Title (Preliminary):

Patterns and Drivers of Unlicensed Cannabis Cultivation Since Legalization

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Abstract

Since the legalization of cannabis in California (USA), unlicensed cultivation has continued to occur. Spatial patterns are likely shaped by 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. Using multi-year spatial data, we found that physical characteristics such as topography, building density, and remoteness consistently influenced cultivation, 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 consistent predictor of reduced unlicensed activity, 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

Scholars, officials, and media have utilized many methods to measure cannabis cultivation over the past 50 years. Many measurements, however, are derivative, formulaic, and blunt and have continued to be used even after cannabis legalization in California, among other places. Mischaracterizations and inaccurate assessments can contribute to inappropriate policy responses, particularly responses that emphasize punitive enforcement, undermine legalization goals, and reproduce patterns associated with prohibition (Adinoff and Reiman, 2019; Polson, 2019; Getz, Petersen-Rockney and Polson, 2024). Further, prior estimates have generally neglected to explore drivers behind unlicensed cultivation, leading to misattribution of causality and the policy, fiscal, social, and ecological consequences that follow.

Reliable information on unlicensed cannabis cultivation has historically been difficult to obtain. Much of the existing knowledge has come from ethnographic studies (Corva, 2014; Polson, 2021), while quantitative assessments have relied on incomplete or inconsistent law enforcement estimates (Kalacska and Bouchard, 2011; Leggett and 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; Gianotti et al., 2017; Franklin et al., 2018; Meisel, 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.

Accurate assessments of the geography and changes in unlicensed cultivation are needed to address the environmental and social dynamics correlated with cannabis growing. Previous research has shown that illicit production carries potential environmental impacts, especially in Northern California where cultivation occurs within ecologically sensitive watersheds (Carah et al., 2015; Butsic and Brenner, 2016; Gabriel et al., 2018). Concerns include land clearing, unpermitted road development, sedimentation of streams, and water extraction during low-flow summer months when freshwater species are most vulnerable (Katz et al., 2013; Zipper et al., 2019). Unlicensed cultivation has also been a critical source of revenue and community development for numerous rural communities in California (Corva 2014; Polson 2015; Polson et al 2024) and its introduction to new places has been fraught with tension (Dillis et al 2024). Understanding how cultivation has changed can inform responses to likely social and environmental pressures.

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 legalization, counties and municipalities have adopted highly variable permitting rules, zoning frameworks, and enforcement practices (Biber et al 2022; 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 2022). 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. These 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 unlicensed cannabis agriculture since legalization. These local dynamics create uneven regulatory landscapes that influence where and why unlicensed activity expands or contracts. It remains unclear the extent to which contemporary patterns of unlicensed cultivation are driven by physical conditions and/or by sociopolitical factors. Addressing this issue is critical for understanding the dynamics of the unlicensed market, crafting policy responses to those dynamics, and informing strategies to reduce environmental and social harms that can result from cultivation and responses to it.

Recent advances in the development of CannaVision, a multispectral object detection system developed by the California State Water Resources Control Board (SWRCB), provides an opportunity to address limitations in previous approaches to studying unlicensed cannabis cultivation. Unlike ethnographic studies, 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 unlicensed cultivation.:

1) Which physical and socio-political variables best explain interannual growth or decline in the amount of unlicensed cultivation?
2) Which physical and socio-political variables best explain patterns of relocation, spatial redistribution, and clustering of unlicensed cultivation?
3) What is the relation of unlicensed cultivation to potential environmental impacts?

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 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 (Figure 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 km^2. 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 km^2. For each grid cell and each imagery year, cannabis density (m^2 / km^2) was calculated, and year-to-year differences (2018-2020, 2020-2022, 2022-2024) were derived as outcome variables for statistical analysis.

Predictor variables were developed from multiple datasets describing local land-use policy, socioeconomic conditions, demographics, and biophysical terrain. County-level policy variables were constructed from an analysis compiled for a report to the California Department of Cannabis Control (Polson et al forthcoming). Additional socioeconomic and demographic predictors were constructed using data from the California State Franchise Tax Board (CSFTB Year), the U.S. Census Bureau (USCB Year), and voting records from the California Secretary of State (CSoS Year). Terrain and environmental variables were assembled from the Microsoft Building Footprint Layer (Dao 2020), PRISM annual precipitation estimates (PRISM Year), CALTRANS transportation layers (CALTRANS Year), the U.S. Geological Survey's National Hydrography Dataset (USGS Year), National Land Cover Database (NLCD 2024), and National Elevation Dataset (USGS 2024), as well as fire history and vegetation data from CALFIRE (CALFIRE Year) and licensing and permitting datasets from the California Department of Cannabis Control (DCC Year), the California Department of Food and Agriculture (CDFA Year), and the California Division of Water Resources (CDWR Year). 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 data sources is provided in Table 1.

Relative Contributions of Physical and Socio-Political Factors

All models were implemented as Generalized Additive Models (GAMs) to account for spatial clustering through the use of smoother functions 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). Models were hierarchical, including county as a random effect to control for unmeasured county-specific factors. For each model, 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. Hierarchical 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.

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. Data were structured with grid cells nested within counties, and predictors variables were modified and aggregated to the county level where necessary. For example, the presence of licensed farms in a cell was aggregated to instead employ this variable as 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:

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 km² using the USGS National Hydrography Dataset.

3) The proportion of undeveloped and uncultivated land, derived from the National Land Cover Database.

Each metric was calculated for all counties in the study, and county rankings were summed to produce a composite environmental sensitivity score (Table S1). Changes in cannabis cultivation from 2018–2020, 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)

During this period, cultivation overall expanded markedly (mean = 165.99 m^2 / km^2; SD = 507.24). Densities increased most strongly in flatter areas (average slope: MLE = -6.67, SE = 0.83; Figure 2; Table 3) and in locations with higher building density (MLE = 3.40, SE = 0.16). Expansion was influenced by fire hazard: remoteness was associated with increasing cannabis density only where fire hazard was low (remoteness: MLE = 1.19, SE = 0.60; remoteness × high fire hazard interaction: MLE = -2.32, SE = 0.63). Fire-prone areas were common across the study area, with over 60% of grid cells containing areas classified as high fire hazard severity.

