

Research Paper

Patterns and correlates of unlicensed cannabis cultivation in California (USA) following adult-use legalization

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ABSTRACT

Since the legalization of cannabis in California (USA), unlicensed cultivation has unevenly persisted. Spatial patterns are likely associated with a combination of physical and socio-political factors, though their relative importance remains unexplored. This study examines interannual growth and decline in unlicensed cultivation, the spatial patterns of relocation, redistribution, and clustering, and the relationship between unlicensed cultivation and potential environmental impacts. It uses multi-year spatial data (from 2018–2024) and Generalized Additive Models (GAMs) to conduct landscape-scale analyses of geographic trends, changes in cultivation density, and associations with physical and socio-political characteristics. We found that physical characteristics such as topography, building density, and remoteness were associated with changes in cultivation density, though the direction and magnitude of effects varied across periods. Socio-political factors, including enforcement intensity, fines, bans, and the presence of licensed farms, exhibited complex and sometimes opposing temporal patterns. Licensed farms were the single largest and most consistent predictor of reduced unlicensed cultivation (estimates ranged from -207.79 to -660.06 m² per km²), suggesting that active participation in permitting regimes fosters stability, norm formation, and deterrence. In contrast, bans and enforcement alone often redistributed cultivation, producing “whack-a-mole” dynamics that increased volatility and, in some cases, environmental exposure. Environmental sensitivity emerged as a significant factor in later periods, with regulated counties showing reductions in cultivation in vulnerable areas, highlighting the potential for permitting systems to mitigate ecological impacts. These findings emphasize the importance of participatory, stable, and well-implemented regulatory frameworks for managing unlicensed cultivation and provide broader insights for formalizing informal or illicit resource use in varied socio-ecological contexts.

Introduction

Since the 19th century, the cultivation of illegalized cannabis has been cast as a problem by nations worldwide (Mills & Richert, 2021). Though prohibition inhibited what could be known about this activity (Gianotti et al., 2017), innovative and perceptive research has managed to investigate this shrouded activity, coming to understand its contours in specific times, places, and ecologies (Clarke & Merlin, 2016; Potter et al., 2013). In the case of Northern California, research has shown that illicit production carries potential environmental impacts, where cultivation occurs within ecologically sensitive watersheds (Butsic & Brenner, 2016; Carah et al., 2015). Concerns include land clearing, unpermitted road development, sedimentation of streams, and water extraction during low-flow summer months when freshwater species are most vulnerable (Bauer et al., 2015; Zipper et al., 2019). When it is

highly lucrative and enforcement is intensive, it can degrade social cohesion and incite violence and insecurity (Anders, 1990; Raphael, 1985). That said, unlicensed cultivation has also been a critical source of revenue and community development for numerous rural California communities (Corva, 2014; Polson, 2018) and has generated its own forms of stewardship, care, and belonging (Polson & Bodwitch, 2021). Building from this knowledge foundation, this article advances a novel approach to understanding the geographic changes in unlicensed cultivation since legalization and the social, policy, and physical factors associated with this change.

Given the complex dynamics of unauthorized cultivation, it is important to accurately and even-handedly assess unlicensed cultivation. Scholars, officials, and media have utilized many methods to measure unlicensed cannabis cultivation over the past 50-plus years. These methods were developed under prohibition conditions, where

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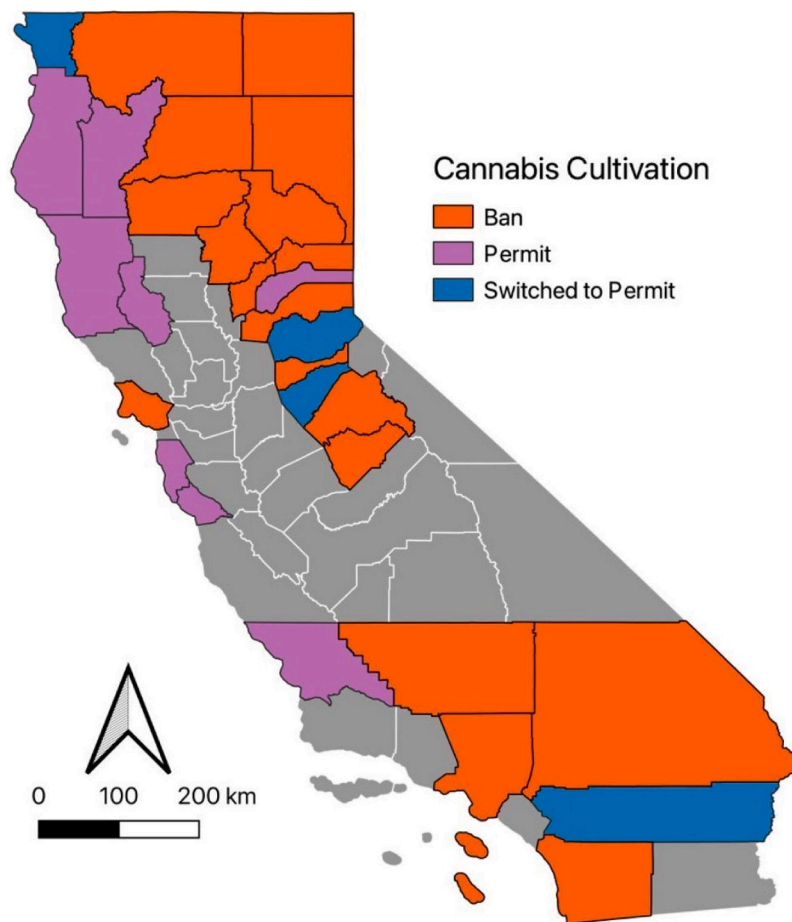


Fig. 1. Study area map. All counties included in the dataset are depicted in one of three colors: orange (counties with cultivation bans for the duration of the study period), purple (counties with permit programs for the duration of the study period), and blue (counties which switched from bans to permit programs during the study period). Remaining counties of California are depicted in gray. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

evasion, secrecy, and elusiveness are paramount for cultivators, making measurement difficult. As a result, measurements are derivative, formulaic, and blunt, when compared with other agricultural and natural resource assessments (Gianotti et al., 2017). After cannabis decriminalization these methods continue to be employed, even when new data sources and monitoring methods emerged. Mischaracterizations and inaccurate assessments can contribute to inappropriate policy responses, particularly responses that overestimate cultivation and subsequently emphasize punitive enforcement, reproduce patterns associated with prohibition, and undermine legalization goals (Adinoff & Reiman, 2019; Getz et al., 2024; Polson, 2019). Further, prior estimates have generally neglected to explore geographical and sociopolitical correlates of unlicensed cultivation, leading to misattribution of causality from which numerous policy, fiscal, social, and ecological consequences follow. Inadequate methods are symptomatic of a broader path dependency established under prohibition, where policy and public debate continue to be shaped through stigma and prohibitionist reflexes (Heidt & Wheeldon, 2024).

Reliable information on unlicensed cannabis cultivation has historically been difficult to obtain. Much of the existing knowledge has come from ethnographic studies (Corva, 2014; Hafley & Tewksbury, 1995; Polson, 2021), while quantitative assessments have relied on incomplete or inconsistent law enforcement estimates (Kalacska & Bouchard, 2011; Leggett & Pietschmann, 2008). Remote sensing approaches have offered valuable insights into cultivation patterns, but these methods often require substantial interpretation and sometimes produce uncertain results (Dillis et al., 2020; Franklin et al., 2018; Gianotti et al., 2017).

While these approaches have provided useful information at local or site-specific scales, none have allowed for landscape-level analysis capable of testing fundamental questions about what drives the growth or decline of unlicensed cannabis cultivation. Here we review our efforts to model just such an approach.

