Landscape and Urban Planning 237 (2023) 104783

Contents lists available at ScienceDirect

Landscape and Urban Planning

journal homepage: www.elsevier.com/locate/landurbplan

Research Paper

Where money grows on trees: A socio-ecological assessment of land use change in an agricultural frontier

Phoebe Parker-Shames [a,b,*], Hekia Bodwitch [b,c], Justin S. Brashares [a,b], Van Butsic [a,b]

[a] Department of Environmental Science, Policy & Management, University of California Berkeley, Berkeley, CA, USA
[b] Cannabis Research Center at Berkeley, University of California Berkeley, Berkeley, CA, USA
[c] Marine Affairs Program, Dalhousie University, Nova Scotia, Canada

HIGHLIGHTS

- Provides a social-ecological systems (SES) approach for assessing drivers of cannabis production at a development frontier.
- Farmer interviews inform potential spatial drivers for cannabis production.
- Models demonstrate importance of interview-derived covariates for cannabis land use.
- Interdisciplinary approach contributes to deeper understanding of agricultural land use and community dynamics.

ARTICLE INFO

Keywords:
Social-ecological systems
Land use modeling
Cannabis or marijuana legalization
Farmer interviews
Environmental impacts
Formalization

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 farmer decisions to use land for cannabis production 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 distribution and change. Finally, we quantified these drivers as spatial covariates and evaluated their value as predictors in three models: 1) logistic regression of cannabis land use distribution 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 in a formalizing sector, 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.

1. Introduction

"Money actually does grow on trees out here, and that's a blessing."
– Josephine County cannabis farmer, 2019.

Land use change is a global conservation concern, and the dynamics that drive it are often complex, involving the interaction of cultural, economic, historical, political, and environmental forces (Ellis et al., 2013; Foley, Defries, Asner, Barford, Bonan, Carpenter, & Snyder, 2005). To describe or predict land use change dynamics, it is therefore important to account for both social and ecological drivers and to consider land use as part of a social-ecological system (Ostrom, 2009; Turner, Lambin, & Reenberg, 2007). This is often done by integrating

* Corresponding author at: Department of Environmental Science, Policy & Management, University of California Berkeley, Berkeley, California, USA.
E-mail addresses: phoebe_parkershames@berkeley.edu (P. Parker-Shames), hekia.bodwitch@dal.ca (H. Bodwitch), brashares@berkeley.edu (J.S. Brashares), vanbutsic@berkeley.edu (V. Butsic).

https://doi.org/10.1016/j.landurbplan.2023.104783
Received 19 December 2022; Received in revised form 14 April 2023; Accepted 22 April 2023
Available online 10 May 2023

quantitative and qualitative methods (Bennett et al., 2017; Kinnebrew, Shoffner, Farah-Pérez, Mills-Novoa, & Siegel, 2021). Interdisciplinary approaches are increasingly recognized as necessary to develop effective policies, management practices, or conservation outreach targeting land use change, and have been shown to produce better performing models, as well as more nuanced system understanding (Bennett et al., 2017; Kinnebrew et al., 2021; Siegel et al., 2022).

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 (Turner et al., 2007). 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 (Kinnebrew et al., 2021). 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; Lamarque et al., 2013; Siegel et al., 2022).

An example of a complex social-ecological system that has undergone rapid land use change is rural outdoor cannabis farming in the Western US. The boom in outdoor cannabis farming corresponds to county and state-level legalization initiatives in cannabis production, which via the formalization process created a rapid development frontier (Butsic, Carah, Baumann, Stephens, & Brenner, 2018; Dillis et al., 2021). For decades, outdoor cannabis was grown illicitly, often in rural, remote areas. When legalization occurred, production in those same "legacy" regions rapidly expanded (Dillis et al., 2021).

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 (<1 acre, or 4,047 m^2) 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 illicit 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; Bodwitch, Polson, Biber, Hickey, & Butsic, 2021; Polson, Bodwitch, Biber, Butsic, & Grantham, 2023). 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 (Parker-Shames et al., 2022). 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).

In some of these rural, legacy-production regions, cannabis production on private lands can transform development patterns at a regional scale (Butsic et al., 2018; Butsic, Schwab, Baumann, & Brenner, 2017; Parker-Shames et al., 2022). This development frontier can foster new cultural, economic, and demographic dynamics (Polson & Bodwitch, 2021; Polson, 2015). 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). In turn, these environmental concerns often manifest as regulatory barriers to legal market access (Polson & Bodwitch, 2021; Polson et al., 2023).

For farmers and policy makers to understand, reduce, or mitigate potential environmental impacts and plan equitable policy responses, it is important to identify the social and ecological factors that drive cannabis development on private lands across space and time. However, federal restrictions on research funding to study cannabis (due to its designation as 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, Harrower, Baird, & Sepaniak, 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. 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 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.

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., 2018, 2017; Wengert, Higley, Gabriel, Rustigian-Romsos, Spencer, Clifford, & Thompson, 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.

In this study, our goal was to identify, assess, and contextualize potential drivers of farmers' decisions to cultivate private land for cannabis production in Josephine County, Oregon, between pre- and post-recreational legalization (2013/2014 and 2016), using both sociological and environmental variables. We conducted interviews with cannabis farmers to generate a list of sociological and ecological covariates for models of cannabis distribution and development 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 literature on cannabis production, and the lead author's experience living in Josephine County for two years during data collection. Our objectives were to:

1. Interview cannabis farmers to: i) identify potential drivers of cannabis land use distribution and change; ii) 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 distribution 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.

