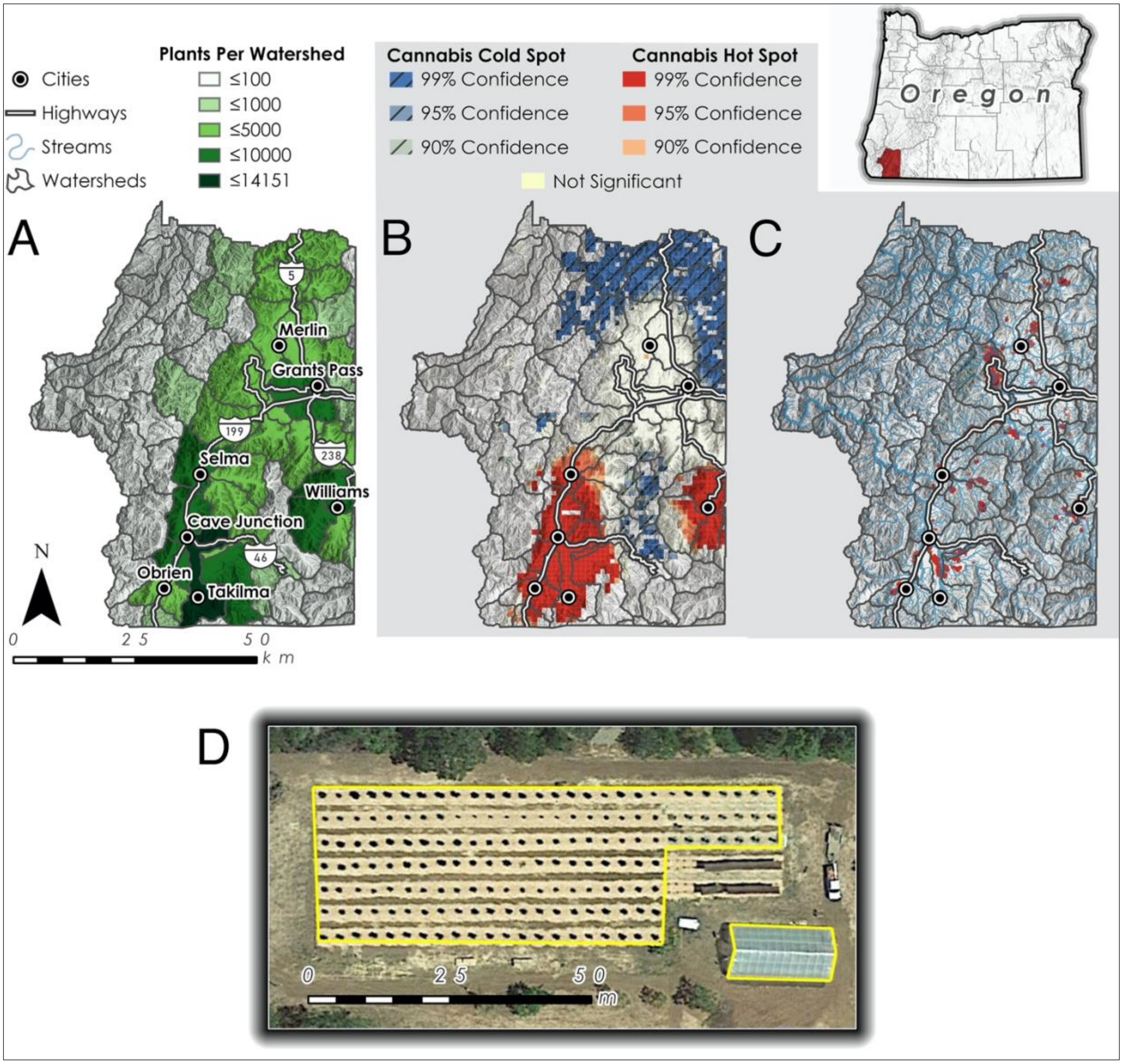


Figure 1. Distribution of cannabis in Josephine County. A) Plants per subwatershed. B-C) Cannabis hotspots (in red) at two different scales: B) county (excluding public lands) and C) individual subwatersheds with at least 30 sites. Hotspots generated using the Getis-Ord Gi* analysis and indicate significant clustering. D) Example of what an outdoor garden and greenhouse look like from aerial imagery with digitized polygons around the cultivated area and greenhouse.

Next, we characterized the farms themselves. Digitizers counted the number of plants visible in outdoor gardens, recorded whether there was a visible fence surrounding each cannabis production site, and recorded whether each site was new (i.e., whether it was visible in the previous imagery year of 2013 or 2014). To estimate the number of plants produced in greenhouses, we used 180 instances where we could count the number of plants through the see-through top of greenhouses and divided this count by greenhouse area. This yielded an average of one plant per 7.23 m^2 of greenhouse area, which we then used to estimate greenhouse plant counts. See supplement online (Appendix S1) for full mapping procedure.

To test the accuracy of image-based data collection, we visited approximately 30 farms between 2017-2019 to verify and refine our mapping protocol after a pilot mapping process. Because systematic ground-verification for all grow sites was not possible, we used a qualitative confidence score to represent digitizers relative certainty about each mapped site (based on characteristics such as plant size, color, and shape, use of individual planter boxes, etc.). For consistency, we thoroughly checked all mapped polygons and associated scoring using the same person who conducted on-the-ground site verification (PPS). We used only high confidence sites for these analyses, but see supplemental materials for a comparison to the full data set (Appendix S2 & S3). Finally, we used only sites with more than four plants for analyses because we were focused on the cannabis industry rather than plants grown for personal consumption (Oregon law permitted four plants per household for personal use).

Describing the spatial configuration of cannabis farms

To generate a baseline characterization of cannabis production post-legalization, we grouped cannabis production in two ways: 1) by the individual digitized polygons (site), and 2) by the surrounding/containing parcel (farm). We used 2018 county tax lot information for parcel boundaries (parcel lines and zoning are unlikely to be different between years) (Josephine County 2018). We characterized cannabis farm size, use of fences, and new production using multiple per site and per farm metrics (see Table 2). We joined farm-level data to parcels in ArcGIS Pro (Esri Inc, 2020), and we calculated all other summaries using R (R Core Team, 2020).

Table 2. Summary of mapped cannabis in 2016 Josephine County for outdoor gardens, greenhouses, all sites (gardens + greenhouses), and all farms (parcel-level summaries). For farms, percentages are for farms containing at least one site that is fenced or new.

	n	**Plant count**	**Median number of plants per group (IQR*)**	**Total cultivated area in km^2**	**Median area in m^2 (IQR)**	**Fenced (%)**	**New (%)**
Outdoor Gardens	2,593	91,922	26 (14-48)	1.20	282 (114-629)	55.5%	58.5%
Greenhouses	1,317	23,760	14.4 (8.4-22.5)	0.14	85.8 (49.8-134)	40.7%	73.4%
All sites	3,910	115,682	21 (12-42)	1.34	163 (73.5-428)	50.5%	63.6%
All farms	2,227	115,682	41.5 (19-61)	1.34	414 (161-811)	59.0%	67.4%

*Interquartile Range

The distribution and clustering of rural development can change the ways in which land use change affects local biodiversity. First, to assess the relationship between scale and spatial clustering of cannabis cultivation, we used a Ripley's K analysis (with an isotropic edge correction) on cannabis sites with the 'spatstat' package in R (Baddeley et al., 2015; Ripley, 1977). Then, to identify the location of cannabis clusters, we conducted a Getis Ord Gi* hotspot analysis (Ord & Getis, 2010) to test for statistically significant clustering of cannabis farms on private land at the county level and individual subwatershed level (USGS Hydrologic Unit Code 12) based on methodology from Butsic & Brenner 2016. To conduct the Getis Ord analysis, we used the optimized hotspot analysis tool on farm centroids in ArcGIS Pro. For the county-level analysis, we excluded public tax lots from the study area. For the individual watershed level analysis, the optimized hotspot analysis required at least 30 points per watershed to test for statistical significance, so we only used 25 out of 73 watersheds to meet this requirement.

Quantifying spatial metrics of conservation concern

To assess the potential ecological effects of cannabis at the landscape scale, we quantified spatial characteristics and proximity of cannabis to landscape features, fish populations, and carnivore distributions (Butsic et al., 2018). This proximity doesn’t directly infer effect, but rather whether the configuration of cannabis may increase the opportunities for negative environmental outcomes. We focused on spatial metrics that might approximate some of the five main hypothesized effects of cannabis farming on local environments (Table 1).

To approximate the potential loss of wildlife habitat, we assessed cannabis production in developed versus undeveloped lands. We extracted elevation and 2013 land cover at the centroid of each farm, and then grouped land cover classes into developed (Developed, Cultivated) and undeveloped (Herbaceous, Forest, Shrubland, Wetland) categories (Table 1). The National Land Cover Database (NLCD) Cultivated category includes hay, annual crops such as corn, or perennial crops such as orchards and vineyards; given the resolution of the NLCD dataset compared to average farm size, this is unlikely to include cannabis pre-recreational legalization.

To approximate the potential degradation of forested habitat, we assessed the forest structure on farms used for cannabis production (Table 1). To do so, we extracted canopy cover and stand age at the centroid of each farm (but see supplement for other metrics; Appendix S4).

To approximate the potential effects on carnivores, we examined the overlap of cannabis with projected carnivore richness and individual carnivore species distributions. We extracted the average carnivore richness, and individual carnivore occupancy value at the centroid of each farm (Table 1). For carnivore richness and individual carnivore distributions, we used projected model data for southern Oregon, from Barry (2018) and Moriarty et al., unpublished data (see Appendix S5 online for description of occupancy and richness methods). Within our study area, the richness layer represents the total number of carnivores expected in a given grid cell for the following species: fisher, coastal marten, ringtail, cougar, bobcat, gray fox, and coyote. For individual species, we used calculated distribution data from projected occupancy and this represented the average probability that a given area would be occupied by that species. Marten projected occupancy was almost entirely absent in this region and was not included in individual species summaries.

Finally, to approximate the potential effects of freshwater extraction or declines in freshwater quality due to cannabis production, we assessed the proximity of cannabis to freshwater rivers or streams and fish habitat for potentially sensitive species. For vector data with the proximity analysis (Table 1), we calculated the distance from the centroid of each cannabis farm to the nearest river and fish habitat in R using the ‘simple features’ package (Pebesma, 2018). For rivers, we used the National Hydrography Database (NHD Plus). We filtered out canals/ditches and underground aqueducts (Fcode > 42000) (U.S. Geological Survey 2018). For fish habitat data, we used Oregon Fish Habitat Distribution data for coho salmon, fall and spring run Chinook salmon, and winter and summer run Steelhead (Bowers, 2020). The fish dataset includes any areas used within the past five reproductive cycles for each species. We then calculated summaries of proximity and overlap metrics in R. In order to inform the interpretation of the fish habitat data, we also extracted the stream order (level of stream branching, starting at headwaters) of the nearest stream to each cannabis site, and summarized results in R.

The conservation effect of these metrics for cannabis likely depends on how they compare to the potential effect of surrounding land uses and available land for development (i.e., the landscape baseline). Therefore, we contextualized the proximity metrics by comparing cannabis farms to all private land parcels in the county. We used all private parcels instead of parcels without visible, high-confidence cannabis because we were mainly interested in how cannabis production fits into the surrounding landscape context of available private lands. See the supplement for a more local comparison in which we calculated the proximity and overlap metrics (Table 1) for all parcels within a buffer around each cannabis site. For buffer size we used the average home range of fishers from southern Oregon (specifically, the range for females of 16.27 km^2) (T. Smith, 2021) (Appendix S6).

Results

Characterization and spatial configuration of cannabis farms

Outdoor cannabis production across Josephine County in 2016 was generally small-scale but also pervasive, and suggested that recreational legalization greatly expanded the industry locally. We mapped nearly 4,000 individual gardens and greenhouses on 2,220 different farms, all identified as highly likely to be cannabis (Table 2; Fig. 1A; for results from the full dataset see Appendix S2 & S3). Most sites (63.6%) were new since legalization (Table 2). Most production was in outdoor gardens (66.3%), but a greater proportion of greenhouses were new (73.4 %) (Table 2). Farms contained an average of 1.76 individual sites, with a maximum of 14. The average size of individual sites and farms was small (outdoor garden median area 282 m^2 or 0.07 acres) but highly variable in terms of cultivated area and number of plants (Table 2). The average parcel size for farms was 0.098 km^2 (24.2 acres). 99.6% of detected farms were on private land parcels. Out of all private land parcels in the county, 5.7% contained a farm identified as highly likely to be cannabis.

Cannabis sites were clustered at multiple spatial scales. The Ripley's K analysis indicated that cannabis sites were clustered at all observed spatial scales (Appendix S7). At the county level, the Getis-Ord Hotspot maps identified two regional hotspots (in red) near Williams in the South-East, and in the Illinois Valley in the South-West (Fig. 1B). The subwatershed analysis indicated that even within these larger regional hotspots, there were pockets of more and less intensive production (Fig. 1C). Both the county and subwatershed hotspots seem to follow primary roads or river networks.

Spatial relation of cannabis farms to measurements of conservation concern

Overall, cannabis was produced on more undeveloped and forested parcels compared to all available private lands as a whole (Table 3). The most common land cover for individual outdoor gardens was shrubland (29%), followed by cultivated (25%), and forest (21%). Greenhouse cannabis production occurred in areas already cultivated with other crops (29%), followed by shrubland (26%), and forest (22%). At the farm scale, however, where outdoor and greenhouse production was combined, forest was the most common land cover type (32%). The predominance of cannabis in forest and undeveloped land covers was also supported by the Gradient Nearest Neighbor (GNN) data on forest structure. Although the GNN dataset uses a broader categorization for forest, it also indicated that cannabis was disproportionately grown in forested areas (Table 3). Nevertheless, the forest structure (canopy cover and stand age) of farms was similar to that on all available private parcels (Table 3).

Table 3. Characteristics and proximity metrics for cannabis farms and all private land parcels.

	Cannabis	**Private Land**
Number of parcels	2,227	41,158
Elevation (m): median*	1,388 (1,185-1,503)	1,059 (948-1,300)
Land cover: % undeveloped	68%	43%
Forest structure: % forested	68%	43%
Forest structure: median canopy cover	49% (31-65)	52% (35-67)
Forest structure: median stand age	76 (61-100)	77 (63-98)
Rivers (m): median distance	94 (47-177)	140 (61-294)
Coho (m): median distance	538 (229-1,126)	811 (341-1,541)
Chinook (Fall) (m): median distance	807 (309-1,718)	1,194 (542-2,186)
Chinook (Spring) (m): median distance	12,147 (3,762-27,819)	2,291 (1,015-7,918)
Steelhead (Winter) (m): median distance	458 (190-969)	590 (265-1,147)
Steelhead (Summer) (m): median distance	1,724 (415-18,877))	683 (297-1,518)
Carnivore richness: median number of species	2.6 (2.5-2.9)	2.5 (2.4-2.8)
Bobcat projected occupancy: median probability of occupancy	0.37 (0.32-0.46)	0.36 (0.31-0.45)
Cougar projected occupancy: median probability of occupancy	0.51 (0.46-0.55)	0.49 (0.44-0.53)
Ringtail projected occupancy: median probability of occupancy	0.49 (0.30-0.59)	0.24 (0.21-0.40)
Gray fox projected occupancy: median probability of occupancy	0.61 (0.20-0.92)	0.92 (0.88-0.93)
Fisher projected occupancy: median probability of occupancy	0.69 (0.24-0.87)	0.12 (0.11-0.34)

* For median results, interquartile range (IQR) given in parentheses.

Cannabis farms occurred in areas with intermediate carnivore richness, similar to all available private parcels (Table 2; Fig. 2). However, at the individual species level, cannabis farms overlapped with higher projected fisher (median 0.69) and ringtail (0.49) occupancy, and lower gray fox occupancy (0.61) (Fig. 2). These differences were consistent across land cover, forest structure, and zoning. However, median fisher occupancy values were larger on high elevation (>1,500 m) parcels, and a greater proportion of cannabis farms (25.5%) were at higher elevations compared with private (5.3%) parcels. There was no difference in richness between existing or new cannabis farms, and no difference at the species level except for gray fox, which had a slightly higher median occupancy on existing farms (0.80) compared with new farms (0.60).

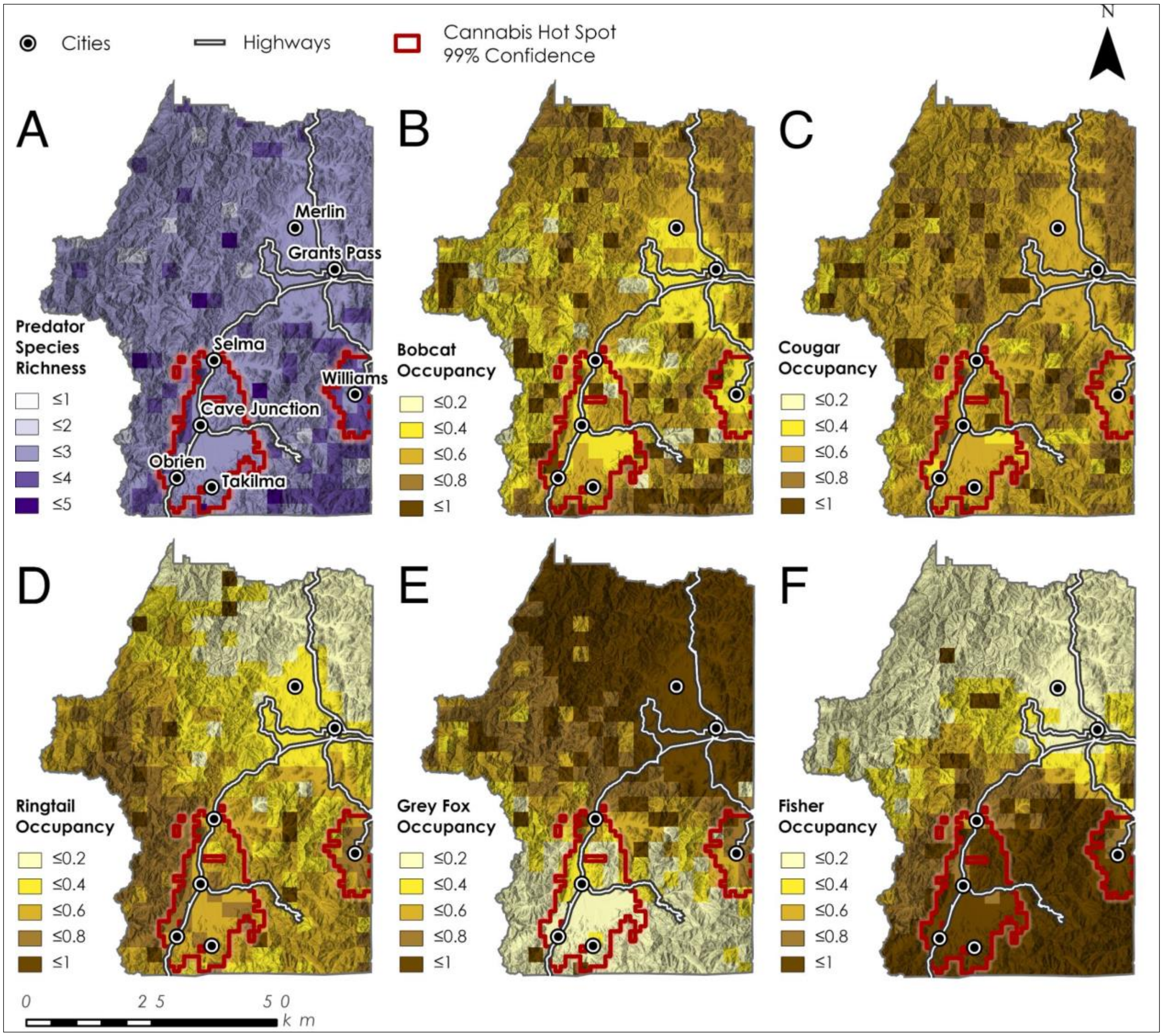


Figure 2. Projected carnivore richness (estimated number of carnivores present in a cell) and individual projected occupancy (average probability that a grid cell would be occupied by the given species) in relation to regional cannabis production hotspots.

Cannabis was located slightly closer to rivers compared with all available private parcels, though the interquartile range (IQR) intervals overlap (Table 3). There were also a higher proportion of cannabis farms located within 15 m (50 ft) of a river or stream, compared to private parcels (8.3% vs. 5.9%). However, the proximity of farms to threatened fish species was mixed. For example, although there was a large variation in distances and overlap of IQR intervals, on average cannabis was nearly 1.5 times closer to coho salmon habitat than all private parcels, yet more than 5 times farther from spring chinook habitat. The variation in proximity to fish habitat may be in part due to the proximity of cannabis to smaller streams by order (Appendix S8).

Discussion

This study is one of the first landscape-scale assessments of small-scale outdoor cannabis farming and its potential broad-scale ecological effects in a rural biodiversity hotspot. Our results suggest two main conclusions. First, private land cannabis farming in Josephine County, Oregon in 2016 was common and spatially clustered, expanded post-recreational legalization (67.4% of farms were new), and yet only covered a small portion (0.0003%) of the total land area. This supports our expectation that cannabis farming in Josephine County would exhibit characteristics typical of the legacy development pathway, but that these farms would largely be new post-legalization. Second, our spatial proximity results highlighted areas of overlap or proximity of cannabis farms and sensitive habitats and species. Compared to the surrounding context of all available private land parcels, cannabis was more frequently located in forested areas and undeveloped land, closer (though perhaps not significantly so) to rivers/streams and coho salmon habitat, and in areas of high value as fisher habitat. These results provided mixed support for our expectation that cannabis production would be in areas that increase its potential ecological impact.

Recent research on public land production in the broader region (Wengert et al., 2021) highlights similarities and differences between public and private land production. For example, both seem to be located relatively close to rivers and streams, with ~50% canopy cover, and in relatively young stands (less than 120 years) (Wengert et al., 2021). However, while we may presume that all production on public lands represents new clearing for production, our results indicate that 32% of farms are on already developed and unforested parcels. Additionally, public lands provide critical refuges for many of the region’s carnivores, which may help explain why public land production appears to overlap more with carnivore habitat than our results for private land production (Wengert et al., 2021). Perhaps most importantly at a landscape scale, farm size and total extent appear to be much smaller for legacy pathway private land cannabis mapped in this study compared to estimates of public land production practices (Bauer et al., 2015, Wengert et al., 2021).

Despite the differences between public and private land cannabis production, private land cannabis farming still has characteristics that warrant continued research and planning. Our results suggest that legacy pathway cannabis farming could be compatible and comparable with existing rural land use in Josephine County. In order to ensure this continues to be the case, however, further attention should be given to conservation outreach, policies to support small-scale farming, and attention to land use practices on farms, particularly those that may affect carnivores and coho salmon. As the industry continues to expand, policymakers and conservationists need to clarify landscape level strategies to ensure a sustainable future.

Care should be taken when interpreting these results, since cannabis agriculture takes many forms and often exhibits regional differences in production practices that may influence its ecological impact (Wartenberg et al., 2021). Our study, by nature of our mapping approach, evaluated outdoor production on private lands. We were unable to quantify whether the farms we mapped were illegal or licensed medically or recreationally, nor how many farms we may have missed by farmers effectively concealing their crop. Given our mapped sites included 2,227 farms in 2016 compared to the 43 recreationally licensed locations in 2016 (Oregon Liquor Control Commission Public Records Request 2020), it is likely that most of the farms we georeferenced were not licensed. If this is the case, the lack of effort to conceal crops is notable. We suspect because cannabis was pervasive (6% of private parcels), that enforcement would not have been feasible (Corva, 2014). Therefore, we were confident that our study accurately quantified the distribution of private-land cannabis production because of the visibility of both licensed and unlicensed farms from aerial imagery. Further, our data likely does not capture all of the cannabis being grown in Josephine County as we were unable to quantify concealed farms on public land or indoor cannabis production. Instead, our study offers critical insights into the ecological consequences of the growing industry in legacy production regions.

Potential ecological effects of outdoor cannabis

The overall cultivated area of private land cannabis agriculture at the landscape scale in Josephine County in 2016 appears to be similar to small-scale rural development already occurring regionally. For example, in a county of 4,250 km^2 (~1 million acres), the total cannabis cultivation area was only 1.34 km^2 (331 acres; or up to 1.57 km^2, 388 acres including all confidence levels, see Appendix S2). This small size is similar to other agricultural production in the county: in 2017, Josephine County produced 2.98 km^2 (733 acres) of grapes and 0.48 km^2 (118 acres) of vegetables (USDA Census of Agriculture, 2017). Cannabis in Josephine County was also considerably smaller in scale than other legacy cannabis-producing regions in Northern California in 2016, where averages ranged from 53-119 plants per site, compared with the median of 21 found in our study (Butsic et al. 2018). While we do not have comparative research on the ecological effects of other agriculture in the study area, small-scale agriculture in rural areas often creates a landscape mosaic that supports species richness (Kremen & Merenlender, 2018; Mendenhall et al., 2014). The ability of small-scale cannabis farming to function like agriculture in other working lands systems, however, requires a deeper understanding of land use practices associated with cannabis production. Specifically, to be ecologically sustainable, small-scale private land cannabis farms would need to create a significantly smaller ecological footprint than public land cannabis (Levy, 2014; Carah et al., 2015).

Although the area of cultivation for cannabis in Josephine County was small, this study did not evaluate the edge effects of cannabis cultivation, nor take into account other forms of disturbance associated with the sites, such as clearing beyond the cultivated area, road construction, or water storage development. Therefore, the actual overlap and potential ecological effect from cannabis farming in the region is likely to be larger than what was documented in this study. Our understanding of these broad scale impacts would be enhanced in future studies that may be able to assess the fine scale response of wildlife on and surrounding cannabis farms.

While our study does not address direct effects of cannabis production, we did identify spatial relations of cannabis development that could pose unique risks to terrestrial and freshwater ecosystems. We found that cannabis production was clustered in its distribution, which is consistent with research from northern California (Butsic & Brenner, 2016; Butsic et al., 2018). This clustering could be an ecological concern if cannabis is occurring disproportionately in sensitive ecological areas. Similarly, the proliferation of fences associated with cannabis (59% of mapped farms had a visible fence) could be a concern for habitat fragmentation as the industry expands (McInturff et al., 2020). The overlap results indicate that cannabis may be grown disproportionately in forests and at higher elevations, which suggests cannabis could be associated with greater land clearing than other development on private parcels. However, the forests where cannabis was grown did not appear to be denser or older than comparable parcels.

Our results indicate a large overlap of cannabis farms with areas of high projected fisher occupancy. This overlap was greater on cannabis farms than private land generally, but could be due to a higher proportion of cannabis farms located at higher elevations (>1,500 m). However, elevation alone doesn't explain this overlap. Fisher occupancy was projected to be higher on cannabis farms than the areas immediately surrounding them (Appendix S4). This suggests that even at fine scales, farms are appearing in areas of potential for high quality habitat for fisher. What this overlap may mean for fisher populations is unclear, given the lack of research on the impacts of private land cannabis production. Private land cannabis has not been documented to have the same negative effects on fishers as public land production, and in particular pesticide and toxicant use appears to be lower on private land farms, according to self-reported farmer surveys (Wilson et al., 2019). However, anecdotal reports and local news stories raise concerns for these private land farms as well, and many grower organizations have emphasized a need for stronger environmental norms among farmers. Given the remaining uncertainty, these results emphasize the potential need for conservation attention to private land farms as well.

Surprisingly, the individual species differences did not add up to differences in overall carnivore richness, which was relatively consistent across the study area. This raises the possibility that the differences in carnivore distributions might be driven by competitive interactions (Green et al., 2018), though finer scale research would be needed to disentangle the drivers of these species distribution patterns in relation to cannabis production.

Regarding potential interactions between cannabis production and freshwater ecosystems, the picture was also somewhat mixed. There were a number of farms (8.3%) within 15 m (50 ft) of rivers and streams, but this was not surprising given the high density of rivers and streams in the study area. On average, most farms were only slightly closer to rivers and streams than the surrounding context of all private land parcels. Cannabis was located on average 273 m closer to coho salmon habitat than private parcels overall, 387 m closer to fall run chinook, and 132 m closer to winter run steelhead, though the IQR intervals overlap. This proximity to freshwater in Josephine County was also generally closer than observed in other legacy cannabis regions (Butsic et al., 2018). For example, the proportion of sites in Josephine County within 500 m of coho habitat (47.7%) was more than twice the proportion in northern California (17.9%) (Butsic et al., 2018). Butsic et al. (2018) used intrinsic potential data rather than direct fish population data, which may overestimate fish populations (Sheer et al., 2009), so this difference could be even more extreme. Coho salmon spawn in smaller upstream tributaries that may be particularly susceptible to drought or water withdrawals (Bauer et al., 2015; Brown et al., 1994). This proximity to coho may be explained by the large number of cannabis sites in proximity to small, headwater streams (Appendix S8), which could further indicate potential threat to other species that depend on these habitats, such as headwaters-dwelling amphibians. Therefore, this proximity to fish habitat could be an ecological concern if farms are drawing water from small rivers or shallow wells during the dry season (Zipper et al., 2019).

Whether or not metrics summarizing the proximity of farms and sensitive habitats result in actual ecological harm largely depends on the individual land use practices occurring on cannabis farms. There is a rich history of different approaches to cultivating cannabis (Corva, 2014; Wilson et al., 2019), which could lead to variation in how cannabis affects ecosystems. Unfortunately, we still do not have a complete picture of cannabis land use practices, nor their mechanisms underlying their ecological effects. So far, available published research suggests that much of small-scale private land cannabis production may not be as ecologically damaging as previously believed (Bodwitch et al., 2019; Parker-Shames et al., 2020; Wartenberg et al., 2021), though a consensus has not been reached, and effects may vary over time. Given our current knowledge, therefore, the snapshot of private land cannabis in 2016 in Josephine County does not on its own indicate widespread ecological effects. There could however be an increased concern for local biodiversity if cannabis development expands in size or intensity while remaining in the same spatial configuration—located in forested vegetation, and in proximity to a few key sensitive carnivore and fish species. Certainly, the large number of new farms in the first year of legalization (67.4%) suggest a rapidly expanding industry. This concern suggests a need to consider development pathways and future trajectories that sustain conservation values.