California's adult-use legalization stands to alter the geography of unlicensed cultivation. Historical patterns indicate that illicit farms were concentrated in remote, rugged terrain in Northern California, where producers sought to avoid detection (Corva, 2014). It is likely, however, that legalization would not only recompose the geography and siting of cultivation but also *the reasons why* cultivation expands and declines in certain places. Since the state-level legalization of adult-use cannabis in 2016 and the rollout of a statewide regulatory apparatus in 2018, counties and municipalities have adopted highly variable permitting rules, zoning frameworks, and enforcement practices (Biber et al., 2023; Getz et al., 2024). In particular, California implemented a dual licensing program for cannabis, that requires both state and local approval to cultivate cannabis. Local jurisdictions (counties and cities) that elected to permit cultivation exhibit wide variability in program design, execution, and efficacy (Biber et al., 2023). The majority of localities, however, have availed themselves of state-designated powers to "ban" cultivation altogether, a policy that also exhibits wide variation in agency involvement, budget allocations, and enforcement intensity (Getz et al., 2024). This policy diversity across 58 counties and 483 cities is further compounded by complexities in demography, economy, and political dynamics, not to mention geophysical and ecological diversity. There are a wide range of cultivators, too. Legal operators run the gamut

Table 1
Predictor variables for GAMs.

Variable	Description	Source
Physical variables		
Building Density	Continuous; Measured at beginning of study period; number of buildings per km ²	Microsoft
Road Network Density	Continuous; Measured at beginning of study period; length of paved public roads per km ²	UCSB
Stream Network Density	Continuous; Measured at beginning of study period; length of streams per km ²	USGS NHD
Proportion Forest	Continuous, bounded (0–1); Measured for each time period; proportion of sample cell that is covered in forest	NLCD
Proportion Planted	Continuous, bounded (0–1); Measured for each time period; proportion of sample cell that is cultivated (non-cannabis agriculture)	NLCD
Proportion Barren	Continuous, bounded (0–1); Measured for each time period; proportion of sample cell that is barren rock	NLCD
Average Slope	Continuous, bounded (0–1); Measured at beginning of study period; average hill slope of the sample cell	USGS DEM
Remoteness	Continuous; Measured at beginning of study period; distance from sample cell to nearest incorporated area	CALFIRE
Groundwater Present	Binary; Measured at beginning of study period; presence/absence of SGMA groundwater basin within the sample cell	DWR
High Fire Hazard Severity	Binary; Measured at beginning of study period; presence/absence of area mapped as either “high” or “very high” fire hazard severity within the sample cell	CALFIRE
Socio-Political Variables		
Cultivation Ban	Binary; Measured for each time period; presence/absence of cultivation ban during time period	Planning Code Summaries
Fine Amount	Integer; Measured for each time period; Dollar value of daily fine for uncultivated cultivation	Planning Code Summaries
Fine Per Plant Basis	Binary; Measured for each time period; whether/not fines are assessed on a per-plant basis	Planning Code Summaries
Land Owner Responsibility	Binary; Measured for each time period; whether/not landowners are responsible for tenant cannabis cultivation violations	Planning Code Summaries
Personal Cultivation	Binary; Measured for each time period; whether/not personal cultivation allowances (up to six plants) were present (note: CannaVision does not map cannabis cultivation at the scale of six plants or smaller)	Planning Code Summaries
Enforcement Rank	Rank; Measured for each time period; rank among study counties of lbs of cannabis seized since 2011	ERA Economics
Public Land Boundary	Binary; Measured at beginning of study period; presence/absence of public land within the sampling grid cell	CALFIRE
Presence of Licensed Farm	Binary; Measured for each time period; presence/absence of a licensed cannabis farm within the sample cell	DCC
Presence of Hemp	Binary; Measured for each time period; presence/absence of a hemp license within the sample cell	CDFA
Proportion Conservative	Continuous, bounded (0–1); Measured at beginning of study period; proportion of county registered voters identifying as Republican	CSoS
Median Income	Continuous; Measured at beginning of study period; county median income	CSFTB
Proportion Retirement Age	Continuous, bounded (0–1); Measured at beginning of study period; proportion of county population aged 65 or older	USCB

Table 2
Ranking Metrics for Environmental Impact Analysis.

Variable	Description	Source
Proportion Undeveloped	Continuous, bounded (0–1); the proportion of private land in a county that is not classified as developed or cultivated	USGS
Stream Network Density	Continuous; the length of streams on private land within a county, divided by the area of private land	USGS
Proportion of Watersheds Sensitive	Continuous, bounded (0–1); the proportion of watersheds within a county that contain critical habitat for protected fish species	NMFS

from small family farms to large, corporate entities in both “legacy” (pre-legalization) cultivation areas and regions with no cultivation history (Dillis et al., 2021). Uncultivated cultivators are often unable to overcome barriers to enter the formal market, operate in marginal, remote areas, have little access to alternative livelihoods, and as the wholesale price of cannabis declines, earn meager livelihoods from cannabis (Polson et al., 2024). Variegated policy, social, and geophysical factors comprise a real-time societal laboratory to assess what kinds of variables are important (and not important) in the rearrangement of uncultivated cannabis agriculture since legalization. These local dynamics create uneven regulatory landscapes that influence where and why uncultivated activity expands or contracts. It remains unclear the extent to which contemporary patterns of uncultivated cultivation are driven by physical conditions and/or by sociopolitical factors, especially at the local level. Illuminating patterns of uncultivated cultivation across diverse environments is critical for understanding the dynamics of the uncultivated market, crafting effective policy responses to those dynamics, and informing strategies to reduce environmental and social harms that can result from cultivation and inadequate or misdirected responses to it.

Recent advances in the development of CannaVision, a multispectral object detection model developed by the California State Water Resources Control Board (SWRCB), provides an opportunity to address limitations in previous approaches to studying uncultivated cannabis cultivation. Unlike ethnographic or remote sensing methods that are time and resource intensive, or law enforcement estimates, which rely on numerous assumptions and inferences, CannaVision offers spatially consistent mapping of outdoor and mixed-light cultivation features. These data allow for landscape-scale analysis of geographic trends, changes in cultivation density, and associations with physical and jurisdictional characteristics. By enabling this comprehensive perspective, CannaVision supports the investigation of the following key questions about the factors shaping the distribution, persistence, and environmental impacts of uncultivated cultivation:

- 1) Which physical and socio-political variables best explain interannual growth or decline in the amount of uncultivated cultivation?
- 2) Which physical and socio-political variables best explain patterns of spatial redistribution of uncultivated cultivation between time periods?
- 3) What is the relation of uncultivated cultivation to potential environmental impacts, specifically around water resources, wildlife, and land use change?

Methods

Data

Source data for cannabis mapping were derived from the U.S. Department of Agriculture’s National Agricultural Imagery Program (NAIP), which provides statewide aerial imagery at two-year intervals. This project utilized NAIP datasets from 2018, 2020, 2022, and 2024. The CannaVision computer vision model was applied to these imagery

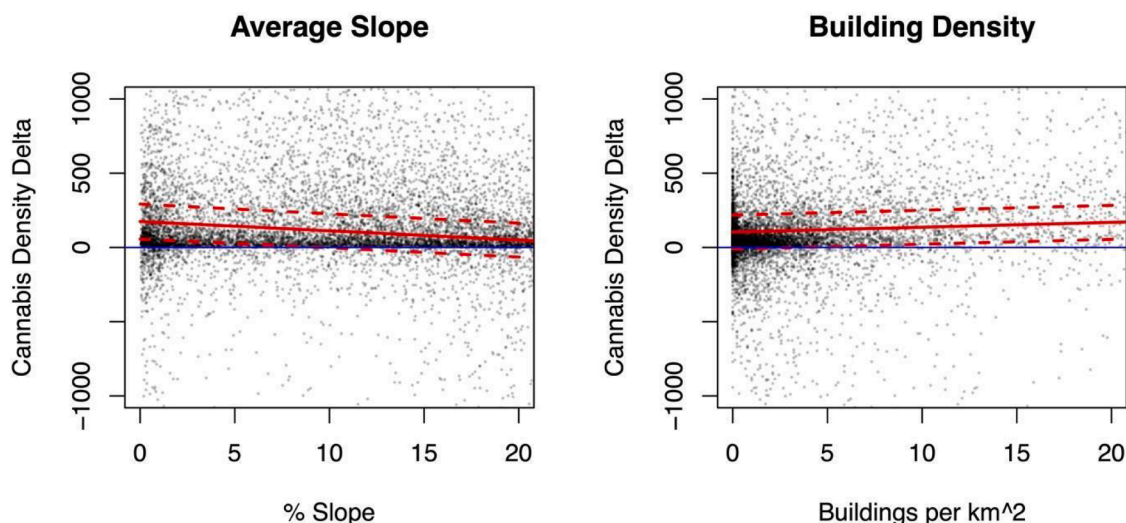


Fig. 2. Physical predictor variables - first time period (2018–2020). The predicted effects of important variables on the amount of change in cannabis cultivation are depicted as maximum likelihood estimates (solid red line) with 95% confidence intervals (dashed red lines). The threshold of no change is depicted as a solid blue line. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

sets to generate spatial predictions of cannabis cultivation. The model produced polygonal representations of outdoor and greenhouse cultivation sites across the study area.