This paper outlines an approach that may be useful for other mixed-methods modeling of socio-ecological systems, particularly in land use frontiers or formalizing industries.

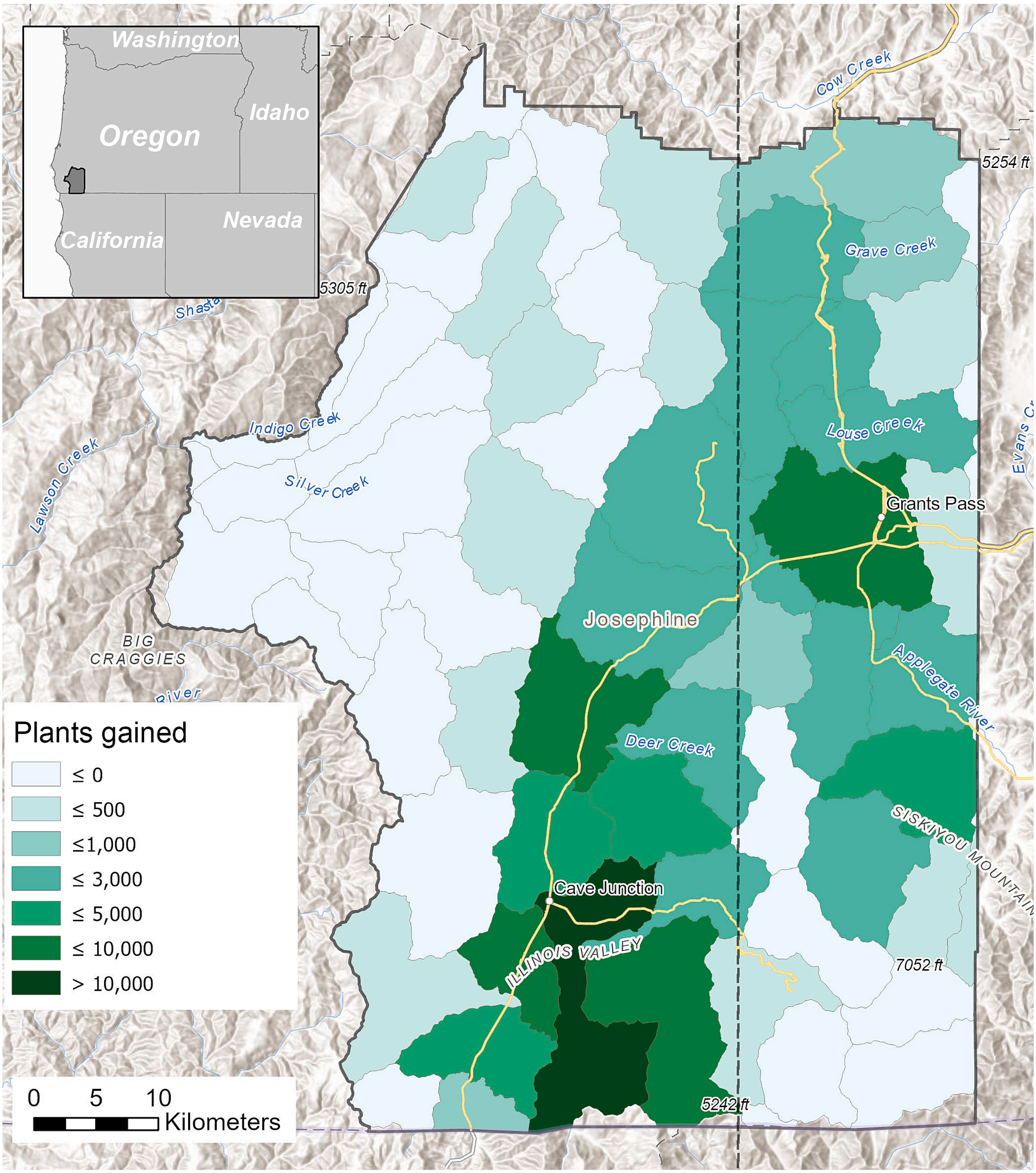

Fig. 1. Map of the study area in Josephine County, Oregon. The map also includes surveyed watersheds shaded by the increase in number of plants for each watershed from 2013/2014 to 2016 (see Cannabis Data in Model Results). Dashed line shows the approximate split in available imagery for the pre-legalization timepoint (see Cannabis Data in Methods).

2. Methods

2.1. Study area

To understand cannabis land use drivers within the context of a rapid policy shift, we focused our study on Josephine County in Southern Oregon (4250 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 (Parker-Shames et al., 2022; Smith, Powell, Mungeam, & Emmons, 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.

2.2. 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 and covariates as a result instead of a method, since it is a key finding from the interview data.

2.3. 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. Semi-structured 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 (see Appendix A). 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 handwritten 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 h, but ranged between 1 and 8 h, depending on the time constraints and preferences of the interviewee. All interviews were conducted under University of California, Berkeley Human Subjects Protocol CPHS# 2018–11-11619. Our purpose in conducting interviews was largely generative. We therefore conducted an inductive coding process, through which we identified and summarized themes and concepts that arose in the interviews. We then used the summaries to identify potential quantitative variables (predictors) for our land use models, and to select key quotes that illustrate each emerging theme.