Conclusions

This study presents a baseline understanding of cannabis production post-legalization in a legacy production region. The ecological metrics and maps presented here could be useful tools to begin prioritizing conservation and development tradeoffs in a complex and rapidly changing industry. Landscape-scale cannabis management for conservation is increasingly urgent, particularly as cannabis legalization expands to more states, and federal legalization is being considered. Additionally, cannabis agriculture may offer important insights for other emerging development patterns that occur over longer time spans, or policy-induced rapid land use change frontiers in other regions. For example, development patterns of cannabis have similarities with small scale slash and burn agriculture in parts of South America (le Polain de Waroux et al., 2018), or wealthy exurban development at wildland-urban interfaces in regions of southern California (Radeloff et al., 2005; J. A. Smith et al., 2019). Ultimately, policy shifts around cannabis and their resulting development impacts offer an exciting opportunity to study rapid land use change and its potential consequences for biodiversity.

Acknowledgments

We thank the undergraduate assistants who helped map cannabis farms (A. Mazur, F. Bingham, J. German, A. Clements, P. Bohls, L. Jameson, K. Gonzales, J. Pulaski, E. Resendiz, M. Xiao, A. Hua, A. Thompson, C. Tilton, and T. Snow); the Geospatial Innovation Facility at UC Berkeley for providing computing space for undergraduate assistants; the Cannabis Research Center at Berkeley, the Brashares Lab, and the Land Use Change Lab for providing early feedback on study objectives and design; ESPM 281 Writing Seminar, K. Norman, M. Chapman, and A. Van Scoyoc for manuscript feedback; and the NSF GRFP for fellowship support for P. P. S.

Supplement to Chapter 1:

Appendix S1. Mapping protocol (available online)
Appendix S2. Summary of the full dataset
Appendix S3. Summary of full dataset filtered for all confidence levels excluding less than 4 plants
Appendix S4. Additional comparison metrics.
Appendix S5. Description of occupancy models and richness calculations (available online)
Appendix S6. Buffer comparison.
Appendix S7. Results for Ripley's K analysis of spatial clustering
Appendix S8. Summary of sites by stream order

Appendix S1. Protocol for mapping and hand-digitizing cannabis farms using Google Earth images pdf available on publication website: https://doi.org/10.1111/csp2.602

Appendix S2. Summary of the full dataset (all confidence levels and any number of plants) of mapped cannabis in 2016 Josephine County for outdoor gardens, greenhouses, and all sites (gardens + greenhouses).

	n	**Plant count**	**Median number of plants per group (IQR*)**	**Total cultivated area in km^2**	**Median area in m^2 (IQR)**	**Fenced (%)**	**New (%)**
Outdoor Gardens	3,959	118,465	20 (9-42)	1.365	150.8 (43.3-451.3)	56	58
Greenhouses	2,357	33,709	9.3 (4-18)	0.20	55.1 (24.7-106.9)	39.2	59.4
All sites	6,310	152,174	15 (6.3-30.9)	1.57	89.9 (32.5-266.6)	49.7	58.5

*Interquartile Range

Appendix S3. Summary of all confidence levels excluding less than 4 plants for mapped cannabis in 2016 Josephine County for outdoor gardens, greenhouses, and all sites (gardens + greenhouses).

	n	**Plant count**	**Median number of plants per group (IQR*)**	**Total cultivated area in km^2**	**Median area in m^2 (IQR)**	**Fenced (%)**	**New (%)**
Outdoor Gardens	3,558	117,038	23 (12-46)	1.356	181.7 (61.5-511.5)	56.6	56.3
Greenhouses	1,806	32,136	13.3 (7.3-22.1)	0.19	79.2 (43.5-131.6)	38.5	63
All sites	5,364	149,174	18 (10-35.5)	1.55	117 (51-314)	50.5	58.5

*Interquartile Range

Appendix S4. Additional metrics for cannabis farms, all private land parcels, and all parcels within a 16.27 km^2 (Pacific fisher home range size) buffer around cannabis sites. Results given with median and interquartile range (IQR).

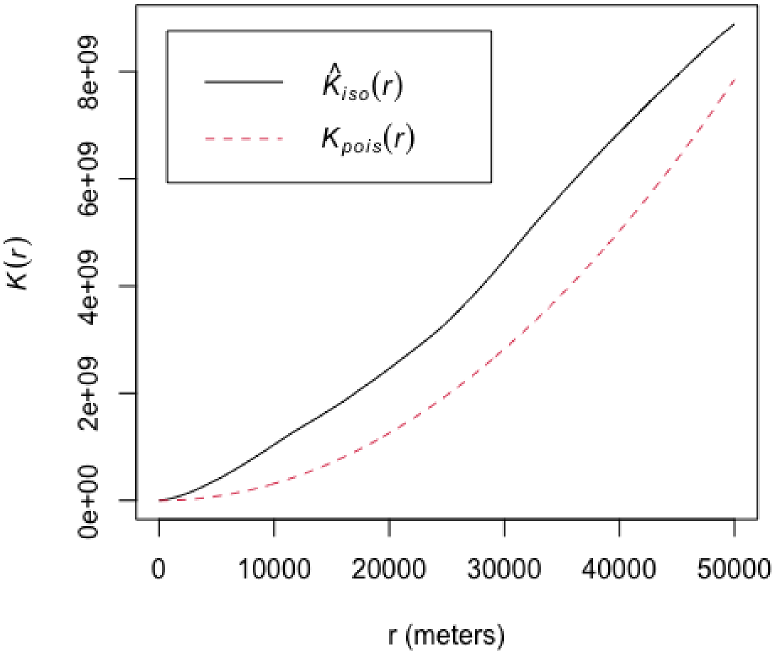
	Cannabis	**Private Land**	**Buffer**
Forest quality: basal area of live trees (m^2/ha)	17.8 (10.9-28.8)	18.7 (12.0-29.9)	19.2 (12.3-30.9)
Forest quality: basal area of conifers (m^2/ha)	6.7 (2.4-17.1)	7.1 (2.9-16.9)	7.5 (3.1-18.3)
Forest quality: biomass of trees (kg/ha)	78,900 (44,200-131,600)	81,400 (50,200-135,000)	84,300 (51,000-140,000)
Forest quality: biomass of conifers (kg/ha)	30,000 (9,300-87,900)	31,900 (11,100-87,500)	33,500 (11,500-92,400)
Forest quality: volume of live trees (m^3/ha)	135 (77-230)	141 (87-235)	145 (88-243)
Forest quality: volume of conifers (m^3/ha)	52 (16-154)	56 (19-152)	58 (20-159)
Forest quality: stand height (m)	11.4 (8.7-17.0)	11.8 (9.2-16.5)	12.0 (9.2-17.1)
Median slope (degrees):	2.5 (1.1-6.69)	2.79 (0-6.0)	2.3 (0.93-5.97)
Median distance to nearest GAP I or II protected area (km)	3.3 (1.5-5.2)	3.4 (1.5-5.4)	3.6 (2.0-5.3)

Appendix S5. Description of occupancy models and richness calculations
Document available on publication website: https://doi.org/10.1111/csp2.602

Appendix S6. Proximity metrics for all parcels within a 16.27 km^2 (female fisher home range size) buffer around cannabis sites.

	Buffer
Number of parcels	40,942
Elevation (m): median*	1,068 (950-1,323)
Land cover: % undeveloped	44%
Forest structure: % forested	44%
Forest structure: median canopy cover	52% (35-68)
Forest structure: median stand age	78 (63-100)
Rivers (m): median distance	138 (60-290)
Coho (m): median distance	813 (340-1,544)
Chinook (Fall) (m): median distance	1,200 (539-2,200)
Chinook (Spring) (m): median distance	2,319 (1,015-8,074)
Steelhead (Winter) (m): median distance	591 (265-1,152)
Steelhead (Summer) (m): median distance	687 (296-1,538)
Predator richness: median number of species	2.5 (2.4-2.8)
Bobcat projected occupancy: median probability of occupancy	0.36 (0.32-0.46)
Cougar projected occupancy: median probability of occupancy	0.49 (0.44-0.53)
Ringtail projected occupancy: median probability of occupancy	0.24 (0.21-0.40)
Gray fox projected occupancy: median probability of occupancy	0.92 (0.88-0.93)
Fisher projected occupancy: median probability of occupancy	0.12 (0.11-0.34)

* For median results, interquartile range (IQR) given in parentheses.



Appendix S7. Results of K-test with isotropic edge correction indicating spatial clustering of cannabis sites at all observable scales. The dotted red line shows a random Poisson distribution of sites, and the black lines show the observed distribution of sites. When the observed distribution has a greater K(r) value (is above) the expected line at a given scale (indicated on the x axis) then the distribution is clustered; if it is below the line it indicates over-dispersion.

Appendix S8. Stream order for nearest river or stream for each cannabis site. Lower numbers indicate smaller, headwater streams and increase in size with branching tributaries.

Nearest Stream Order	Number of Sites
1	1552
2	668
3	573
4	457
5	296
6	309
7	35
8	18

Chapter 2

Where money grows on trees: a socio-ecological assessment of cannabis land use change

Abstract

Integrating social or cultural data into ecological models is critical for understanding complex social-ecological systems. In this study, we used an interdisciplinary approach to identify, assess, and contextualize possible drivers of cannabis land use and development shortly after adult use of cannabis was legalized in Josephine County, Oregon. First, we interviewed 14 cannabis farmers about their relationship with the land, their land use decision making process, and reflections on the local industry. Second, we identified recurring responses in farmer interviews that highlighted perceived social and geographic drivers of cannabis land use. Finally, we quantified these drivers as spatial covariates and evaluated their value as predictors of cannabis land use in three models: 1) Logistic regression of cannabis land use post legalization (2016); 2) Logistic regression of cannabis development from pre- to post-legalization (2013/2014 to 2016); and 3) Linear regression of existing farm plant count change from pre- to post-legalization. We assessed the relationship of covariates with the model output and contextualized their patterns using the interview data. We found that most of the interview-derived covariates were significantly associated with cannabis distribution and development, including parcel size, human footprint, distance to nearest cannabis farm, density of local cannabis production, clearable land cover, farm zoning, elevation, roughness, and distance to rivers. These results provide useful insights into the dynamics of a rapid land use change frontier, as well as its potential environmental repercussions. The contextualized understanding of cannabis land use drivers may serve to mitigate environmental harm or predict changes occurring in other rural cannabis systems.

Introduction

“Money actually does grow on trees out here, and that’s a blessing.” - Josephine County cannabis farmer, 2019

The recent boom in outdoor cannabis farming has created a rapid development frontier in the 19 US states that have legalized cannabis production (Butsic et al., 2018). For decades, outdoor cannabis was grown illegally, often in rural, remote areas, but with state-level legalization, production in those same “legacy” regions has rapidly expanded (Dillis, Biber, et al., 2021). In some of these rural, legacy-production regions, cannabis production on private lands can transform development patterns at a regional scale (see Chapter 1) (Butsic et al., 2017, 2018). This development frontier can foster new cultural, economic and demographic dynamics (Polson, 2015; Polson & Bodwitch, 2021). Importantly, these new patterns of land use also incite concerns for ecological impact related to habitat fragmentation or degradation, potential effects on freshwater quality/availability, and direct or indirect effects on wildlife populations (Wartenberg et al. 2021). To understand, reduce, or mitigate these potential impacts, it is important to identify the social and ecological factors that drive cannabis development on private lands across space and time. For example, understanding why farmers choose to cultivate at particular sites may help lawmakers craft and prioritize appropriate regulations for licensed cannabis. Additionally, spatial distribution and socio-cultural drivers are important for understanding where risks of environmental impact or human-wildlife conflict may arise, and for predicting the future trajectory of the cannabis industry. However, there remain many challenges to understanding drivers of cannabis development in these complex systems.

Outdoor cannabis production in legacy regions is unique from other forms of traditional agriculture and functions as a closely tied social-ecological system. In these small-scale cannabis systems, the history of illicit farming lays a foundation for production practices that are vastly different from crops that did not have to be concealed, or that were grown following standardized agricultural practices across an industry (Corva, 2014). Given the continued barriers to bringing legacy farmers into legalized cannabis systems and the existence and persistence of illegal markets, historical context is likely to influence current growing patterns, even as they move into licit markets and expand on private lands (Bodwitch et al., 2019, 2021). In addition to historical practices that initiated the industry, there are other factors that likely influence whether, where, and how cannabis is produced, including federal, state, and local regulation and enforcement, social acceptance of cannabis within a region, access to education and communication of production practices among growing communities, short- and long-term economic tradeoffs, and others. These factors will influence the spatial distribution and predominant production practices of cannabis over time, which could shift the proximity of cannabis to terrestrial and aquatic wildlife habitats, or alter cannabis impacts on the local environment. These perceived or actual environmental impacts from cannabis can feed back into cannabis land use via shifts in attitudes that could lead to voluntary changes of production practices, increased enforcement, regulatory changes, or shifts in community acceptance for local production (for an example of local environmentally-based cannabis policy advocacy, see Hall 2022).

Previous attempts to assess the drivers of cannabis land use or predict the current or future distribution of cannabis production have relied heavily on biophysical and bioclimatic models, using variables such as slope, forest land cover, distance to streams, aspect, canopy cover, and precipitation (Butsic et al., 2017, 2018; Wengert et al., 2021). These models have demonstrated that compared to other forms of farming, cannabis is generally less influenced or predicted by biophysical variables (Butsic et al., 2017). This is unsurprising, however, given that social and cultural variables are likely to profoundly shape the spatial distribution of cannabis production. For example, depending on the production style, a cannabis farmer might forgo a less biophysically ideal production area in order to stay concealed, or to grow near hospitable neighbors or close to other cannabis farmers with whom they can share labor or knowledge. Thus, social variables may be relatively more predictive of cannabis industry dynamics than biophysical variables. Ultimately, bridging social and ecological knowledge may be key to understanding the spatial dynamics of cannabis land use.

Integrating a more complete social-ecological context into models of land use presents multiple challenges. First, it requires an in-depth understanding of the system to be modeled. In the case of cannabis agriculture, its illicit history is an impediment to research. Federal restrictions on research funding to study an illicit crop have meant that there are few studies to draw on for characterizing patterns or trends in cannabis production, particularly on private lands (Short Gianotti et al., 2017). Given the lack of formal research on the fledgling recreational cannabis industry, those who understand the industry best are likely those engaged in it directly. Thus, interviews of cannabis farmers may be a particularly valuable approach for identifying and understanding potential drivers of cannabis land use. Interviews come with weaknesses, however; small or biased interview pools may fail to uncover the most important drivers of cannabis land use, or farmers themselves may be unable or unwilling to articulate the drivers that are most relevant to their landscape-scale decision-making.

The second major challenge to integrating social and ecological understandings into land use models is that some potential drivers may not readily lend themselves to quantitative analysis. The transformation of qualitative knowledge into quantitative data is an inherent challenge for many interdisciplinary studies that attempt to merge opposing ontologies. For example, translating attitudes or perceptions into numerical data is a longstanding dilemma in quantitative social science where doing so risks losing context and being misunderstood (Stockemer, 2019). Nonetheless, integrating environmental modeling with social, economic and political drivers will enhance our understanding of system dynamics (Bloemraad, 2007; Kurz, 2021; Siegel et al., 2022; Wilkinson, 2021).

In this study, our goal was to identify, assess, and contextualize potential drivers of private land cannabis farming in Josephine County, Oregon, between pre- and post-recreational legalization (2013/2014 and 2016), using both sociological and environmental variables. We used cannabis farmer interviews to generate a list of sociological and ecological covariates for models of cannabis land use early in the process of recreational legalization. Our method for addressing issues around the translatability of qualitative to quantitative data was to mitigate risk of misinterpretation by only looking at drivers conducive to quantitative modeling, while those that were less conducive were used to help interpret the results. We supported our driver selection with insights from existing cannabis literature, and experience living in Josephine County for two years during data collection. Our objectives were to:

1. Use cannabis farmer interviews to identify potential drivers of cannabis land use and land use change. Identify which potential drivers were most conducive to quantitative modeling, and which were not.
2. Using the quantifiable variables, model drivers of cannabis land use in an early stage of recreational legalization. Model drivers of cannabis land use change pre- and post-legalization.
3. Interpret and contextualize modeling results using the cannabis farmer interviews, particularly the qualitative data that were less amenable to modeling.

Finally, we discuss the environmental and policy implications of cannabis land use change based on cannabis farmer environmental concerns and knowledge.

Methods

Study Area

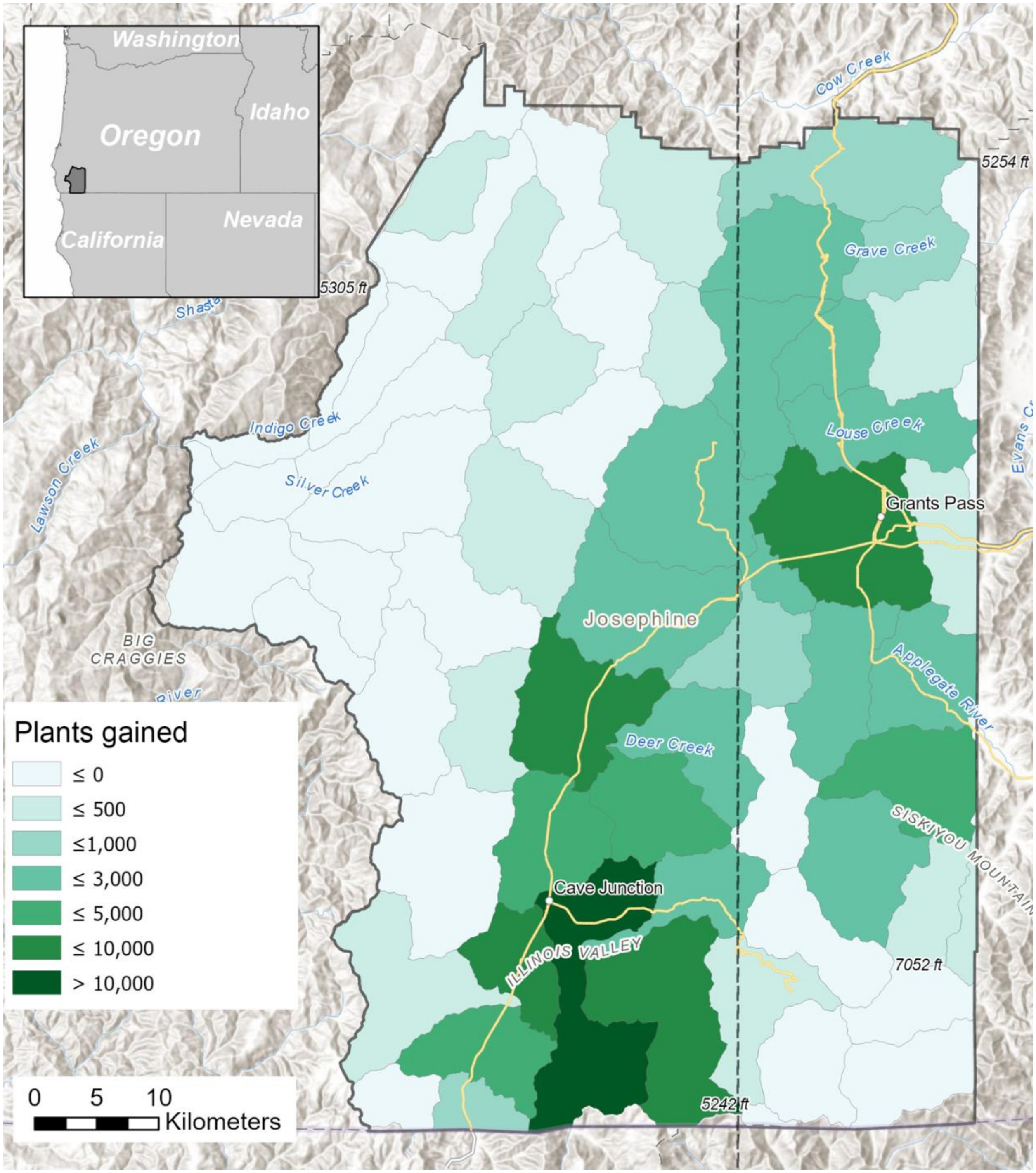


Figure 1. Map of the study area in Josephine County, Oregon, with mapped watersheds shaded by the increase in number of plants for each watershed from 2013/2014 to 2016. Dashed line shows the approximate split in available imagery for the pre-legalization timepoint.

To understand cannabis land use drivers within the context of a rapid policy shift, we focused our study on Josephine County in Southern Oregon (4,250 km^2) (Fig. 1). Josephine County is an ideal location to study cannabis because of the crop's importance in the local economy with few other major competing non-timber agricultural commodities, as well as its rural location that typifies legacy cannabis production systems. Josephine County has a long history of illicit and medical cannabis cultivation, and has an active presence in the growing legal industry in Oregon (see Chapter 1) (Smith et al., 2019). In addition to being an ideal example of cannabis farming in this region, there were two logistical reasons for selecting Josephine County as a study site. First, recent efforts to map cannabis farming and expansion in the region during the first season of recreational cannabis production provided ground-verified data on spatial trends. Second, one of the authors (PPS) grew up in the region, and thus had existing access to cannabis farming communities in the area. This enabled us to conduct interviews with both permitted and illicit producers, which required significant time to build the trust needed to conduct this study.

Methodological Framework

Our research approach integrated qualitative and quantitative socio-ecological data. We started with the interpretation of qualitative interview data, then translated findings into major themes and quantified potential drivers, for use in land use models (Fig. 2). This meant our process was partially iterative in that interview results influenced the design of the model methods (Fig. 2). In this section, we present an overview of our methodology, but have included the description of model drivers as a result instead of a method, since it is a key finding from the interview data.

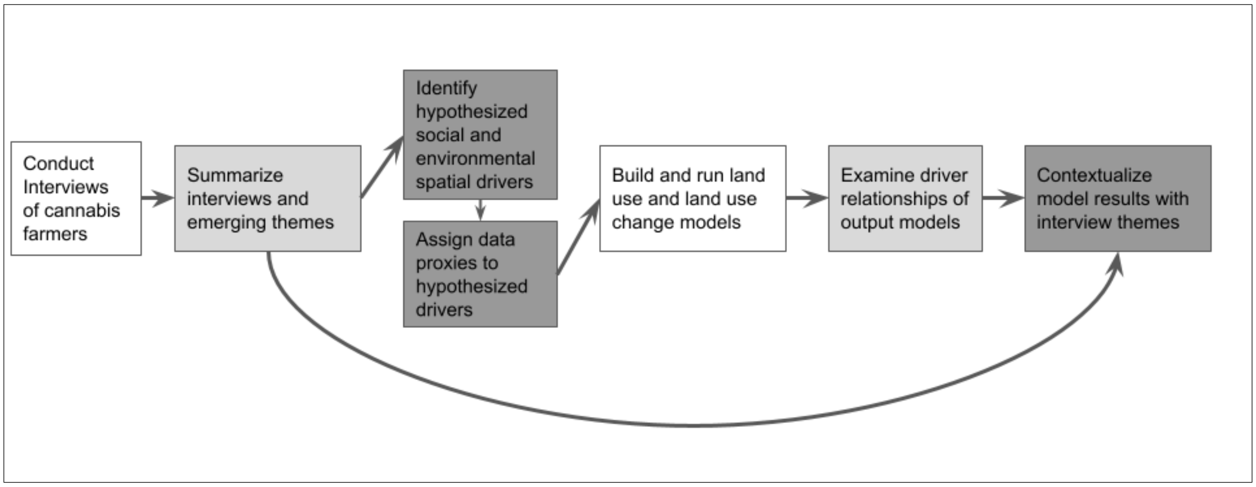


Figure 2. Conceptual framework for our methodological process. White boxes represent methods, light gray boxes represent results, and dark gray represents interpretation or discussion. Note that the results from the interview data feed into both the methods for the modeling approach and its interpretation.

Interviews

In order to both generate a list of potential land use drivers, and to interpret and contextualize model results, we conducted semi-structured, in-depth interviews with 14 cannabis farmers in Josephine County in 2019. Farmers had to be over the age of 21, but could be engaged in any type of cannabis production on private land, whether licensed or unlicensed. Interviews were conducted by the same researcher (PPS) for consistency, while living in Josephine County over a two year period. We interviewed farmers about drivers of cannabis land use, farming practices, influences on production methods, and farmer connection with the land. Although some farmers were also producing cannabis under a hemp license, we focused our questions on the cannabis industry because the hemp industry in Josephine County largely emerged after 2018, which is after the mapped data were collected. (Here, we use the word hemp to refer to industrial hemp which is a low THC variety of cannabis. In our study system, hemp plants are generally grown for CBD, and are similar to recreational cannabis plants.)

We initially used known contacts in formal and informal cannabis producer networks, invited voluntary participation, and thereafter used a snowball recruitment method. We continued interviews until we reached saturation (no new major themes emerged), at which point we considered the number of farmers interviewed to be sufficient. Because of the difficulties in attaining a representative sample of all cannabis farmers in the region, these interviews were viewed as generative rather than representative of all producers in the area.

Interviews were recorded with permission, alongside hand written notes. Most interviews took place on the cannabis farm, or another location selected by the farmer, and often included a tour of the farm. Interviews typically lasted 2 hours, but ranged between 1 - 8 hrs, depending on the time constraints and preferences of the interviewee. All interviews were conducted under UC Berkeley Human Subjects Protocol CPHS# 2018-11-11619. We summarized interviews, grouped main themes or concepts, and transcribed quotes that represented the key emerging themes. We did not conduct a formal coding process because our purpose was largely generative. We then used these summaries to identify potential quantitative variables (predictors) for our land use models.

Cannabis Models

Cannabis Data

To model drivers of cannabis land use and change over time, we used hand-digitized cannabis production sites across Josephine County using Google Earth Images. See Chapter 1 for detailed mapping methods. We used high confidence sites on private land with no restrictions on the number of plants for our models. Note that these mapped sites included both licensed and unlicensed cannabis on private land parcels, though we were unable to distinguish license status of a given parcel.

To assess change over time, we mapped an additional year of cannabis production prior to recreational legalization. For these maps, we followed the same basic protocol Chapter 1, using high spatial resolution Google Earth imagery to record location of outdoor gardens and greenhouses. Depending on the available year of imagery in Google Earth, we used either 2013 or 2014 data. The split in available imagery ran North-South through Wilderville, OR, splitting regional hotspots (see Chapter 1) such that the Illinois Valley was mapped in 2013, and Grants Pass and Williams were mapped in 2014 (Fig. 1). For the remap, we retained the 2016 mapped sites and updated, removed, or added cannabis polygons as we digitized to maintain consistency across years. For watersheds that did not contain cannabis in 2016 (n = 27), they were unlikely to have cannabis in 2013/2014, so we remapped only a subset (n = 7) to confirm the validity of this assumption, and then assumed that the rest were also empty.

We summarized cannabis production data to the parcel level and recorded the number of cannabis sites (individual outdoor gardens or greenhouses), total cultivated area, and number of plants per parcel. We then filtered our data to include only private land parcels.

Land Use Models

For models of cannabis land use on private land, we used the post-legalization (2016) cannabis data aggregated to the parcel level, and filtered to private ownership. We modeled the presence or absence of cannabis on a given private parcel using a logistic regression with the 'glm' function in R (R Core Team, 2021). We selected the variables for all models based on the interview data (see *Results* and Table 1). The following model represents the covariate relationships with the distribution of cannabis land use in 2016.

$$C_{presence} = B_0 + B_1 \text{ x } Area_{parcel} + B_2 \text{ x } HFP + B_3 \text{ x } Dist_{cann} + B_4 \text{ x } Density_{cann} + B_5 \text{ x } Clearable + B_6 \text{ x } Zoning_{Farm} + B_7 \text{ x } Elevation_{max} + B_8 \text{ x } Roughness_{max} + B_9 \text{ x } Dist_{rivers} + B_{10} \text{ x } Aspect_{south}$$

Where the response variable $C_{presence}$ is binary for cannabis presence, $Area_{parcel}$ is the area of each private land parcel log-transformed to reduce skew, and HFP is the average Human Footprint value extracted for each parcel, $Dist_{cann}$ is the non-zero nearest distance to the next cannabis farm in 2016 with a square-root transformation to reduce skew. $Density_{cann}$ is the density of cannabis sites within a 1 km radius buffer in 2016 with a square-root transformation to reduce skew. *Clearable* is a binary variable for whether or not the parcel's predominant 2013 land cover is easily cleared, and $Zoning_{Farm}$ is a binary variable for whether or not the parcel is zoned for agriculture. $Elevation_{max}$ is the maximum elevation of a parcel. $Roughness_{max}$ is the maximum roughness of a parcel with a square-root transformation to reduce skew. $Dist_{rivers}$ is the distance to nearest river or stream, and $Aspect_{south}$ is a binary variable for whether the majority of the parcel has a southern aspect (between 225 and 135 degrees).

We assessed the models using P-values, and generated predictive graphs for each covariate relationship using the 'predict' function in base R, holding all other covariates at their mean value. We calculated pseudo r-squared values for the models using the 'r.squaredGLMM' function from the package MuMIn in R (Bartoń, 2022).

Land Use Change Models

For models of cannabis land use change, we used the post-legalization (2016) cannabis parcel data as above, with the addition of the pre-legalization (2013 or 2014) data. We used two different models to capture different aspects of land use change. First, we modeled new farm expansion. We excluded all parcels with farms present pre-legalization, so as to only capture new farms post-legalization. We used the following logistic regression model to examine the relationship between each covariate and the development of a new cannabis farm:

$$C_{development} = B_0 + B_1 \text{ x } Area_{parcel} + B_2 \text{ x } HFP + B_3 \text{ x } Dist_{cann} + B_4 \text{ x } Density_{cann} + B_5 \text{ x } Clearable + B_6 \text{ x } Zoning_{Farm} + B_7 \text{ x } Elevation_{max} + B_8 \text{ x } Roughness_{max} + B_9 \text{ x } Dist_{rivers} + B_{10} \text{ x } Aspect_{south} + B_{11} \text{ x } Year$$

Where $C_{development}$ is a binary variable representing whether or not the parcel developed cannabis in 2016. All model variables are the same as in the single year model except that $Dist_{cann}$ and $Density_{cann}$ both use the 2013/2014 cannabis data, and *Clearable* uses 2011 land use. *Year* is the image year (either 2013 or 2014) that the pre-legalization data was mapped. Note that *Year* is also a spatial grouping because roughly half the county was mapped in each time point, with 2013 encompassing the Illinois Valley and Selma, and 2014 covering Williams and Grants Pass.