The study area consisted of 30 California counties for which sufficient model training data were available: Amador, Butte, Calaveras, Del Norte, El Dorado, Humboldt, Kern, Lake, Lassen, Los Angeles, Marin, Mendocino, Modoc, Nevada, Placer, Plumas, Riverside, San Bernardino, San Diego, San Luis Obispo, San Mateo, Santa Cruz, Shasta, Sierra, Siskiyou, Tehama, Trinity, Tuolumne, and Yuba (Fig. 1). Analyses were restricted to private lands, as public-land trespass grows tend to be concealed from aerial imagery and are not subject to the landowner decision-making processes addressed in this study.

To protect anonymity, the SWRCB aggregated CannaVision-derived cultivation polygons onto a standardized grid with a nominal cell size of 9 km². The grid was aligned to county boundaries to facilitate county-level summarization. Where county borders intersected grid cells, adjacent units were merged to ensure a minimum cell size of 1.5 km². For each grid cell and each imagery year, cannabis density (m² / km²) was calculated, and year-to-year differences (2018–2020, 2020–2022, 2022–2024) were derived as outcome variables for statistical analysis. Three datasets were generated to fit three separate models: for the first time period (2018–2020; $n = 22,153$), the second time period (2020–2022; $n = 22,118$), and the third time period (2022–2024; $n = 21,750$).

Predictor variables were developed from multiple datasets describing local land-use policy, socioeconomic conditions, demographics, and biophysical terrain. For organizational and reporting purposes, variables were divided into two categories: physical variables and socio-political variables.

Physical variables

Terrain and environmental variables were assembled from the Microsoft Building Footprint Layer (Dao, 2020), US Census Bureau road layers (USCB, 2024), the U.S. Geological Survey's National Hydrography Dataset (USGS, 2024a), National Land Cover Database (USGS, 2024b), and National Elevation Dataset (USGS, 2020), as well as fire history and vegetation data from CALFIRE (CALFIRE, 2024) and licensing and permitting datasets from the California Department of Cannabis Control (DCC, 2024), the California Department of Food and Agriculture (CDFA, 2024), and the California Division of Water Resources (CDWR, 2019). Data used to evaluate potential ecological impacts were sourced from the National Land Cover Database, the National

Hydrography Dataset, and species distribution information from the National Marine Fisheries Service (NMFS, 2023). A full listing of variables and these corresponding data sources is provided in Table 1.

Socio-political variables

County-level policy variables were constructed from an analysis compiled for a report to the California Department of Cannabis Control (Polson et al., 2026). Additional socioeconomic and demographic predictors were constructed using data from the California State Franchise Tax Board (CSFTB, 2023), the U.S. Census Bureau (USCB, 2023), and voting records from the California Secretary of State (CSoS, 2018).

Relative contributions of physical and socio-political factors

All models were implemented as Generalized Additive Models (GAMs) to account for spatial autocorrelation through the use of smoother functions ($k = 200$) applied to the latitude and longitude of each spatial unit (grid cell). Model fitting used the mgcv package (Wood, 2023) in R statistical Software (R Core Team, 2018). For each model (i.e., for each time frame), the full set of predictors was pared down using stepwise Akaike Information Criterion (AIC) selection to retain the most informative variables.

Because many grid cells showed no change in cultivation density between time points, the data were zero-inflated. GAMs were therefore fit as hurdle models, which consist of two component models: a binary model predicting whether change in cultivation density is non-zero, and a conditional model predicting the magnitude of change, given that it is non-zero. Hurdle models are appropriate when zero values arise for a particular reason, rather than randomly. In this dataset, zero values were almost always (>99.99% of cases) due to the absence of cannabis cultivation rather than cultivation remaining exactly the same between time periods. Because the focus of this analysis was on predictors of change, the results presented here focus exclusively on the conditional component, which includes only grid cells with non-zero changes in cultivation density.

To ensure the stability and interpretability of the model coefficients, we conducted rigorous diagnostic checks for multicollinearity and spatial confounding (Table S1). For each model, we calculated Variance Inflation Factors (VIFs) for all parametric predictors; all final variables yielded VIF values below 2.6, well within the conservative threshold of 5.0 (Zuur et al., 2010). Furthermore, we assessed concurvity, which is the non-linear equivalent of multicollinearity in GAMs. Observed

Table 3

Results for GAMs. Maximum likelihood estimates are accompanied by standard error estimates in parentheses. Dashes indicate that the variable was not included (based on stepwise AIC) in the model iteration.

Variable	2018–2020	2020–2022	2022–2024	IntraCounty
Intercept	73.91 (76.15)	−134 (32.21)	22.34 (17.85)	2.48 (0.44)
Physical Variables				
Building Density	3.27 (0.16)	−2.25 (0.14)	0.73 (0.06)	–
Road Network Density	0.0007 (0.0004)	–	0.0004 (0.0001)	–
Stream Network Density	–	−0.007 (0.003)	0.003 (0.001)	–
Proportion Forest	–	46.53 (18.18)	–	0.70 (0.33)
Proportion Planted	−62.17 (29.85)	−117.63 (28.04)	36.59 (10.95)	–
Proportion Barren	–	–	43.97 (23.03)	–
Average Slope	−6.24 (0.95)	4.65 (0.77)	–	–
Remoteness	–	−0.36 (0.74)	0.71 (0.31)	–
Groundwater Present	13.33 (12.98)	−15.91 (10.17)	–	–
High Fire Hazard Severity	–	−26.80 (16.86)	−12.01 (6.79)	–
Remoteness X High Fire Hazard	–	−0.66 (0.55)	0.39 (0.22)	–
Socio-Political Variables				
Cultivation Ban	−98.07 (84.41)	−95.54 (22.71)	86.71 (17.23)	−1.65 (0.32)
Fine Amount	−0.01 (0.002)	0.005 (0.002)	−0.005 (0.0007)	–
Fine Per Plant Basis	−47.12 (36.31)	–	13.37 (11.56)	–
Land Owner Responsibility	24.95 (27.45)	91.40 (18.93)	−26.93 (9.16)	−0.36 (0.18)
Personal Cultivation	110.14 (32.63)	−49.08 (23.13)	–	–
Enforcement Rank	10.69 (4.09)	–	−1.33 (1.08)	−0.03 (0.01)
Public Land Boundary	−48.17 (11.94)	72.06 (9.37)	−14.33 (3.80)	−2.09 (0.46)
Presence of Licensed Farm	−207.79 (22.62)	−660.06 (17.41)	−322.85 (7.72)	–
Presence of Hemp	137.63 (23.15)	−173.29 (19.44)	18.96 (8.35)	–
Proportion Conservative	–	–	–	–
Median Income	–	–	–	–
Proportion Retirement Age	215.44 (68.28)	–	−61.34 (22.03)	–
Fine Amount X Fine Per Plant	0.03 (0.01)	–	−0.004 (0.002)	–
Ban X Enforcement Rank	−1.59 (4.08)	–	−2.50 (1.08)	0.06 (0.02)

concurvity indices remained consistently low, with all values below 0.35, confirming that the socio-political and physical predictors provide independent explanatory power distinct from the spatial trend.

Spatial autocorrelation in the model residuals was addressed by optimizing the basis dimension (k) and the smooth basis type. We implemented a Gaussian Process basis for the spatial term with the basis dimension set to $k = 200$. While the large sample sizes ($n = \sim 22,000$) resulted in statistically significant Global Moran's I values, the I statistics remained low, ranging from 0.11 to 0.13, indicating that the spatial smoothers successfully accounted for the majority of mid-scale and broad-scale spatial dependencies in the data.

Spatial stability of cultivation

This analysis assessed how spatial patterns of unlicensed cannabis cultivation changed within counties over time. The goal was to evaluate whether hotspots of unlicensed cultivation persisted in the same locations across years or shifted over time (i.e., the degree to which redistribution of cultivation sites occurred). Analysis was conducted by aggregating grid cell values to the county level and predictors variables were modified and aggregated to the county level where necessary. For example, the presence of licensed farms in a cell was translated into the proportion of cells in a county containing licensed farms.