Counties with historically lower enforcement experienced larger increases in cannabis cultivation (MLE = 7.09, SE = 2.89; Figure 3). Per-plant fines had a negative effect on cannabis cultivation (MLE = -111.97, SE = 28.45), and higher total fine amounts were negatively associated with density change (MLE = -0.02, SE = 0.002). Social variables also mattered: the proportion of conservative voters was negatively associated with cannabis density change (MLE = -1548.39, SE = 202.42), presence of a hemp farm was positively associated (MLE = 151.17, SE = 23.28), and the presence of licensed farms had a strong negative effect (MLE = -227.20, SE = 22.26).

Second Time Period (2020–2022)

During the second time period, cultivation decreased overall (mean = -140.59 m^2 / km^2, SD = 456.05). Average slope had a positive effect (average slope: MLE = 4.69, SE = 0.64; Figure 4), meaning that the general trend of decline was mediated (but not entirely reversed) in areas with steeper slopes. Cells with lower building density (MLE = -2.39, SE = 0.13) also experienced smaller reductions. The presence of public/private boundaries had a small positive effect (MLE = 68.36, SE = 9.14), but typically not sufficient to overcome the overall decline trend. Remote areas showed decreases (remoteness: MLE = -1.05, SE = 0.42). Stream network density had an additional effect, with cells containing more streams experiencing larger decreases in cannabis density (MLE = -0.02, SE = 0.003).

Policy variables had weaker effects than in the previous period. Fine amounts were associated with declines only when not assessed per plant (fine amount: MLE = 0.01, SE = 0.001; interaction with per-plant fine: MLE = -0.01, SE = 0.004; Figure 5). Landowner responsibility for tenant cultivation had a positive effect on cultivation (MLE = 101.33, SE = 13.45). Cultivation bans had a negative effect (MLE = -55.40, SE = 14.53), resulting in stronger declines than counties without bans. The presence of licensed farms had the strongest effect, with cannabis density declining dramatically where licensed farms existed (MLE = -674.52, SE =

17.11). In areas without licensed farms, the model estimated continued increases. Hemp presence shifted to a negative association (MLE = -212.96, SE = 19.85).

Third Time Period (2022–2024)

No strong overall trend in cannabis cultivation was observed, though spatial variation remained (mean = -3.06 m^2 / km^2, SD = 190.68). Remoteness (MLE = 0.29, SE = 0.11) and building density (MLE = 0.65, SE = 0.06) were weakly positively associated with increases in density. Stream network density also showed a positive association (MLE = 0.005, SE = 0.001), reversing the prior trend. Effect sizes were smaller than in earlier periods, indicating limited practical significance despite statistical significance.

Enforcement history was negatively associated with cannabis density change (MLE = -2.45, SE = 0.70; Figure 6), indicating historically enforcement-heavy counties saw larger increases. Fine amounts continued to be negatively associated (MLE = -0.007, SE = 0.001), while per-plant fines were not significant (MLE = -0.01, SE = 0.002). Landowner responsibility for tenant cultivation had a negative effect on cultivation (MLE = -34.37, SE = 6.05). Cultivation bans were estimated to have a small positive effect (MLE = 59.03, SE = 10.13). Social effects reversed, with higher proportions of conservative voters now positively associated with cannabis density change (MLE = 131.68, SE = 56.46). Licensed farm presence remained the strongest negative factor (MLE = -339.10, SE = 7.74).

Spatial Stability of Cultivation

Over the study period (2018–2024), cannabis cultivation was significantly more variable in counties with local cannabis bans (MLE = -1.65, SE = 0.32; Figure 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.

Several spatial and environmental factors were also linked to cultivation stability. 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.

Environmental Risk Assessment

In the first two time periods (2018–2020 and 2020–2022), there was 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 (~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; Figure 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 indicates that ban versus permit status alone may not fully explain reductions in cultivation relative to environmental sensitivity.

Discussion

Summary

Since legalization, a combination of physical landscape features and socio-political conditions shaped how, where and why unlicensed cannabis cultivation occurred, but the influence of each factor often changed over time. Physical characteristics consistently affected where cultivation occurred, yet the direction and magnitude of these effects varied between periods. Flatter areas and locations with higher building density generally supported higher cultivation densities, while remote or fire-prone areas were more variable. At times, the effect of remoteness depended on fire hazard, with remote areas supporting growth only when fire risk was low. Stream networks and proximity to public/private land boundaries also influenced patterns, but their effects shifted over time, with some features associated with larger decreases in one period and slight increases in another. 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 Board, or local environmental health agencies), and local social attitudes around cannabis.

Socio-political factors also had complex and sometimes shifting impacts. Historically high enforcement counties first experienced decreases in cannabis density, but saw larger increases in cannabis density in later periods. Specific enforcement and fine policies had different effects over time, too. Early in the study period, per-plant fines were associated with smaller than average density increases, but had no effect in later years. As fine amounts rose, density decreased but only weakly. Cultivation bans sometimes reduced growth, but in the final period they were associated with small increases in density. Other factors, such as county political conservativeness, liability for landlords whose tenants cultivate, and hemp presence, also showed changing associations with cultivation, often reversing direction between periods. The presence of licensed farms stood out as the one consistent predictor, reducing unlicensed cultivation in all periods, with an increasing magnitude over the three time periods.