Our second land use change model examined only the farms present pre-legalization (2013/2014), modeling the change in number of plants to post-legalization (2016). We used the following gaussian regression model to assess the relationship between each covariate and the number of cannabis plants gained or lost over recreational legalization.

$$C_{change} = B_0 + B_1 \times Area_{parcel} + B_2 \times HFP + B_3 \times Dist_{cann} + B_4 \times Density_{cann} + B_5 \times Clearable + B_6 \times Zoning_{Farm} + B_7 \times Elevation_{max} + B_8 \times Roughness_{max} + B_9 \times Dist_{rivers} + B_{11} \times Year$$

Where C_{change} is the change in plant number from pre to post legalization, and all variables are the same as in the land use change model for new farms above.

We assessed the models using estimated P-values, and generated predictive graphs for each covariate relationship using the ‘predict’ function in R holding all other covariates at their mean value. We calculated pseudo r-squared values for the models using the ‘r.squaredGLMM’ function from the package MuMIn in R.

Results

Interviews

We interviewed 14 self-identified cannabis farmers from 10 different farms in Josephine County, Oregon, in 2019. All interview subjects were over the age of 21, and the majority were white and male. These cannabis farmers were engaged in a variety of markets, including personal production, medical marijuana, licensed recreational cannabis, legal hemp, illegal black market cannabis, and combinations of the above. All farmers interviewed had been producing for at least three years, although we interviewed a mix of legacy producers (some of whom have been producing for 50+ years) and farmers who had started more recently. All farmers identified as small or medium scale producers, and several were also part of formal cannabis advocacy and grower best-practice organizations.

After 14 interviews, we reached a saturation point whereby no new themes were emerging in farmer responses, though this seemed likely due to similarities among farmers, rather than an indication that we had exhaustively summarized the perspectives of all cannabis farmers in the region. Below we describe some of the emerging themes from the interviews as they relate to land use drivers and the context for interpreting model results. We then relate each theme to a hypothesized driver of cannabis land use and land use change (Table 1), or indicate where an emerging theme did not readily translate to a quantifiable driver.

Table 1. Hypothesized drivers of cannabis land use and/or land use change generated from interviews of cannabis farmers. See interview results for more detailed justifications.

Potential Driver	Spatial Proxy and hypothesized direction (-/+)	Justification	Source or method
Proximity to other cannabis farms	Distance to next nearest cannabis farm (-)	Nearby support of other cannabis farmers desired	Calculated for this study based on 2013/2014 and 2016 cannabis data
Supportive community attitudes	Density of farms within 1 km radius (+)	Neighborhood acceptance critical for long term success	Calculated for this study based on 2013/2014 and 2016 cannabis data
Ruralness	Human Footprint (-)	Remoteness desired for general connection to rural spaces	2009 Human Footprint (Venter et al., 2016)
Zoning	Whether or not a parcel is zoned for farming (+)	Farm zoned parcels preferred	County taxlots (Josephine County 2018)
Distance from law enforcement	Distance from Grants Pass Sheriff's office (-)	Reduced enforcement pressure (for both licensed and unlicensed farmers)	Straight line distance from Grants Pass (using Sheriff's Office as point location)
Parcel size	Parcel area (m^2) (+)	Larger parcels more desired for buffer space and privacy	County taxlots (Josephine County 2018)
Easily cleared or open land cover	Open land covers for 2011 or 2013 (+)	Open area to develop farm on, reduced labor for clearing land desired when selecting parcel	NLCD 2011 and 2013 (Dewitz, 2019)
Elevation	Maximum elevation (-)	Intermediate elevation preferred for optimal growing conditions, maximum likely to be limiting factor	DEM 10m
Roughness	Maximum roughness (-)	Available flat land preferred to reduce terracing labor	Derived from DEM 10m
Access to sunlight	South-facing aspect (+)	Cannabis plants will grow better with access to sunlight, which is enhanced on south-facing slopes	Derived from DEM 10m
Proximity to water	Distance to rivers and streams (-)	Water needed for irrigation, assuming proximity incorporates use for both licensed and unlicensed farmers	NHDplus (U.S. Geological Survey, 2018)

Major Themes and Spatial Drivers

Below, we describe the major themes that emerged from cannabis farmer interviews. The first four (Connection to Community, Environmental Stewardship, Regulation, and Parcel Qualities) were translated into model covariates, while the final two (Economics, and Future of the Industry) were not used for model covariates but rather provide context for the results.

Connection to Community

"There's always a human side to the equation I consider when making land use decisions."

One of the most common factors mentioned in farmer interviews was the importance of community, both in terms of their connection to other cannabis farmers as well as to their surrounding neighbors. For example, in the quote above, the farmer was describing how his relationship with his neighbors instilled a sense of both community and responsibility that translated into on-the-ground decisions he made on his farm, such as when or how to use grow lights. The interviewed farmers explained that having a good relationship with neighbors was critical for surviving in the industry, regardless of whether they were licensed or not. In addition, they described that best growing practices were often communicated through social networks, both online and in person, and so they often relied on other cannabis farmers for advice or assistance. Interviewed farmers explained that cultural norms dictated practices, which in Josephine County are often influenced by legacy production styles and attitudes. Some farmers also mentioned the advantage of being able to help each other with labor when living close to other farmers.

In translating this theme into quantitative variables for potential land use drivers, we focused on farmer reliance on other local cannabis producers. We quantified proximity to other cannabis farms by calculating the smallest non-zero distance from each parcel to the nearest cannabis farm both pre- and post-legalization, using the 'st_nn' function from the nngeo package for R (Dorman, 2022). This package calculates the k-nearest neighbor distance between features. We calculated a large number ($k = 17$) of neighbor distances for each parcel, then selected the minimum distance excluding all zero values.

We also attempted to estimate neighborhood tolerance for cannabis farming. To do so, we used the density of cannabis within a 1 km radius around each parcel both pre- and post-legalization as our spatial proxy. Cannabis production in Josephine County is clustered at multiple spatial scales (Chapter 1) and so any distance threshold that represents a localized area might be appropriate, but we chose 1 km because this generally encompasses a local neighborhood. Using the sf package in R, we generated buffers around parcel centroids, intersected them with centroids of cannabis sites, and then converted the count to density by dividing by buffer area.

Environmental Stewardship

*"It's the big corporations that are f**king this land. We're taking care of it."*

All farmers interviewed expressed personal values related to environmental stewardship. In the context of the quote above, the farmer was comparing his impact from cannabis farming to nearby clearcut logging, and explaining his deep conviction that his style of land use was environmentally sustainable compared to larger industrial and extractive land uses. In the opening quote from the introduction, "*Money actually does grow on trees out here, and that's a blessing*," a different farmer expressed similar sentiments, connecting his farming to both nature and livelihood/profit, while expressing gratitude that the place itself, Josephine County, enabled that relationship. Many of the interviewed farmers explained that their motivations for growing cannabis stemmed from a desire to connect with the land or nature, although only a few had been farmers before cultivating cannabis. Interviewees often mentioned that the ruralness of Josephine County was an attraction because of its biodiversity. Many farmers reported personal connections with and fondness for the wildlife on their production sites. Many also expressed concerns about ecological damage from the cannabis industry. For example, farmers highlighted concerns about pesticide or rodenticide use, trash/plastic waste, animals caught in netting, water pollution (and associated algae blooms), excessive water withdrawals, waterway diversion, imported soils, clearcuts, and paving. Multiple farmers raised concerns that the state or county regulatory process did not support environmental stewardship, and some expressed concerns that following regulations made it more difficult to practice what they saw as sustainable or regenerative farming practices such as intercropping, or crop rotation. The interviewed farmers generally considered themselves as having less impactful growing practices than other cannabis producers in the region, while farmer descriptions and farm visits both demonstrated a wide variety of production practices across all farms. Farmers mentioned the need for more crop research, information-sharing, and stronger norms around acceptable environmental practices.

While this theme did not translate easily into quantifiable spatial proxies, we focused on farmers' expressed desire to grow in remote areas because of the opportunity to work the land in proximity to wild flora and fauna. We quantified this ruralness using the Human Footprint layer, which combines data on the built environment, population density, night-time lights, crop and pasture lands, roads and railways, and navigable waterways to create an index of direct and indirect human pressures at a 1 km^2 resolution. We extracted the mean human impact value for each parcel using the exactextractr package in R (Baston, 2021).

Regulation

"Some regulations dictate what we do, but it's a case-by-case basis."

There was a wide range of responses regarding the importance of regulation for farmer decision-making. In the quote above, the farmer explained how some aspects of regulation (such as the track and trace systems) were more impactful to his daily farm management decisions than others as he navigated the licensed industry. Most farmers did not perceive that enforcement influenced their land use decisions, although the farmers navigating the licensed recreational market said that regulations were often their first consideration. One unlicensed farmer compared law enforcement to wildfire risk, explaining both as factors that were constant background risks but ultimately outside of his control. There was widespread confusion and frustration with the regulations around recreational cannabis. Multiple farmers said that they started growing hemp, or had considered growing hemp, to avoid the legal hurdles of recreational cannabis. Others raised questions about what the new recreational market would mean for medical producers. Some interviewees mentioned that a rural location made things easier from an enforcement perspective, particularly in avoiding the Grants Pass area (the county seat and law enforcement center). Even those who were attempting to navigate the legal industry expressed that it was useful to be less closely monitored because of the difficulty in complying with all regulations, the time needed to demonstrate compliance, or fear that they may be breaking rules without knowing it.

To translate the preference for distance from law enforcement into a spatial driver, we estimated this both with ruralness (see *Environmental Stewardship* above) as well as the straight line distance from the Grants Pass Sheriff's office to each parcel using the sf package in R (Pebesma, 2018). However, because these measurements were significantly correlated, we ultimately dropped distance to law enforcement as a variable in our models.

There were also a number of regulatory designations that cannabis farmers discussed as important when considering where to grow. Water rights and zoning were some of the most frequently mentioned. Water rights were considered critical for legal production but specifics of parcel-level rights were often hard to acquire or interpret. Water rights were not generally discussed by unlicensed farmers, but water access, storage, and application were all considered critical. Because of the mixed response to regulated water use, we assessed water access as part of *Parcel Qualities* below, rather than in *Regulation*.

The shifting policies in Josephine County around zoning restrictions, particularly for Rural Residential zones, led farmers to identify exclusive farm zoned parcels (EF) as the safest and highest quality lands for cannabis production. One farmer also mentioned Farm Resource (FR) zoned properties. To translate this into a land use driver, we created a binary variable that assigned a '1' to each parcel that was zoned for either EF (Exclusive Farm) or FR (Farm Resource) zones and a 0 for those that did not. Zoning information was provided by Josephine County (Josephine County 2018).

Parcel Qualities

"Why don't you just buy land that doesn't have trees on it to begin with?"

Farmers identified multiple biophysical properties of parcels that factored into decisions about where to produce cannabis. In the quote above, the farmer was expressing confusion as to why some cannabis producers selected parcels that required a large labor input to clear or terrace land to begin farming, when other, more open parcels seemed to him to be a more ideal choice. In addition to open/cleared areas with access to sunlight, some of the other factors mentioned included relatively flat slopes, and medium elevation zones as helpful qualities for production. Several interviewees mentioned that the climate in Josephine County was ideal for cannabis, while others expressed the belief that it was primarily grown in the region because of history and culture. One farmer mentioned that owning versus renting land for cannabis farming might change the relative importance of the physical factors of a parcel that a farmer prioritizes, as might living on the property where they are growing, but they weren't sure how often producers rented versus owned their farms.

We translated the above biophysical parcel qualities into multiple spatial drivers. First, we grouped land cover classes (NLCD 2011 and 2013) into a binary variable based on ease of clearing for crops. We included the following classifications in the easy to clear category, based on land cover descriptions: Developed Low Intensity, Grassland/Herbaceous, Developed Open Space, Pasture/Hay, Barren Land, and Cultivated Crops. In addition to clearing, we created a binary variable to describe if the majority aspect of a parcel was southern-facing, to reflect parcels with greater sunlight access, using the raster package in R. We also used maximum elevation per parcel to capture elevation as a potential limiting factor, using a 10 m DEM and the exactextractr package in R (Baston, 2021). We calculated maximum roughness to capture potential preference for overall flat parcels using the 'terrain' function in the raster package in R (Hijmans, 2022). In the raster package, roughness measures the difference between the maximum and minimum elevation value of a cell and its surrounding cells.

Farmers discussed parcel size as a potential factor that could influence where to locate a cannabis farm. One farmer mentioned that parcels in Josephine County were smaller than in other regions where he had farmed cannabis, while other farmers implied that they had looked for larger parcels within the county. Multiple farmers discussed the importance of space on the property, whether directly for cannabis production (e.g., space for greenhouses, gardens, drying sheds, water storage or ponds, etc.), multiple kinds of cannabis production (e.g., space for both a licensed and unlicensed garden, or for both recreational or medical cannabis and hemp), or for other reasons, for example to provide a treed buffer or space for a fence between the farm and its neighbors, to have enough room for setback distances required by regulation, or to accommodate other land uses on the same parcel (e.g., vegetable farming, homestead, commercial timber, etc.). To translate this into a spatial driver, we used the calculated area of each parcel polygon using the sf package in R.

Not all farmers interviewed operated licensed production sites, and many were in a "gray zone" of legality, and so for some, proximity to water on a parcel was more important than specific water rights. Most farmers mentioned that in 2016, regulations on cannabis farming were not yet enforced, and so access to water at that time point might have had more to do with physical parcel qualities than legal access. Because of this, we used proximity of farmed parcels to water as a spatial driver instead of specific water rights on a given parcel for our model. We used the NHDplus flowlines database, filtering to include rivers and streams, as well as artificial paths (U.S. Geological Survey, 2018). We then calculated distances using the sf package in R (Pebesma, 2018).

While some farmers mentioned that soil quality (for example, PH, or whether the parcel had previously been grazed or farmed) mattered to them when selecting a site, most said that existing soil was not a primary concern for them, or for most farmers that they knew. Instead, most reported that the industry standard was to grow with imported soils in grow bags or boxes. Some farmers did report growing in native soil, but that they still had to add amendments to do so. Given the mixed comments on soil quality, we did not include this as a potential spatial driver of cannabis land use.

Economics

"Most people are just looking at the economics… If it weren't so hard to make a living and support a family [by growing sustainably], I think most people would be open to it."

While all farmers interviewed discussed the difficulties of supporting themselves or their families economically in the cannabis industry, none of them specifically mentioned land prices as a factor in their decision making, and we did not ultimately include any drivers based on this theme. In the quote above, the farmer expressed that it was difficult to make a secure living with cannabis farming, which often made it risky to attempt new sustainable techniques. In this case, the farmer was also explaining that in their own attempts to grow with lowered environmental impacts in mind, it sometimes meant an income tradeoff. Thus, farmers reported that economics primarily influenced their decisions on specific land use practices, as well as whether or not to enter the licensed market. The farmers did see broader drivers of supply and demand being important for the industry as a whole, but for their individual decisions, economics was influential in deciding how much to grow, how much to spend on equipment or labor, how to balance different types of production (e.g., hemp versus cannabis), or when they might have to leave the industry altogether. Most expressed that the industry, both licensed and unlicensed, was full of uncertainty, and economic vulnerability. Many expressed concerns that when operating under economic uncertainty, farmers were unlikely to take a risk on more sustainable or less ecologically-impactful farming practices.

Future of the industry

"Our county has a long history of boom-bust, with the gold and timber. And the west coast in general has a boom bust history with oil, gold, and timber. And I see this next boom bust economy is this Marijuana industry."

All interviewed farmers said that the cannabis farming industry had expanded with legalization, and expressed concerns or uncertainty for the future of the industry. In the quote above, the farmer was looking at their own long history in the cannabis industry and seeing an uncertain future, and comparing it to the other major land-based industry cycles in Josephine County. Most interviewed farmers compared the cannabis industry to the gold rush, and expressed concern that its rapid increase might not be sustained in the long term. Many farmers, both legacy producers that associated themselves with hippie culture or renegade counter-culturalists, as well as younger farmers that came from more indoor or urban production cultures, described a shift in the industry from one that was culturally or spiritually motivated to one that is primarily economically driven. They expressed concerns that the industrialization of cannabis with the legal market would lead to further ecological harm, while the money involved in the black market would encourage other criminal activities (e.g., sex trafficking or labor abuse).

Many farmers expressed a desire for more research and education, particularly around best growing practices. Most of those interviewed agreed that there was a general lack of knowledge or research-supported farming practices. While few were optimistic about the future, most expressed a belief in small-scale farms to produce in a way that was less harmful to the environment than conventional agriculture, and for persistence of a "craft cannabis" market.

Model results

Cannabis data

For the high-confidence cannabis on private land with no restrictions on the number of plants, we identified 1,171 parcels with cannabis pre-recreational legalization (2013/2014), and 2,525 parcels post-legalization (2016), for a total of 35,512 plants pre-legalization and 116,162 plants post-legalization (Fig. 2). In the pre-legalization timepoint, 8,531 private parcels were mapped in 2013 in the western half of the county (550 of which contained high-confidence cannabis), and 30,784 private parcels were mapped in 2014 in the eastern half of the county (621 with cannabis). Average values for each covariate are listed in Table 2.

Table 2. Average or proportion values of covariates used in the cannabis land use and land use change models.

		Parcel area (m^2)	**Human footprint**	**Distance to cannabis (m)**	**Density of cannabis (in 1km)**	**Elevation**	**Roughness**	**Distance to rivers (m)**	**Clearable**	**Farm Zoned**	**South Facing**
Cannabis 2013/2014	*Avg*	53,212	10.4	166.5	7.8	1,435.6	21.4	46.9	34.7%	8.7%	18.6%
	Min	483	1.3	0.0	0.0	870.1	0.3	0.0			
	Max	966,343	42.8	5,344.3	32.2	3,459.4	150	980.3			
	Sd	94,000	7.9	339.1	6.3	337.6	22.1	114.4			
Cannabis 2016	*Avg*	60,000	10.1	160.3	8.0	1,424.2	21.6	49	37.7%	9.3%	16.5%
	Min	244	1.3	0.0	0.0	857.8	0.3	0.0			
	Max	4,160,000	45.7	14,906.8	32.5	3,492.9	150	1071			
	Sd	135,578	7.8	466.8	6.4	330	22.5	113.4			
All private parcels	*Avg*	29,900	23.1	358.8	3.5	1,190	14.6	105.2	45.1%	4.0%	24.3%
	Min	1.5	1.2	0.0	0.0	653.9	0.0	0.0			
	Max	9,890,000	46.3	25,884.1	32.8	6,247.6	212.2	1,120.2			
	Sd	127,129	13.9	438.3	4.1	340.3	19.4	140.5			

Cannabis land use post-legalization

For the single year post-legalization (2016) cannabis land use model for private parcels, we found that the following hypothesized drivers had a significant relationship ($p<0.01$) with parcels that contained high-confidence cannabis: larger parcels, lower human footprint, lower distance to nearest cannabis, higher density of local cannabis, easily cleared land cover, and lower distance to rivers (Table 3). All significant drivers performed in the direction we predicted (see Table 1). The relationship of human footprint, cannabis density, and distance to rivers were approximately linear, but area and distance to nearest cannabis indicated nonlinear relationships and a possible threshold effect (Fig. 4). The change in probability attributable to individual covariates was generally small (<10%), except for parcel area and density of cannabis (Fig.4).

Table 3. Coefficient estimates for the model of cannabis land use in 2016. Any transformations are listed in parentheses. * $p< 0.05$, ** $p<0.01$, ***$p<0.001$. Pseudo r-squared (delta) = 0.16.

Variable	**Estimate (SE)**
Intercept	-6.159 (0.2686) ***
Parcel Area (log)	0.3940 (0.02278) ***
Average Human Footprint	-0.03923 (0.003628) ***
Distance to nearest 2016 cannabis parcel (square-root)	-0.06761 (0.004152) ***
Density of 2016 cannabis within 1-km radius (square-root)	0.4987 (0.02763) ***
Easily cleared 2013 land cover	0.2104 (0.05309) ***
Farm zoning	-0.1158 (0.08836)
Maximum Elevation	0.0001630 (0.00008721) *
Roughness (square-root)	-0.001227 (0.01540)
Distance to rivers	-0.0005793 (0.0002248)**
Southern-facing aspect	0.05558 (0.06095)

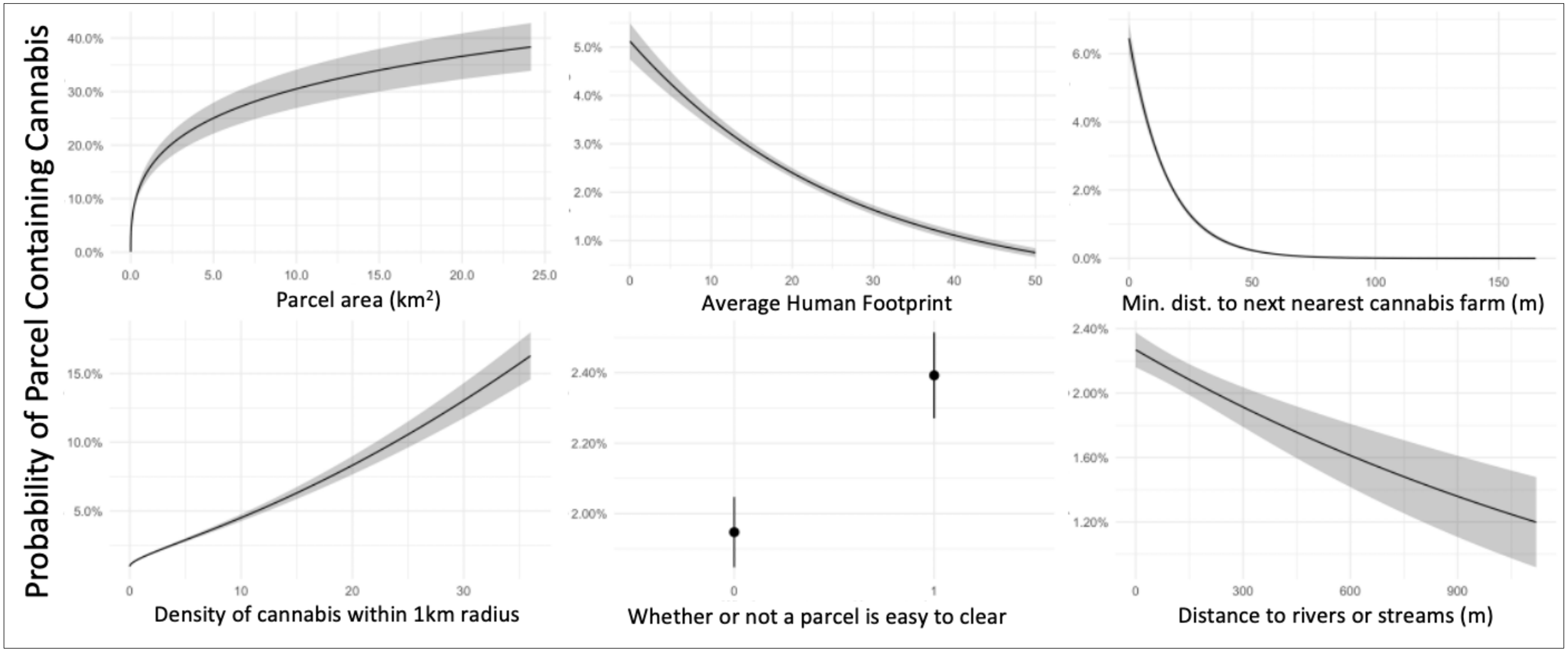


Figure 4. Prediction graphs of the six significant covariates for cannabis land use in Josephine County, OR. Note that the scale of the y-axis is different for each graph in order to illustrate the probability relationship of individual covariates. Error bars show the standard error.

Cannabis development on new parcels

For the model of cannabis development onto new parcels post-legalization in 2016 (parcels that had no detected cannabis pre-recreational legalization in 2013/2014), we found that the following hypothesized drivers had a significant relationship ($p<0.01$) with parcels that developed new cannabis: larger parcels, lower human footprint, lower distance to nearest cannabis, higher density of local cannabis, easily cleared land cover, non-farm zoned, lower elevation, less rough, lower distance to rivers, and mapped in 2013 (Table 4).

All significant drivers performed in the direction we predicted (see Table 1), except for farm zoning, which was negatively associated with the development of new farms, and image year, which did not have an associated prediction. Distance to nearest cannabis, local cannabis density, parcel elevation, and distance to rivers or streams all had approximately linear relationships with the probability of new cannabis development (Fig. 5). Parcel area and roughness on the other hand had non-linear relationships with possible threshold effects (Fig.5). The change in probability attributable to individual covariates was generally small (<10%), except for parcel area and human footprint (Fig.5).

Table 4. Coefficient estimates of the model of new cannabis development from 2013/2014 to 2016. Any transformations are listed in parentheses. * $p< 0.05$, ** $p<0.01$, ***$p<0.001$. Pseudo r-squared (delta) = 0.084

Variable	Estimate (SE)
Intercept	-5.444 (0.2927) ***
Parcel Area (log)	0.4206 (0.02690) ***
Average Human Footprint	-0.05424 (0.004483) ***
Distance to nearest 2016 cannabis parcel (square-root)	-0.01266 (0.003213) ***
Density of 2016 cannabis within 1-km radius (square-root)	0.2950 (0.04473) ***
Easily cleared 2013 land cover	0.3759 (0.06398) ***
Farm zoning	-02371 (0.1056) **
Maximum Elevation	-0.0001896 (0.00009273) **
Roughness (square-root)	-0.07568 (0.01803) ***
Distance to rivers	-0.0008174 (0.0002863)***
Southern-facing aspect	-0.06056 (0.07648)
Image year	-0.6917 (0.06289) ***

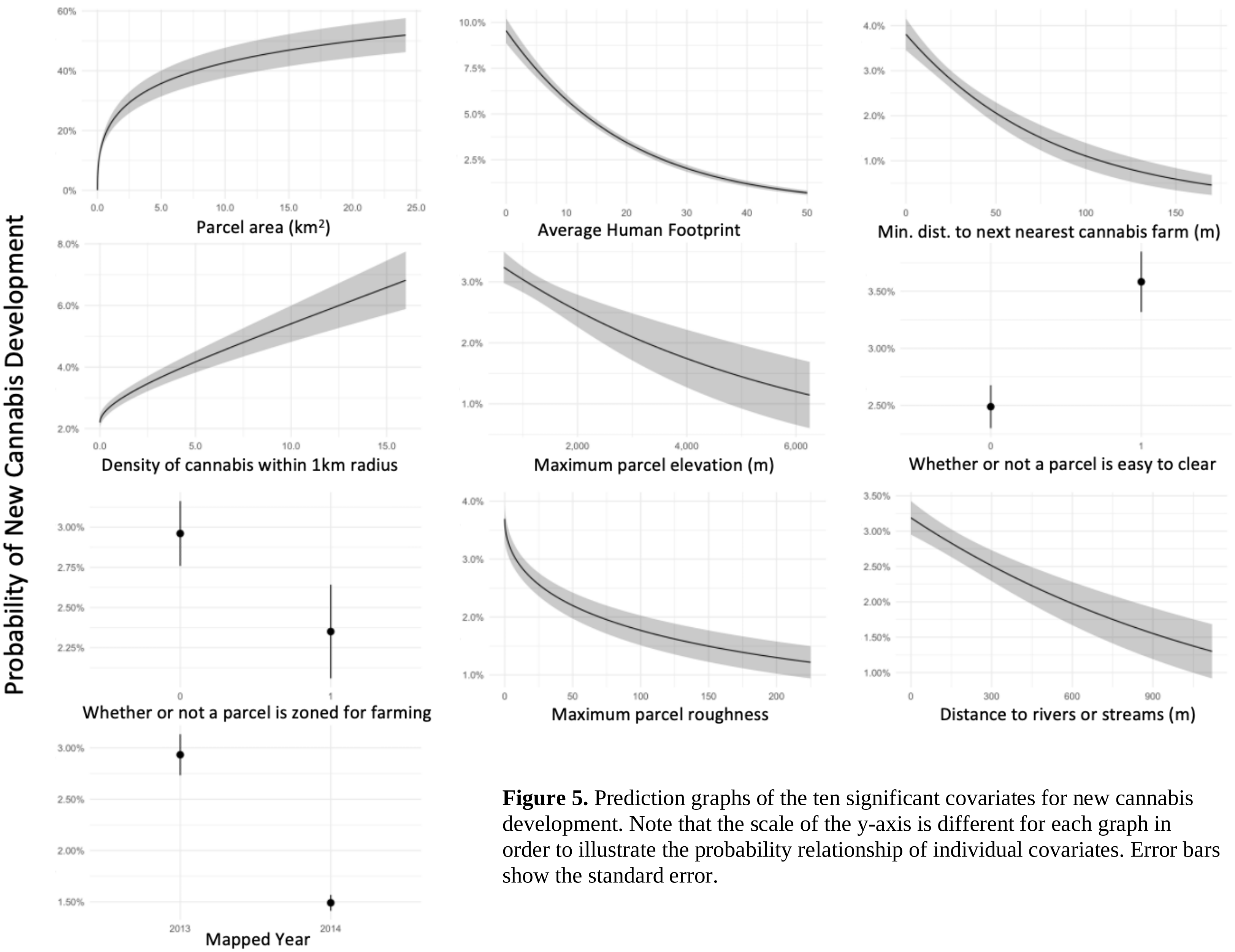


Figure 5. Prediction graphs of the ten significant covariates for new cannabis development. Note that the scale of the y-axis is different for each graph in order to illustrate the probability relationship of individual covariates. Error bars show the standard error.

Existing pre-legalization cannabis land use trajectory

For the model of cannabis growth or decline, we found that only parcel area, roughness, and image year were significantly associated with the change in plant count post-legalization (2016) (Table 5). All significant drivers performed in the direction we predicted (see Table 1), except image year, which did not have an associated prediction. The relationship of predicted change in plant count and parcel roughness was approximately linear, and the relationship with parcel area was non-linear with a possible threshold effect (Fig. 6). Parcel area was associated with the greatest predicted change in plant count, from a decrease of 25 plants to an increase of 50 (Fig. 6).