The outcome variable chosen to quantify stability used a nonparametric, rank-based approach. Within each county, grid cells were assigned ranks based on cultivation density for the years 2018, 2020, 2022, and 2024. Ranks were then compared across three consecutive year-pairs (2018–2020, 2020–2022, 2022–2024) using Spearman correlation coefficients. A high correlation indicates that cells with high cultivation in one year remained high in the next, reflecting spatial stability. A low correlation indicates movement or replacement of hotspots, suggesting dynamic spatial distribution.

For each county, the three Spearman correlation coefficients were averaged to produce a single rank stability score, ranging from 0 (maximum volatility) to 1 (perfect stability). This score reflects the persistence of hotspots over time. The outcome variable was modeled

using beta regression with a logit link function.

Environmental risk assessment

To assess potential environmental impacts of unlicensed cultivation, changes in cultivation were compared to county-level environmental sensitivity. Environmental sensitivity was measured using a composite of three metrics (Table 2):

- 1) The proportion of county watersheds containing critical salmonid habitat, based on data from NFMS.
- 2) Aquatic habitat density, measured as the length of perennial streams per km^2 using the USGS National Hydrography Dataset.
- 3) The proportion of undeveloped and uncultivated land, derived from the National Land Cover Database.

These measures together reflect the extent to which sensitive habitat, vulnerable freshwater resources, undisturbed natural areas are present. Each metric was calculated for all counties in the study, and county rankings were summed to produce a composite environmental sensitivity score (Table S2). Changes in cannabis cultivation from 2018 to 2020, 2020–2022, and 2022–2024 were measured using CannaVision data for each county. Separate ordinary least squares (OLS) models were fit for counties with cannabis permit programs, counties with bans, and for all counties combined, with the dependent variable being the average change in cultivation over each period and the independent variable being the county environmental sensitivity rank.

Results

Relative contributions of physical and socio-political factors

First time period (2018–2020)

Physical variables. During this period, cultivation overall expanded markedly (mean = $165.99 \text{ m}^2 / \text{km}^2$; SD = 507.24). Densities increased

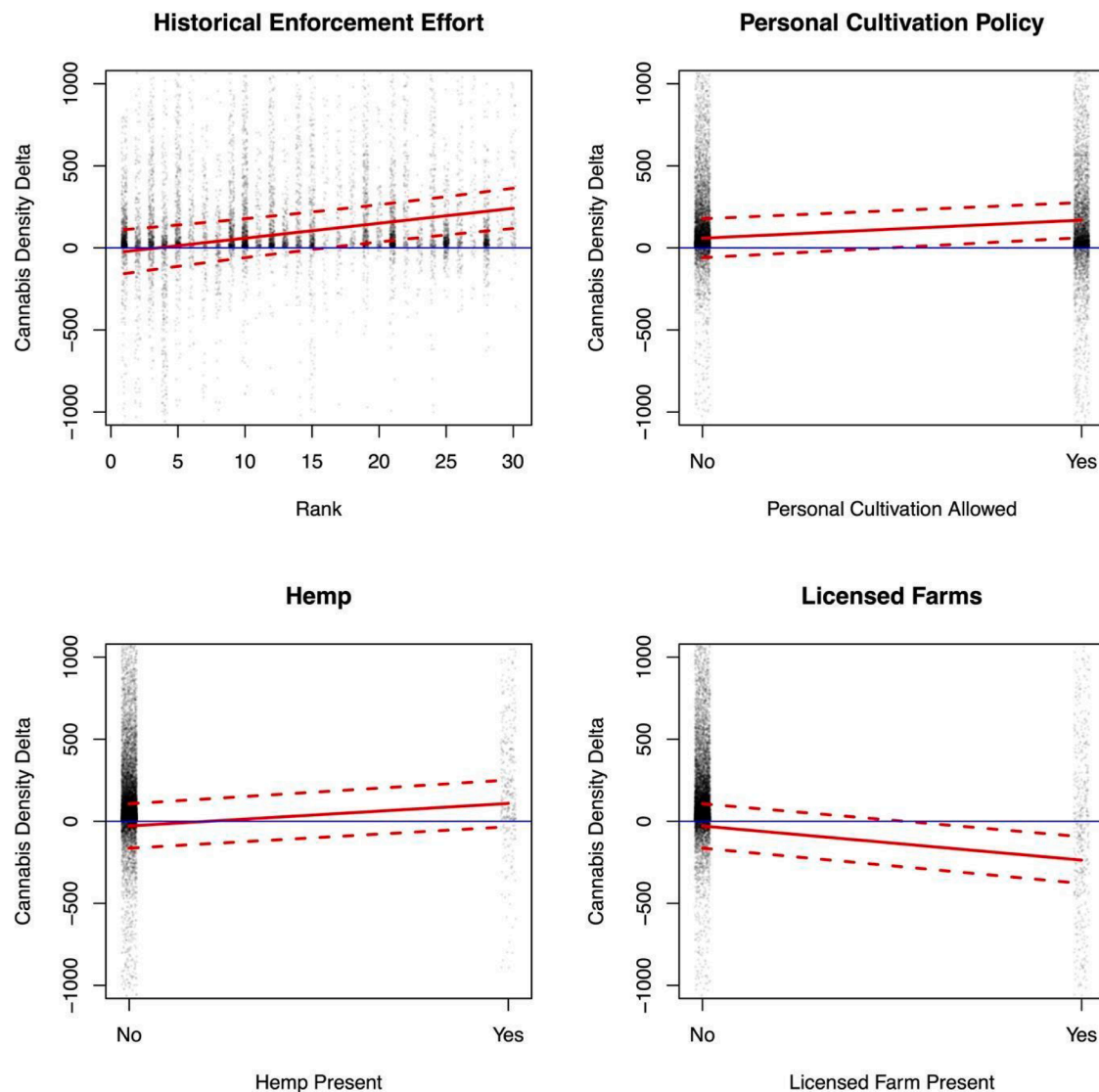


Fig. 3. Socio-political predictor variables - first time period (2018–2020). The predicted effects of important variables on the amount of change in cannabis cultivation are depicted as maximum likelihood estimates (solid red line) with 95% confidence intervals (dashed red lines). The threshold of no change is depicted as a solid blue line. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

most strongly in flatter areas (average slope: MLE = -6.24 , SE = 0.95 ; Fig. 2; Table 3). Locations with higher building density also experienced greater increases in cannabis cultivation (MLE = 3.27 , SE = 0.16).

Socio-political variables. Counties with historically lower enforcement experienced larger increases in cannabis cultivation (MLE = 10.69 , SE = 4.09 ; Fig. 3). Personal cultivation allowance was positively associated with cannabis density change (MLE = 110.13 , SE = 32.63), although personal gardens themselves were unlikely direct contributors to the change in cannabis density. The presence of a hemp farm was positively associated with cannabis density change (MLE = 137.63 , SE = 23.15). The presence of licensed cannabis farms had a strong negative effect on cannabis density change (MLE = -207.79 , SE = 22.62), the magnitude of which exceeded any other variable.

Second time period (2020–2022)

Physical variables. During the second time period, cultivation decreased overall (mean = $-140.59 \text{ m}^2 / \text{km}^2$, SD = 456.05). Densities were higher in hillier areas (average slope: MLE = 4.65 , SE = 0.77 ; Fig. 4; Table 3). Locations with higher building density experienced lower cannabis

cultivation density (MLE = -2.25 , SE = 0.14). Areas with greater forest cover were positively associated with cannabis cultivation density (MLE = 46.53 , SE = 18.18). Stream network density was negatively associated with cannabis cultivation density (MLE = -0.007 , SE = 0.003).

Socio-political variables. Rather unintuitively, higher total fine amounts were positively associated with cannabis cultivation density (MLE = 0.005 , SE = 0.002 ; Fig. 5). Counties with cultivation bans experienced decreases in cannabis cultivation density (MLE = -95.54 , SE = 22.71). The presence of a hemp farm was negatively associated with cannabis cultivation density (MLE = -173.29 , SE = 19.44). The presence of public/private land boundary had a positive effect (MLE = 72.05 , SE = 9.37). The presence of licensed cannabis farms had a strong negative effect on cannabis cultivation density (MLE = -660.06 , SE = 17.41), again far exceeding the magnitude of any other variable.