2.4. Cannabis models

2.4.1. Cannabis data

To model drivers of cannabis land use and change over time, we hand-digitized cannabis production sites across Josephine County using Google Earth Images. At each site, we counted the number of visible plants in outdoor gardens, and estimated the number in covered greenhouses based on area. See (Parker-Shames et al., 2022) for detailed mapping methods. We used sites on private land that we identified with high confidence as being cannabis (hereafter just 'cannabis') with no minimum number of plants required for use in our models (range: 1–1,058). 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. We mapped all private parcels in the county, providing a dataset of private parcels with and without detected cannabis.

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, using high spatial resolution Google Earth imagery to record location of outdoor gardens and greenhouses. Depending on the available year of imagery in Google

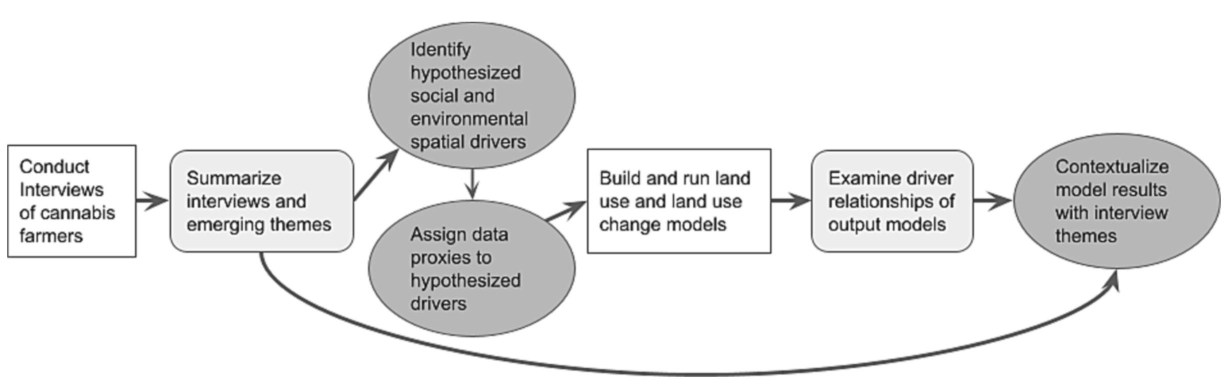

Fig. 2. Conceptual framework for our methodological process. White rectangles represent methods, light gray boxes represent results, and dark gray circles represents interpretation or discussion. Note that the results from the interview data feed into both the methods for the modeling approach and its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

Earth, we used either 2013 or 2014 data. The split in available imagery ran North-South through Wilderville, OR, splitting regional hotspots of production such that the Illinois Valley was mapped in 2013, and Grants Pass and Williams were mapped in 2014 (Fig. 1). For the 2013/2014 mapping, 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 mapped only a subset (n = 7) in the earlier time point 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.

2.4.2. *Cannabis distribution modeling*

For models of cannabis distributions 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 opted for a logistic regression rather than a Poisson due to our primary interest in the relationship of potential drivers to cannabis presence and note that logistic models do not require equal number of presence and absence (Woolridge, 2015). We selected the variables for all models based on the interview data (see *Results* and Table 1 for the included covariates and model equation). Many covariates are also supported by their use in previous studies of cannabis cultivation.

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).

2.4.3. *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, to only capture new farms post-legalization. We used a logistic regression model to examine the relationship between each covariate and the development of a new cannabis farm (see *Results* for the model equation).

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 a gaussian regression model to assess the relationship between each covariate and the number of cannabis plants gained or lost over recreational legalization (see *Results* for the model equation).

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 (Bartoń, 2022).

3. Results

3.1. *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 or licensed recreational cannabis, legal hemp, illicit "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 (with cultivation areas typically smaller than 1 acre), 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 distribution and change (Table 1), or indicate where an emerging theme did not readily translate to a quantifiable driver.

3.1.1. *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.

3.1.2. *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. The value placed on neighborly relationships stems from a heterogeneity in social acceptance or tolerance of cannabis production, or even particular styles of cannabis farming. In addition, farmers 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 were 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 (Parker-Shames et al., 2022) 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

Table 1
Hypothesized drivers of cannabis land use distribution and/or 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	$Dist_{cann}$: 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	$Density_{cann}$: 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	*HFP*: Human Footprint (−)	Remoteness desired for general connection to rural spaces	2009 Human Footprint (Venter, Sanderson, Magrach, Allan, Beher, Jones, & Watson, 2016)
Zoning	$Zoning_{Farm}$: Whether or not a parcel is zoned for farming (+)	Farm zoned parcels preferred	County taxlots (Josephine County 2018)
Distance from law enforcement	$Dist_{GP}$: Distance from Grants Pass Sheriff's office (−) (not included in final models due to correlation with *HFP*)	Reduced enforcement pressure (for both licensed and unlicensed farmers)	Straight line distance from Grants Pass (using Sheriff's Office as point location)
Parcel size	$Area_{parcel}$: Parcel area (m^2) (+)	Larger parcels more desired for buffer space and privacy	County taxlots (Josephine County 2018)
Easily cleared or open land cover	*Clearable*: 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	$Elevation_{max}$: Maximum elevation (−)	Intermediate elevation preferred for optimal growing conditions, maximum likely to be limiting factor	DEM 10 *m*
Roughness	$Roughness_{max}$: Maximum roughness (−)	Available flat land preferred to reduce terracing labor	Derived from DEM 10 *m*
Access to sunlight	$Aspect_{south}$: South-facing aspect (+)	Cannabis plants will grow better with access to sunlight, which is enhanced on south-facing slopes	Derived from DEM 10 *m*
Proximity to water	$Dist_{rivers}$: 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)

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.

3.1.3. *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.