Table 4. Coefficient estimates of the model of existing cannabis change in plant count from 2013/2014 to 2016. Any transformations are listed in parentheses. * $p< 0.05$, ** $p<0.01$, ***$p<0.001$. Pseudo r-squared = 0.034

Variable	**Estimate (SE)**
Intercept	-0.3777 (0.1876) **
Parcel Area (log)	6.780 (1.717) ***
Average Human Footprint	-0.02121 (0.2706)
Distance to nearest 2016 cannabis parcel (square-root)	0.1152 (0.1946)
Density of 2016 cannabis within 1-km radius (square-root)	-3.425 (2.463)
Easily cleared 2013 land cover	5.643 (3.713)
Farm zoning	-4.101 (5.792)
Maximum Elevation	-0.0008123 (0.006414)
Roughness (square-root)	-2.290 (1.071) **
Distance to rivers	-0.005536 (0.01417)***
Southern-facing aspect	-0.1651 (4.015)
Image year	-9.898 (3.451) ***

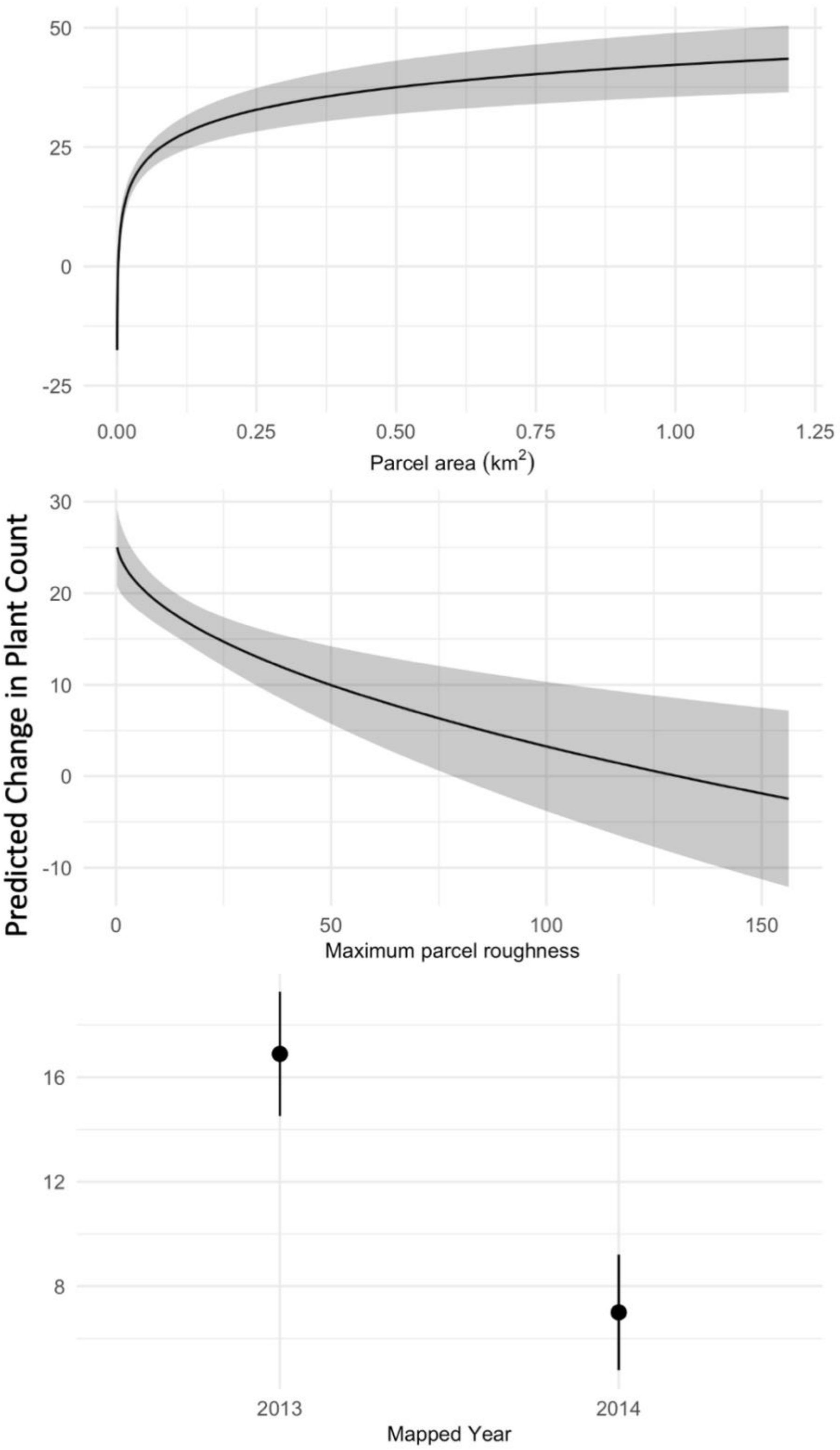


Figure 6. Relationships between predicted change in cannabis plant count on farms and three significant covariates from 2013-16. Note that the scale of the y-axis is different for each graph in order to illustrate the probability relationship of individual covariates. Error bars show the standard error.

Discussion

Rural cannabis land use in the western US has traditionally been a difficult topic for research. In this study, we demonstrated the effectiveness of an interdisciplinary approach to identify, assess, and contextualize drivers of cannabis land use and development. We combined generative cannabis farmer interviews with three models of cannabis land use in Southern Oregon during the early period of recreational legalization (2013-2016), to examine the relationship of spatial covariates with cannabis distribution, new development post-legalization, and plant density over time. The majority of our covariates were significant in at least one model, and combined with the context from the farmer interviews, suggest that they are likely reliable predictors of land use in this system.

Strength of interdisciplinary approach

Previous studies examining cannabis land use and land use change (Butsic et al., 2017, 2018; Wengert et al., 2021) have relied on biophysical covariates. Building on this foundational approach for understanding cannabis distributions, the addition of interview data to inform and contextualize models adds depth to the interpretation of modeling results, and generates new covariates that might otherwise be missed. For example, in Butsic et al. (2017), the authors noted strong network effects on the distribution of cannabis production, and postulated that producer networks might be important in the development of the industry. The interview data in our current study support this interpretation and produce the same finding in an additional legacy production region.

Our approach of incorporating social or cultural data into ecological modeling is not unique to cannabis production, and is becoming more common in contexts as varied as deforestation (Siegel et al., 2022), marine conservation (Österblom et al., 2013), and human-wildlife conflict (Wilkinson et al., 2020). One strength of incorporating qualitative data into quantitative models is the ability to capture nuances that may be left out or simplified in traditional modeling efforts. For example, while we did not identify any economic covariates functioning at the parcel level for our models, the interview data helped us recognize that broader economic changes are likely to influence changes in regional cannabis production over time. Another example was our use of local cannabis density as a proxy for supportive local attitudes towards cannabis farming. The interview data allows us to simplify a much larger concept of connection to community with this variable, while recognizing that in doing so, we may lose some local nuances – such as locations where there is a high neighborhood cannabis density but also strong negative community attitudes towards cannabis production.

Environmental Implications

Some of the drivers identified in our study raise concerns that farmers may be actively selecting parcels that are in areas of greatest environmental sensitivity. For example, as farmers seek out more rural parcels, these are also likely to be ones with greater terrestrial wildlife habitat—in fact, as the interviews indicate, this faunal biodiversity is often something farmers appreciate and seek on the land in which they live and farm. Similarly, the preference for parcels closer to rivers and streams may result in negative impacts on freshwater systems. Previous research has illustrated a potential overlap of cannabis agriculture in Josephine County with terrestrial and aquatic biodiversity (see Chapter 1), and our findings here suggest that this overlap is not incidental. It is possible that the ecological overlap observed in other rural cannabis-producing regions (Butsic et al., 2018; Wengert et al., 2021) could be influenced by similar social/cultural drivers. The significance of ruralness and distance to freshwater in the model of new farm development further raises concerns that this proximity could increase over time. The emergent theme of connection to community, and the strength of its associated drivers for cannabis distribution (distance to nearest cannabis farm and local cannabis density) illustrated the network reliance of cannabis farmers, which further suggests that development over time is likely to occur in areas that are current cannabis hotspots.

The context provided by the interview data suggests that some of the same motivations leading farmers to grow in rural areas may also provide opportunities to mitigate potential environmental harm. While our sample of farmer perspectives is relatively narrow, they all expressed strong environmental stewardship values. Similarly, other studies from California have identified commitments to environmental practices among outdoor cannabis farmers (Bodwitch et al., 2021; Polson & Bodwitch, 2021). These values alone do not mean that private land cannabis farming has a low environmental footprint — the farmers themselves even expressed concerns over the impacts of the industry. Rather, environmental stewardship values, combined with farmer concerns about the lack of education on best management practices for cannabis, implies that there is a research, education, and outreach gap for sustainable cannabis farming. This gap is one that researchers have repeatedly noted (e.g., Short-Gianotti et al., 2017, Carah et al., 2015, Wartenberg et al., 2021). Moreover, in their connection to community, farmers explained that they rely heavily on learning from other farmers' practices. Thus, there may also be opportunities to enforce conservation-minded practices via cultural dissemination to receptive farming communities.

The Future of the Cannabis industry in Josephine County

Our land use models illustrate a rapidly expanding cannabis farming industry, with a 116% increase in parcels with cannabis, and a 227% increase in plant count over 2-3 years from pre- to post-recreational legalization county-wide. Despite this rapid increase in cannabis production, most interviewed farmers were not optimistic about the future of the industry, with frequent comparisons to other "boom-bust" natural resource trajectories. Moreover, many farmers also described an industry that was currently unpredictable, difficult to navigate (particularly in the licensed recreational system), and unlikely to result in long term financial stability. This disconnect between the farmers' perceptions of the industry compared with its rapid expansion could mean that the specific type of producers we interviewed (mostly small-scale private land outdoor or mixed-light farmers) were not benefitting from the industry increase that accompanied legalization. Other research on small scale cannabis producers from northern California supports this interpretation (Bodwitch et al., 2019, 2021). It is also possible that landscape-scale industry change does not translate to the scale of an individual farm. If this is the case, it might help explain why the model of change in plant count had the fewest significant predictors—rather than being a more simplified process, it might instead be that the drivers for farms that existed before legalization are highly individualized or localized.

Despite the uncertainty surrounding the trajectory of legacy cannabis farms, the models for new cannabis development provide insights into predicting the growth of the industry. While we did not project our predictions into the future, due in part to large policy changes that were not explicitly addressed in our interviews or models (e.g., 2018 federal hemp legalization, and a three year pause on issuing new licenses in Oregon), our results do provide a baseline and contextualized understanding that could be used for future predictions. For example, based on farmer descriptions for why they may seek out large and rural parcels, it is unlikely that the strength of those drivers would decrease over time. On the other hand, farmers' stated preference for farm-zoned parcels, which by contrast ended up as a significant driver in the opposite direction for new farm development, might be more likely to change over time as a potential driver due to shifts in regulation, enforcement, or social pressures for those renting/selling farm zoned parcels.

Limitations

While our results are broadly useful for understanding cannabis landscapes in southern Oregon, there are many levels of complexity that are not captured by the models. For example, we treat cannabis agriculture as a single entity for these models, while in reality it contains a diversity of production styles and regulatory statuses. It is entirely likely that a large-scale licensed hemp farmer and a small-scale unlicensed cannabis farmer will reveal different drivers of their land use. Similarly, whether a farmer owns their own land or rents it, or whether a farmer lives on site or off, could also change the relationship with potential drivers. While we did not have detailed information on each cannabis producer at the county level to classify or group production styles, this would be an important avenue for future research.

Future research would also benefit from added timepoints, particularly after the 2018 federal hemp legalization. In addition, this study was largely confined to a small number of small-scale farmers, and thus an expanded interview or focus group data collection process might reveal new drivers that would be relevant for other production styles. The relatively low pseudo r-squared values for our models suggests that there may be additional drivers functioning in this system, which extended interviews could help uncover. Our study focused on private land production, but it is important to remember that public land production also occurs in this area (e.g., Wengert et al., 2021) and influences not only the local environment, but the public perceptions of cannabis in the region. Incorporating the links between public and private industries might strengthen our understanding of these systems. Similarly, linking different scales of drivers would be a valuable next step. The interview data indicates that the southern Oregon industry is tied to regional and national markets (e.g., many Oregon farmers learned growing techniques in northern California, or moved to Oregon from other states that are perceived to be less receptive to cannabis farming), and that much of the economic decisions are either very fine scale at the level of the farm, or broader scale at the level of the state. Within the scale of Josephine County, the significant effect of mapped year (Fig. 5) implies that there may also be different dynamics in the two halves of the county that were mapped at different timepoints (Fig. 1). Although it did not directly emerge in the interviews, while living in Josephine County, PPS observed different local approaches to integrating cannabis farmers into the community in Williams as opposed to the Illinois Valley. This is an example of a secondary way in which the observations that occur during the interview process can assist with model interpretation. Further research on differences in local policies, community standards, or other regional differences might elucidate this pattern. Capturing interrelated dynamics such as local to county-wide processes would require a complex modeling approach but might lend insights into multi-scalar drivers.

Conclusions

This study demonstrates the strength of an interdisciplinary approach when attempting to understand the socio-ecological dynamics of cannabis land use. Future research on cannabis will continue to benefit from cross-disciplinary collaboration. Our research may also be of use for those making policy or conservation management decisions for cannabis land use and conservation. These conservation-relevant decisions should be based in an understanding of land use drivers, and as our research demonstrates, discussions with cannabis farmers themselves are likely to lend a better understanding of the dynamics underlying land use drivers. We therefore recommend policymakers consult with cannabis farmers in the creation or modification of regulations, to avoid unintended consequences and achieve intended conservation goals. Finally, the interview results indicate that education and outreach may be underused tools for conservation with cannabis. Many interviewed farmers expressed a desire to learn more about sustainable farming. Education and outreach programs on best management practices for reducing environmental impacts of cannabis production, particularly those that provide funding for interventions, could take advantage of network-reliant farming communities, and existing environmental stewardship values. In the long run, these approaches may provide a useful alternative or supplement to enforcement-based efforts that have had mixed effectiveness historically (Corva, 2014).

Chapter 3

Wildlife response to small scale cannabis farming

Abstract

The recent expansion of cannabis agriculture in rural areas of the western United States provides an ideal opportunity to study wildlife responses to disturbance at a land use frontier. This study examined local wildlife space use at a gradient of distances to active small-scale (<1 acre) private-land outdoor cannabis farms. We used data from 149 cameras on and surrounding eight cannabis farms in the Klamath-Siskiyou Ecoregion in southern Oregon, collected between 2018–2019. Using single species occupancy analyses, we assessed how cannabis production influenced the occupancy (defined here as space use) and detection (defined here as a combination of detectability and space use intensity) of nine wild and one domestic species in our study area. We also used multi-species models to assess the responses of 24 different species, by functional group: carnivores, omnivores, herbivores, small mammals, ground birds, and domestic animals. We found that 8 out of 10 species in single-species models and 13 out of 24 in multi-species models responded to the presence of cannabis farms in either the detection or occupancy process, though the responses were species-specific. Our results suggest that some omnivore or mesopredator species may show a greater flexibility to use spaces near cannabis farms, while some herbivores and ground birds may compensate for spatially avoiding cannabis farms by using spaces near farms more intensively. These results highlight the complexity of wildlife response to disturbance, and the importance of examining response patterns to novel disturbances.

Introduction

Understanding wildlife response to disturbance across landscape gradients is a complex endeavor. Individual animals can respond to anthropogenic disturbance with a variety of different behavioral changes (e.g., altering their space use by avoiding a disturbance, or altering space use intensity or adjusting their activity peaks around disturbance sources), but these responses are all context dependent (Frid & Dill, 2002; Gaynor et al., 2018). For example, in some studies, coyotes demonstrate a space use preference for agricultural areas (e.g., Hinton et al., 2015), while in others, they avoid farmland (e.g., Atwood et al., 2004); similarly, at times they are labeled as urban exploiters (e.g., Bateman & Fleming, 2012), and at times avoiders (e.g., Atwood et al., 2004). These differences are often tied to context-dependent responses and differences in landscape configurations (Fidino et al., 2021; Padilla & Sutherland, 2021; Van Scoyoc et al., 2022). At a wildlife community level, the complexity of responses increases even more. Disturbance may affect some species more than others, or in opposite directions, leading to broader contractions or expansions in species assemblages (Mendenhall et al., 2014) and interactions (Schmitz et al., 2004; Y. Wang et al., 2017). Changes in species interactions, especially if they involve keystone species, can have cascading effects on ecosystem function (Estes et al., 2011; Power et al., 1996; Prugh et al., 2009). The context-dependence of these shifts means that consistently predicting how wildlife communities will respond to rapid land use change at a local level is very difficult and requires understanding multiple interacting mechanisms (Alberti et al., 2020; Padilla & Sutherland, 2021; Power et al., 1996). Nevertheless, wildlife community responses to disturbance matter because the context-dependent consequences in turn can affect ecosystem health (Alberti et al., 2020), effectiveness of wildlife management strategies (Wilkinson et al., 2020), and human-wildlife conflict (Crespin & Simonetti, 2019; Wilkinson et al., 2020). Thus, there is a continuing need to examine the effects of disturbance on wildlife in order to develop strategies to mitigate the negative effects of land use change.

Understanding wildlife response to disturbance is particularly important in areas where land use change is occurring rapidly. Spaces of rapid development for agriculture are called frontiers, and are often spurred by the growth of a new industry, while accompanied by the movement or growth of human populations, and transportation structure improvements (Rindfuss et al., 2007). Frontiers are naturally spaces of rapid land use change, and often sites where different approaches to land use planning and conservation clash (e.g., le Polain de Waroux et al., 2018). While frontiers present a novel disturbance scenario, most studies of wildlife response to agricultural land use have been concentrated in Asia, South America, and Europe (Ferreira et al., 2018), and often in areas that have long been dominated by agriculture. Such studies may miss some of the immediate responses of wildlife to development that occur over shorter spatial and temporal scales (Lark et al., 2020).

Recreational cannabis agriculture represents an ideal opportunity to study wildlife community response to disturbance generated by a currently expanding land use frontier. In the US, state-level legalization of recreational cannabis has initiated a rapid land use frontier for outdoor cannabis production (Butsic et al., 2018). This frontier is particularly noticeable in rural areas of the western US. Influenced by its illicit history, outdoor cannabis is often grown in remote, biodiverse regions with minimal other non-timber agriculture (see Chapter 1) (Corva 2014; Butsic and Brenner 2016; Butsic et al. 2018). Regardless of individual legal status, private land cannabis farms are typically smaller than those of other commercial crops, and are clustered in space, creating a unique land use pattern of small points of development surrounded by less developed land (see Chapter 1) (Butsic et al., 2018; Butsic & Brenner, 2016; I. Wang et al., 2017). This pattern of development locates the cannabis frontier directly at the wilderness boundary—a somewhat rare characteristic for agriculture in the United States (see Chapter 1) (Butsic et al., 2018).

Previous studies have raised many concerns about the cannabis industry’s potential effect on wildlife (Wartenberg et al., 2021; Carah et al., 2015). At a broad scale, cannabis development in rural areas overlaps with regions that may be important habitat for wildlife (see Chapter 1) (Butsic & Brenner, 2016; Butsic et al., 2018), yet it is unclear whether, where, and to what extent this broad scale spatial overlap actually results in negative impacts on animals at a local scale. There have been studies suggesting that cannabis production may lead to habitat destruction or modification (Wartenberg et al,. 2021; Carah et al., 2015), and wildlife death due to toxicant use and poaching (Carah et al., 2015; Gabriel et al., 2012; Levy, 2014). However, most studies on direct impacts of cannabis farming have largely been conducted on illegal public land production sites (so-called “trespass grows”), as opposed to private land sites. The research conducted to date on private land has not encompassed a full landscape gradient around cannabis farms

(Parker-Shames et al., 2020). Not only have private land sites likely seen the largest production increases due to legalization in recent years (see Chapter 1) (Arcview Market Research, 2016; Butsic et al., 2018; Klassen & Anthony, 2019), they are also often characterized by very different production practices (and therefore risks to wildlife) than public sites. For example, on many private land farms, indirect sources of disturbance to wildlife such as noise and light are more common than direct causes of mortality. Private land sites (whether licensed or unlicensed) may use high-powered grow lights, drying fans, and visual barrier fencing, which could create potential wildlife disturbance (Rich, Baker, et al., 2020; Rich, Ferguson, et al., 2020). Such practices are less common on public land. It is possible that as cannabis production expands, particularly in the licensed industry, these forms of indirect impact may be more typical of cannabis production overall. Indeed, indirect effects of production practices on wildlife space use and behavior is a common concern for other agricultural crops (Ferreira et al. 2018), and may also interact with direct effects on mortality (Muhly et al., 2011). Therefore, it is critically important to study both indirect and direct effects of cannabis on wildlife communities, particularly on private lands where research is lacking.

Because outdoor cannabis farming is a land use frontier and therefore often characterized by different land use practices and patterns from traditional established farming in the US, it is uncertain whether (and which) other agricultural systems provide the best models to predict wildlife responses to cannabis development. Wildlife may use, avoid, or display differential responses to cannabis development, depending on whether production more resembles small-scale countryside farming (e.g., Mendenhall et al., 2014), industrial agriculture (e.g., Lark et al., 2020), or exurban/suburban development (e.g, Fidino et al., 2021). In the case of differential responses, it’s also unclear whether cannabis production would have widespread enough effects to trigger mesopredator release (Prugh et al., 2009), or generate novel food sources that could be exploited by behaviorally adaptable species like omnivores and small mammals (Alberti et al., 2020).

To address some of the above research gaps, we deployed arrays of wildlife cameras to observe animal space use on and surrounding active small-scale cannabis farms on private land, and modeled wildlife responses using single- and multi-species occupancy models. In doing so, we asked the following questions: How does wildlife space-use change as a function of distance to cannabis farms? Are there consistent patterns to wildlife responses along functional groups? Specifically, we assessed the following hypotheses:

- H1A: All wildlife species will all avoid cannabis farms, and use the spaces nearby less intensively than undeveloped areas.
    - H1B: Alternatively, individuals may display species-specific responses. Specifically, where species tolerate or are attracted to cannabis farms, they will instead compensate with lower space use intensity on these sites.
- H2A: At the community level, each wildlife functional group will avoid cannabis farms, and use the spaces nearby less intensively.
    - H2B: Alternatively, functional groups will have specific space use patterns. For example, carnivores will avoid cannabis farms, small mammals will be attracted to cannabis farms, and omnivores, herbivores, and ground birds will have mixed responses.

This research is important because it provides a baseline for understanding potential space use effects of private land cannabis production on wildlife in rural areas. Given that there are multiple potential pathways of impact, this study may generate hypotheses about mechanisms of effect for future study. In addition, it will provide insights into whether localized effects on wildlife happening directly at production sites may influence broader surrounding communities (Parker-Shames et al., 2020). While this work is specifically focused on rural cannabis farming, our approach and methodology may be useful for other studies of wildlife along agricultural frontiers or other rapid development landscapes.

Methods

Study Area

We based our study in Josephine County, in southwestern Oregon (42.168, -123.647), in 2018-2019, three years after statewide recreational legalization took effect. Josephine County was an ideal location to capture the start of the cannabis frontier expansion post-legalization in a rural, biodiverse legacy production region. Our study area sits within the Klamath-Siskiyou Ecoregion, which is one of the most biodiverse temperate forest regions on Earth (D. Olson et al., 2012; D. M. Olson et al., 2006). The Klamath-Siskiyou Ecoregion straddles the Oregon-California border and contains several areas identified as critical climate change refugia (D. Olson et al., 2012; D. M. Olson et al., 2006). Within this ecoregion, Josephine County contains several protected areas including state and federal protected lands (68.8% of the county is state or federal land), as well as several species of concern, including native salmonids, threatened Humboldt martens (*Martes caurina humboldtensis*), fishers (*Pekania pennanti*), and spotted owls (*Strix occidentalis*), all of which are hypothesized to be directly or indirectly affected by cannabis agriculture (Butsic et al., 2018; Carah et al., 2015; Gabriel et al., 2012, 2015; Thompson et al., 2014).

Unlike other forms of traditional agriculture, outdoor cannabis is often grown directly alongside or nestled within areas of high biodiversity (see Chapter 2). Southern Oregon, and Josephine County in particular, has a long history of illicit and medical cannabis cultivation, as well as an active presence in the growing legal industry in Oregon (see Chapter 2) (Klassen & Anthony, 2019; V. Smith et al., 2019). Southern Oregon became known as a prime destination for outdoor cannabis production even before legalization, and Josephine County had the highest number of licensed producers relative to population size in the state by 2019 (Oregon Liquor Control Commission, 2019; V. Smith et al., 2019). Production in the county accelerated after recreational legalization went into effect in 2015 (see Chapters 1 and 2), in a similar pattern to cultivation occurring across the border in northern California, with clusters of small farms surrounded by undeveloped or less developed rural land (see Chapter 1) (Butsic et al., 2018; Butsic & Brenner, 2016; V. Smith et al., 2019; I. Wang et al., 2017).

Our study area consisted of farms spread across three sub-watersheds (Slate Creek, Lower Deer Creek, and Lower East Fork Illinois River; defined by USGS hydrologic unit code 12) in Josephine County (Fig.1). We set cameras at 1,110 m to 2,470 m above sea level. The study area included a mix of vegetation types, including open pasture, serpentine meadows, oak woodland, and mixed conifer forest. Rainfall in this region varied seasonally and by elevation, with an average of 82.7 cm annually (Borine, 1983). Mean temperatures ranged between 3.9-20.6°C in 2018–2019 (NOAA https://www.ncdc.noaa.gov/cdo-web/).

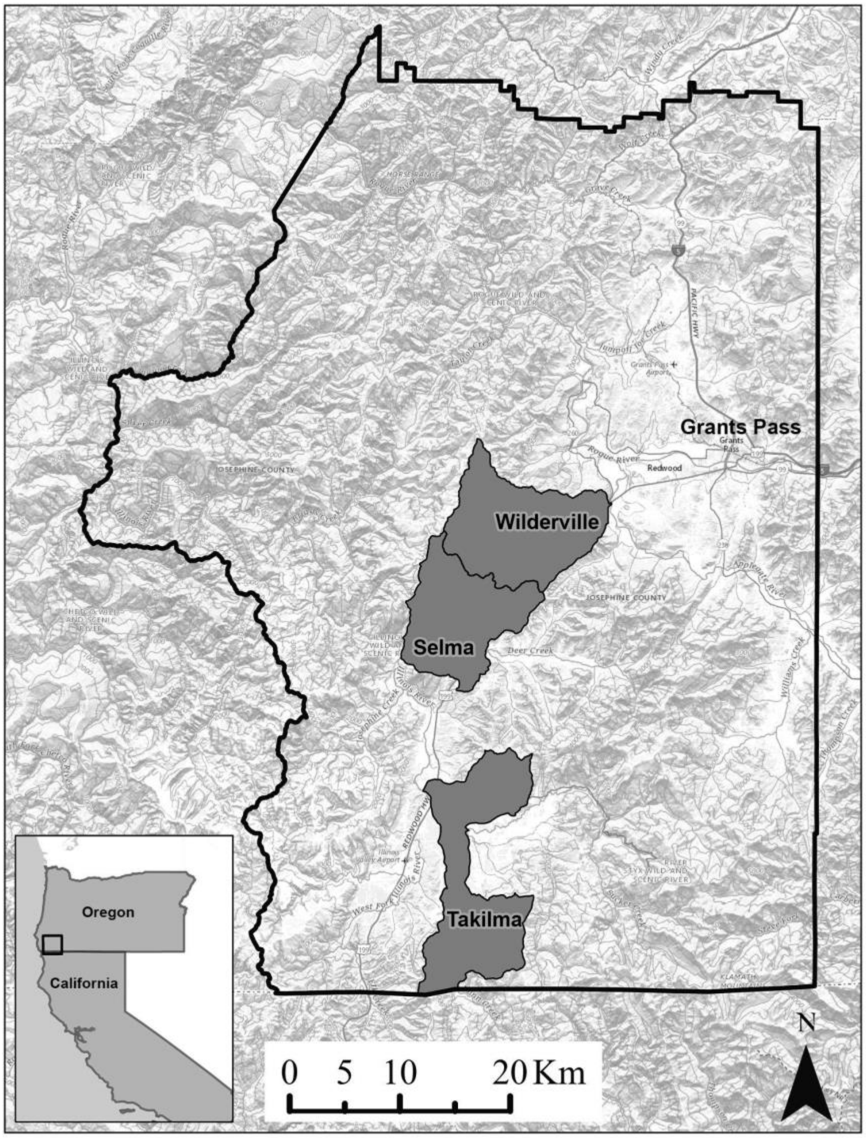


Figure 1. Map of study area with local population centers identified. The study sites are indicated as USGS hydrologic unit code 12 sub watersheds within Josephine County, southern Oregon. All wildlife cameras were contained within these three watersheds, and are summarized at this scale to anonymize specific farm locations. From the top down, the sub watersheds are: Slate Creek, Lower Deer Creek, and Lower East Fork Illinois River.

Wildlife camera surveys

The small-scale, private-land cannabis farms for this study included one licensed recreational production site, one medically licensed (though non-compliant) production site, and six unlicensed sites. All farms were producing cannabis for sale, though in different markets depending on their access to licensed markets. We also had cameras placed in three hemp fields next to cannabis farms. We selected these eight cannabis farms because they: (1) were representative of the size and style of cultivation predominant in Josephine County in the years immediately following recreational legalization in 2015 (see Chapters 1 and 2), (2) were all established after recreational legalization except for the medical farm, (3) did not replace other plant-based agriculture, (4) granted us permission to set up cameras on site, and (5) were located next to a large section of unfarmed land (e.g., BLM, private, timber) that could grant researchers access in order to place cameras across a gradient of distance to cannabis farms. Our sampled farms were small (typically < 1 acre), had conducted some form of clearing for production space, and three had constructed some form of fence or barrier around their crop. Nonetheless, specific land use practices and production philosophies differed between farms (e.g., pesticide use, type of fencing, presence of dogs, number of people working on the site, attitudes towards conservation, etc.). We cannot disclose farm locations, as per our research agreement for access.