Third time period (2022–2024)

Physical variables. No strong overall trend in cannabis cultivation was observed, though spatial variation remained (mean = $-3.06 \text{ m}^2 / \text{km}^2$, SD = 190.68). Remoteness (MLE = 0.71 , SE = 0.31) and building density

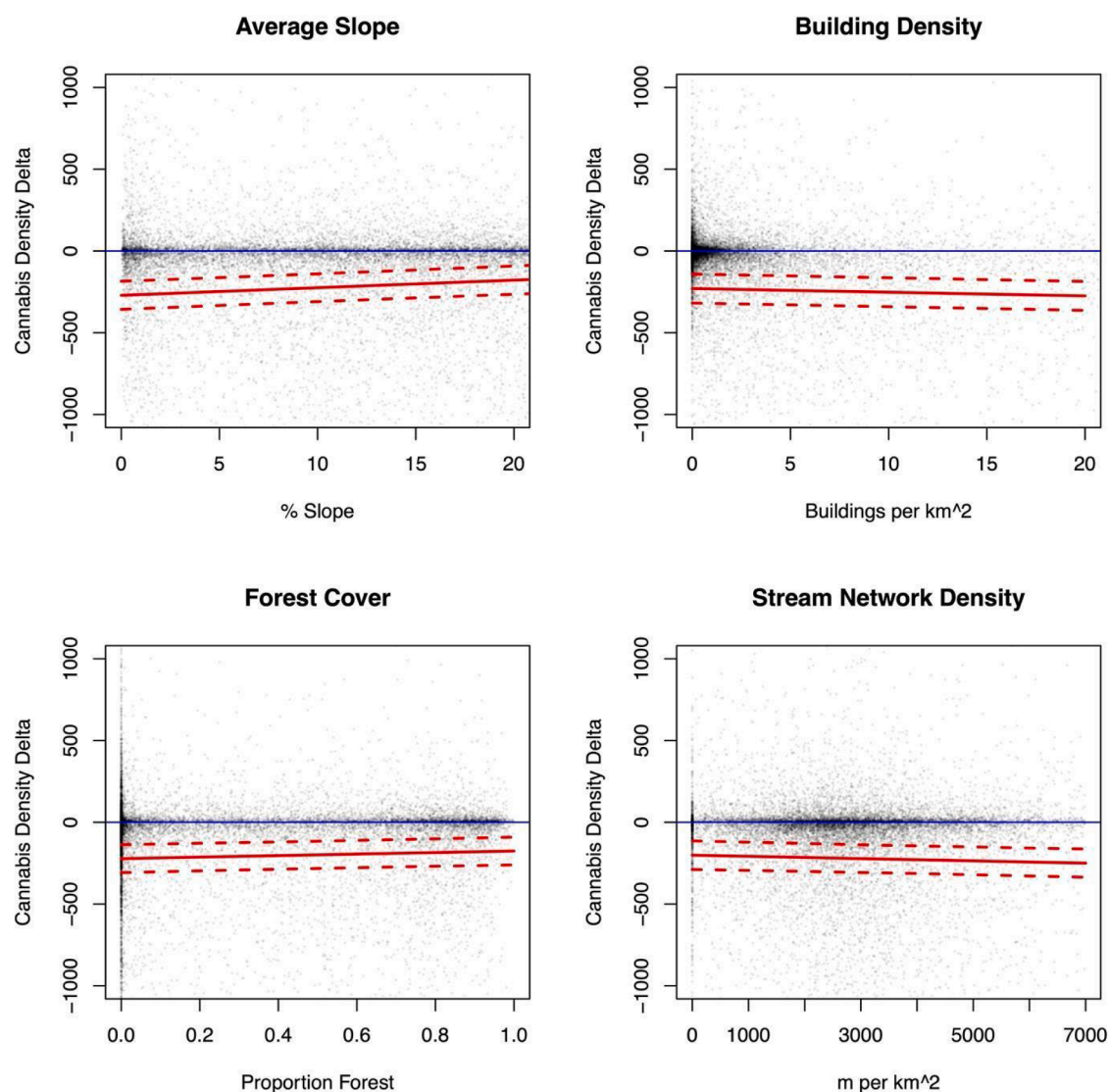


Fig. 4. Physical Predictor variables - second time period (2020–2022). The predicted effects of important variables on the amount of change in cannabis cultivation are depicted as maximum likelihood estimates (solid red line) with 95% confidence intervals (dashed red lines). The threshold of no change is depicted as a solid blue line. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

(MLE = 0.73, SE = 0.06) were weakly positively associated with increases in density. Stream network density also showed a positive association (MLE = 0.003, SE = 0.001), reversing the prior trend. Effect sizes were smaller than in earlier periods, indicating limited practical significance despite statistical significance.

Socio-political variables. Higher total fine amounts were negatively associated with cannabis cultivation density (MLE = -0.01 , SE = 0.0007; Fig. 6). Counties with cultivation bans experienced higher cannabis cultivation density (MLE = 86.71, SE = 17.23). The presence of a hemp farm was positively associated with cannabis cultivation density (MLE = 18.96, SE = 8.35). The presence of licensed cannabis farms had a strong negative effect on cannabis cultivation density (MLE = -322.85 , SE = 7.72), the magnitude of which was once again larger than that of any other variable.

Spatial stability of cultivation

Physical variables

Counties with higher average building density exhibited greater stability (MLE = 0.08, SE = 0.01), as did counties with more forest cover

(MLE = 0.70, SE = 0.33). Conversely, stability was significantly lower in counties with a larger proportion of grid cells containing both public and private land (MLE = -2.09 , SE = 0.46), a pattern that may reflect uncertainty or complexity in land access and enforcement.

Socio-political variables

Over the study period (2018–2024), cannabis cultivation was significantly more variable in counties with local cannabis bans (MLE = -1.65 , SE = 0.32; Fig. 7; Table 3), exhibiting “whack-a-mole” dynamics. Stability of cultivation was also lower in counties with stronger historical enforcement reputations, as indicated by enforcement rankings (MLE = -0.03 , SE = 0.02); however, this effect was only significant in counties with a ban, as shown by a statistically significant interaction (MLE = 0.07, SE = 0.02). Policies that held landowners liable for tenant cultivation were similarly associated with reduced stability (MLE = -0.36 , SE = 0.18), suggesting these measures may contribute to more transient or mobile cultivation activity.