Overall, these results highlight that both physical and socio-political factors are variable over time, with their influence shifting in direction and strength across periods. The patterns also suggest that these types of factors are somewhat interrelated, with changes in one dimension potentially interacting with or amplifying effects in the other. However, the presence of licensed farms remains the single consistently stable influence across this dynamic landscape and this effect is worthy of further exploration. Permitted farms require a permitting program, suggesting that permit counties can more effectively address unlicensed cultivation. The lack of consistent efficacy of bans on unlicensed cultivation (except to increase “whack-a-mole” mobility of cultivation within a county) accords with this finding. Yet, it is not the presence of a permitting program, per se, but the presence of a farm within a given area that is critical, suggesting that there are likely localized effects of licensed farms that discourage unlicensed activity. These farms may draw regulatory attention 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. Farms may also create social norms that foster a "culture of compliance." In enforcement terms, farms may create a social deterrence to unlicensed activity in ways that even strong law enforcement approaches do not exhibit. 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. 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 government policy (Bodwitch et al 2021; Getz et al 2024; Polson et al 2024). 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 they can most consistently affect the formation of social norms, social deterrence, and a culture of compliance.

Cannabis cultivation stability – the degree to which unlicensed activity stayed in place or moved around within a county – was shaped by both physical and socio-political factors. Counties with higher building density and more forest cover tended to have more stable cultivation, while stability was lower in areas with a greater mix of public and private land. Specific policy factors were significant in increasing volatility of cultivation siting. Local cannabis bans were associated with higher volatility, producing a clear "whack-a-mole" pattern (i.e. cultivation is discouraged 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 often merely redistribute activity across space rather than reliably suppress it. This confirms prior research on the topic (Getz et al 2024; Polson et al 2024).

Environmental sensitivity eventually emerged as an important factor in shaping unlicensed cannabis cultivation patterns. In the early periods, 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 require 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 bans and 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). Finally, as suggested in other research (Polson et al 2024), permitting programs can spread norms and education around environmental impacts and protection that can influence how and where unlicensed cultivators operate. This can, in turn, serve to moderate environmental impacts.

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 shape cultivation decisions, which are difficult to measure consistently across space and are not well represented in available quantitative datasets.

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 their practical limits are reached. While enforcement can suppress activity in some contexts, its effects are often weak, inconsistent, or temporary. In many cases, these strategies primarily redistribute cultivation across space, producing whack-a-mole dynamics that raise enforcement costs without addressing underlying drivers. 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, 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, permitting plays a critical role in shaping environmental outcomes. The emergence of environmentally sensitive effects in later periods, particularly in permit counties, suggests that regulation is more effective than prohibition at steering cultivation away from vulnerable landscapes and diffusing environmental norms beyond the licensed sector.

These insights extend beyond cannabis. As legalization and formalization efforts expand globally across diverse markets and geographies, this case illustrates broader lessons for regulating informal activities, including fisheries, mining, and property systems, and highlights the value of participation, stability, and norm-building over prohibition and displacement.

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Tables

Table 1. Predictor variables for GAMs.		
Variable	**Description**	**Source**
Cultivation Ban	Binary; presence/absence of cultivation ban during time period	Planning Code Summaries
Fine Amount	Integer; Dollar value of daily fine for unlicensed cultivation	Planning Code Summaries
Fine Per Plant Basis	Binary; whether/not fines are assessed on a per-plant basis	Planning Code Summaries
Land Owner Responsibility	Binary; whether/not landowners are responsible for tenant cannabis cultivation violations	Planning Code Summaries
Personal Cultivation	Binary; whether/not personal cultivation allowances (up to six plants) were present	Planning Code Summaries
Enforcement Rank	Rank; rank among study counties of lbs of cannabis seized since 2011	ERA Economics
Public Land Boundary	Binary; presence/absence of public land within the sampling grid cell	CALFIRE
Presence of Licensed Farm	Binary; presence/absence of a licensed cannabis farm within the sample cell	DCC
Presence of Hemp	Binary; presence/absence of a hemp license within the sample cell	CDFA
Proportion Conservative	Continuous, bounded (0-1); proportion of county registered voters identifying as Republican	CSoS
Median Income	Continuous; county median income	CSFTB
Proportion Retirement Age	Continuous, bounded (0-1); proportion of county population aged 65 or older	USCB
Building Density	Continuous; number of buildings per km^2	Microsoft
Road Network Density	Continuous; length of paved public roads per km^2	CALTRANS
Stream Network Density	Continuous; length of streams per km^2	USGS NHD
Proportion Forest	Continuous, bounded (0-1); proportion of sample cell that is covered in forest	NLCD
Proportion Planted	Continuous, bounded (0-1); proportion of sample cell that is cultivated (non-cannabis agriculture)	NLCD

Proportion Barren	Continuous, bounded (0-1); proportion of sample cell that is barren rock	NLCD
Average Slope	Continuous, bounded (0-1); average hill slope of the sample cell	USGS DEM
Remoteness	Continuous; distance from sample cell to nearest incorporated area	CALFIRE
Groundwater Present	Binary; presence/absence of SGMA groundwater basin within the sample cell	DWR
High Fire Hazard Severity	Binary; presence/absence of area mapped as either “high” or “very high” fire hazard severity within the sample cell	CALFIRE