Monitored farms were clustered within each watershed: one farm in Slate Creek, five in Lower Deer Creek, and two in Lower East Fork Illinois River; however, most farms were also located near other nearby cannabis farms that were not directly monitored in this study. We placed un-baited motion sensitive cameras (Bushnell E3, Bushnell Aggressor, or Moultriecam models) on cannabis farms as well as in random locations up to 1.5 km from the monitored farms. This is an expansion on previous camera research that only assessed on-site wildlife at these same farms (Parker-Shames et al., 2020). We placed cameras approximately 0.5 m off the ground to capture animals squirrel-sized and larger. We set cameras to take bursts of 2 photos, with a quiet period of 15 seconds. To guide the placement of cameras, we overlaid the area surrounding each cannabis farm cluster with a 50 x 50 m grid and then selected a random sample of at least one quarter of grid cells (a minimum of 45 stations in each watershed). We selected a 50 x 50 m grid size because we wanted to be able to detect fine scale space use responses of wildlife. The random sample was stratified by vegetation openness and distance to cannabis farm in all watersheds, and additionally by distance to clearcut in the Slate Creek watershed, such that cameras were placed in proportion to the landscape attributes and a distance gradient was achieved. When a selected site was inaccessible, we selected a new one that also met the same stratification criteria. We rotated 15-20 cameras through the sampled grid cells, ensuring each camera was deployed for at least one round of two week duration. Because of rotations and field constraints, all cannabis sites were not monitored at the same time or for the same length of time (one to six rounds, with on-farm cameras monitored the most intensively). Altogether, we monitored a total of 149 camera stations for a combined 4,664 trap nights. We then used a team of researchers trained to identify species found in the study area to sort photos by hand, grouping by species.

Covariates

We calculated spatial and descriptive covariates for each site to use in wildlife occupancy and detection models (Table 1). First, we calculated spatial distance covariates. Our main covariate of interest was distance to cannabis farms. To calculate distance to cannabis, we combined the location data for participating farms in our study with mapped data on Josephine County cannabis farms from 2016 aerial imagery (see Chapter 1). Then we calculated the minimum distance from each camera to its nearest farm using the package sf (v. 1.0.6; Pebesma, 2018) in R. We transformed distance to cannabis using a square root to help fit potential thresholds in wildlife responses. Next, we again used the sf package, this time to calculate the distance from each camera to the nearest major paved roadway, which was primarily highway 99 for most sites.

For our two raster-based covariates, we used the raster (v. 3.5.15; Hijmans, 2022), and exactextractr (v. 0.7.2; Baston, 2021) packages in R. We calculated the proportion of forested land cover within a 50 m buffer around each camera, and extracted the elevation in meters at each camera site.

We also included some non-spatial covariates. We included a covariate for Julian date of each interval, as well as Julian date squared, to capture seasonal peaks. We then included an estimated distance at which a camera could still detect an animal (generally lower in dense vegetation and higher in open sites), which was measured at camera setup. We also generated activity indices for dogs and humans by calculating the number of observations of humans or dogs, respectively, at each camera within the last three days, divided by the number of days the camera was active. This produced an activity rate where the beginnings or ends of placement rounds were on the same relative scale as all other days.

All continuous variables were scaled so that they centered on 0 with a standard deviation of 1 (though $Date^2$ was not scaled again after squaring *Date*) and checked for correlations (Pearson's correlation, $r<0.6$) in R.

Finally, we used additional categorical covariates to account for potential effects of geographic region and camera type. We assigned each camera a binary region variable based on which USGS Unit 12 watershed it was located in, such that R*egion1* represents Lower Deer Creek, *Region2* for Lower East Fork Illinois River, and *Region3* for Slate Creek. We created a binary variable for camera type. We gave a 0 to camera models that generally performed well in our study system (Bushnell Aggressors) and a 1 to camera models that generally seemed to perform worse or were older models (Bushnell E3s and Moultriecams).

Table 1. Covariates used for single species and multi-species occupancy models. All continuous covariates were scaled and checked to ensure they were not correlated. See text for more details.

Covariate	**Source**	**Model process**
Region	Generated for this study, representing the following watersheds: Lower Deer Creek, Lower East Fork Illinois River, and Slate Creek	Occupancy
Distance to cannabis	Mapped data on surrounding cannabis farms from 2016 imagery (Parker-Shames et al., 2022) combined with location data on farms participating in this study	Detection and Occupancy
Elevation	10m DEM (citation)	Occupancy

Forest	Proportion of a 50m buffer around each camera that is covered by forested land cover (National Land Cover Database 2016)	Occupancy
Distance to highways	Distance to nearest major paved road (citation)	Occupancy
Camera type	Binary classification generated for this study	Detection
Camera view distance	Estimated distance that a camera can detect an animal, measured at camera setup	Detection
Date and Date^2	Julian dates generated for this study	Detection
HAI and DAI	Human and Dog activity indices, generated for this study (see text for details)	Detection

Analyses

To assess the local space use response of wildlife to cannabis production, we used single-season, hierarchical single and multi-species occupancy models. Our approach is a departure from the typical use of these models to estimate occupancy in that we knowingly violated multiple assumptions of occupancy models: first, because cameras were spaced relatively close together compared to the home range of species included in the study, we have likely violated the assumption of independent cameras; second, as a result of the aforementioned spacing as well as sampling across two years (which was long enough that individuals may move in and out of the study area), we likely violated the model's assumption of geographic and demographic closure (Mackenzie et al., 2006). We have done our best to account for these violations in our use of regional fixed effects, as well as our narrow interval of replication (see *Single species models* below). However, given our interest was in space use associations and not estimates of occupancy, we believe the violations are a minimal issue. This use of occupancy models is not particularly unusual, as the use of occupancy modeling to assess space use is becoming more common in wildlife response studies, and even traditional uses of occupancy modeling are influenced by wildlife space use (Neilson et al., 2018; Nickel et al., 2020).

With the closure assumption violated, the occupancy probability estimate represents the likelihood that the animal occupied the site at any point during the study period, while the detection probability represents a combination of the probability that the species is detected and the intensity of use of the site within its larger range (Burton et al., 2015; Neilson et al., 2018; Stewart et al., 2018). This interpretation is common in camera trapping studies (e.g. Nickel et al. 2020; Suraci et al. 2021), but we proceed while being careful to acknowledge where appropriate that any covariate's influence on detection probability is a combination of its effect on detection and the intensity with which an animal uses a given space. In addition, we have taken care to include variables in the detection process to account for what we anticipate to be the largest sources of variation in detectability, so that the other variables should primarily reflect space use intensity. We therefore interpret occupancy for the models as space use rather than true occupancy (though we still refer to it as "occupancy" for consistency). We operationalize detection as a combination of intensity of use, and camera detectability or error (which we refer to as simply “detection”).

Single species models

To examine animals’ space use in relation to distance from cannabis farms, we first conducted single species occupancy analyses on nine wild and one domestic species (Table 3) (MacKenzie et al., 2002). We summarized species observations on and surrounding cannabis farms and created detection histories (i.e., tables where a “1” indicated the species was photographed at a given camera station during the respective 24-hr time interval when the camera was active, and a “0” that it was not) using the package CamtrapR (CamtrapR v. 2.0.3; Niedballa et al., 2016) in program R (R v. 2021-11-08 “Ghost Orchid”; R Core Team 2021) using Rstudio (v. 2021.09.1 + 372; Rstudio Team, 2021). We used a 24-hr time interval because our focus was on estimating space use associations instead of occupancy (see *Analyses* above), and a short interval reduced the likelihood of the same individual animal being detected on neighboring cameras (Latif et al., 2016; Steenweg et al., 2018).

We modeled the space use probabilities of the most commonly detected species or those of particular ecological interest, including: black-tailed deer (*Odocoileus hemionus*), black bear (*Ursus americanus*), bobcat (*Lynx rufus*), coyote (*Canis latrans*), gray fox (*Urocyon cinereoargenteus*), black-tailed jackrabbit (*Lepus californicus*), striped skunk (*Mephitis mephitis*), California ground squirrel (*Otospermophilus beecheyi*), tree squirrels (including both western gray squirrel *Sciurus griseus* and Douglas’ squirrel *Tamiasciurus douglasii* due to uncertainties in distinguishing individual species in photographs), and domestic dog (*Canis lupus familiaris*) using the NIMBLE and nimbleEcology packages in Program R (de Valpine et al., 2017; Goldstein et al., 2020). We selected these species because they had sufficient detections to model (Table 3), and because they covered a range of functional groups, including predators and mesopredators (bear, coyote, bobcat, gray fox), omnivores (bear, fox, striped skunk), large and small prey (deer, jackrabbit, tree squirrel, ground squirrel), and a domestic predator (dog). We included dogs as an added check on our modeling approach, as their general distributions and associations are already well known in the study system, unlike wildlife species.

We modeled the observed data (y_s) as a binary variable where 1 was an observation for a given species at camera station s, and 0 was a non-detection. We modeled the observed data for each species as a product of both true occurrence (z_s; space use) of a given species at a site and our probability of actually detecting it (p_s), which is also influenced by intensity of use at a given site. The model assumes that true occupancy is an outcome of a Bernoulli-distributed random variable, denoted $z_s \sim \text{Bern}(\psi_s)$, where ψ_s is the probability that a given species used site s on any day during the survey period.

We assumed that occurrence and detection probabilities varied by species, and that cannabis might influence both in different ways. For occupancy, we expected that increasing distance from cannabis farms would increase animal space use (i.e., due to avoidance of cannabis farms) for all species except domestic dogs, and ground squirrels. We also expected that elevation and forested land cover would influence space use based on their importance in other wildlife studies (e.g., Reilly et al. 2017). We expected distance to highways to negatively affect space use, and to function as a proxy for other non-cannabis forms of human land use in our study system. While we initially wished to include distance from clearcuts as the other major source of human disturbance in the study system, it was highly correlated with distance to highways, so we did not include it in our models. Finally, we accounted for potential regional differences in the three watersheds by including a fixed effect of region. We parameterized regional fixed effects using region-specific intercepts as described in the following equations. We previously attempted modeling region as a random effect, but the models converged better with the use of fixed effects. Therefore, we constructed the occupancy submodel as follows:

$$\begin{aligned} logit(\psi_s) = \; & \beta 1 \times I(Region1[s]) + \beta 2 \times I(Region2[s]) + \beta 3 \times I(Region3[s]) \\ & + \beta 4 \times Cannabis[s] + \beta 5 \times Elevation[s] + \beta 6 \times Forest[s] \\ & + \beta 7 \times Highways[s] \end{aligned}$$

Where *I(RegionX[s])* is an indicator variable equal to 1 if site *s* is in Region X, and 0 otherwise, *Cannabis* is the square root of distance to cannabis, *Elevation* is the elevation in meters at the camera site, *Forest* is the proportion of area around each camera site that is forested within a 50 m buffer, and *Highways* is the distance from a major paved roadway. All continuous variables were scaled.

For detection, we expected that increasing distance from cannabis farms would increase intensity of use (e.g., due to temporal avoidance on farms leading to lower activity rates) for all species except domestic dogs. Separately from the general influence of cannabis farms themselves, we expected increased recent activity rate of dogs and humans to decrease intensity of use for all wild species (Nickel et al., 2020; Reilly et al., 2017). We further expected time of the year to influence intensity of use, based on seasonal changes in activity patterns (Furnas & McGrann, 2018). Finally, we expected that the camera model and view distance (how far the camera can detect an animal) of each camera setup might influence its ability to detect animals. Therefore, we constructed the following model:

$$\begin{aligned} logit(p_s) = \; & \alpha 0 + \alpha 1 \times Cannabis[s] + \alpha 2 \times Type[s] + \alpha 3 \times View[s] + \alpha 4 \times Date[s] \\ & + \alpha 5 \times Date^2[s] + \alpha 6 \times HAI[s] + \alpha 7 \times DAI[s] \end{aligned}$$

Where *Cannabis* is the square root of distance to cannabis, *Type* is a binary grouping of camera type, *View* is the estimated distance at which a camera can still detect an animal, *Date* is the julian date, $Date^2$ is the julian date squared, and *HAI* and *DAI* are activity indices for humans and dogs respectively. All continuous variables were scaled.

We fit our models using a Bayesian Markov-chain Monte Carlo (MCMC) method in R using the NIMBLE and nimbleEcology packages (de Valpine et al., 2017; Goldstein et al., 2020). We used weakly informative prior distributions for all parameters (Gelman et al., 2008). Occupancy and detection parameters were calculated from three chains run for 50,000 iterations, thinned by 1. We assessed model convergence by examining trace plots and R-hat values (<1.1) for parameter estimates. We considered parameter estimates as meaningful (i.e. the Bayesian analogue of “significant”) when their 95% credible interval did not overlap zero.

Multi-species models

In addition to individual species responses, we also sought to test how groups of species, and less commonly-detected species, responded to cannabis farming. We therefore also ran additional multi-species occupancy models (MSOMs) (Devarajan et al., 2020; Iknayan et al., 2014; Zipkin et al., 2010). With multi-species occupancy models (MSOMs), detections from more common species can lend power to less frequently detected species, and models produce population-level mean and deviances for each estimate.

We used the following groupings for our multi-species models: domestic animals, ground birds, small mammals, herbivores, omnivores, and carnivores. See Table 2 for MSOM grouping details including species, explanation, and predicted response to distance to cannabis in the occupancy and detection processes.

Table 2. Species groups for multi-species occupancy models. Includes the grouping name, included species, a description of the common features of the group, and hypothesized population-level response to increasing distance from cannabis farms.

Grouping	**Species**	**Description**	**Expected response to cannabis (occupancy, detection)**
Domestic animals (n = 4)	Dog (*Canis lupus familiaris*), Cat (*Felis catus*), Chicken (*Gallus gallus*), Horse (*Equus caballus*)	Domestic species, which are often kept on or nearby cannabis farms	(-,-) expected to be associated with cannabis for space use and intensity of use
Ground birds (n = 3)	California quail (*Callipepla californica*), Mountain quail (*Oreortyx pictus*), Wild turkey (*Meleagris gallopavo*)	Commonly detected bird species in the study area that spend a large portion of their lives on the ground	(+/-, +) depending on sensitivity to disturbance or ability to use new resources on farms, may be variable in space use response to cannabis farming; expected to increase intensity of use further from cannabis farms
Small mammals (n = 5)	Tree squirrels (*Tamiasciurus douglasii* and *Sciurus griseus*), California ground squirrel (*Otospermophilus beecheyi*), Flying squirrel (*Glaucomys sabrinus*), Striped rodents (*Tamias spp.* and *Callospermophilus lateralis*), All other rodents (*Rodentia spp*)	Small (< 1 kg) prey species	(-, +) expected to decrease space use farther from cannabis farms, due to the use of farms as a resource, but expected to increase intensity of use farther from farms due to behavioral shifts around cannabis farms
Herbivores (n = 2)	Black-tailed deer (*Odocoileus hemionus*), Black-tailed jackrabbit (*Lepus californicus*)	Diet classified from Wilman et al., 2014 using the R package traitdata. Classified	(+/-, +) depending on whether they are physically blocked from farms due to fencing or other infrastructure, may or may

		as an herbivore if greater than 75% of diet from plants.	not increase space use with distance to cannabis farms; expected to increase intensity of use farther from farms
Omnivores (n = 7)	spotted skunk (*Spilogale gracilis*) opossum (*Didelphis virginiana*), ringtail (*Bassariscus astutus*), raccoon (*Procyon lotor*), black bear (*Ursus americanus*), striped skunk (*Mephitis mephitis*), gray fox (*Urocyon cinereoargenteus*)	Diet classified from Wilman et al., 2014, if <75% diet from plants, and also >10% of diet from fruit, fish, or invertebrates	(+, -/+) expected to increase space use farther from farms; depending in part on behavioral plasticity or sensitivity to disturbance may have varied intensity of use response
Carnivores (n = 3)	puma (*Puma concolor*), bobcat (*Lynx rufus*), coyote (*Canis latrans*)	Diet classified from Wilman et al., 2014, if diet from plants is 0% and also > 50% diet from vertebrates	(+,+) expected to increase space use and intensity of use farther from farms due to disturbance avoidance

To incorporate a multi-species framework, we added an additional component to the single species model equations where each species parameter was drawn from a community-level distribution for that parameter. This means that for the MSOMs, the species-level occurrence $(\beta 0, \beta 1, \beta 2, \ldots)$ and detection parameters $(\alpha 0, \alpha 1, \alpha 2, \ldots)$ functioned as random effects drawn from community level distributions with "hyper-parameters", where each parameter has a community-level mean (μ) and precision (τ). To do so, we followed the methods outlined in Zipkin et al. (2010).

We fit our models using a Bayesian Markov-chain Monte Carlo (MCMC) method in R using the NIMBLE and nimbleEcology packages (de Valpine et al., 2017; Goldstein et al., 2020). We used weakly informative prior distributions for all parameters (Gelman et al., 2008). Population and species occupancy and detection parameters were calculated from three chains run for 50,000 iterations, thinned by 1. We assessed model convergence by examining trace plots and R-hat values for parameter estimates.

Results

We detected 41 individual non-human species and species groupings (e.g., "bats," "tree squirrels," etc.) for a total of 19,523 detections. We mainly detected common species such as black-tailed deer, jackrabbit, gray fox, turkey, coyote, etc., as well as domestic animals such as dogs, cats, and horses. However, we did document a single sighting of a porcupine (*Erethizon dorsatum*) and a fisher, as well as some other more elusive species such as ringtail (*Bassariscus astutus*) and spotted skunk (*Spilogale gracilis*). We detected humans more frequently than any domestic or wild animal, particularly on and surrounding cannabis farms. Overall, the number of wild species detected at least once at each site was relatively evenly spread across the gradient of distances to cannabis farms (Fig.2). The species we selected for single species modeling were detected relatively frequently and on at least 10% of cameras, aside from bobcats, which were detected on 8% of cameras (Table 3).

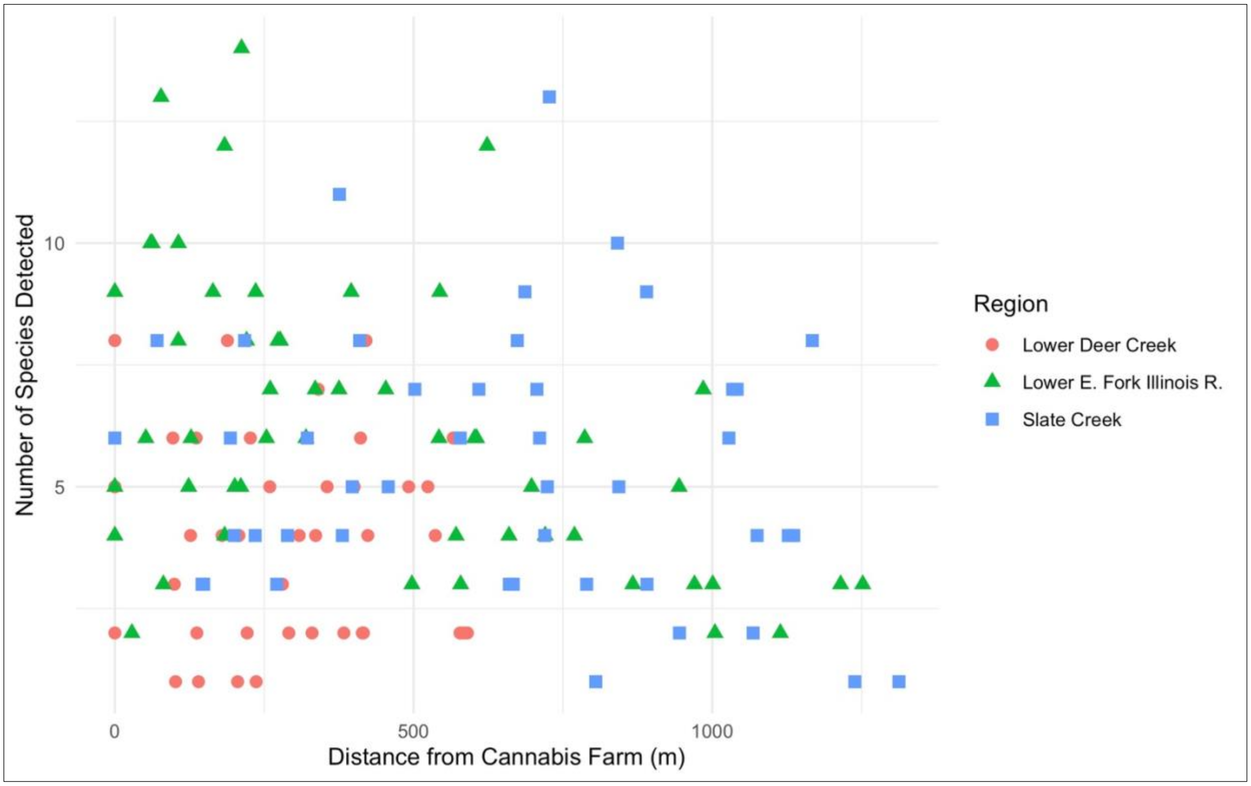


Figure 2. Number of species detected at each camera along the distance gradient from cannabis farms. Cameras are identified by region.

Table 3. Detection rates for species used in single-species occupancy models.

Species	Sites with at least one detection	Proportion of total sites with detections	Total detections
Deer (*O. hemionus*)	121	0.86	820
Tree squirrel (*T. douglasii* and *S. griseus*)	93	0.66	474
Jackrabbit (*L. californicus*)	35	0.25	377
Domestic dog	34	0.24	258
Gray fox (*U. cinereoargenteus*)	56	0.40	236
Striped skunk (*M. mephitis*)	53	0.38	180
Ground squirrel (*O. beecheyi*)	17	0.12	103
Coyote (*C. latrans*)	24	0.17	96
Bear (*U. americanus*)	46	0.33	88
Bobcat (*L. rufus*)	11	0.08	16

Single species models

For the single species occupancy models, occupancy and detection varied by species (Table 4, Fig. 3). Recall that for our models, we are interpreting occupancy as space use, and detection as a combination of detectability and space use intensity (see *Analyses* above) (Nickel et al., 2020; Suraci et al., 2021). Five species had a meaningful space use response to cannabis farms (i.e., their 95% credible interval for distance to cannabis did not overlap zero). Deer and tree squirrel occupancy probability increased with distance from cannabis farms, indicating potential avoidance. Domestic dogs, as expected, decreased in predicted occupancy with distance to cannabis farms. Interestingly, gray fox and ground squirrel occupancy probability also decreased with distance from cannabis farms, indicating that these species may be more likely to be found on and around cannabis farms (Fig. 3).

Six species had a meaningful detection response to cannabis farms (Table 4). As expected, bobcat and ground squirrel detection probability increased with distance from cannabis farms, indicating that they may use areas further from cannabis farms more intensively. For ground squirrels, this implies that although they are more likely to be found closer to cannabis farms, they may use the spaces farther from farms more intensively. Again as expected, domestic dog detection probability decreased with distance from cannabis farms, confirming that they spend most of their time on and surrounding cannabis farms. Surprisingly however, deer, jackrabbit, and striped skunk detection also decreased with distance from cannabis farms. More frequent detections on occupied cannabis farms implies that these species may also be using the space on and surrounding cannabis farms more intensively (Fig. 4).

The other model covariates aside from cannabis also varied by species (Table 4). For a majority of species, at least one regional intercept was meaningfully associated with occupancy probability. Elevation predicted occupancy for coyotes and striped skunks, and forest proportion predicted occupancy for jackrabbits, tree squirrels, and ground squirrels. Distance to highways was the only occupancy covariate that was not credibly non-zero for any species. As for detection, all covariates were meaningful for at least some species. The covariates for detectability, camera type and camera view, were credibly non-zero for four species all together. There was evidence for seasonal effects, with date and date^2 meaningfully predicting detection for a majority of species. The activity indices had meaningful, and somewhat surprising results. Coyotes, bobcats, and tree squirrel detection was negatively associated with human activity, and ground squirrel detection was negatively associated with dog activity. However, coyote, gray fox, and jackrabbit detection probabilities were all positively associated with dog activity.

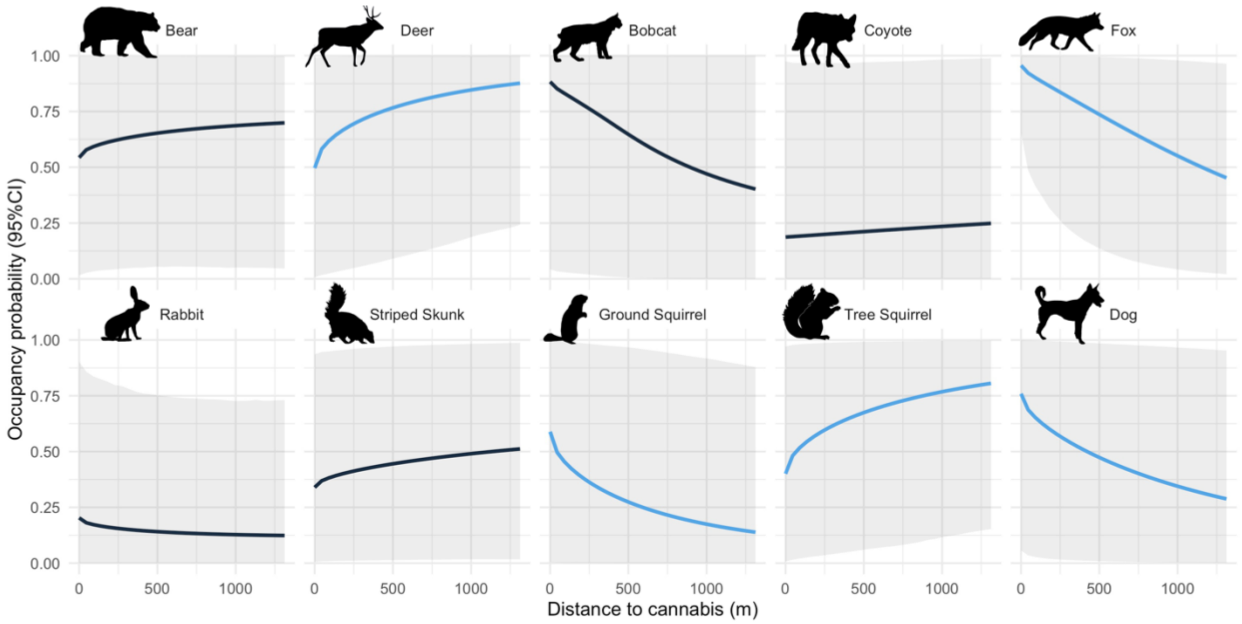


Figure 3. Predicted occupancy probabilities of each single species model to the covariate for distance from cannabis farms. Probabilities correspond to Region 1 with all other covariates held at mean conditions. The gray bars represent the 95% credible interval for the estimated probability. Note that, because we plot absolute occupancy probabilities, credible intervals for predicted occupancy probabilities incorporate uncertainty in the intercept as well as the relationship between distance to cannabis and occupancy (see Table 4 for parameter-specific uncertainties). The species with lines in blue (deer, gray fox, ground squirrels, tree squirrels, and domestic dogs) all had a credibly non-zero response (their 95% credible interval for mean estimate did not overlap zero). Animal silhouettes from phylopic.org.

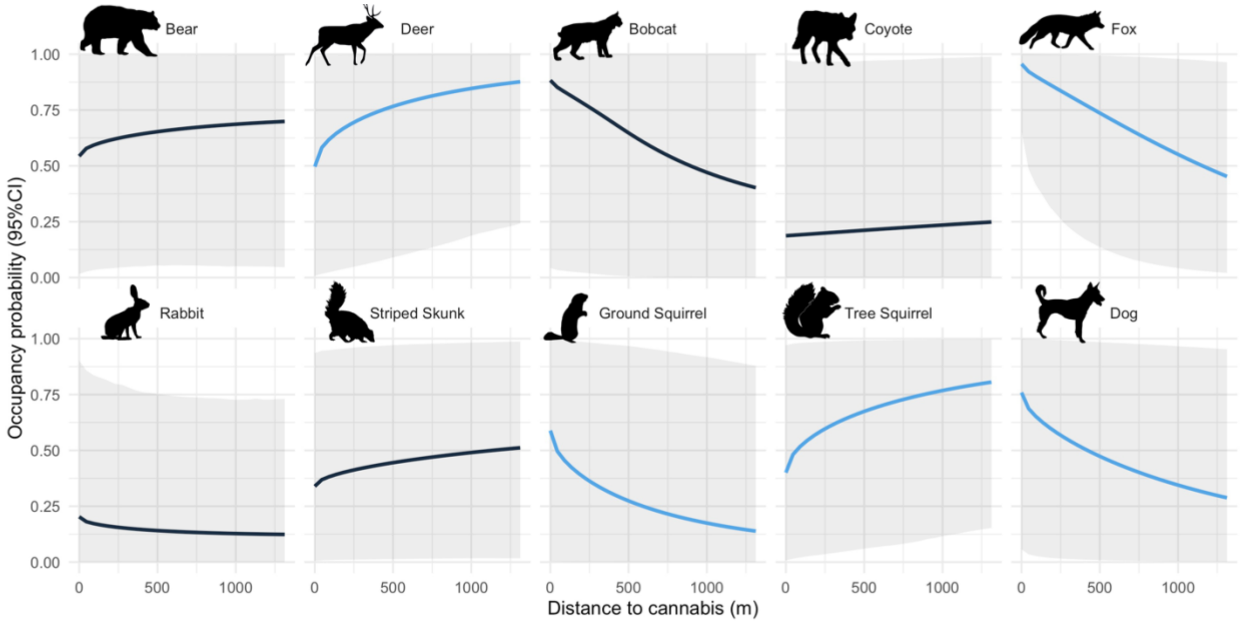


Figure 4. Predicted detection response of each single species model to the covariate for distance from cannabis farms, with all other covariates were held at mean conditions. The gray bars represent the 95% credible interval for the estimated probability. Note that, because we plot absolute occupancy probabilities, credible intervals incorporate uncertainty in the intercept as well as the relationship between distance to cannabis and occupancy (see Table 4 for parameter-specific uncertainties). The species with lines in blue (deer, bobcat, jackrabbit, striped skunk, ground squirrel, and domestic dog) all had a credibly non-zero response (their 95% credible interval did not overlap zero). Animal silhouettes from phylopic.org.