Environmental risk assessment

In the first two time periods (2018–2020 and 2020–2022), there was

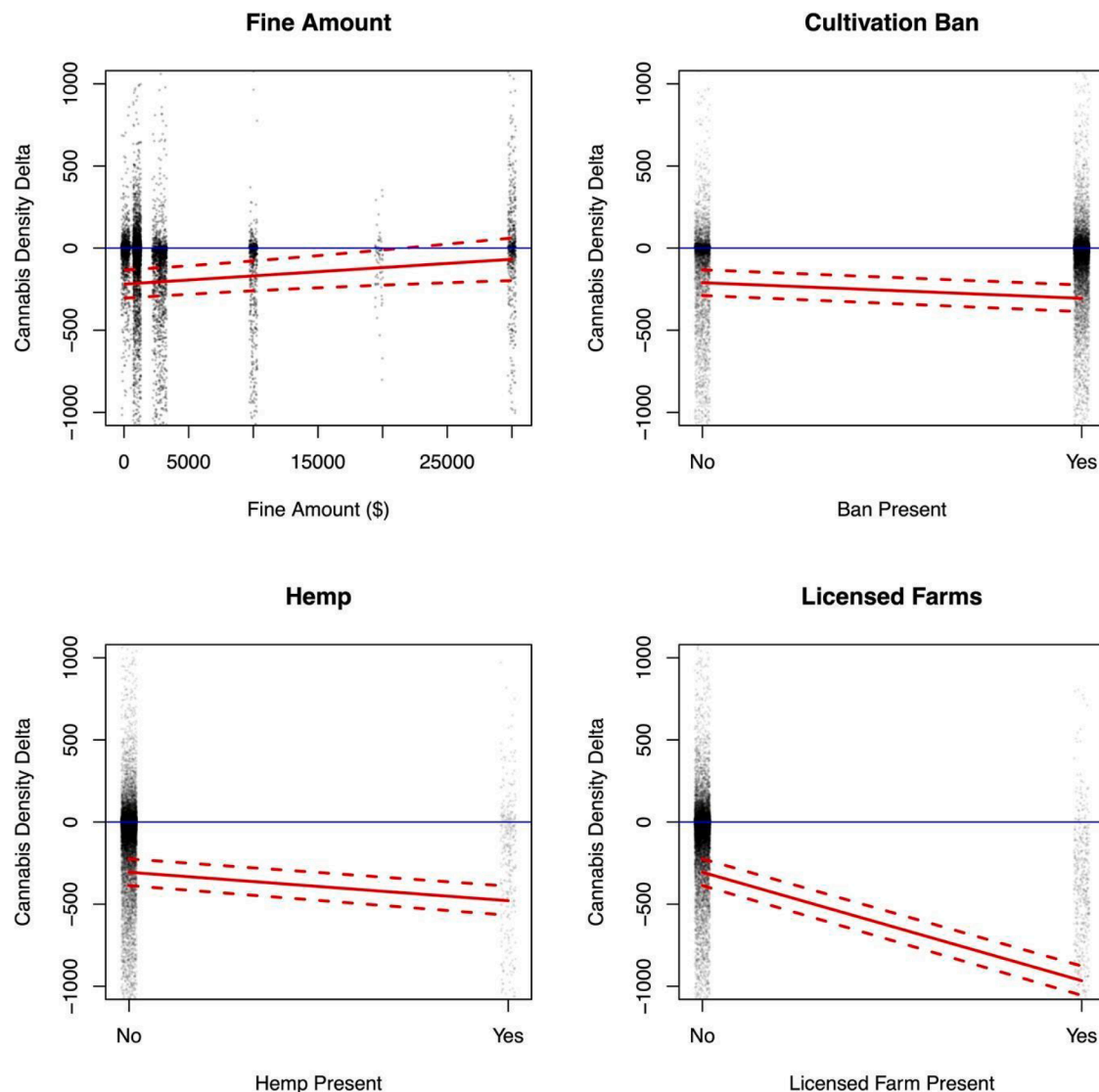


Fig. 5. Socio-political predictor variables - second time period (2020–2022). The predicted effects of important variables on the amount of change in cannabis cultivation are depicted as maximum likelihood estimates (solid red line) with 95% confidence intervals (dashed red lines). The threshold of no change is depicted as a solid blue line. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

no significant relationship between environmental sensitivity rank and changes in cannabis density. By the second period (2020–2022), a trend appeared to be emerging specifically among permit counties of cultivation decreasing more in environmentally sensitive counties. However, the small sample size in this group ($n = 12$) and limited statistical power ($\sim 43\%$) prevented detection of a significant effect, despite a relatively large R^2 of 0.22. By the third period (2022–2024), a similar trend became apparent in the remaining ban counties, resulting in a statistically significant effect when all counties were analyzed together (MLE = 2.40, SE = 0.94; Fig. 8). During this time, more environmentally sensitive counties continued to experience declines in cultivation, while less sensitive counties saw increases. The pattern was primarily driven by permit counties ($R^2 = 0.21$), with ban counties showing a weaker relationship ($R^2 = 0.09$); again, the small permit county sample had limited statistical significance due to low power. The emergence of this pattern in permit counties specifically indicates that permit counties in particular are more responsive to cultivation in environmentally sensitive areas.

Discussion

Summary

Since legalization, a combination of physical landscape features and socio-political conditions have been associated with where unlicensed cannabis cultivation occurred, but these relationships often changed over time. Flatter areas and locations with higher building density generally supported higher cultivation densities during the initial 2018–2020 boom, suggesting that unlicensed cultivators moved away from the hills and into more populated areas, perhaps due to changing social norms, decreased legal consequences, and better proximity to markets and infrastructure. However, the effect reversed and moderated in subsequent periods, suggesting that cultivators may have fled flat, population-dense areas due to factors like recalibrated enforcement or that those who persisted cultivating in greater numbers were in remote, less crowded areas. While some topographical and environmental features are more and less preferable for cannabis cultivation, the movement across different landscapes can also depend on the design of local policies, the extent and intensity to which local and state agencies (particularly environmental agencies like Fish & Wildlife, State Water

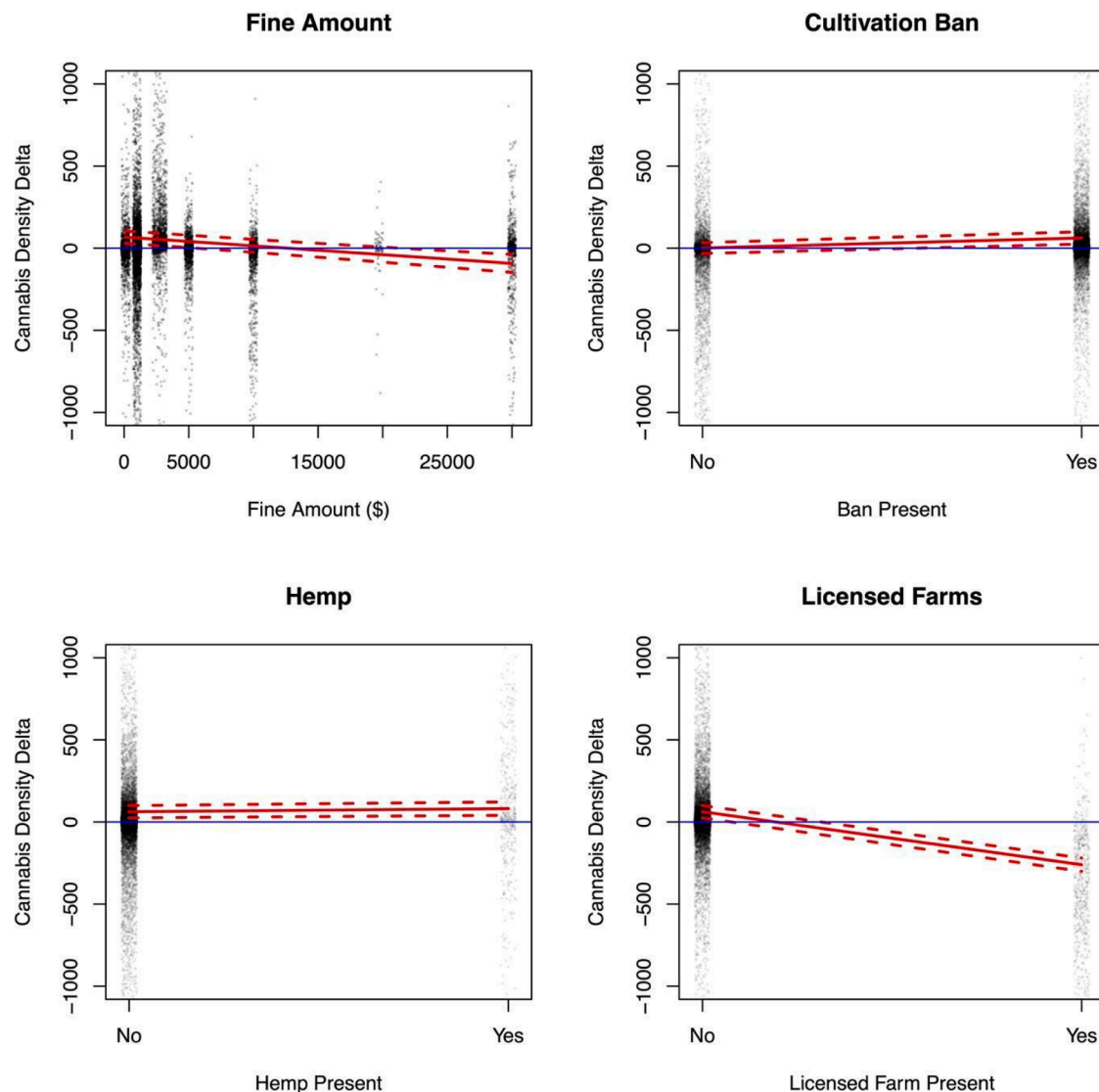


Fig. 6. Socio-political predictor variables - third time period (2022–2024). The predicted effects of important variables on the amount of change in cannabis cultivation are depicted as maximum likelihood estimates (solid red line) with 95% confidence intervals (dashed red lines). The threshold of no change is depicted as a solid blue line. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

Board, or local environmental health agencies), and local social attitudes around cannabis. Socio-political factors also had complex and sometimes shifting impacts. Historical enforcement effort was initially a deterrent to expansion in the first time period, but the effect dissipated in subsequent time periods, suggesting that enforcement dynamics may have initial deterrent effects but over time those effects decrease as those who are not responsive to enforcement risk persist in cultivation. Cultivation bans and higher fine amounts sometimes correlated with reduced growth, but in other time periods were associated with increasing growth. Notably, the varying efficacy of bans in reducing unlicensed cultivation undermines the main argument for bans – to reduce unlicensed cultivation – and suggests that other factors may mitigate the success or failure of bans, including shifts in the risk/benefit calculations of cultivators. Other factors, such as fine amounts and liability for landlords whose tenants cultivate also showed changing associations with cultivation density, often reversing direction between periods. By contrast, the presence of licensed farms stood out as the one consistent predictor, reducing unlicensed cultivation in all periods.