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	NOAA

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	714.00 (72.14)	-147.96 (23.24)	-9.49 (23.15)	2.48 (0.44)
Cultivation Ban	-27.15 (56.18)	-55.40 (14.53)	59.03 (10.13)	-1.65 (0.32)
Fine Amount	-0.02 (<0.01)	0.01 (<0.01)	-0.01 (<0.01)	-
Fine Per Plant Basis	-111.97 (28.45)	24.97 (20.18)	5.73 (8.79)	-
Land Owner Responsibility	-	101.33 (13.45)	–34.37 (6.05)	-0.36 (0.18)
Personal Cultivation	-	-32.19 (16.57)	-	-
Enforcement Rank	7.09 (2.89)	-	-2.45 (0.70)	-0.03 (0.01)
Public Land Boundary	-43.24 (11.70)	68.36 (9.14)	-9.66 (3.66)	-2.09 (0.46)
Presence of Licensed Farm	-227.20 (22.26)	-674.52 (17.11)	-339.10 (7.74)	-
Presence of Hemp	151.17 (23.28)	-212.96 (19.85)	25.32 (8.55)	-
Proportion Conservative	-1548.39 (202.42)	-	131.68 (56.46)	-
Median Income	-	-	-	-
Proportion Retirement Age	-	97.45 (47.26)	-37.74 (18.92)	--
Building Density	3.40 (0.16)	-2.39 (0.13)	0.65 (0.06)	-
Road Network Density	<0.01 (<0.01)	-	<0.01 (<0.01)	-
Stream Network Density	-	-0.02 (<0.01)	<0.01 (<0.01)	-
Proportion Forest	-	-	-	0.70 (0.33)

Proportion Planted	-62.17 (29.85)	-91.93 (23.44)	49.48 (9.09)	-
Proportion Barren	-	-	-	-
Average Slope	-	4.69 (0.64)	-	-
Remoteness	1.19 (0.60)	-1.05 (0.42)	0.29 (0.11)	-
Groundwater Present	-	-	-	-
High Fire Hazard Severity	93.17 (18.05)	-70.71 (14.28)	8.11 (4.15)	-
Fine Amount X Fine Per Plant	0.04 (0.01)	-0.01 (<0.01)	<0.01 (<0.01)	-
Ban X Enforcement Rank	-0.18 (2.94)	-	-1.04 (0.70)	0.06 (0.02)
Remoteness X High Fire Hazard	-2.32 (0.63)	0.26 (0.45)	-	-

Figure Captions

Figure 1. Study Area Map. Counties depicted in green offered cannabis cultivation permits during at least one of the three study time periods, while those in red banned cultivation for the duration of the study.

Figure 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.

Figure 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.

Figure 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.

Figure 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.

Figure 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.

Figure 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.

Figure 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.

Figures

Figure 1.

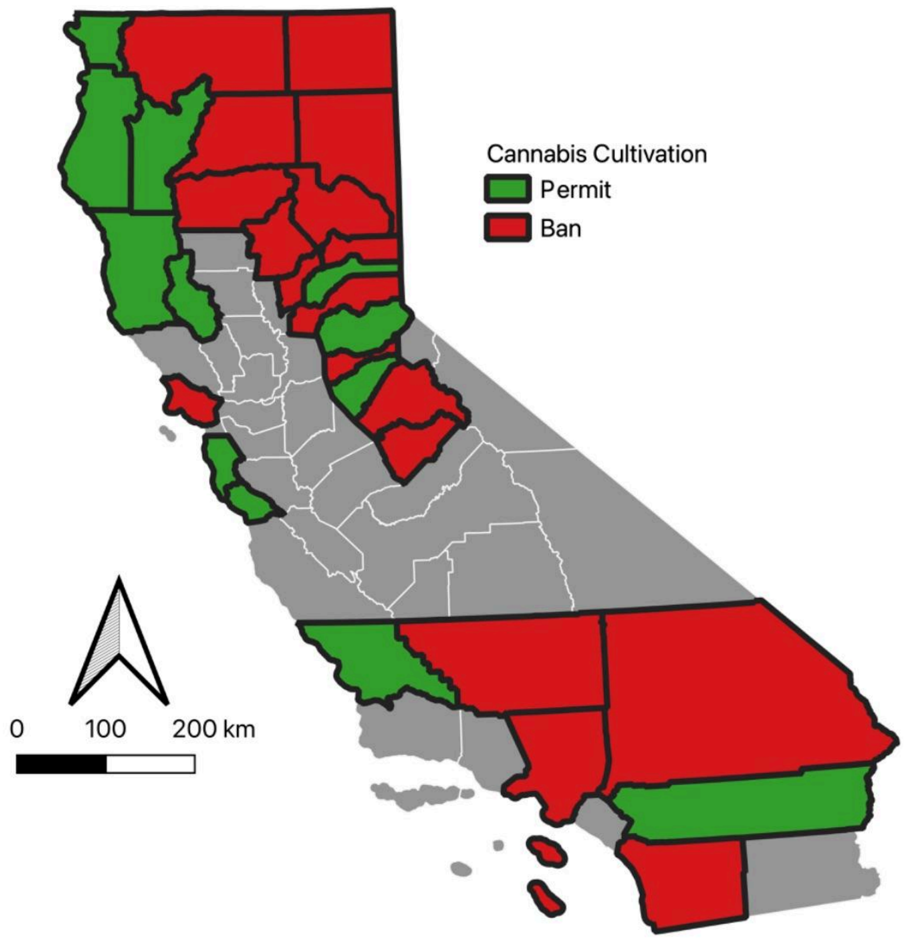


Figure 2.