Table 4. Single species occupancy model results, given as estimate means and standard deviations. Cells bolded and with a star (*) indicate that the 95% credible interval for that estimate does not overlap zero. Wild animal species are listed in descending body size order, with domestic dogs at the end.

	Detection Covariates								Occupancy Covariates						
Species	Intercept	Dist. to cannabis	Cam. Type	Cam. View Dist.	Date	Date^2	HAI	DAI	Region 1	Region 2	Region 3	Dist. to cannabis	Elevation	% Forest	Dist. to Highways
black bear (*Ursus americanus*)	**-3.03 (0.34)***	-0.03 (0.16)	-0.35 (0.27)	-0.08 (0.17)	**1.61 (0.34)***	**-1.26 (0.34)***	0.05 (0.55)	-0.22 (0.34)	0.62 (2.5)	-0.72 (3.08)	3.65 (2.89)	0.33 (0.66)	-0.1 (0.86)	-0.11 (0.59)	1.09 (2.22)
black-tailed deer (*Odocoileus hemionus*)	**-0.8 (0.08)***	**-0.19 (0.05)***	-0.17 (0.09)	0.07 (0.04)	**0.21 (0.05)***	**-0.58 (0.06)***	-0.01 (0.03)	-0.06 (0.07)	1.84 (2.37)	**6.02 (2.23)***	-0.99 (1.26)	**0.87 (0.44)***	-0.85 (0.46)	-0.06 (0.31)	-1.87 (1.79)
bobcat (*Lynx rufus*)	**-4.9 (1.38)***	**1.36 (0.57)***	0.17 (0.64)	0.38 (0.34)	0.16 (0.34)	-0.85 (0.76)	**-6.34 (3.67)***	0.44 (0.36)	2.15 (3.82)	-0.73 (4.04)	0.74 (3.06)	-1.94 (1.81)	-1 (1.92)	0.56 (1.8)	-1.59 (2.98)
coyote (*Canis latrans*)	**-1.89 (0.34)***	-0.06 (0.22)	-0.33 (0.3)	**0.49 (0.13)***	**0.91 (0.27)***	**-1.09 (0.54)***	**-0.37 (0.19)***	**0.93 (0.23)***	-3.61 (3.73)	-3.02 (2.97)	**-9.18 (3.02)***	0.26 (0.76)	**-4.66 (1.67)***	-0.13 (0.46)	4.07 (2.65)
gray fox (*Urocyon cinereoargenteus*)	**-2.67 (0.18)***	-0.1 (0.08)	**0.4 (0.17)***	**0.25 (0.08)***	0.04 (0.09)	0.08 (0.11)	-0.12 (0.1)	**0.14 (0.04)***	1.57 (1.85)	**-3.8 (1.92)***	**3.01 (1.29)***	**-1.28 (0.38)***	-0.42 (0.43)	-0.32 (0.26)	2.47 (1.66)

black-tailed jackrabbit (*Lepus californicus*)	**-1.17 (0.16)***	**-0.48 (0.08)***	0.21 (0.16)	**0.13 (0.06)***	**-0.26 (0.12)***	**-0.55 (0.18)***	0.03 (0.04)	**0.36 (0.12)***	-3.29 (2.51)	0.77 (2.47)	**-4.07 (1.59)***	-0.21 (0.49)	-1.15 (0.64)	-1.11 (0.35)*	0.49 (2.13)
striped skunk (*Mephitis mephitis*)	**-1.95 (0.2)***	**-0.44 (0.1)***	-0.14 (0.19)	-0.06 (0.1)	**0.28 (0.13)***	**-0.89 (0.17)***	-0.02 (0.05)	-0.16 (0.11)	-0.26 (1.94)	2.47 (1.9)	**-2.92 (1.21)***	0.31 (0.39)	**-1.64 (0.61)***	-0.42 (0.28)	-1.33 (1.62)
California ground squirrel (*Otospermophilus beecheyi*)	**1.31 (0.39)***	**0.63 (0.21)***	**-2.65 (0.34)***	0.23 (0.14)	**-0.63 (0.24)***	**-1.54 (0.33)***	-0.21 (0.15)	**-0.92 (0.39)***	-1.1 (2.65)	-2.98 (2.67)	**-3.97 (1.81)***	**-1.19 (0.55)***	-1.09 (1.02)	**-1.05 (0.44)***	1.05 (2.32)
tree squirrels (*Sciurus griseus* and *Tamiasciurus douglasii*)	**-1.84 (0.12)***	0 (0.07)	-0.04 (0.11)	-0.04 (0.06)	**0.11 (0.05)***	0.01 (0.07)	**-0.63 (0.33)***	-0.09 (0.08)	0.58 (2.01)	1.49 (2.15)	1 (1.3)	**0.79 (0.39)***	-0.62 (0.43)	**1.28 (0.3)***	-0.65 (1.83)
dog (*Canis lupus familiaris*)	**-2.91 (0.24)***	**-0.39 (0.12)***	0.26 (0.21)	0.2 (0.11)	-0.07 (0.12)	0.01 (0.14)	0 (0.04)	**1.16 (0.1)***	-0.03 (2.18)	-2.28 (2.29)	0.25 (1.34)	**-0.97 (0.43)***	-0.27 (0.52)	-0.08 (0.31)	1.91 (1.93)

Table 5. Multispecies occupancy model results. Bolded cells with a star (*) indicate that the 95% credible interval for that estimate does not overlap zero.

Species Groups	**Occupancy covariates (population)**							**Detection covariates (population)**							
	R1	R2	R3	Cann.	Elev.	Forest	Hwys	Intcpt	Cann.	Type	View	Date	Date^2	HAI	DAI
Carnivores	0.84 (3.87)	-0.32 (3.75)	0.01 (3.83)	-0.72 (2.08)	-2.29 (2.89)	1.63 (2.53)	-0.57 (3.46)	-3.71 (2.38)	0.22 (1.25)	0.17 (1.16)	0.53 (0.8)	0.25 (1.16)	-0.52 (1.06)	-1.47 (2.49)	0.36 (1.09)
Omnivores	0.1 (1.96)	-3.19 (1.85)	-0.75 (1.73)	-0.16 (0.51)	-0.47 (0.59)	-0.2 (0.19)	1.3 (1.35)	**-3.08 (0.54)***	-0.33 (0.35)	0.12 (0.27)	0.03 (0.16)	0.12 (0.53)	-0.64 (0.44)	-0.07 (0.15)	-0.05 (0.3)
Herbivores	-1.38 (3.22)	3.4 (3.28)	-2.39 (2.86)	0.35 (2.03)	-0.76 (1.84)	-0.49 (2)	-1.61 (2.74)	-0.85 (1.73)	-0.3 (1.73)	0.01 (1.72)	0.1 (1.38)	-0.02 (1.81)	-0.52 (1.48)	0.01 (1.4)	0.13 (1.75)
Small mammals	0.67 (2.08)	-2.79 (2.49)	-0.36 (1.72)	0.11 (1.15)	-0.89 (0.75)	0.98 (1.52)	1.2 (1.89)	-3.59 (2.38)	0.49 (0.59)	-0.21 (1.24)	-1.79 (1.76)	-0.67 (0.82)	-1.13 (1.31)	-0.23 (0.74)	-0.46 (0.66)
Ground birds	-1.98 (2.99)	-0.46 (3.08)	-1.24 (3.31)	2.22 (2.14)	-0.46 (2.9)	-0.11 (1.51)	-0.08 (2.91)	-3.57 (2.32)	-1.22 (1.6)	0.17 (1.33)	0.32 (1.24)	0.14 (0.66)	0.32 (1.42)	0.68 (1.39)	-0.52 (1.66)
Domestic animals	-2.44 (2.98)	-3.85 (2.86)	-1.25 (2.38)	-0.99 (1.37)	-0.68 (1.48)	-0.19 (0.66)	1.91 (2.3)	**-3.17 (1)***	-0.83 (1.18)	0.2 (0.83)	0.3 (0.54)	0.61 (0.99)	-1.18 (1.75)	-0.11 (0.52)	0.42 (0.74)

Multi-species models

For the multi-species occupancy models, almost no population-level parameters were meaningful (95% credible intervals did not overlap zero) (Table 5; see Appendix 1 for modeled standard deviations). No group meaningfully responded to cannabis in either detection or occupancy processes. No covariates were meaningful for occupancy or detection at the population level, aside from omnivore detection intercept. However, there was more variation at the species level (Appendix 2-7). For the species that also had single species model results, the MSOM results largely matched, with occasional changes in credibility. For instance, for the deer SSOM, date and date^2 were not credibly non-zero, but in the MSOM they were, even though the actual estimated values were similar in both (Appendix 5).

Despite the lack of population-level associations, some groups did have common responses to cannabis at the species level. For example, the occupancy probability for all ground bird species was credibly positive, increasing with distance from cannabis farms, which implies possible spatial avoidance of cannabis farms (Appendix 3). For all ground bird species and both herbivore species, detection probability credibly decreased with increasing distance from cannabis farms, which may imply that these groups use areas around farms more intensively (Appendix 5). Domestic species largely responded as predicted at the species level: cat and dog occupancy decreased with distance to cannabis, and dog and horse detection decreased with distance from cannabis (Appendix 2). The other groupings were more mixed. Carnivores largely did not respond meaningfully to cannabis in either detection or occupancy (Appendix 7). Omnivores had slightly more sensitivity, with three out of seven species responding meaningfully to cannabis in either occupancy or detection (fox occupancy probability decreased with distance to cannabis, and raccoon and striped skunk detection probability decreased with distance to cannabis) (Appendix 6). For small mammals, tree squirrels and ground squirrels had opposite occupancy responses, and only ground squirrels had a credibly non-zero detection response (Appendix 4).

Discussion

This study assessed wildlife space use responses to active small-scale outdoor cannabis farms on private land. Our work provides a timely baseline for understanding potential wildlife community consequences from an emerging land use frontier. Our application of occupancy modeling to space use responses has yielded two main conclusions: 1) even at small scales, rural cannabis farming can affect local wildlife space use; 2) patterns of animal space use responses are species-specific, but there may be common patterns for herbivores, ground birds, and some mesopredators in how they use spaces near to cannabis farms. These results have implications for the cannabis industry and small farm strategies for conservation.

Overall cannabis farm effects

Eight out of ten species modeled individually had a meaningful response to distance from cannabis farms, either in occupancy or detection. Although the population-level means were not meaningful, at an individual level, 13 out of 24 of the species included in multi-species models had a meaningful response to distance from cannabis farms, either in occupancy or detection. Our hypothesis that a majority of species would avoid farms was not supported, since the strength and direction of effects were species-specific. However, the results imply a general ability for cannabis farming to affect local wildlife space use. The relationships between occupancy and detection probabilities and distance to cannabis also indicate that there could be threshold effects relatively close to farms where the slope of the relationship is steeper (Fig. 3; Fig.4), though further steps would be needed to confirm this relationship.

These results are in contrast with research from the western US on vineyards and avocado production that indicates the ability of some wildlife to use farmed land in seeming preference over surrounding land uses (Hilty & Merenlender, 2004; Nogeire et al., 2013). However, these other studies were conducted in areas where the agricultural land formed a corridor through more human-dominated land covers, which is the inverse of the landscape studied here. Our results are similar to studies on agroforestry systems with annual and perennial croplands, where there may be differential responses to agricultural land use and potential for filtering responses (Brashares, 2010; Ferreira et al., 2018).

Compared to the other covariates in the models, distance to cannabis farms meaningfully affected more species than any other single covariate other than the intercepts, or *Date* and $Date^2$. It was particularly surprising that wildlife responded to the physical land use of cannabis farms even more than human or dog activity, given that in other systems their space use intensity often responds more to human activity than human footprint (Nickel et al. 2020), and is often negatively affected by the presence of dogs (Reilly et al., 2017). This implies that cannabis farms may combine multiple potential sources of disturbance that wildlife may react to, and/or that the physical modifications for cannabis farms on their own are enough to trigger wildlife responses. More research is needed to disentangle some of the potential mechanistic pathways by which cannabis farms may affect wildlife.

Space use patterns

Overall, space use responses to cannabis were species-specific, confirming our alternative hypothesis for individual responses. While functional- or diet-group patterns are not as clear in this case as in other study systems (e.g., Ferreira et al., 2018; Rich et al., 2016), a few general patterns may be emerging, specifically in regard to herbivores/ground birds, and mesopredators. Our approach of using an occupancy modeling framework to assess wildlife space use associations was useful to identify some of these emerging patterns, because it allowed us to look at space use, separately from inferences on space use intensity (although we acknowledge that these are more difficult to disentangle from detectability). This is important because it helps capture different types of responses: attraction and deterrence, as well as potential behavioral shifts in activity patterns (Nickel et al., 2020; Neilson et al., 2018; Burton et al., 2015). For example, this helped identify opposing occupancy and detection responses from some herbivore and ground bird species.

For medium to large herbivores and ground birds (deer, jackrabbits, California quail, mountain quail, and turkey), occupancy (i.e., space use, see *Analyses*) credibly increased with distance from cannabis farms, while detection (i.e., space use intensity and detectability) credibly decreased. This is the inverse of our alternative hypothesis that species using cannabis farms would decrease their activity intensity near to cannabis and suggests that while these species may generally avoid cannabis farms in space (or, in the case of deer, are often physically blocked from accessing them due to fencing), the few areas that they do use, they may use more intensively. If this pattern is indeed driven by space use intensity, there are many possible explanations— for instance, perhaps these species, in an attempt to avoid cannabis farms, end up concentrated in smaller areas. The results for deer are at least partially consistent with other studies that indicate they generally have a neutral occupancy response to human presence and footprint, but have an increased intensity of use response (Suraci et al., 2021).

Another potential emerging pattern is the possible behavioral flexibility of some mesopredator/omnivore species, lending limited support to our alternative hypothesis that omnivores would display greater variation in space use responses. While less consistent across all omnivores than the pattern with herbivores and ground birds above, gray fox, striped skunk, and raccoons all displayed different potential ability to use the space on and nearby cannabis farms. Fox occupancy probability decreased with distance to cannabis, implying a potential attraction to cannabis farms. Raccoon (as part of the MSOM) and striped skunk detection probability decreased with distance to cannabis, implying that they may have a higher space use intensity near to cannabis farms. This is consistent with other studies that demonstrate that these species are often behaviorally flexible and able to coexist in human-dominated spaces (Suraci et al., 2021; Nogeire et al., 2013). This association with mesopredator use of human spaces is also often explained via mesopredator release, when larger predators avoid an area of disturbance and thereby open a niche for smaller predators (Prugh et al., 2009). What is interesting is that in this case, however, our alternative hypothesis that carnivores would avoid farms was not supported, and predators largely did not respond to cannabis. Bear and coyote occupancy and detection did not respond to cannabis, and although puma did not have enough detections to include in the single species models, one was photographed in the middle of one of our study farms. Bobcat detection probability did increase with distance from cannabis farm but did not have a meaningful occupancy response. In fact, all four of these large predators were photographed at least once in the middle of a cannabis farm (Appendix 8).

Also interesting is that there was not a clear pattern of response for small mammal species that might be prey for the mesopredators. Unlike our alternative hypothesis that predicted a general attraction for all small mammals to cannabis farms, tree squirrels and ground squirrels had opposing responses. Tree squirrel occupancy increased with detection from cannabis farms, indicating avoidance, while ground squirrel occupancy decreased. For ground squirrels, our models suggest that while they are frequently found near cannabis farms, their space use intensity may be lower closer to farms. Again, there may be multiple reasons for this, but one possibility is that cannabis farms are being developed on ideal ground squirrel habitat, and while the squirrels have not yet relocated away from the farms, they are not as active on these sites due to the disturbance associated with the farms. Alternatively, cannabis farms may be creating new habitat for ground squirrels by clearing vegetation and irrigating the land, and the lower detection may simply reflect lower population densities as fewer individuals have discovered the new sites. It would be interesting to see whether these patterns change over time.

Limitations

This study has many limitations that are important to acknowledge. First, cannabis production comes in many forms in different locations, and this study does not represent all of them. This study is most applicable for small-scale and mixed light outdoor cannabis cultivation occurring on private lands in legacy production regions of the rural Western US. It is very likely that larger farms would have a greater impact on wildlife than those included in this study, or that farms developed in areas with existing agriculture might have less, or different kinds of effects. Because cannabis production is often unique from other forms of agriculture, these types of observational studies are valuable and merit repeating in different contexts.

Next, we recognize we are applying occupancy modeling for a purpose that it was not directly designed for, and in doing so, we are violating multiple assumptions of the model. The use of occupancy modeling to assess space use relationships is increasingly common in wildlife studies (Nickel et al., 2020; Suraci et al.. 2021), and we have done our best to account for the violation of assumptions in our modeling approach. Ultimately, we have confidence in our results. For example, we included domestic dogs because their space use patterns are already well understood on the landscape. That the models reflect our understanding of reality on the ground for this domestic species gives us confidence in the results for the unknown wild species.

One major limitation of our approach to interpreting detection as a combination of detectability and space use intensity is that the two are not entirely separable. We have included covariates that we believe address one aspect more than the other, but there could be unaccounted for detectability variables that confound our interpretation of space use intensity. More caution should therefore be taken when interpreting the detection results compared to the occupancy results. Future studies might be able to help disentangle some of these effects by examining temporal activity patterns of wildlife (Gaynor et al., 2018) in addition to space use intensity.

Finally, these data are all observational, and therefore cannot address specific mechanisms by which cannabis may affect local wildlife. Future studies isolating potential mechanisms of deterrence and attraction would help elucidate some of the species-specific behaviors documented in this study (see Chapter 4).

Conclusions

The results of our study hold implications for conservation and cannabis. We find evidence for on-site overlap between small scale outdoor cannabis farms and local wildlife. The negative detection responses of many species to cannabis farms suggests that some animals may be using the farms regularly for rest and forage. This emphasizes the importance of best management practices on-site for cannabis farms to ensure that this overlap does not result in harm to wildlife. This would be an opportunity for future research to study the long-term population effects on wildlife that share space with cannabis production. It is important to acknowledge that some of this wildlife overlap may not be beneficial for farmers, however. Some of the species with higher occupancy or detection rates close to farms, such as turkeys, ground squirrels, and deer, may also cause crop damage for farmers. Balancing coexistence with livelihoods will be as important for the cannabis industry as it is with any small scale agriculture seeking to minimize local impacts (Crespin & Simonetti, 2019).

On the other hand, our results also demonstrate a broad ability for cannabis agriculture to influence local wildlife. While the implied indirect effects from cannabis farming on wildlife are, by and large, not extreme, it emphasizes the importance of land use planning for cannabis development, as even small disturbances in relatively undeveloped rural areas may have an effect on local wildlife communities. This is valuable information, as efforts to formulate appropriate regulation, best management practices, or wildlife friendly certifications for cannabis are still ongoing. More research is needed on this rapidly changing agricultural frontier, but we hope that our research here may offer small insights into an ecologically uncertain industry.

Supplement to Chapter 3:

Appendix 1. Multi-species occupancy model results for population standard deviations. Cells bolded and with a star (*) indicate that the 95% credible interval for that estimate does not overlap zero.

Groups	**Occupancy covariates (population)**							**Detection covariates (population)**							
	R1	R2	R3	Cann.	Elev.	Forest	Hwys	Intcpt.	Cann.	Type	View	Date	Date^2	HAI	DAI
Carnivores	**6.17 (2.69)***	**4.14 (2.77)***	**7.95 (1.6)***	**3.03 (2.37)***	**4.07 (2.64)***	**4.05 (2.56)***	**4.97 (2.64)***	**4.3 (2.19)***	**1.74 (1.78)***	**1.49 (1.66)***	**0.89 (1.32)***	**1.59 (1.69)***	**1.29 (1.54)***	**4.04 (2.93)***	**4.3 (2.19)***
Omnivores	**3.36 (2.36)***	**3.33 (1.75)***	**3.9 (1.83)***	**0.91 (0.61)***	**1.07 (0.76)***	**0.24 (0.23)***	**1.56 (1.27)***	**1.05 (0.65)***	**0.71 (0.41)***	**0.45 (0.34)***	**0.25 (0.19)***	**1.2 (0.59)***	**0.92 (0.49)***	**0.16 (0.22)***	**1.05 (0.65)***
Herbivores	**5.18 (2.56)***	**4.91 (2.67)***	**4.5 (2.56)***	**2.86 (2.45)***	**2.36 (2.42)***	**2.85 (2.43)***	**3.66 (2.67)***	**2.17 (2.37)***	**2.21 (2.36)***	**2.2 (2.36)***	**1.45 (2.08)***	**2.41 (2.35)***	**1.65 (2.18)***	**1.48 (2.15)***	**2.17 (2.37)***
Small mammals	**2.6 (2.2)***	**4.48 (2.34)***	**3.03 (1.82)***	**1.88 (1.46)***	**0.87 (1.07)***	**2.83 (1.92)***	**2.67 (2.05)***	**5.74 (1.89)***	**0.85 (0.83)***	**2.49 (1.37)***	**3.86 (1.85)***	**1.43 (1.06)***	**2.61 (1.6)***	**0.92 (1.14)***	**5.74 (1.89)***
Ground birds	**3.78 (2.68)***	**4.63 (2.61)***	**6.23 (2.13)***	**3.35 (2.44)***	**5.67 (2.14)***	**2.18 (1.95)***	**4.27 (2.62)***	**4.14 (2.2)***	**2.56 (1.99)***	**1.94 (1.78)***	**1.83 (1.7)***	**0.66 (1.07)***	**2.03 (1.95)***	**1.73 (2.04)***	**4.14 (2.2)***

Appendix 2. Multi-species occupancy model results for domestic animals. Cells bolded and with a star (*) indicate that the 95% credible interval for that estimate does not overlap zero.

Species	**Occupancy covariates**							**Detection covariates**							
	R1	R2	R3	Cann.	Elev.	Forest	Hwys	Intcpt.	Cann.	Type	View	Date	Date^2	HAI	DAI
dog (*Canis lupus familiaris*)	-0.01 (2.32)	-2.4 (2.42)	0.18 (1.39)	**-0.97 (0.41)***	-0.32 (0.5)	-0.11 (0.26)	1.99 (2.03)	**-2.93 (0.23)***	**-0.4 (0.12)***	0.27 (0.2)	0.2 (0.1)	-0.05 (0.12)	0.03 (0.13)	0 (0.04)	**1.15 (0.1)***
cat (*Felis catus*)	-2.05 (2.63)	-3.67 (2.64)	-1.93 (1.71)	**-2.27 (0.8)***	-0.74 (0.88)	-0.37 (0.45)	2.1 (2.24)	**-3.2 (0.39)***	0.06 (0.21)	0.24 (0.27)	0.03 (0.15)	0.15 (0.15)	**0.61 (0.17)***	-0.11 (0.14)	0.07 (0.06)
chicken (*Gallus gallus*)	-6.23 (5.4)	**-9.29 (5.26)***	-0.27 (4.27)	-1.03 (1.87)	-1.63 (2.98)	-0.18 (0.91)	1.09 (3.01)	**-3.98 (1.88)***	-1.13 (1.32)	0.75 (1.08)	0.57 (0.77)	1.52 (1.28)	-3.15 (1.84)	-0.42 (1.09)	-0.13 (0.31)
horse (*Equus caballus*)	-4.56 (5.05)	-4.15 (3.24)	-3.94 (4.27)	0.07 (1.14)	-0.33 (2.39)	-0.13 (0.45)	3.24 (2.78)	**-3.08 (0.55)***	**-2.05 (0.59)***	-0.43 (0.4)	**0.43 (0.21)***	0.95 (0.57)	**-2.93 (1.03)***	0.05 (0.16)	**0.63 (0.31)***

Appendix 3. Multi-species occupancy model results for ground birds. Cells bolded and with a star (*) indicate that the 95% credible interval for that estimate does not overlap zero.

Species	**Occupancy covariates**							**Detection covariates**							
	R1	R2	R3	Cann.	Elev.	Forest	Hwys	Intcpt.	Cann.	Type	View	Date	Date^2	HAI	DAI
California quail (*Callipepla californica*)	-4.31 (4.86)	1.16 (4.16)	-3.55 (5.43)	**3.96 (2.86)***	-2.49 (3.53)	-0.37 (1.34)	2.66 (4.07)	**-6.69 (1.23)***	**-2.52 (0.81)***	0.03 (0.76)	**0.64 (0.33)***	0.13 (0.36)	1.36 (1.15)	0.55 (0.27)	0.09 (0.42)
mountain quail (*Oreortyx pictus*)	-2 (3.33)	-3.94 (4.06)	3.99 (3.35)	**3.29 (1.94)***	**4.32 (2.21)***	-0.63 (0.8)	-2.76 (3.2)	**-4.52 (0.9)***	**-1.21 (0.39)***	0.9 (0.52)	**0.76 (0.2)***	0.14 (0.19)	-0.15 (0.29)	1.16 (2.06)	-1.88 (2.8)
wild turkey (*Meleagris gallopavo*)	-1.37 (2.52)	0.88 (2.52)	**-5.92 (1.84)***	**0.98 (0.47)***	**-3.73 (1.09)***	**0.63 (0.31)***	-0.01 (2.23)	**-2.14 (0.3)***	**-0.38 (0.18)***	-0.37 (0.31)	**-0.4 (0.14)***	0.17 (0.14)	-0.1 (0.19)	**0.56 (0.24)***	-0.18 (0.21)

Appendix 4. Multi-species occupancy model results for small mammals. Cells bolded and with a star (*) indicate that the 95% credible interval for that estimate does not overlap zero.

Species	**Occupancy covariates**							**Detection covariates**							
	R1	R2	R3	Cann.	Elev.	Forest	Hwys	Intcpt.	Cann.	Type	View	Date	Date^2	HAI	DAI
tree squirrels (*Tamiasciurus douglasii* and *Sciurus griseus*)	1.57 (1.7)	0.33 (1.89)	1.49 (1.21)	**0.71 (0.36)***	**-0.71 (0.35)***	**1.24 (0.29)***	0.31 (1.57)	**-1.83 (0.12)***	0.02 (0.07)	-0.04 (0.11)	-0.03 (0.06)	**0.11 (0.05)***	0.01 (0.07)	-0.47 (0.3)	-0.11 (0.08)
California ground squirrel (*Otospermophilus beecheyi*)	0.21 (1.99)	-4 (2.2)	-2.77 (1.58)	**-1.06 (0.53)***	-0.94 (0.63)	**-0.97 (0.4)***	2.09 (1.83)	**1.22 (0.38)***	**0.58 (0.2)***	**-2.56 (0.33)***	0.23 (0.14)	**-0.6 (0.24)***	**-1.54 (0.32)***	-0.21 (0.15)	**-0.69 (0.37)***
flying squirrel (*Glaucomys sabrinus*)	0.44 (4.06)	-2.39 (4.81)	-0.86 (3)	0.5 (2.46)	-0.77 (1.38)	3.48 (3.22)	2.21 (3.17)	**-9.22 (2.11)***	0.53 (0.89)	-0.64 (1.39)	**-2.65 (1.61)***	-1.04 (1)	-0.3 (0.97)	-0.37 (1.4)	-0.7 (1.13)
striped rodents (*Tamias spp.* and *Callospermophilus lateralis*)	0.25 (4.07)	-7.24 (4.75)	0.34 (1.98)	-0.01 (1.86)	-1.32 (1.29)	2.03 (1.92)	-0.27 (3.27)	**-9.3 (2.73)***	1.01 (1)	1.16 (1.27)	**-6.43 (1.89)***	**-1.88 (0.9)***	**-4.05 (1.71)***	-0.25 (1.52)	-0.57 (1.23)
all other rodents (*Rodentia spp*)	0.97 (1.65)	**-3.45 (1.79)***	-0.17 (1.09)	0.46 (0.43)	**-0.8 (0.38)***	-0.2 (0.29)	2.11 (1.47)	**-3.86 (0.34)***	0.34 (0.21)	**0.95 (0.29)***	**-1.31 (0.27)***	-0.01 (0.16)	-0.2 (0.19)	0.12 (0.31)	-0.31 (0.29)

Appendix 5. Multi-species occupancy model results for herbivores. Cells bolded and with a star (*) indicate that the 95% credible interval for that estimate does not overlap zero.