This theme did not translate easily into quantifiable spatial proxies, and we were unable to find a suitable proxy for site-level stewardship practices. Instead, 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 as the basis for their stewardship of these remote sites. It is also possible, however, that farmers seek remoteness to avoid detection (see Regulation below). We quantified this remoteness (i.e. 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).

3.1.4. *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. Note that because remoteness is used for both a connection to rural spaces and for avoidance of law enforcement, we are unable to separate their effects in our results.

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*.

In Oregon, counties, and even cities, were allowed to create additional local restrictions on cannabis, many of which were in flux during the course of the study. 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 (dated 2018) was provided by Josephine County (see Appendix B for a zoning summary).

3.1.5. 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.

3.1.6. 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, we were unable to identify quantifiable, spatially-explicit drivers corresponding to the scale at which economics operates for most producers. None of the farmers 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.

3.1.7. 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.

3.2. Model results

3.2.1. Cannabis models

Based on the interview themes, we selected covariates for our final models. The following model represents the covariate relationships with the distribution of cannabis land use in 2016.

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

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 and estimates remoteness, $Dist_{cann}$ 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 used the following logistic regression model to examine the relationship between each covariate and the development of a new cannabis farm:

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

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 (Fig. 1).

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.

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

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.

3.2.2. Cannabis data

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. 1). In the pre-legalization timepoint, 8,531 private parcels were mapped in 2013 in the western half of the county (550 of which contained cannabis), and 30,784 private parcels were mapped in 2014 in the eastern half of the county (621 with cannabis) (see Fig. 1). Average values or proportions for each covariate are listed in Table 2.

3.2.3. Cannabis distribution post-legalization

For the single year post-legalization (2016) cannabis land use distribution model for private parcels, we found that the following hypothesized drivers had a significant relationship ($p < 0.01$) with parcels that contained 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. 3). The change in probability attributable to individual covariates was generally small (<10%), except for parcel area and density of cannabis (Fig. 3).

3.2.4. 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. 4). Parcel area and roughness on the other hand had non-linear relationships with possible threshold effects (Fig. 4). The change in probability attributable to individual covariates was generally small (<10%), except for parcel area and human footprint (Fig. 4).

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

		Parcel area (m^2)	Human footprint	Distance to cannabis (m)	Density of cannabis (in 1 km)	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	*Prop.*	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	*Prop.*	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	*Prop.*	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				

Table 3
Coefficient estimates for the model of cannabis land use distribution 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)

3.2.5. *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. 5). Parcel area was associated with the greatest predicted change in plant count, from a decrease of 25 plants to an increase of 50 (Fig. 5).

4. 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.

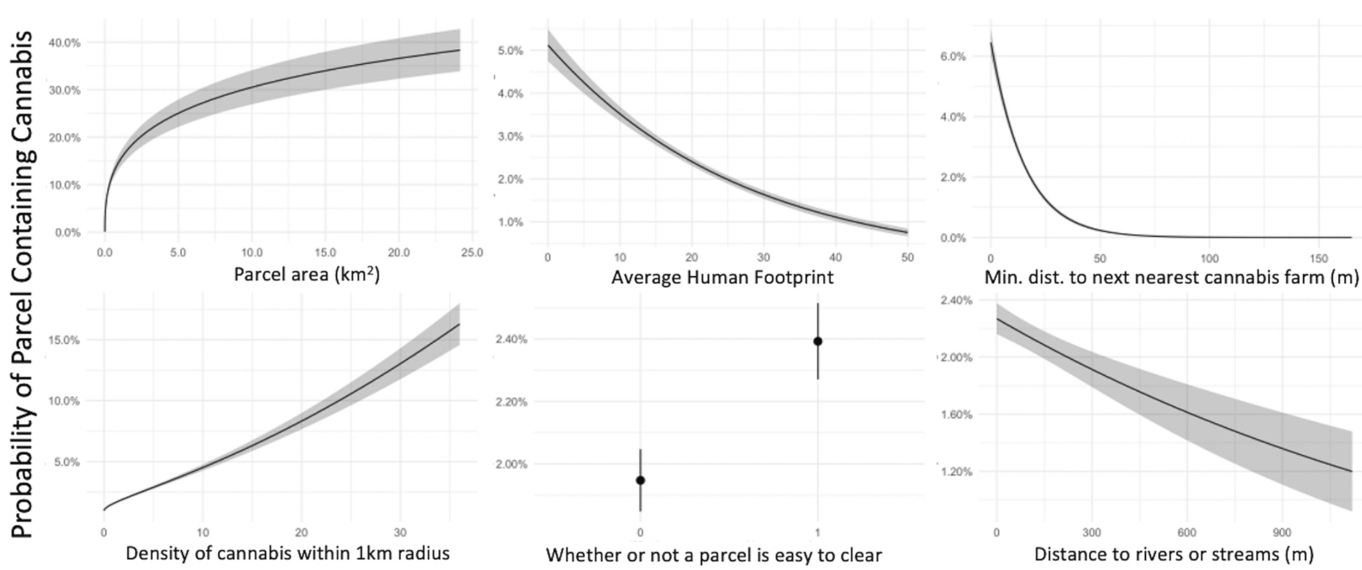

Fig. 3. Prediction graphs of the six significant covariates for cannabis land use distribution in Josephine County, OR. Note that the scale of the y-axis is different for each graph in order to illustrate the probability relationship of individual covariates. Error bars show the standard error.