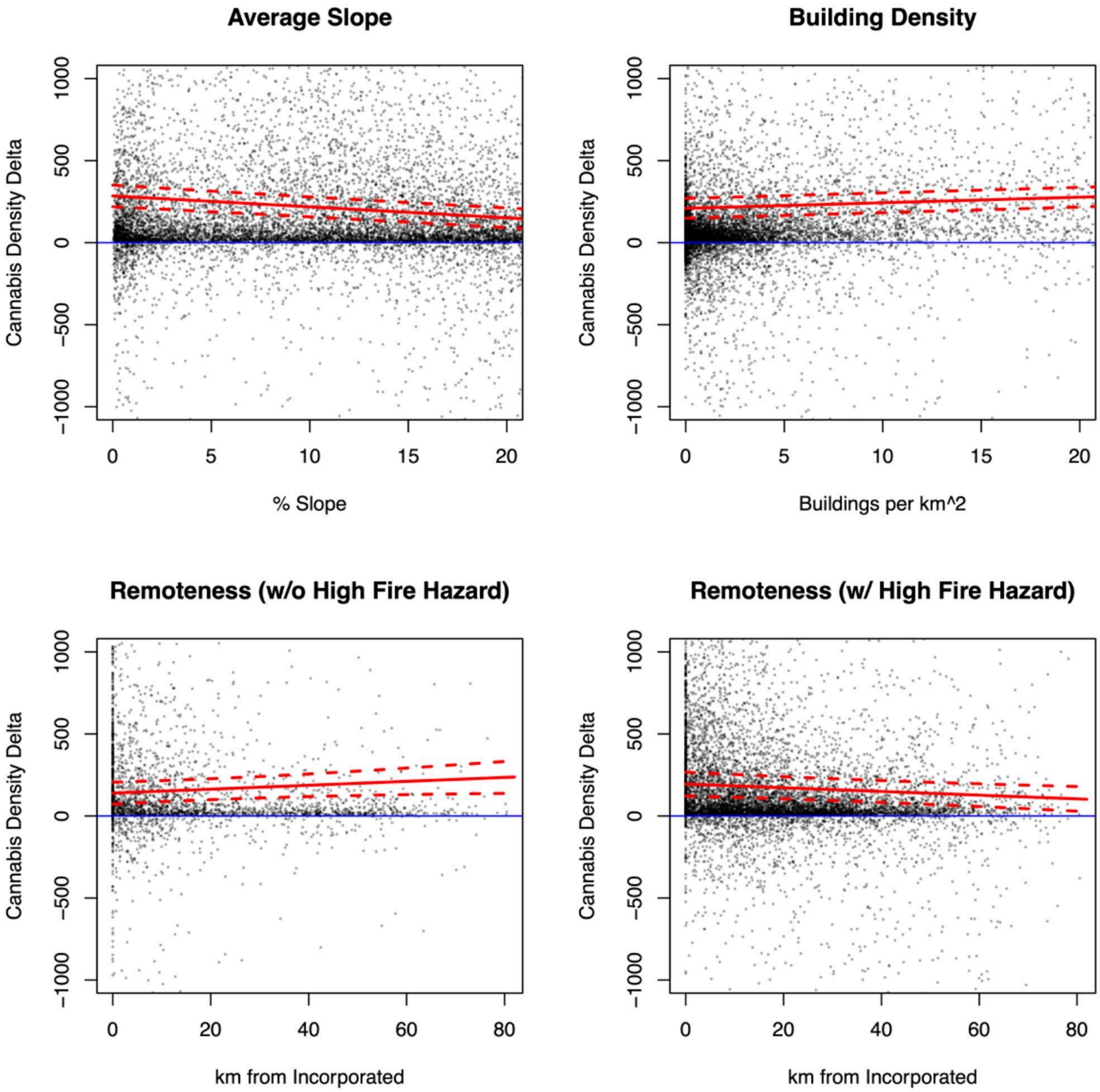

Average Slope
Cannabis Density Delta
% Slope
Building Density
Cannabis Density Delta
Buildings per km^2
Remoteness (w/o High Fire Hazard)
Cannabis Density Delta
km from Incorporated
Remoteness (w/ High Fire Hazard)
Cannabis Density Delta
km from Incorporated

Figure 3.