Species	**Occupancy covariates**							**Detection covariates**							
	R1	R2	R3	Cann.	Elev.	Forest	Hwys	Intcpt.	Cann.	Type	View	Date	Date^2	HAI	DAI
Black-tailed deer (*Odocoileus hemionus*)	0.81 (2.89)	**7.22 (2.54)***	-1.65 (1.38)	**0.9 (0.44)***	**-0.8 (0.43)**	-0.13 (0.32)	-2.86 (1.99)	**-0.81 (0.09)***	**-0.19 (0.05)***	-0.16 (0.09)	0.07 (0.04)	**0.21 (0.05)***	**-0.58 (0.06)***	-0.01 (0.03)	-0.06 (0.07)
Black-tailed jackrabbit (*Lepus californicus*)	-5.04 (2.74)	2.8 (2.7)	**-5.13 (1.8)***	-0.07 (0.49)	-0.97 (0.58)	**-1.05 (0.35)***	-1.27 (2.3)	**-1.12 (0.15)***	**-0.48 (0.08)***	0.18 (0.16)	**0.13 (0.06)***	**-0.25 (0.12)***	**-0.57 (0.16)***	0.02 (0.04)	**0.35 (0.12)***

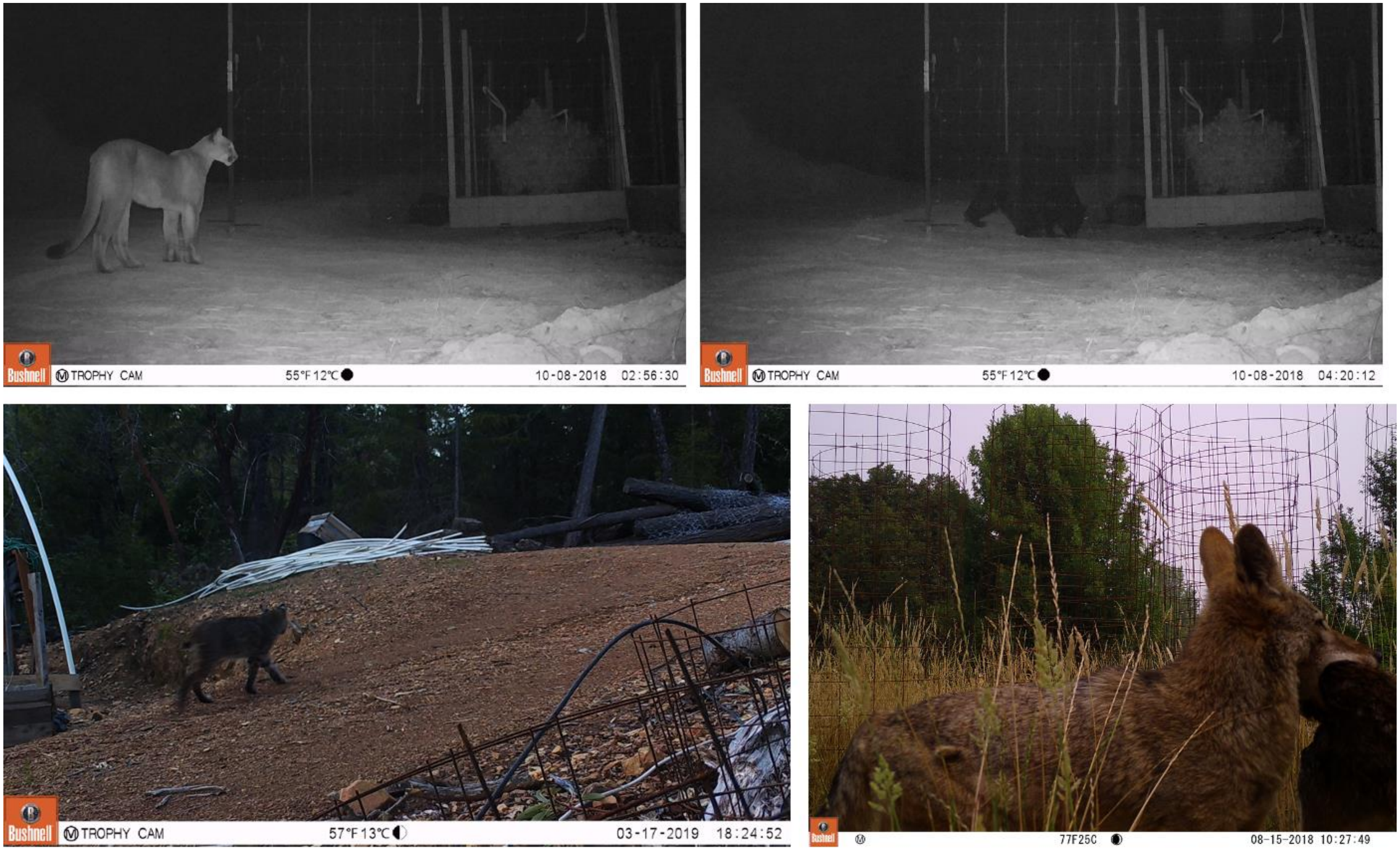
Appendix 6. Multi-species occupancy model results for omnivores. Cells bolded and with a star (*) indicate that the 95% credible interval for that estimate does not overlap zero.

Species	**Occupancy covariates**							**Detection covariates**							
	R1	R2	R3	Cann.	Elev.	Forest	Hwys	Intcpt.	Cann.	Type	View	Date	Date^2	HAI	DAI
spotted skunk (*Spilogale gracilis*)	1.34 (3.58)	**-6.76 (3.56)***	-0.35 (2.49)	-0.26 (0.92)	0.27 (0.99)	-0.12 (0.33)	0.58 (1.99)	**-4.09 (1.13)***	-0.32 (0.63)	0.24 (0.52)	-0.07 (0.3)	**-1.11 (0.61)***	-0.97 (0.63)	-0.08 (0.26)	-0.16 (0.57)
opossum (*Didelphis virginiana*)	2.51 (3.53)	**-4.45 (2.21)***	-2.54 (1.93)	-0.5 (0.93)	-0.57 (0.87)	-0.29 (0.31)	0.83 (1.61)	**-3.74 (0.74)***	0.19 (0.51)	0.01 (0.41)	0.09 (0.24)	0.77 (0.64)	**-1.22 (0.61)***	-0.11 (0.32)	-0.24 (0.6)
ringtail (*Bassariscus astutus*)	-2.86 (3.97)	**-5.01 (2.18)***	-1.09 (1.59)	0.21 (0.67)	0.12 (0.77)	-0.14 (0.27)	1.52 (1.68)	**-3.22 (0.73)***	-0.45 (0.57)	0.37 (0.5)	-0.08 (0.32)	-0.64 (0.55)	-0.78 (0.55)	-0.08 (0.31)	-0.09 (0.66)
raccoon (*Procyon lotor*)	-3.13 (3.83)	-3.44 (2.36)	**-5.55 (3.3)***	0.14 (0.57)	-1.13 (0.95)	-0.16 (0.24)	2.6 (2.08)	**-2.98 (0.42)***	**-1.15 (0.41)***	0.07 (0.28)	0.13 (0.18)	0.04 (0.29)	0.3 (0.58)	-0.07 (0.12)	0.24 (0.25)

black bear (*Ursus americanus*)	0.84 (1.64)	-1.81 (1.79)	2.82 (2.37)	0.31 (0.45)	-0.24 (0.51)	-0.15 (0.22)	1.54 (1.45)	**-3.01 (0.29)***	-0.04 (0.15)	-0.19 (0.25)	-0.02 (0.14)	**1.47 (0.29)***	**-1.09 (0.29)***	-0.05 (0.19)	-0.09 (0.24)
striped skunk (*Mephitis mephitis*)	1.18 (1.66)	-0.05 (1.66)	-1.16 (1.08)	-0.06 (0.32)	**-1.32 (0.54)***	-0.28 (0.19)	0.59 (1.41)	**-2.07 (0.2)***	**-0.42 (0.1)***	-0.01 (0.18)	-0.02 (0.09)	**0.3 (0.12)***	**-0.81 (0.16)***	-0.03 (0.05)	-0.11 (0.11)
gray fox (*Urocyon cinereoargenteus*)	0.8 (1.47)	-2.73 (1.54)	**2.13 (1.06)***	**-0.99 (0.36)***	-0.47 (0.37)	-0.27 (0.19)	1.63 (1.31)	**-2.63 (0.18)***	-0.12 (0.08)	**0.34 (0.17)***	**0.21 (0.08)***	0.03 (0.09)	0.08 (0.11)	-0.08 (0.08)	**0.13 (0.04)***

Appendix 7. Multi-species occupancy model results for carnivores. Cells bolded and with a star (*) indicate that the 95% credible interval for that estimate does not overlap zero.

Species	**Occupancy covariates**							**Detection covariates**							
	R1	R2	R3	Cann.	Elev.	Forest	Hwys	Intcpt.	Cann.	Type	View	Date	Date^2	HAI	DAI
puma (*Puma concolor*)	5.6 (6.62)	0.97 (5.43)	**9.15 (5.62)***	-1.55 (2.43)	-1.68 (4.4)	4.46 (3.69)	-3.05 (4.91)	**-6.7 (1.03)***	-0.18 (0.43)	0.59 (0.79)	0.77 (0.33)*	-0.19 (0.39)	-0.21 (0.52)	-0.32 (1.16)	-0.06 (0.31)
bobcat (*Lynx rufus*)	4.16 (6.42)	0.03 (5.26)	3.75 (6.23)	-1.43 (2.4)	-1.64 (3.07)	2.19 (2.93)	-2.84 (4.49)	**-5.29 (1.25)***	0.91 (0.6)	0.17 (0.51)	0.38 (0.26)	0.21 (0.3)	-0.63 (0.55)	-5.82 (5.71)	0.33 (0.38)
coyote (*Canis latrans*)	-5.27 (5.65)	-1.77 (4.18)	**-12.59 (5.12)***	0.22 (0.84)	**-4.89 (2.1)***	0.02 (0.51)	3.04 (3.72)	**-2.04 (0.33)***	-0.02 (0.21)	-0.21 (0.3)	**0.5 (0.12)***	**0.77 (0.27)***	-0.77 (0.48)	**-0.35 (0.18)***	**0.86 (0.23)***



Appendix 8. Examples of predators photographed on cannabis farms. Clockwise from top left: puma (*Puma concolor*), black bear (*Ursus americanus*), coyote (*Canis latrans*), bobcat (*Lynx rufus*).

Chapter 4

Designing experimental field trials for multi-species responses to anthropogenic light and noise

Abstract

Outdoor, mixed light, and greenhouse cannabis production present a particular concern for environmental impacts because of their use of bright lights and loud equipment, and history of production in biodiverse areas. This paper outlines the methods and study design to monitor multi-taxa wildlife response to light and noise disturbance in experimental field trials that mimic disturbance from cannabis farms. I detail our study approach and monitoring installation and then present preliminary summary data from one season of sampling. These results are presented only as an example of the data formats and potential analyses associated with the diversity of monitoring methods I employed. More data needs to be collected, sorted, and analyzed before conclusions regarding wildlife response to noise and light can be reached, but the methodology and preliminary results are promising in that they indicate an pathway to quantify relationships and response thresholds across a breadth of taxonomic groups.

Introduction

Understanding the pathways by which wildlife respond to disturbance is critical for mitigating the impacts of anthropogenic change (Blickley & Patricelli, 2010; Suraci et al., 2021). It is well understood that wildlife respond to human disturbance in complex ways, which can have individual, population, and community effects (Frid & Dill, 2002; Gaynor et al., 2018; Suraci et al., 2021). To piece apart these complex interactions, it can be useful to isolate particular sources of disturbance and their effects on wildlife.

Two sources of disturbance that have been identified as major anthropogenic drivers of wildlife behavioral change are light and noise pollution. Artificial light at night is an increasing global phenomenon, with the coverage of outdoor areas illuminated by artificial light increasing by 2.2% per year (Kyba et al., 2017). This global increase in light can have far ranging consequences across taxa, including by causing animal disorientation, and by disrupting behavior or interactions (Aulsebrook et al., 2020; Longcore & Rich, 2004). Noise pollution has been less studied than light pollution, however, the effects of noise on wildlife are also global, and may have individual, population, and community level impacts including disrupted reproductive signaling or prey vigilance, and added cumulative stress (Aulsebrook et al., 2020; Blickley & Patricelli, 2010; Shannon et al., 2016; Shilling et al., 2018).

Controlled experiments provide a powerful tool for exploring causal relationships between disturbance sources, such as light and sound, and wildlife responses (Blickley & Patricelli, 2010; Suraci et al., 2017). Experiments on noise and light effects are typically focused on individual species or taxa, but field experiments in particular offer an opportunity to study interactive effects of noise and light pollution (Blickley & Patricelli, 2010). However, this approach is largely under-utilized, due to the logistical challenges of implementing such studies (Blickley & Patricelli, 2010).

Here, I describe an experimental approach to studying the separate and interactive effects of point source noise and light pollution on multi-taxa wildlife communities. Specifically, my approach applies a comprehensive experimental design to understand the effects of noise and light pollution commonly associated with cannabis farming.

Recreational cannabis production in the western United States has been increasing rapidly following state-level legalization (see Chapters 1 and 2) (Butsic & Brenner, 2016; Butsic et al., 2018). Influenced by its illicit history, outdoor cannabis is often grown in remote and biodiverse regions with minimal other non-timber agriculture (see Chapters 1 and 2) (Corva, 2014; Butsic & Brenner 2016; Butsic et al., 2018). In these legacy systems, the proximity of cannabis to wilderness areas may lead to unusual disturbance patterns associated with cannabis cultivation where relatively small point source disturbances are surrounded by a matrix of more intact vegetation (see Chapter 1) (I. Wang et al., 2017). Outdoor and mixed light cannabis farming presents a particular concern for environmental impacts because of their use of bright lights and loud equipment such as generators and fans (Rich, Baker, et al., 2020; Rich, Ferguson, et al., 2020). Observational research indicates that cannabis production is likely to affect wildlife space use (see Chapter 3). However, current research has not distinguished between sources of disturbance on cannabis farms, which is critical for designing appropriate interventions, including policy, to mitigate the effect of these disturbances.

In this study, I designed and implemented an experiment to investigate the individual and combined effects of light and noise from cannabis farms on local wildlife. I was particularly interested in the impact of new developing farms in rural areas. To approach this question, I designed a series of experimental field trials that mimic light and sound disturbance from outdoor, greenhouse, and mixed light cannabis production, and a monitoring array to measure resulting wildlife responses.

The primary goals of this study were to:

1. Experimentally quantify the impacts on wildlife from a range of simulated light and sound disturbances that mimic cannabis production;
2. Identify thresholds of impact for different wildlife species and taxonomic groups, including threatened and endangered species;
3. Create and test general predictions for community-level and cascading effects of disturbances from these impacts.

Due to fieldwork delays caused by the COVID-19 pandemic, data collection and analyses are not yet complete. Here, I describe the study design and approach, and plans for future analysis. To provide an example of the types of data produced by this study design, I present preliminary data and summarize trends from the first experimental season. Considering the large amount of time, effort, and resources needed to establish this type of field experiment, this description of the approach and potential pitfalls should be useful to others wishing to attempt similar research.

Methods

Study Area

Field experimental trials were based at two research reserves in Mendocino County, California (Figure 1). I selected reserves that allowed for manipulation of experimental treatments and were representative of local cannabis-producing regions. The first reserve, the University of California Hopland Research and Extension Center (HREC), is located in southern Mendocino County (39°00′N, 123°04′W). The landscape on and surrounding HREC was predominantly chaparral/shrubland, oak woodland, and grassland, and the types of cannabis production in the region include medium to large-scale mixed light and greenhouse cannabis production facilities that were characterized by larger infrastructure, higher powered LED grow lights, and heavy-duty cooling and drying fans. The second research site was the Angelo Coast Range Reserve (ACRR), a protected research reserve maintained by the University of California Natural Reserve System in northern Mendocino (39°43’N, 123°39’W). The area on and around ACRR was more heavily forested, with Douglas fir (*Pseudotsuga menziesii*) dominated mixed conifers, riparian areas, and interspersed meadows. Cannabis production in northern Mendocino was typically smaller scale, more remote, and characterized by generator-powered greenhouse lighting, and gas-powered equipment on site.

Figure 1. Map of Mendocino County, California (red outline), showing the locations of the two research reserves where this study occurred.

Study Design

I used a modified before-after-control-impact (BACI) design for field experiments. At each reserve, my field team and I established three experimental replicates, for a total of six sites. I selected sites that would be suitable for cannabis production in terms of existing clearing, and flat ground. Neither HREC nor ACRR cultivate cannabis for research, and because I wanted to isolate the effects of light, noise, or light and noise combined, I did not want a site that was already an established cannabis farm. Therefore, I selected sites with minimal existing infrastructure (within the constraints of access to power, see *Treatments* below).

My basic approach was to set up treatment infrastructure and monitoring equipment, monitor multi-taxa wildlife for a control period, and then alternate (as randomly as possible given equipment constraints) between control, light, noise, or combined light and noise periods, ensuring that each treatment period was preceded and followed by a control. At each reserve, there was always at least one site serving as a control at any given time. To reduce habituation of wildlife to treatments, I selected a short interval of two weeks for each control and treatment period. For the first season of data collection, I ran experiments from May 2021 to January 2022, though not all sites were active until November 2021. Below, I describe the setup for treatments, as well as the data collection methods used for each taxonomic group that I monitored in this study.

Treatments

For light treatments, at HREC I used a full spectrum LED light that is commonly used in indoor, greenhouse, and mixed light production, the California Lightworks SolarSystem 1100 (https://californialightworks.com/solarsystem/). I set the light at 5' off the ground, and protected it with a corrugated metal shield (Figure 2). During light treatments, the lights were turned on and run for 24 hours a day.

For ACRR, I used a white-light LED that would be more typical for small-scale outdoor or mixed light cannabis farms. We used a 6000-6500K White 152 Watt Linkable LED Omni Ray light bar (https://www.omniraylighting.com/). I placed the light bar in a miniature greenhouse 3' off the ground to protect it and scatter light (Fig. 2). During light treatments, the solar system was set to a timer where the lights were active for 8 hours each night.

For noise treatments, I used a portable mp3 player and waterproof speaker, playing at full volume continuously alternating between two different white noise tracks: a high powered drying fan, and an equipment motor. However, due to frequent equipment failures, sound treatments often did not last the full two weeks.

Figure 2. Central power source and treatment setups. **Left:** solar panel setup at ACRR with miniature greenhouse and small LED light bar. **Right:** Electrical box setup at HREC with high powered LED array.

To power equipment for each treatment, I relied on two different power sources at HREC and ACRR (Fig. 2). At HREC, staff on site were able to trench lines and place power boxes at the three sites, such that the amount of electricity needed to power the lights and speakers was not a limiting factor. At ACRR, given that it was a more remote location, direct power was not an option, so I obtained assistance to install solar systems instead. Although generators might have been more representative of the power sources used for cannabis production in the region, I wanted to be able to separate the effects of light from the effect of noise from a generator, necessitating a quieter power source.

Monitoring Equipment

At each site, noise and light treatment sources were located at the center, and surrounded by an array of monitoring equipment designed to capture attraction, space use, and activity rates of specific animal taxa (Figure 3). Below I describe the methods used to sample responses of each taxonomic group.

Medium-large mammals

I used an array of wildlife cameras to monitor space use and activity patterns of medium to large mammals (body weight > 1 kg) in relation to disturbance treatments. At HREC, I used Reconyx Hyperfire 2 cameras (a slightly more expensive model better for open habitats that have lots of grass), and at ACRR, I used Bushnell Aggressors (a more affordable option that works well in more closed-canopy habitats or shorter grass). At both sites, cameras were set to take photos in bursts of 2, with a quiet period of 15 seconds. For cameras set in open, grassy areas where misfires were frequent, I lowered camera sensitivity and increased the quiet period to 30 seconds.

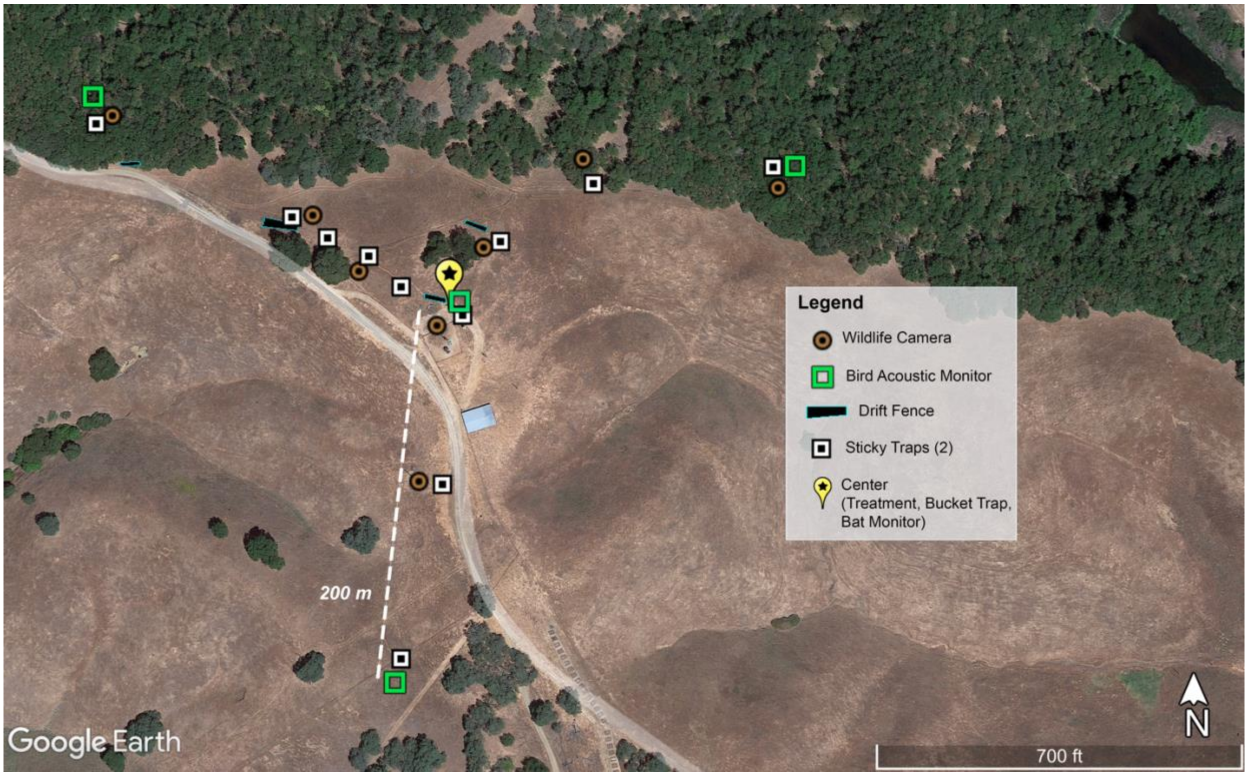


Figure 3. Diagram from one treatment site (HREC1) demonstrating the distribution of monitoring equipment. Each site consists of three transects extending out to 200 m, with the spacing of monitors based on taxonomic and equipment considerations (see text). One transect (in this case, the NW transect in the upper left) contains a higher density of monitoring equipment closer to the treatment source to test for finer scale and distance threshold effects.

Figure 4. Example of wildlife camera photos documenting deer during light treatments.

I used nine cameras per site, with three each at “close”, “medium”, and “far” distances respectively, in transects out from the center treatment source (Figure 3). The “close” set included one camera directly at the treatment source, facing the light/speaker (e.g, Figure 4), and two others 50 m away, forming a triangle. The “medium” set included three cameras at 100 m, and the “far” set included three cameras at 200 m, each adding a larger triangle farther from the site center (Figure 3).

Camera photos were manually sorted by species, using a team of trained identifiers. In future analyses, these data will be used to assess patterns of wildlife space use and activity.

Small mammals and reptiles

I used drift fence cameras to monitor small mammals and reptiles. This is a relatively new technique for capturing responses of species that are otherwise difficult to monitor passively (Boynton et al., 2021). Drift fences work by funneling small animals along a low barrier on the landscape which intersects a potential pathway where they may travel (e.g., between a water source and cover). The barrier, typically a tight mesh fabric (we used landscape fabric), then directs the animal from either side of the fence under a camera, which is modified to produce a close focal range photo (Figure 5). I used both square box and round bucket designs for drift fences, though I do not anticipate the different structures would influence detection rate. For the drift fence cameras, I used the Reconyx Hyperfire 2 with a custom focal length of 40 cm.

Figure 5. Examples of drift fences. **Top:** two different drift fence designs. Square construction (left) with flap open revealing camera. Bucket construction (right) with completed fence. **Bottom:** example photos from each setup. Square construction (left) and bucket construction (right).

Drift fences require more space and labor than camera stations, hence, I only deployed four per site at HREC, spaced <10 m, 50 m, 100 m, and 200 m from the center (Fig. 3). Due to bear activity and the associated potential for damage to research installations, I only implemented drift fences on one site at ACRR, at <10 m, 50 m, and 100 m, for a total of three fences.

To date, drift fence camera photos have not been sorted but will be identified manually by species, using a team of trained identifiers. These data will then be used to assess space use intensity and activity patterns. However, because reptile detections are most reliable during the day when there is ambient heat to set off the camera sensors, they will be excluded from analyses of diel activity.

Insects

I used two different methods to assess the response of flying insects to treatments: sticky traps and bucket traps (Figure 6). Sticky traps are designed to intercept flying insects, and were constructed out of clear acrylic 4” x 6” sheets covered in stikem glue (http://www.seabrightlabs.com/stikem.htm). I placed two traps on poles or trees at 3’ and 6’ off the ground (labeled A on top and B on bottom). Sticky traps were placed at all camera poles at HREC, plus one additional pole at 25 m and 75 m to form a more continuous gradient in one direction per site (Figure 3). Due to logistical constraints and bear activity at ACRR, I deployed fewer at those sites. ACRR2 and ACRR3 only used sticky traps at the center, and ACRR1 had one transect of traps (at 0, 25, 50, 75, and 100 m).

Figure 6. Collection methods for flying insect used in this study. Sticky traps at high and low heights (left) and bucket traps for collection of insects at light treatments (right).

Sticky traps were collected at the end of each treatment and control round and placed in binders using photo sleeves interspersed with foam padding. I used a light box to photograph the sticky traps (Figure 7). Insects on photographed traps will be identified to order or species by trained assistants and counted. This will provide data on numerical responses of insects to light and noise treatments along a distance gradient.

In addition to being photographed, each sticky trap was assessed using a semi-quantitative estimate of insect density. Each trap was overlaid with a 12 x 8 grid, and the number of squares that contained insects were counted. This provided a proxy for density of insects by distance and treatment.

Figure 7. Example of light box (left) used for photographing insect sticky traps. The sticky traps are placed on the pegs next to the scale bar and label, and then moved into the box to be photographed (right). Dots, such as the one in the photo on the right, are placed on the side that faces the light for future orientation.

In addition to sticky traps, I used bucket traps to capture insects specifically attracted to the light treatments at HREC (Figure 6). Bucket traps consist of a plastic bucket filled with a shallow layer of antifreeze, with a funnel resting on top of the bucket such that insects can fall into the bucket but cannot crawl out. This method primarily captures moths but also includes other insect families. Buckets were left overnight at artificial lights, and then in the morning, collected samples were rinsed and stored in ethanol. I only deployed bucket traps for 2-4 nights during light treatments, and only when the moon phase was less than a quarter full. Due to the extra logistic effort needed to deploy bucket traps, I did not use them on every treatment round. I also did not use bucket traps at ACRR out of concerns for bear activity, and because I was unable to ensure that the traps would be checked each day. Insect samples from the bucket traps will be identified by trained entomologists to order or species.

Birds

I deployed an array of acoustic monitors to monitor bird response to treatments. Specifically, I used Audiomoths (https://www.openacousticdevices.info/audiomoth) set to record at 32 kHz for 5 minutes each at sunrise, 30 minutes before sunrise, and 30 minutes after sunrise (Furnas & Callas, 2015). To reduce the likelihood of simultaneous detections, I used only four monitors per site, one at the center and one each at the end of the three 200 m transects (Figure 3). I used the Audiomoth IPX7 Waterproof Cases, and placed audiomoths ~6’ off the ground, or as high as field technicians could access at a given site.

I automatically classified bird calls using BirdNET by location and date (Kahl et al., 2021). While in future I will explore further quality control and validation measures, for the preliminary assessments reported here, I filtered results to only include calls with at least a 99% confidence of classification. This provides bird richness and detection rate as a function of treatment type and distance to disturbance.

Bats

I installed acoustic monitors to monitor bat attraction or avoidance of point source disturbance. I used Wildlife Acoustic Song Meter Mini Bat detectors, which automatically detect and record bat calls. I deployed monitors for only 4 nights per each round of sampling because of data storage limitations. Due to the extra logistic effort needed to deploy the bat monitors, I did not use them on every round, and only deployed them at HREC, though I plan to expand monitoring to ACRR in future field seasons.

I used automatic classification to identify bat calls in SonoBat 4 (Arcata, CA, USA; www.sonobat.com), using the North American region and the "Western" regional package. I used a sound quality cutoff of 0.7. In future I will explore further validation measures. This classification provides data on bat species abundance and call intensity by treatment.

Analyses

Descriptive summaries

To produce a summary of the data collected in the first season of field experiment trials, I listed the number of rounds completed at each site, as well as the occurrence data that had been sorted as of June 2022. For data collected by wildlife cameras and bird acoustic monitors, I summarized the species detected, and the average detections per day by treatment and distance. For bat acoustic monitors, I summarized the species detected, and average detections per second by treatment. For sticky trap densities, I summarized the categorized density estimate by distance and treatment. Summaries were calculated in R (R v. 2021-11-08 "Ghost Orchid"; R Core Team 2021) using Rstudio (v. 2021.09.1 + 372; Rstudio Team 2021). These summaries provide an example of the data formats produced by the collection methods used in this study.

Future analyses

Once data from the second season of field trials is collected, and all data is processed, I will quantify wildlife response to disturbance treatments in terms of space use and activity patterns (Table 1). For data collected along a distance gradient, I will build species- and taxa-level general linear mixed models, using detection rates or richness as the response variable (depending on the data collection method). To compare results across sites, I will examine the magnitude of change from treatment to control periods. I will also consider pairing each treatment round to the control rounds on either side of them to control for seasonal changes, and possible wildlife habituation. A hypothetical example of results from such data are presented in Figure 8.

For bat data, I will begin by using a t-test or a paired t-test to compare detection rates and richness with and without treatments. For moths, I will provide a descriptive summary of the insects attracted to the grow lights, and compare how species composition and richness changes seasonally. Considering that moths are likely a prey source for bats, I will also assess their activity peaks in relationship to each other.

Table 1. Taxonomic groups monitored in the study design, and their predicted responses to treatments.