Localized benefits of licensure

Upon closer analysis, it is not the presence of a permitting program (i. e., lack of a ban), per se, but the presence of a licensed farm within a given area that is critical. This suggests that there are likely localized effects of licensed farms that discourage unlicensed activity. First, these farms may draw regulatory attention (e.g., on-site inspections) that can more easily identify and address unlicensed cultivation. Indeed, permitting programs often draw from a wide range of government agencies and capacities that can address unlicensed cultivation from numerous angles beyond simple law enforcement, thus dispersing the potential to remediate unlicensed cultivation. Second, farms may also create social norms that foster a “culture of compliance.” In enforcement terms, farms may create a social deterrence to unlicensed activity with a power that even strong law enforcement approaches do not exhibit in this study. It remains to reason that consistent rules and known consequences can bolster norm formation and deterrence effects by fostering and discouraging certain behaviors over time (Polson et al., 2026). Indeed, prior research has shown that shifting rules and arbitrary enforcement activity discourages compliance and licensing and incites maladaptive behaviors to what is perceived as arbitrary and capricious

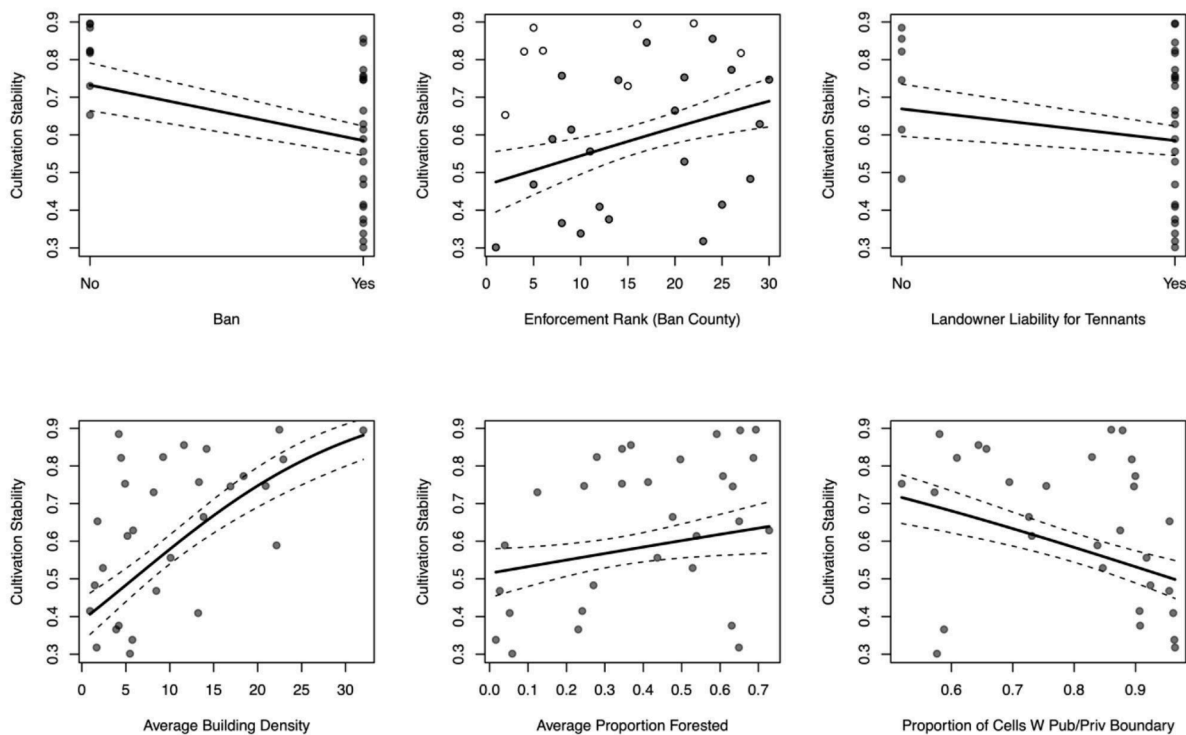


Fig. 7. Stability of cultivation. Maximum likelihood estimates of statistically important predictors of stability are depicted as solid lines, with 95% confidence intervals as dashed lines. Raw data are plotted as filled circles. Raw data for the enforcement rank X ban interaction depict ban counties as filled circles and permit counties (for which an estimated effect is not shown) are depicted as open circles.

government policy (Bodwitch et al., 2021; Getz et al., 2024; Polson et al., 2024). As discussed below, strong enforcement and bans also create geographic instability, or “whack-a-mole” dynamics, that unsettle communities and prevent the formation of norm creation, regulatory agency contact, and positive adaptation over time. Given the localized effects of farms, maximizing the quantity and dispersion of farms may be the most effective guard against unlicensed cultivation. Owner- or operator-occupied farms may be best suited to this task, as their occupants can most consistently affect the formation of social norms, social deterrence, and a culture of compliance. Needless to say, jurisdictions that ban cultivation do not benefit from the localized effects of licensed farms on unlicensed production.

Minimizing “Whack-a-Mole” dynamics and environmental impacts

Local cannabis bans were associated with higher volatility, producing a clear “whack-a-mole” pattern (i.e., cultivation is targeted in one place and emerges in another). Stronger historical enforcement reputations were also linked to reduced stability, but this effect was significant only in counties with a ban. Policies that held landowners liable for tenant cultivation similarly coincided with more transient activity. Taken with the findings presented above, these results indicate that regulatory measures designed to combat unlicensed cannabis cultivation – like bans, strong enforcement activities, and landlord liability – often merely redistribute activity across space rather than reliably suppress it. This confirms prior research on the topic (Chouvy, 2013; Getz et al., 2024; Magliocca et al., 2019; Polson et al., 2024).

Environmental sensitivity eventually emerged as an important factor in shaping unlicensed cannabis cultivation patterns. From 2018 to 2022, there was no clear relationship between environmental sensitivity and changes in cannabis density. By the second period, a trend appeared among permit counties, though the small sample size limited statistical power and prevented detection of a significant effect. By the third period, however, declines in cultivation were evident in more

environmentally sensitive counties, while less sensitive counties saw increases. This pattern was driven by permit counties, suggesting that mechanisms that regulate cannabis (rather than banning it outright) were more effective at reducing environmental impacts. This accords with prior analyses that indicate the power of regulation to command a high degree of environmental compliance measures (Biber et al., 2022) and to direct licensed cultivation toward less environmentally sensitive areas (Dillis et al., 2021), even if socio-political factors discourage licensed cultivation in those areas (Dillis et al., 2024). It also supports findings that suggest bans and intensive enforcement can promote maladaptive behaviors, like moving into more remote, environmentally sensitive areas and jumping between sites to avoid detection (Getz et al., 2024; McSweeney, 2015). Finally, permitting programs can spread norms and education around environmental impacts and protection that can influence how and where unlicensed cultivators operate (Polson et al., 2024). This can, in turn, serve to moderate environmental impacts.