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	−0.2371 (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) ***

4.1. Strength of interdisciplinary approach

Previous studies examining cannabis land use distribution and change have relied on biophysical covariates (Butsic et al., 2018, 2017; Wengert et al., 2021). Building on this foundational approach for understanding cannabis spatial patterns, 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

Table 5
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) ***

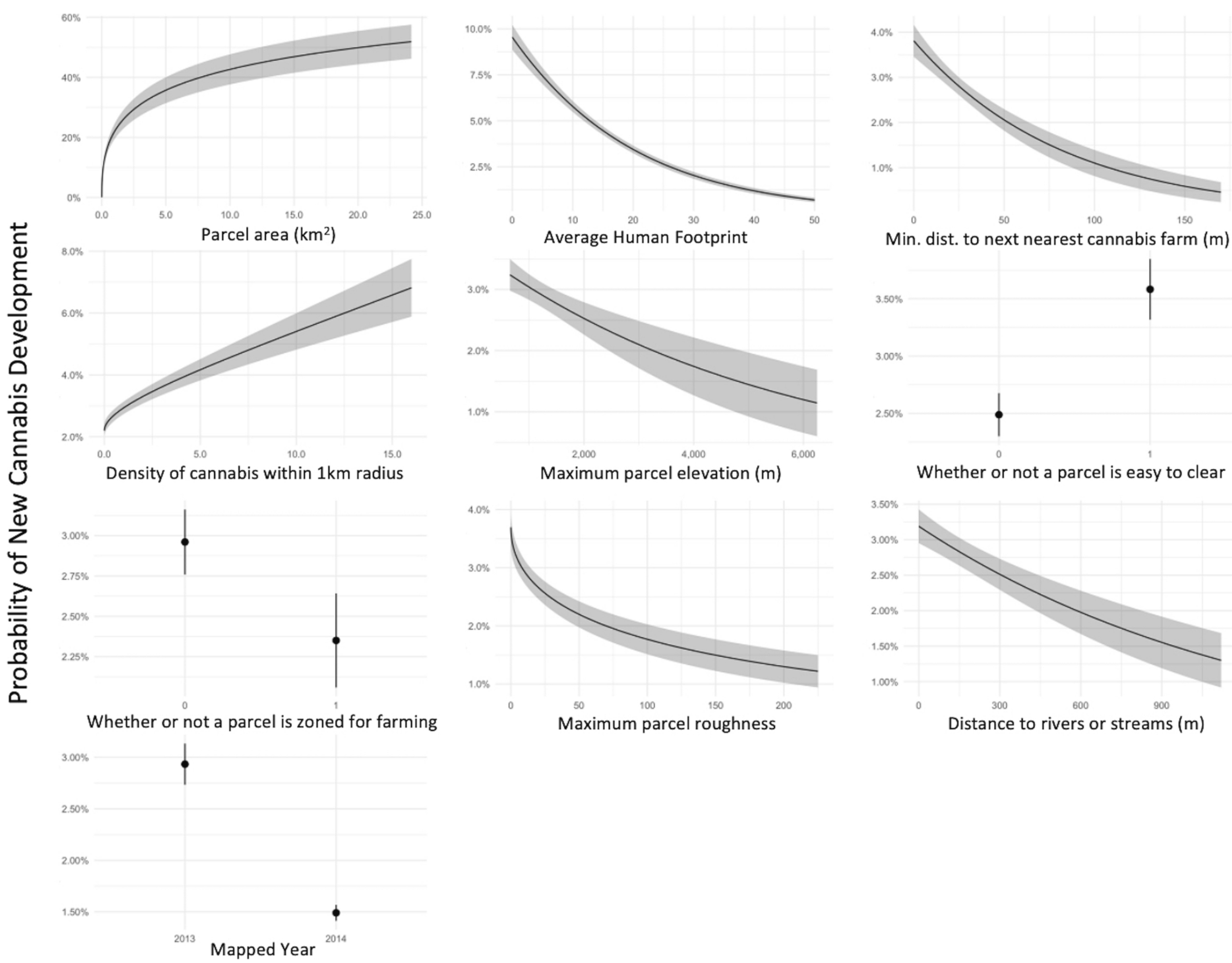

Fig. 4. Prediction graphs of the ten significant covariates for new cannabis development. Note that the scale of the y-axis is different for each graph in order to illustrate the probability relationship of individual covariates. Error bars show the standard error.