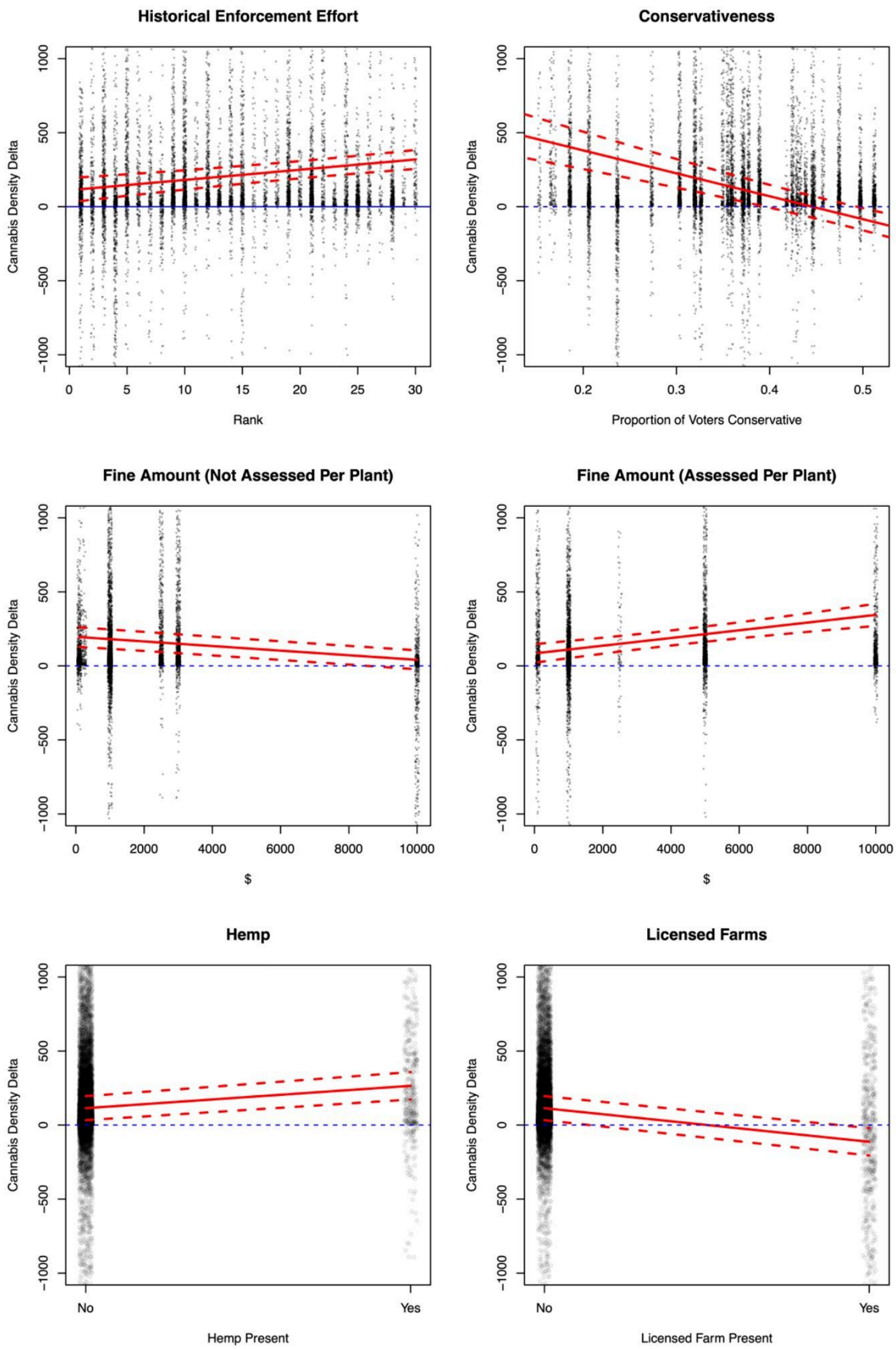
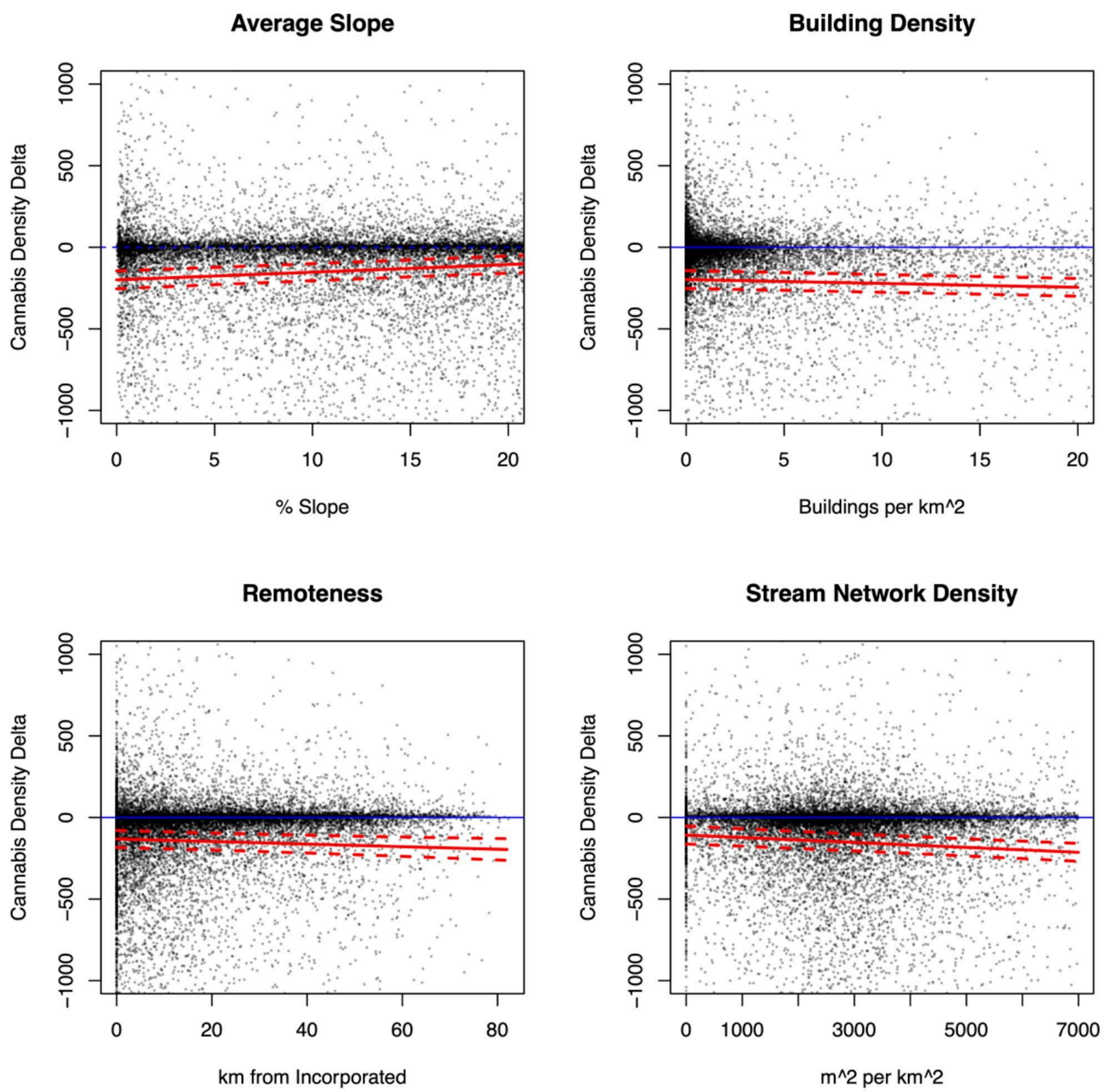

Historical Enforcement Effort
Cannabis Density Delta
Rank
Conservativeness
Proportion of Voters Conservative
Fine Amount (Not Assessed Per Plant)
$
Fine Amount (Assessed Per Plant)
Hemp
Hemp Present
No
Yes
Licensed Farms
Licensed Farm Present

Figure 4.



Average Slope
Cannabis Density Delta
% Slope
Building Density
Cannabis Density Delta
Buildings per km^2
Remoteness
Cannabis Density Delta
km from Incorporated
Stream Network Density
Cannabis Density Delta
m^2 per km^2

Figure 5.