Broader context and study limitations

This analysis contributes to social studies of cannabis, drug policy, and governance. First, it affirms the relationship of anti-“drug” enforcement to environmental impacts (McSweeney, 2015) and suggests that enforcement can, counterintuitively, be associated with increases in cultivation and illegal market activity (Magliocca et al., 2019). Second, this study supports analyses that argue for support of small, owner-operated farms and community-integrated cultivation circuits (Belackova et al., 2019; Bewley-Taylor et al., 2020; Bodwitch et al., 2021; Decorte, 2010; Sogaard et al., 2025) for reducing social and ecological harms from both unlicensed cultivation and intensive enforcement. Finally, this study adds to a literature that has long queried the accuracy of drug crop estimates, particularly as they emanate from enforcement and prohibition-mandated agencies (Andreas & Greenhill, 2011; Bewley-Taylor, 2017; Mansfield, 2018). Indeed, we consider this

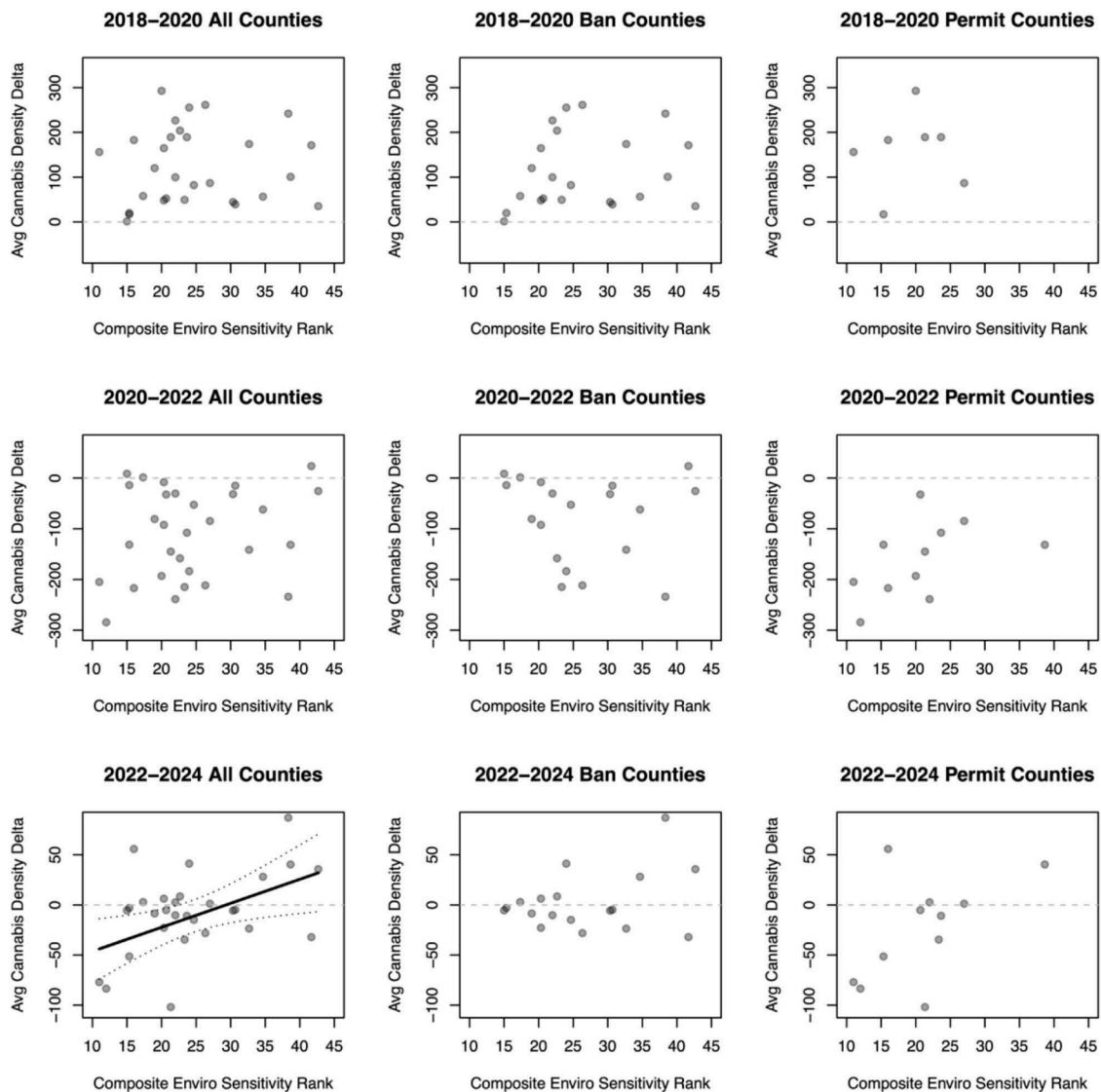


Fig. 8. Cultivation relative to environmental sensitivity. Raw county-level data are depicted as filled circles. Statistically significant relationships are depicted with solid lines for the maximum likelihood estimate and dashed lines for the 95% confidence interval.

study to be an exercise in what a post-prohibition methodology might model – namely, a query that openly assesses not only the harms but also the benefits of particular approaches to social regulation. Legalization and the normative shift it brings allows researchers to employ methodologies that are not simply sutured to prohibition and stigmatizing hypotheses (and findings; [Campbell, 2007](#); [Heidt & Wheeler, 2022](#); [Werner, 2012](#)) but, instead, reframe cannabis from a matter of vice to a matter of effective and ineffective governance.

Future research would benefit from qualitative approaches that can ground-truth and contextualize the spatial and temporal patterns identified here. Interviews and case studies with cultivators, regulators, and community members could help explain why policy effects shift over time, how regulatory signals are interpreted on the ground, and how processes such as norm formation, deterrence, and displacement unfold in practice. Such approaches could also address factors that this analysis could not capture directly, including how land values and local market conditions influence cultivation decisions, which are difficult to measure consistently across space and are not well represented in available quantitative datasets. Further limitations of the current study include spatial constraints and granularity. The current study was limited to slightly over half of the counties in California, where greenhouses could

be safely assumed to be cultivating cannabis. For instance, in portions of the Central Valley and the Central Coast, similar greenhouse infrastructure is used for non-cannabis agriculture that cannot be distinguished from cannabis using aerial imagery. In terms of granularity, the spatial unit of observation was aggregated cells of approximately nine square kilometers (required for the preservation of non-personally identifying data). Finer granularity may have been able to capture trends in variables like proximity to streams, roads, or other meaningful geographic features.

Conclusion

Taken together, these findings suggest several key interpretations with implications for cannabis policy and regulatory design more broadly. First, reducing unlicensed cultivation requires not only permitting policies, but meaningful participation in them. The consistent association between the presence of licensed farms and declines in unlicensed activity indicates that formalization is most effective when it is visible, spatially distributed, and embedded within local landscapes rather than merely available in principle. Second, the results point to declining returns from bans and enforcement-oriented approaches once

limits to their deterrent effect are reached. These strategies instead appear most effective at redistributing cultivation across space, producing whack-a-mole dynamics that raise enforcement costs. Third, the temporal evolution of policy effects underscores the importance of allowing time for civil regulatory systems to mature. Stable rules, predictable enforcement, and sustained institutional capacity appear necessary for compliance, social deterrence, and norm formation to emerge, whereas frequent policy shifts may encourage adaptive but counterproductive behaviors. Fourth, differences between mobility under bans and stability under permitting regimes reveal important social and environmental tradeoffs. Displacement-oriented policies tend to increase transience and push cultivation into new, sometimes more sensitive areas, while permitting regimes are associated with more stable spatial patterns that can reduce social conflict and environmental harm. Finally (and relatedly), permitting plays a critical role in shaping environmental outcomes. Declining cultivation in environmentally sensitive areas in later periods, particularly in permit counties, suggests that regulation is more effective than bans at steering cultivation away from vulnerable landscapes and diffusing environmental norms beyond the licensed sector.

As legalization and formalization efforts expand globally across diverse markets and geographies, this case offers guidance for jurisdictions with historic cultivation. These insights also extend beyond cannabis, illustrating broader lessons for regulating informal activities, including fisheries, mining, and property systems, and highlighting the value of participation, stability, and norm-building over prohibition and dislocation.

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Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work, the author(s) used Google Gemini for drafting of the Results section in order to transfer model coefficient outputs into the text. The author(s) reviewed and edited the output as needed and take full responsibility for the content of the published article.

CRedit authorship contribution statement

Christopher Dillis: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Michael Polson:** Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization.

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.

Supplementary materials

Supplementary material associated with this article can be found, in

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