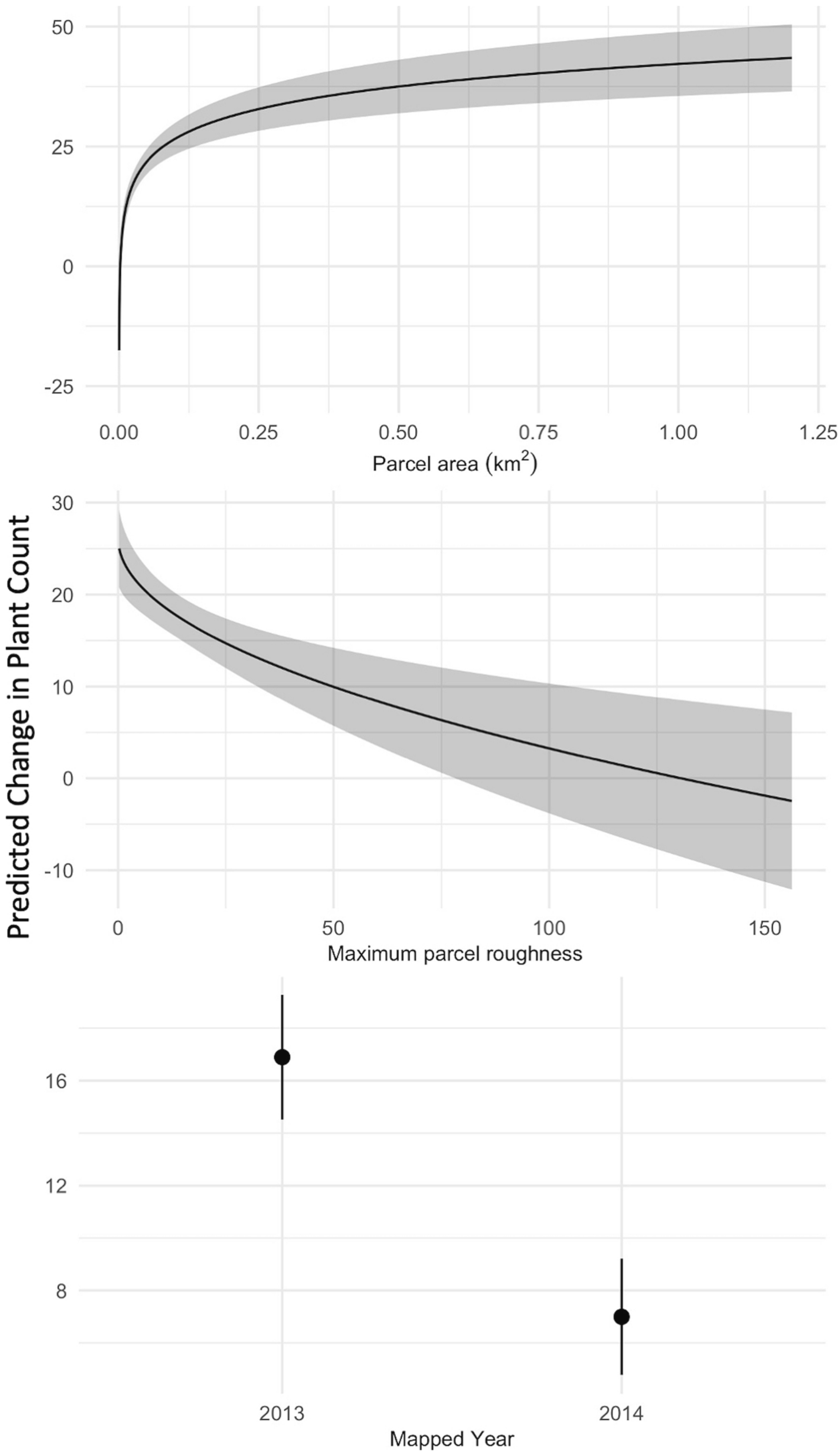

Fig. 5. Relationships between predicted change in cannabis plant count on farms and three significant covariates from 2013 to 16. Note that the scale of the y-axis is different for each graph in order to illustrate the probability relationship of individual covariates. Error bars show the standard error.

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, provide a possible explanation, 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, Merrie, Metian, Boonstra, & Blenckner, 2013), and human-wildlife conflict (Wilkinson et al., 2020). One strength of incorporating qualitative data into quantitative models is the ability to identify which factors may be most important to analyze, while simultaneously capturing nuances that may be left out or simplified in traditional modeling efforts. This is where interpreting drivers that we were not able to quantify spatially is particularly useful. The low pseudo r-squared values are less mysterious when we consider the level of nuance that we were unable to capture in our models, particularly on the themes of environmental stewardship, economics, and the future of the industry. 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.

Our methods help avoid one critique of the social-ecological systems approach in which it can generate long lists of factors, but may struggle to address causal processes (Cole, Epstein, & McGinnis, 2019). Instead, the interview themes help suggest the mechanisms and motivations behind the modeled relationships. Nevertheless, because there can be multiple mechanisms influencing each covariate relationship, some caution should be taken when interpreting results. For example, our selection of the human footprint variable to represent remoteness is influenced by both farmers' desire to connect with nature, and to avoid law enforcement. Below, we interpret some of the model results within the context of the interview themes.

4.2. 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 and our findings here suggest that this overlap is not incidental (Parker-Shames et al., 2022). It is possible that the ecological overlap observed in other rural cannabis-producing regions could be influenced by similar social/cultural drivers (Butsic et al., 2018; Wengert et al., 2021). 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; Polson et al., 2023). 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 (Carah et al., 2015; Short Gianotti et al., 2017; 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.

4.3. 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, particularly as these zones are a small proportion of all private parcels (see Appendix B).

5. 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 likely that many of the drivers that were successful in explaining meaningful amounts of variance in the models (for example, parcel area) were important for all or most cannabis farms in the region, but for other drivers, their relationship may be dependent on production type. 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, most of whom reported that they had been cultivating for longer, and in a more intentional and environmentally conscious manner than the majority of farmers in the county. 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. For example, a broader interview pool might uncover more spatially-explicit economic drivers for individual farms, or nuances in how the demographics of individual farmers (e.g. race, gender, etc.) influences their relationship with drivers. Thus, an expanded interview or focus group data collection process might reveal new drivers that would be relevant for other production styles. Additionally, iterative feedback on model drivers from study participants would likely strengthen the identification and quantification of drivers. In the case of this study, participant feedback on final model covariates was complicated by the COVID-19 pandemic, but future research should seek direct participant feedback on the covariate selection process.

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 or nation. Within the scale of Josephine County, the significant effect of mapped year (Fig. 4) which is also confounded as a spatial variable, 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 (in the East) as opposed to the Illinois Valley (in the West), with different social expectations, communication with neighbors, and regional production practices. This in turn could change how each region develops. 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.