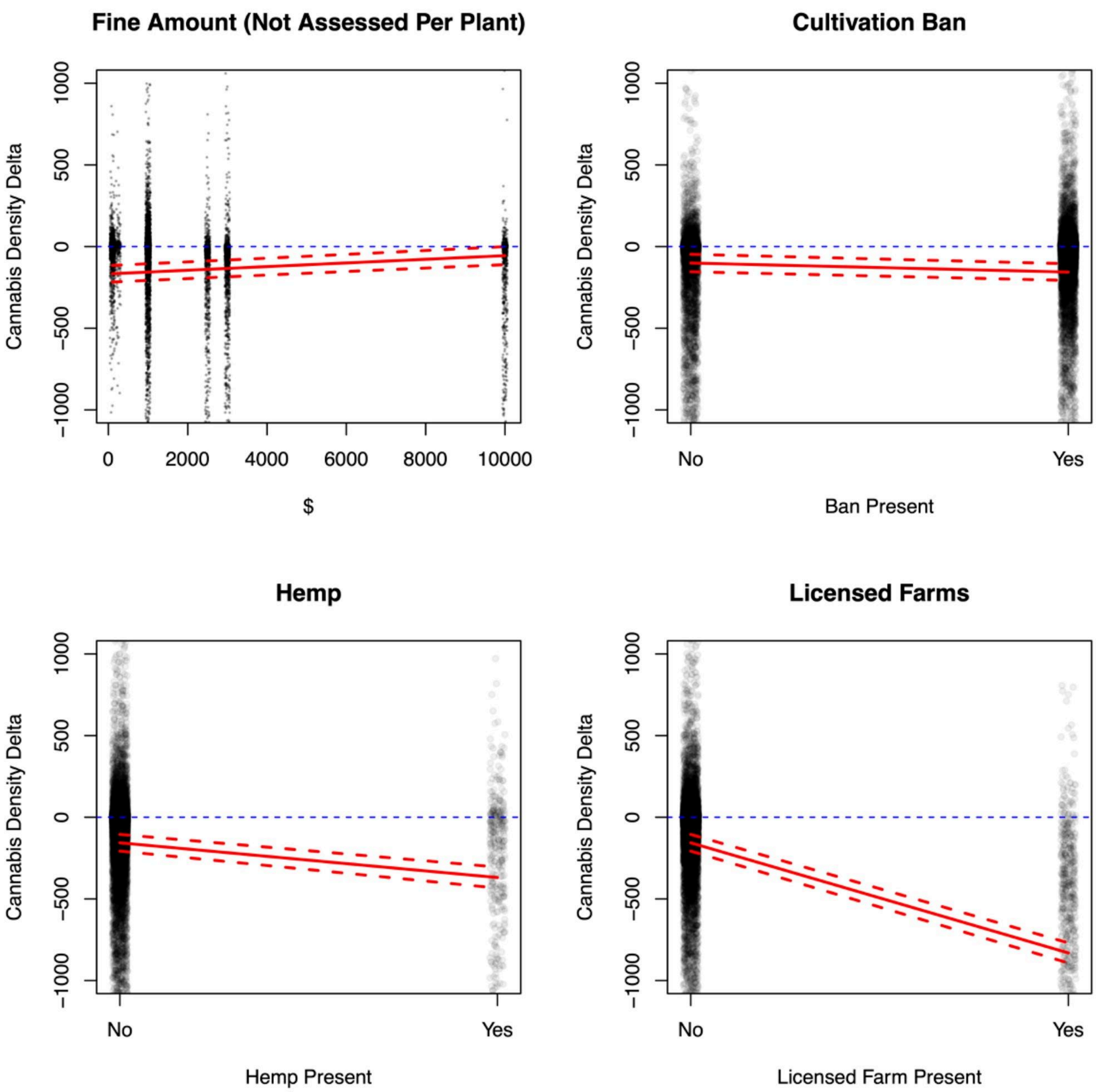
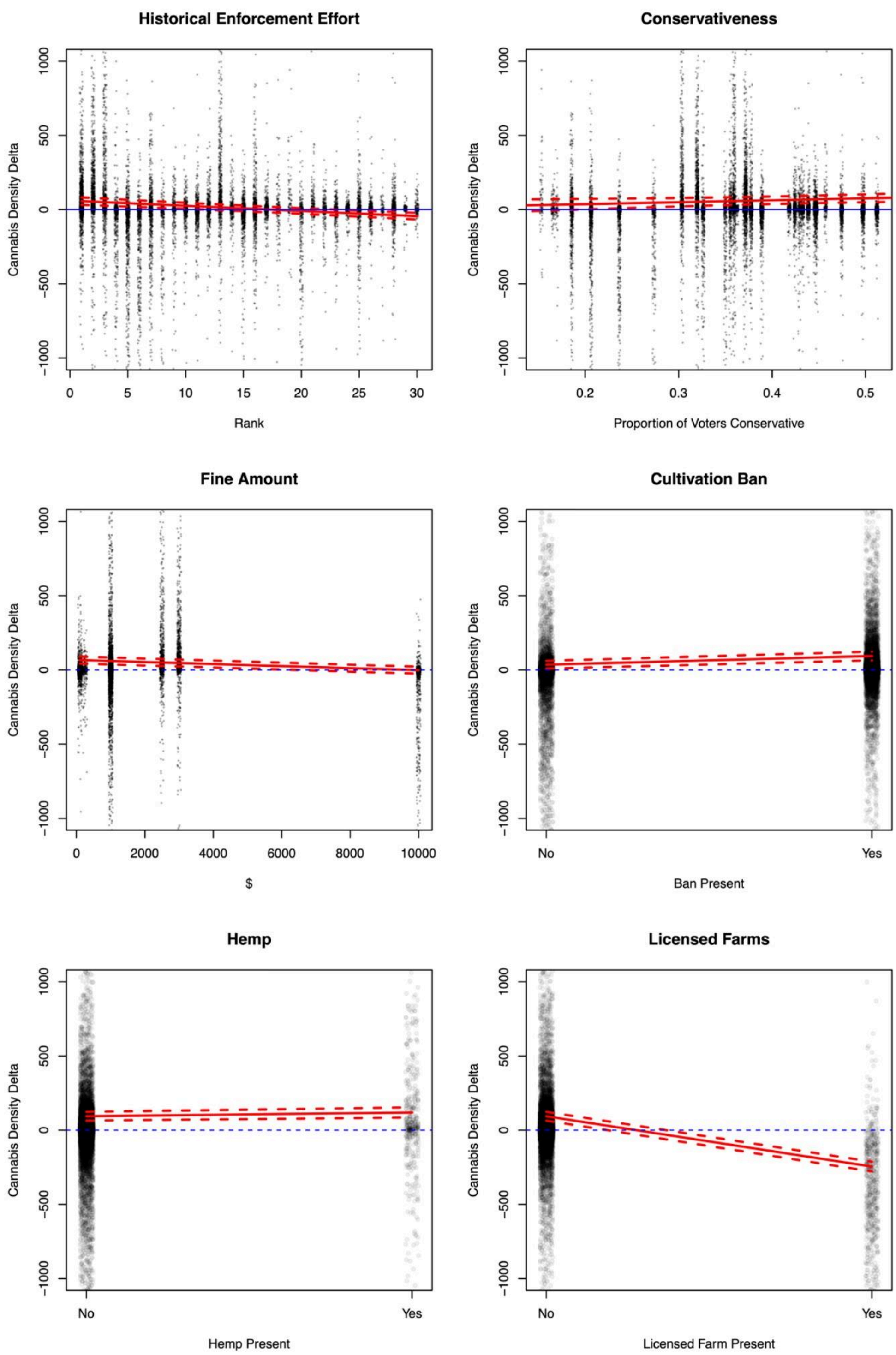