Taxonomic group	Monitoring source	Type of response measurement(s)	Predicted response(s) to treatments (light, sound, light + sound)
Medium-large mammals	Wildlife cameras (distance gradient)	Species composition, Detection rate, Daily activity patterns	(-,-,-) negative response to treatments overall, with species-specific responses by functional group and thresholds based on body size; species that do not avoid in space will shift diel activity peaks
Small mammals	Drift fence (distance gradient)	Species composition Detection rate, Daily activity patterns	(-,-,-) negative response to treatments overall, but only at closest drift fences
Reptiles	Drift fence (distance gradient)	Species composition, Detection rate	(-,-,-) negative response to treatments overall, but only at closest drift fences
Moths	Bucket trap (point source)	Species composition, Numeric attraction	(+, N/A, +) positive attraction to light source, with high richness
Other flying insects	Sticky trap (distance gradient)	Species composition, Density, Richness	(+, - , +/-) attraction to light, negative response to sound, and species-specific responses to both combined
Birds	Acoustic monitors (distance binary)	Species composition, Detection rate	(+/-, -, -) species-specific responses to light depending on diet, negative response to sound, and negative response to both combined
Bats	Acoustic monitors (point source)	Species composition, Detection rate	(+,- , -) attraction to light due to prey availability, negative response to sound and combined light and sound

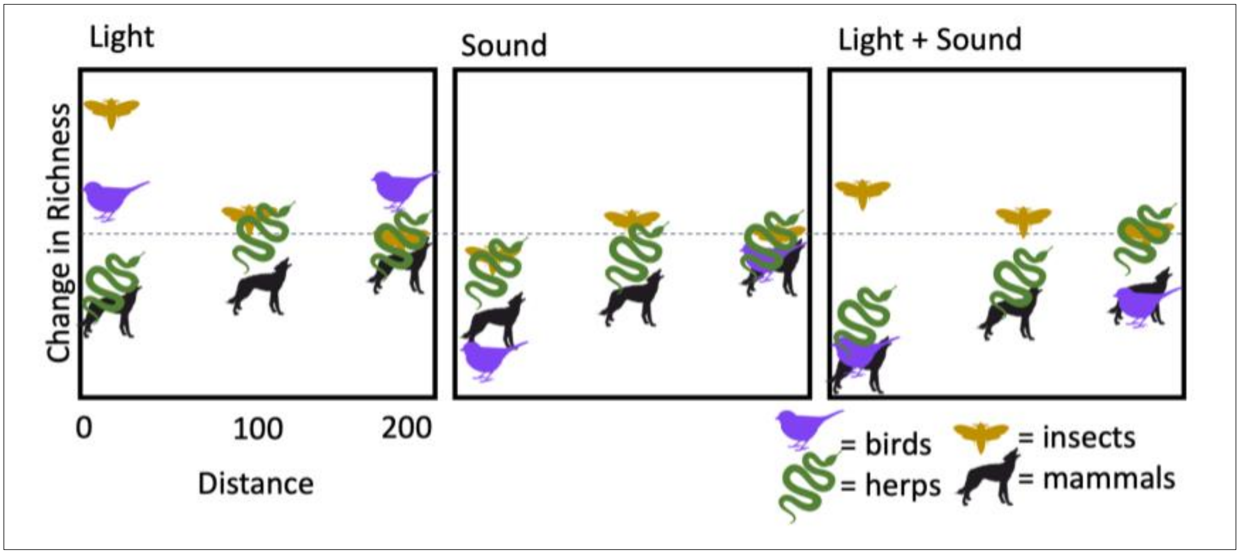


Figure 8. Hypothesized response of taxonomic groups to light and noise trials. In this example, taxonomic groups are compared by measuring magnitude of change from control periods by distance and treatment.

Results

As stated previously, I summarized results for the first season of data collection to provide an example of the types of inference made possible by my study design. These results should be viewed as preliminary.

In the first season of field experiments, there was a total of 50 rounds (i.e., 2-week sampling periods) across all sites, which includes 35 rounds at HREC and 15 at ACRR (Table 2). There were a total of 20 treatment rounds, the majority of which were light treatments (Table 2).

Table 2. Summary of data collected during first season of field trials. For each site, the number of total rounds. (2-week sampling periods), and each treatment round is listed.

Site	Total rounds	Control	Light	Sound	Light + Sound
HREC1	19	11	5	2	1
HREC2	8	5	2	0	1
HREC3	8	4	3	1	0
ACRR1	6	4	2	0	0
ACRR2	5	3	2	0	0
ACRR3	4	3	1	0	0

Medium-large mammals

For wildlife camera data, only one site at HREC was sorted as of June 2022 (HREC1). For that site, the rounds that were sorted included 11 total rounds: 6 control, 3 light, 1 sound, and 1 sound/light combination. There were 9 wild mammal species detected, with black-tailed deer (*Odocoileus hemionus*) being the most frequently detected (Table 3). Preliminary data visualizations suggest there may be an effect of treatment by distance on detection rates at close distances (Figure 9).

Table 3. Wild mammals detected at HREC1 for the sorted subset, ordered in descending detection rate.

Species	**Number of detections**	**Average detections per day**
Black-tailed deer (*Odocoileus hemionus)*	82	2.50
Coyote (*Canis latrans*)	47	0.52
Gray squirrel *(Sciurus griseus)*	26	0.87
Striped skunk (*Mephitis mephitis*)	21	0.26
Raccoon (*Procyon lotor*)	12	0.20
Turkey (*Meleagris gallopavo*)	10	0.61
Bobcat (*Lynx rufus*)	9	0.14
Wild pig *(Sus scrofa)*	4	0.25
Gray fox (*Urocyon cinereoargenteus*)	2	0.14

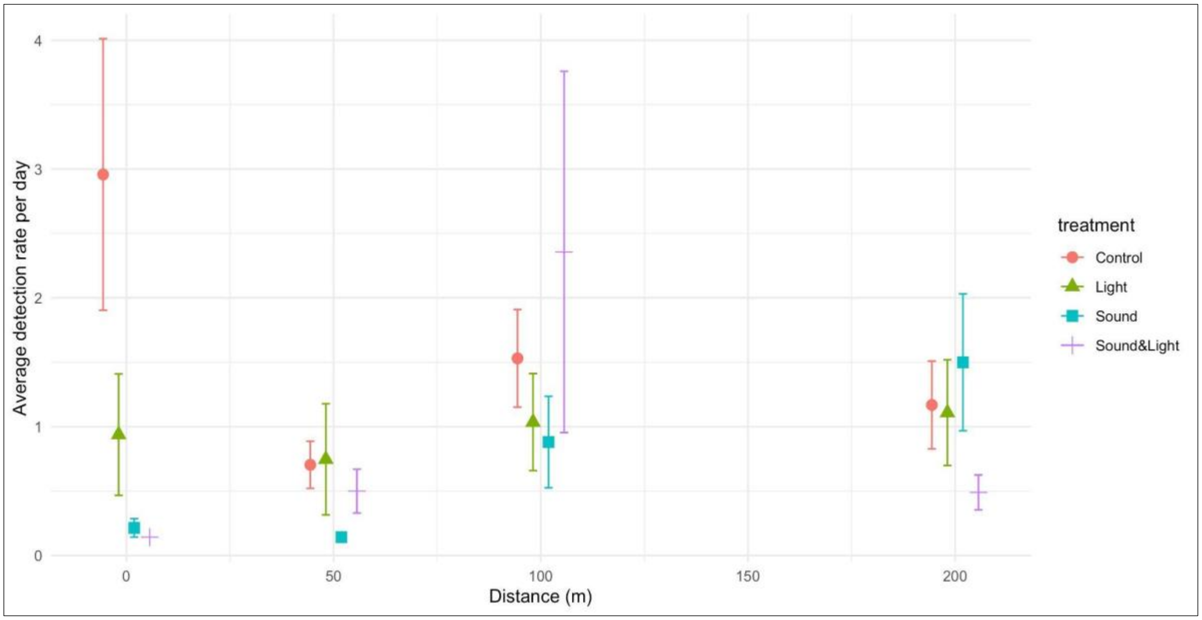


Figure 9. Average animal detection rate by distance to treatment source for data from one site at the Hopland Research and Extension Center (HREC1). Error bars represent standard errors.

Birds

For bird acoustic monitors, data were successfully classified for all six sites, for almost all treatment rounds (missing 1 control from HREC2, 1 light from HREC3, and 1 control from ACRR1). After filtering species detections by 99% confidence, there were 66 species detected. The top ten species by average detection rate are listed in Table 4. Preliminary data visualizations seem to indicate that the effect of treatment on detection rate may be site-specific (Figure 9), however, there are likely seasonal effects I have not yet accounted for.

Table 4. Top ten most detected species at HREC and ACRR by automatic classification (filtered by 99% confidence), arranged in descending order.

Species	**Average detections per day**
Acorn Woodpecker	51.87
Violet-green Swallow	25.00
Black Phoebe	21.10
Western Kingbird	14.55
Western Bluebird	7.29
Oak Titmouse	6.26
Pacific-slope Flycatcher	4.35
California Towhee	4.33
Golden-crowned Sparrow	4.32
Chestnut-backed Chickadee	3.98

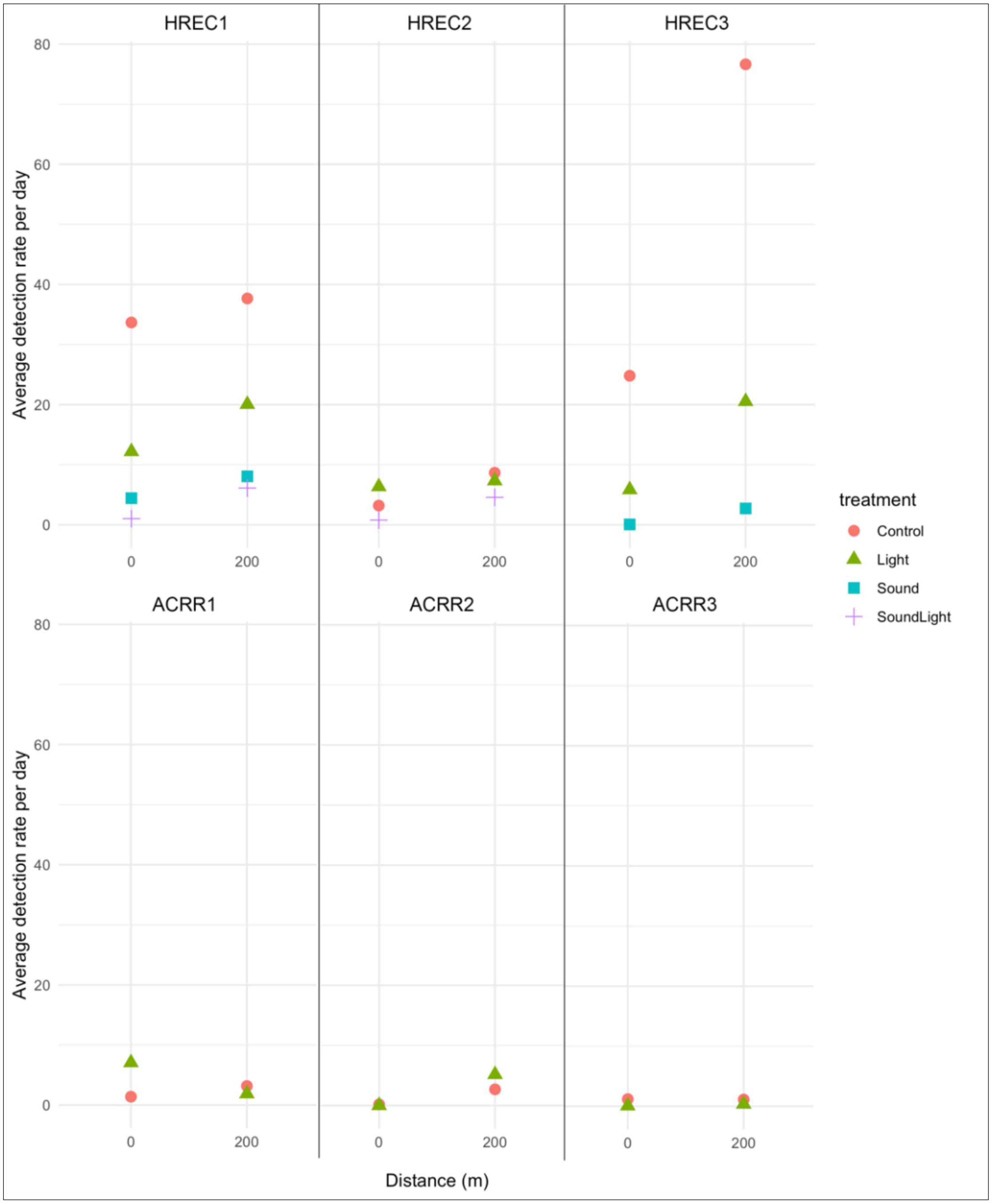


Figure 10. Detection rate of all bird species by treatment and distance for each site.

Bats

For bat acoustic monitors, I had data processed for 17 total rounds at the three HREC sites, for a total of 6 control, 7 light, 1 sound, and 2 sound and light rounds. Automatic classification identified 14 species (Table 5), though I have not verified the calls. Preliminary visualizations do not signal any clear patterns in average call rate by treatment (Figure 11A) but may indicate site-specific species composition effects of treatment (Figure 11B).

Table 5. Bat species detected (as identified by automatic classification) at HREC study sites, arranged in descending order of call rate

Species	**Average Calls per Second**
Myotis californicus (California myotis)	8.60
Myotis ciliolabrum (Western small-footed myotis)	8.38
Myotis yumanensis (Yuma myotis)	8.23
Corynorhinus townsendii (Townsend's big-eared bat)	7.73
Lasiurus blossevillii (Western red bat)	7.40
Myotis evotis (Long-eared myotis)	7.09
Parastrellus hesperus (Canyon bat)	6.24
Eptesicus fuscus (Big brown bat)	6.02
Myotis thysanodes (Fringed myotis)	5.59
Antrozous pallidus (Pallid bat)	5.13
Myotis volans (Long-legged myotis)	4.27
Lasionycteris noctivagans (Silver-haired bat)	3.22
Tadarida brasiliensis (Mexican free-tailed bat)	2.73
Lasiurus cinereus (Hoary bat)	2.50

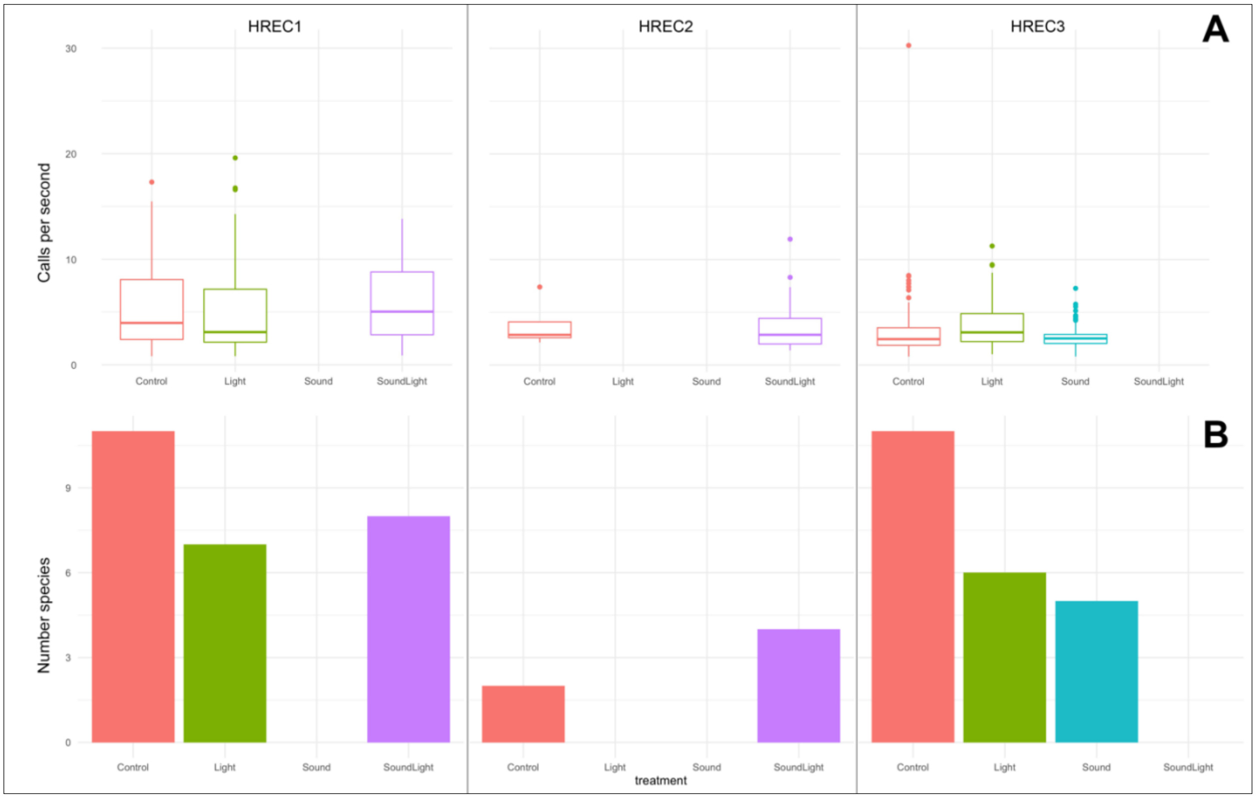


Figure 11. Bat data by call rate (A) and number of species (B), for treatments at each study site at HREC.

Insects

For insect sticky traps, only one site at HREC was assessed for semi-quantitative density (HREC1). For that site, I had 13 total rounds completed: 8 control, 3 light, 1 sound, and 1 sound/light combined. For the density proxy (percent of trap covered), values ranged from 5.2% to 99.0%. Preliminary data visualizations suggest that light treatments may attract a higher density of insects, but that the traps placed higher up (the "A" traps) may have a stronger effect than the lower traps (Figure 12A). Patterns are less clear for the other treatments (Figure 12B).

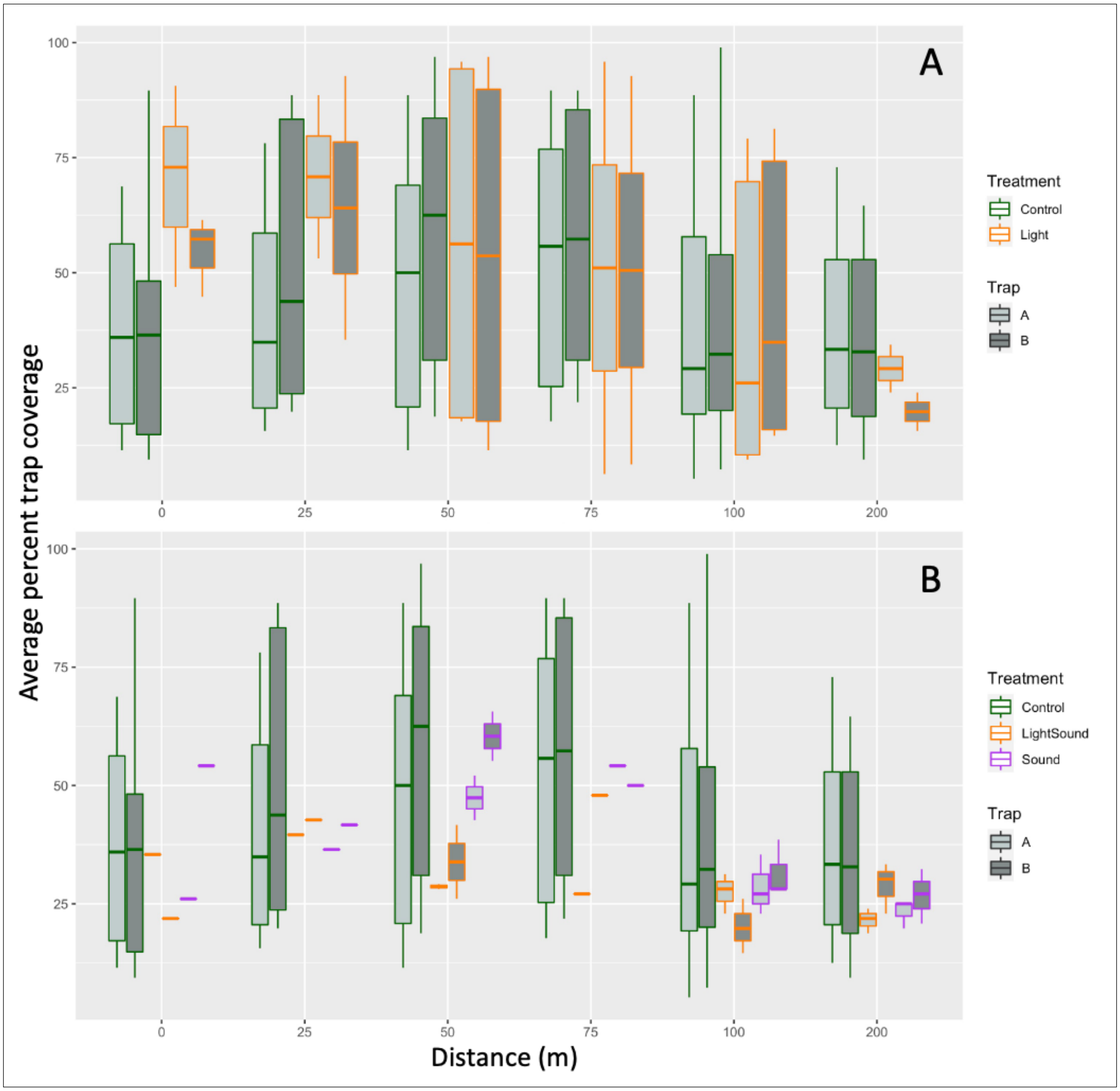


Figure 12. Estimated insect density as a function of distance from each treatment at one site at Hopland Research and Extension Center (HREC1). A: control and light treatment. B: control and sound, and light + sound treatments.

Discussion

The preliminary results of this effort to design and trial a comprehensive study of anthropogenic noise and light effects on wildlife are promising. Results to date suggest that this experimental design may be sufficiently rigorous, with enough sampling to quantify relationships and thresholds for different taxonomic groups in their response to experimental light and noise treatments that mimic conditions on cannabis farms. While more data needs to be collected, sorted, and analyzed, the study design detailed here may be sufficient for this study's objectives and useful for other researchers interested in community responses to disturbance.

Preliminary visualizations indicate that there will likely be species- and taxa- specific responses to each disturbance treatment. These results provide an early indication that I may be able to capture fairly fine-scale responses of at least medium-large mammals and flying insects. Current results mainly provide insights on response to light treatments, since there were fewer sound and combined light/sound trials in the first season of data collection. Considering I have not yet implemented more complex modeling to account for seasonal variations or other covariates, it is surprising that there is already an indication of mammalian avoidance and flying insect attraction to light treatments, providing limited support for hypothesized relationships.

Future analysis of these data will involve more complex Generalized Linear Mixed Model (GLMM) approaches, as has been used in other studies on light and noise effects on wildlife (Shilling et al., 2018; Suraci et al., 2016, 2017). This will allow me to account for seasonal variation or other covariates, examine potential habituation effects over time, and incorporate decibel and light intensity measurements at each site.

Limitations

There are several limitations that I will have to address in future analyses of these data. I do not know whether wildlife will habituate to the treatment effects, and if so, when that occurs. I do not yet see strong signals of habituation in the preliminary data, but more analysis will be needed. If I see signs of habituation, I may need to restructure the analyses to pair treatment and control periods.

Another major limitation of this study is the small number of replicates. This limitation means that natural variation across sites may be large, and it may not be possible to account for it with random effects when using all data within a single model. Therefore, I will likely have to run separate analyses for each site, which reduces my ability to generalize results. However, I will explore analysis options that include comparing the magnitude of difference between control and treatment across sites.

Conclusions

This study is the first of its kind to examine the impacts of noise and light from cannabis cultivation on wildlife in controlled and replicated field experiments. This research is timely and valuable for policymakers, farmers, and the general public. While these preliminary results are not yet enough to support management recommendations, the methods described herein may be useful to others who wish to implement similar study designs. To that end, I will list advice below to avoid some of the potential pitfalls that I have encountered during study design implementation that other researchers should consider when formulating their study plans.

1. Consider options for sourcing power carefully

Speakers and lights require a large energy input. Battery power, such as what has been used for motion-triggered speaker trials (e.g. Suraci et al. 2017) is insufficient to power continuous use. Therefore, careful consideration should be given to power source options available in each study location. Solar power is a useful option for remote locations, but it is important to recognize the weight and equipment needed for installation, and the expertise needed for maintenance. It can also be less reliable than hard-wired power.

2. Select compatible monitoring methods

Labor costs are considerable on a project with repeated ongoing treatment rounds. To reduce the amount of time and energy required for regular data collection, it is useful to coordinate monitoring schedules for different taxa or methods, which might involve limiting monitoring equipment to those which can be rotated at the same interval. So far, I have found all methods to be amenable to the same interval timing, except for the bat acoustic monitors and insect pitfall traps which use a shorter interval.

3. Partner with taxonomic experts

Each taxa-specific monitoring approach has its own considerations and pitfalls. Therefore, it is important to partner with experts on the specific methodology used, particularly when it comes to validating the data.

4. Create realistic budgets

Multi-taxa field experiments take considerable time, effort, and funding (Blickley & Patricelli, 2010). It is important to be realistic about the number of people needed, cost of equipment, and time. This is particularly important considering there may be a pilot period where adjustments need to be made, and additional costs incurred. While the main source of delay for this project was the COVID-19 pandemic, at the original conception of the study design, I also underestimated the number of years implementation would take before data collection could begin.

With these considerations in mind, hopefully this and other studies will add to the mechanistic understanding of wildlife response to disturbance.

Conclusion

This dissertation has explored the ecological outcomes of cannabis legalization at multiple spatial scales and via multiple disciplinary lenses. I integrated methods from landscape ecology, land system sciences, social methods, wildlife biology, behavioral ecology, and community ecology to understand legacy cannabis landscapes, their socio-ecological drivers, and potential consequences for wildlife. The results of my research help inform an urgent information gap on cannabis agriculture, which can assist with policy, regulation, and land use decision-making.

Chapter 1 laid an important baseline for cannabis land use in southern Oregon. In this chapter, I found that while production was relatively small-scale and had a small total cultivated footprint, farms were clustered in hotspots that overlapped with species of concern, such as fishers and coho salmon.

In Chapter 2, I built off the maps from Chapter 1, using farmer interviews to inform models of land use and land use change. I documented a dramatic increase in cannabis production post-legalization, and found multiple drivers of land use that present potential concerns for ecological effects, such as a preference for rural parcels and those closer to rivers. At the same time, however, I identified farmer environmental stewardship values that may also provide opportunities to mitigate potential environmental harm.

In Chapter 3, I monitored wildlife space use and space use intensity on and surrounding cannabis farms, and identified species-specific responses to cultivation. I found that despite their small size, cannabis farms influenced the space use responses of most species.

Finally, in Chapter 4, I described the methods for a first-of-its-kind study on the impacts of noise and light from cannabis cultivation on wildlife in controlled and replicated field experiments. Preliminary data from the first season of data collection hold promise for this approach to detect response thresholds of wildlife including insects, rodents, reptiles, bats, birds and larger mammals.

Here, I take the liberty to apply personal interpretation to summarize some broad conclusions from my work and future research opportunities.

1. There are valid environmental concerns for cannabis agriculture's ecological impacts

At the outset of this dissertation, I was unsure what I would find. I heard everything from "cannabis farming is too green to hurt the environment" to "cannabis will destroy the entire west coast." While the reality is not as extreme as what has been documented on public land production sites (e.g., Gabriel et al., 2015), small-scale private land cannabis farming in rural areas does seem to have a negative ecological effect on surrounding wildlife, which should be expected from almost any new land conversion. This emphasizes the importance of land use planning for cannabis development, and on-site mitigation efforts.

There remain many open questions about the effects of cannabis production on wildlife. While Chapter 3 looked at responses of wildlife with regard to space use, follow up research on health outcomes or long-term survival of individual animals would be useful. Further species-specific studies continue to be valuable to look at population-level impacts for culturally or ecologically significant animals, particularly in freshwater systems. There are also still gaps in understanding wildlife community-level effects of cannabis farming, such as potential decoupling of predator-prey relationships. In addition to observational data, there are also avenues for future experimental research approaches to study the relationship of cannabis and wildlife. For example, specific on-site practices require further research to inform best management practices. While Chapter 4 lays out a methodology to approach future research on cannabis-associated light and noise, similar studies could be done on a wide range of farming practices that may be unique for cannabis, including integrative pest management, water use, plastic use (such as mulch or netting), or soil management.

In addition to specific impact studies, broader research that examines tradeoffs between styles of cultivation in different landscapes would help policymakers design incentives for modes of production that might be least impactful for a given region. For example, while my dissertation focused on small-scale farming, it is likely that the effects documented in Chapter 3 are less than would be seen on larger industrial farms in similar rural areas. Using concepts such as land sparing and land sharing (Kremen, 2015), it might be possible to prioritize areas where cannabis farming should be excluded, areas where it should remain small-scale, or areas where it is appropriate for larger production facilities based on conservation and sustainable development goals. Currently, competition within the cannabis market ties together different modes of production. Future research on how these connections function would be useful to predict trends in the cannabis industry. For example, the future of small-scale farming in the cannabis industry seems to be tenuous at this time, as the interviews from Chapter 2 emphasized (see also Dillis, Polson, et al., 2021). Studies on the declines of small-scale cannabis farming may highlight policy avenues that could preserve a space for regulated craft cannabis production in expanding cannabis markets.

2. Education and outreach may be underused tools for conservation with cannabis

In each stage of this dissertation, whether formally interviewing farmers for Chapter 2, or while setting cameras for Chapter 3, I have repeatedly been struck by the lack of outreach targeting cannabis farmers. As Chapter 2 results emphasize, there may be an untapped environmental ethic of cannabis farmers that could be targeted by conservation efforts. Currently, most conservation tools for cannabis emphasize the role of enforcement, but far less effort has been placed on engaging cannabis-producing communities themselves.

Further research on the effectiveness of outreach tools with cannabis will be critical for designing dynamic conservation interventions. This research could focus on education and outreach methods, such as those produced by resource conservation districts; on certification programs for best management practices; or on equity programs designed to reduce barriers to entry and counter historical marginalization (such as California’s Social Equity Grants for local jurisdictions).

3. Future conservation interventions should partner with farmers

The illicit history of cannabis sometimes prevents cannabis farmers themselves from being included in discussions on regulation (Polson, 2015). During the research for this dissertation, and especially during outreach events with the Cannabis Research Center, I have had the privilege to interface with people who care about conservation in cannabis landscapes across positions, from growers themselves, to those in regulatory or enforcement agencies. Many cannabis farmers have innovative ideas for ways to improve cannabis policy and regulation in ways that support conservation goals. Moreover, they can also often provide insights into unintended consequences of cannabis policy.

Continued research on the effectiveness of cannabis policy and whose voices are included in the policymaking process is important, however, it is equally important to connect this research with policymakers and regulators.

4. The cannabis industry forms a social-ecological system that mirrors many of the land-based conflicts in the western US

It is important to approach cannabis systems in a way that incorporates their social and ecological context, as emphasized in Chapter 2. This is an approach that is useful beyond cannabis systems as well. By spanning issues of land use and human-wildlife conflict/coexistence, the social-ecological cannabis systems reflect many of the conservation challenges facing the rural western US and in other parts of the world. Future research could directly compare cannabis land use to other agricultural frontiers, or explore cannabis systems as a case study for questions on land use prioritization, sustainable agricultural practices, equitable policy solutions, and more. It is my deep hope that interdisciplinary cannabis research continues, due to both its specific timely significance and broader relevance to conservation science.

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