6. 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).

Declaration of Competing Interest

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

Acknowledgements

We thank the undergraduate research assistants who assisted with data collection: Anna Mazur, Frances Bingham, Jamie German, Augie Clements, Parker Bohls, Liam Jameson, Katrina Gonzales, Jordan Pulaski, Ellie Resendiz, Michael Xiao, Alice Hua, Asher Thompson, Theo Snow, Anika Wikramanayake, and Manuel Espinoza. We also thank the Undergraduate Research Assistantship Program (URAP) and the Geospatial Innovation Facility at UC Berkeley for supporting the undergraduate assistants.

Thank you to the Brashares Lab, the Cannabis Research Center at Berkeley, and Mary Power for providing feedback on research concepts and early drafts, which helped shape the direction of this project. We also thank Ben Goldstein, Amy Van Scoyoc, and Dylan Beal for their invaluable modeling advice.

We are grateful to the three anonymous reviewers for their constructive and thoughtful feedback on the manuscript, which helped improve the clarity and impact of our work.

We acknowledge the support of the National Science Foundation Graduate Research Fellowship Program, which funded PPS during data collection. We also thank the community of Takilma, Oregon for being a supportive home base during interview data collection, particularly the Magic Forest Farm and the Meadows. Finally, we extended our deepest gratitude to the farmers who agreed to be interviewed for this project, and recognize the importance of their contributions to our understanding of sustainable agriculture and community resilience.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.landurbplan.2023.104783.

References

Bartoń K., 2022. *MuMIn: Multi-Model Inference*. Retrieved from https://CRAN.R-project.org/package=MuMIn.

Baston, D. (2021). *exactextractr: Fast Extraction from Raster Datasets using Polygons*. Retrieved from https://CRAN.R-project.org/package=exactextractr.

Bennett, N. J., Roth, R., Klain, S. C., Chan, K., Christie, P., Clark, D. A., et al. (2017). Conservation social science: Understanding and integrating human dimensions to improve conservation. *Biological Conservation, 205*, 93–108. https://doi.org/10.1016/j.biocon.2016.10.006

Bloemraad, I. (2007). Of Puzzles and Serendipity: Doing Cross-National, Mixed Method Immigration Research. *Researching Migration: Stories from the Field*. New York: The Social Science Research Council.

Bodwitch, H., Carah, J., Daane, K. M., Getz, C., Grantham, T. E., Hickey, G. M., et al. (2019). Growers say cannabis legalization excludes small growers, supports illicit markets, undermines local economies. *Califorina. Agriculture, 3*(December 2019), 177–184.

Bodwitch, H., Polson, M., Biber, E., Hickey, G. M., & Butsic, V. (2021). Why comply? Farmer motivations and barriers in cannabis agriculture. *Journal of Rural Studies, 86*, 155–170. https://doi.org/10.1016/j.jrurstud.2021.05.006

Butsic, V., Carah, J., Baumann, M., Stephens, C., & Brenner, J. C. (2018). The emergence of cannabis agriculture frontiers as environmental threats. *Environmental Research Letters, 13*, Article 124017. https://doi.org/10.1088/1748-9326/aaeade

Butsic, V., Schwab, B., Baumann, M., & Brenner, J. C. (2017). Inside the Emerald Triangle: Modeling the placement and size of cannabis production in Humboldt County, CA USA. *Ecological Economics, 142*, 70–80. https://doi.org/10.1016/j.ecolecon.2017.06.013

Carah, J. K., Howard, J. K., Thompson, S. E., Short Gianotti, A. G., Bauer, S. D., Carlson, S. M., et al. (2015). High Time for Conservation: Adding the Environment to the Debate on Marijuana Liberalization. *BioScience, 65*(8), 822–829. https://doi.org/10.1093/biosci/biv083

Cole, D., Epstein, G., & McGinnis, M. (2019). The Utility of Combining the IAD and SES Frameworks. *International Journal of the Commons, 13*(1), 244–275. https://doi.org/10.18352/ijc.864. The paper is more about analytical framing than empirics.

Corva, D. (2014). Requiem for a CAMP: The life and death of a domestic U.S. drug war institution. *International Journal of Drug Policy, 25*(1), 71–80. https://doi.org/10.1016/j.drugpo.2013.02.003

Dewitz, J. (2019). National Land Cover Database (NLCD) 2016 Products. U.S. Geological Survey data release. doi:https://doi.org/10.5066/P96HHBIE.

Dillis, C., Biber, E., Bodwitch, H., Butsic, V., Carah, J., Parker-Shames, P., et al. (2021). Shifting geographies of legal cannabis production in California. *Land Use Policy, 105*, Article 105369. https://doi.org/10.1016/j.landusepol.2021.105369

Dorman, M. (2022). *nngeo: K-Nearest Neighbor Join for Spatial Data*. Retrieved from https://CRAN.R-project.org/package=nngeo.

Ellis, E. C., Kaplan, J. O., Fuller, D. Q., Vavrus, S., Klein Goldewijk, K., & Verburg, P. H. (2013). Used planet: A global history. *Proceedings of the National Academy of Sciences, 110*(20), 7978–7985. https://doi.org/10.1073/pnas.1217241110

Foley, J. A., Defries, R., Asner, G. P., Barford, C., Bonan, G., Carpenter, S. R., … Snyder, P. K. (2005). Global consequences of land use. *Science (New York, N.Y.), 309*(5734), 570–574. doi: 10.1126/science.1111772.

U.S. Geological Survey. (2018). National Hydrography Dataset Plus High Resolution.

Hall, C. (2022). *Cannabis Industry Impacts to the Environmental Health of the Illinois River Basin and Community Well-Being*. Illinois Valley Soil and Water Conservation District. Retrieved November 2, 2022 from - http://ivswcd.specialdistrict.org.

R.J. Hijmans raster: Geographic Data Analysis and Modeling Retrieved from 2022 https://CRAN.R-project.org/package=raster.

Kinnebrew, E., Shoffner, E., Farah-Pérez, A., Mills-Novoa, M., & Siegel, K. (2021). Approaches to interdisciplinary mixed methods research in land-change science and environmental management. *Conservation Biology, 35*(1), 130–141. https://doi.org/10.1111/cobi.13642

Lamarque, P., Artaux, A., Barnaud, C., Dobremez, L., Nettier, B., & Lavorel, S. (2013). Taking into account farmers' decision making to map fine-scale land management adaptation to climate and socio-economic scenarios. *Landscape and Urban Planning, 119*, 147–157. https://doi.org/10.1016/j.landurbplan.2013.07.012

Österblom, H., Merrie, A., Metian, M., Boonstra, W. J., Blenckner, T., et al. (2013). Modeling Social-Ecological Scenarios in Marine Systems. *BioScience, 63*(9), 735–744. https://doi.org/10.1525/bio.2013.63.9.9

Ostrom, E. (2009). A General Framework for Analyzing Sustainability of Social-Ecological Systems. *Science, 325*(5939), 419–422. https://doi.org/10.1126/science.1172133

Parker-Shames, P., Choi, C., Butsic, V., Green, D., Barry, B., Moriarty, K., et al. (2022). The spatial overlap of small-scale cannabis farms with aquatic and terrestrial biodiversity. *Conservation Science and Practice, 4*(2), 1–14. https://doi.org/10.1111/csp2.602

Pebesma, E. (2018). Simple features for R: Standardized support for spatial vector data. *R Journal, 10*(1), 439–446. https://doi.org/10.32614/rj-2018-009

Polson, M. (2015). From outlaw to citizen: Police power, property, and the territorial politics of medical marijuana in California's exurbs. *Territory, Politics, Governance, 3*(4), 387–406. https://doi.org/10.1080/21622671.2015.1073613

Polson, M., & Bodwitch, H. (2021). Prohibited commoning. *Elementa: Science of the Anthropocene, 9*(1), 00054. https://doi.org/10.1525/elementa.2021.00054

Polson, M., Bodwitch, H., Biber, E., Butsic, V., & Grantham, T. (2023). After legalization: Cannabis, environmental compliance, and agricultural futures. *Land Use Policy, 126*. https://doi.org/10.1016/j.landusepol.2022.106531

Short Gianotti, A. G., Harrower, J., Baird, G., & Sepaniak, S. (2017). The quasi-legal challenge: Assessing and governing the environmental impacts of cannabis cultivation in the North Coastal Basin of California. *Land Use Policy, 61*, 126–134. https://doi.org/10.1016/j.landusepol.2016.11.016

Siegel, K., Farah Perez, A., Kinnebrew, E., Mills-Novoa, M., Ochoa, J., & Shoffner, E. (2022). Integration of qualitative and quantitative methods for land-use-change modeling in a deforestation frontier. *Conservation Biology*. https://doi.org/10.1111/cobi.13924

Smith, V., Powell, M., Mungeam, D., & Emmons, R. (2019). Stakeholder Perceptions of the Impact of Cannabis Production on the Southern Oregon Food System. *Journal of Agriculture, Food Systems, and Community Development, 8*(4), 1–11. https://doi.org/10.5304/jafscd.2019.084.012

D. Stockemer Quantitative Methods for the Social Sciences 2019 Springer. Retrieved from Ottowa, Ontario, Canada 10.1007/978-3-319-99118-4.

Turner, B. L., Lambin, E. F., & Reenberg, A. (2007). The emergence of land change science for global environmental change and sustainability. *Proceedings of the National Academy of Sciences, 104*(52), 20666–20671. https://doi.org/10.1073/pnas.0704119104

Venter, O., Sanderson, E. W., Magrach, A., Allan, J. R., Beher, J., Jones, K. R., … Watson, J. (2016). Data from: Global Terrestrial Human Footprint Maps for 1993 and 2009. doi: https://doi.org/10.5061/DRYAD.052Q5.

Wartenberg, A. C., Holden, P. A., Bodwitch, H., Parker-Shames, P., Novotny, T., Harmon, T. C., et al. (2021). Cannabis and the Environment: What Science Tells Us and What We Still Need to Know. *Environmental Science and Technology Letters*. https://doi.org/10.1021/acs.estlett.0c00844

Wengert, G. M., Higley, J. M., Gabriel, M. W., Rustigian-Romsos, H., Spencer, W. D., Clifford, D. L., & Thompson, C. (2021). Distribution of trespass cannabis cultivation and its risk to sensitive forest predators in California and Southern Oregon. *PLoS ONE, 16*(9 September). doi: 10.1371/journal.pone.0256273.

Wilkinson, C. E., McInturff, A., Miller, J. R. B., Yovovich, V., Gaynor, K. M., Calhoun, K., et al. (2020). An ecological framework for contextualizing carnivore–livestock conflict. *Conservation Biology, 34*(4), 854–867. https://doi.org/10.1111/cobi.13469

Woolridge, J. M. (2015). *Introductory econometrics: A modern approach*. Boston, MA: Cengage learning.