Fine Amount (Not Assessed Per Plant)
Cannabis Density Delta
1000
500
0
−500
−1000
0
2000
4000
6000
8000
10000
$
Cultivation Ban
Cannabis Density Delta
No
Yes
Ban Present
Hemp
Cannabis Density Delta
No
Yes
Hemp Present
Licensed Farms
Cannabis Density Delta
No
Yes
Licensed Farm Present

Figure 6.



Historical Enforcement Effort
Cannabis Density Delta
Rank
Conservativeness
Proportion of Voters Conservative
Fine Amount
$
Cultivation Ban
Ban Present
Hemp
Hemp Present
Licensed Farms
Licensed Farm Present
No
Yes

Figure 7.

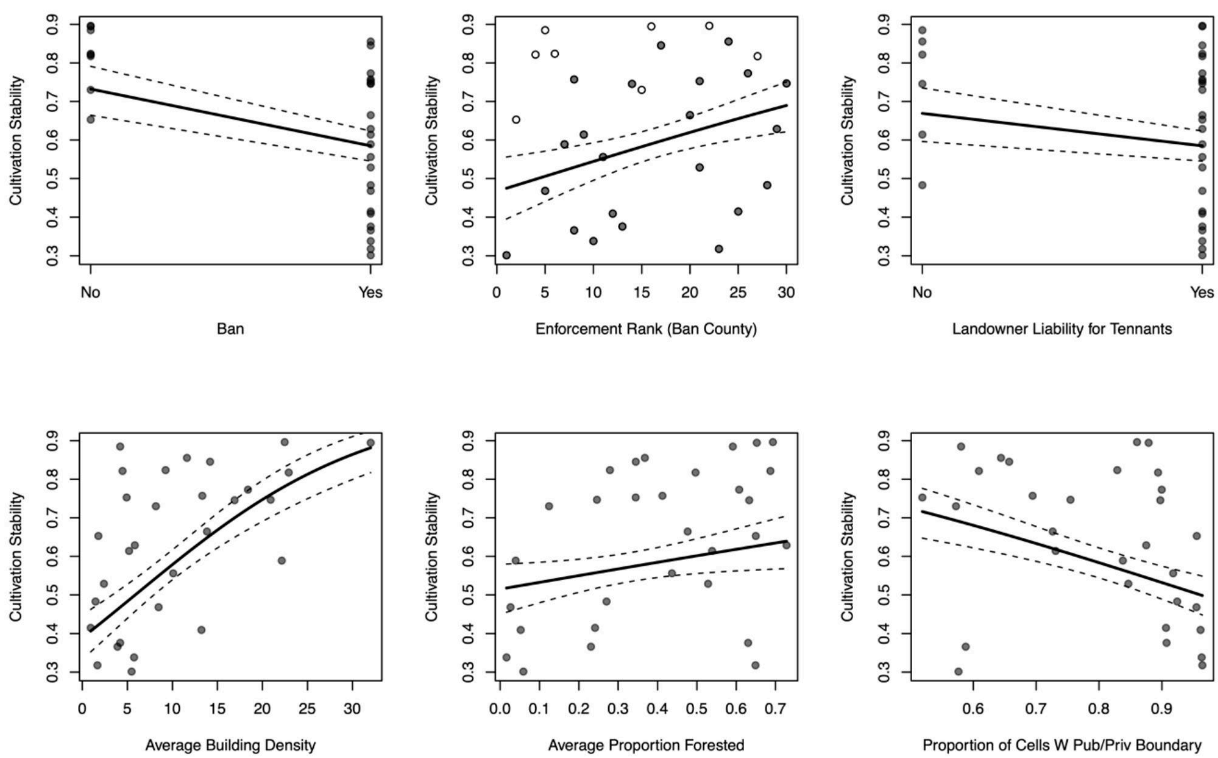
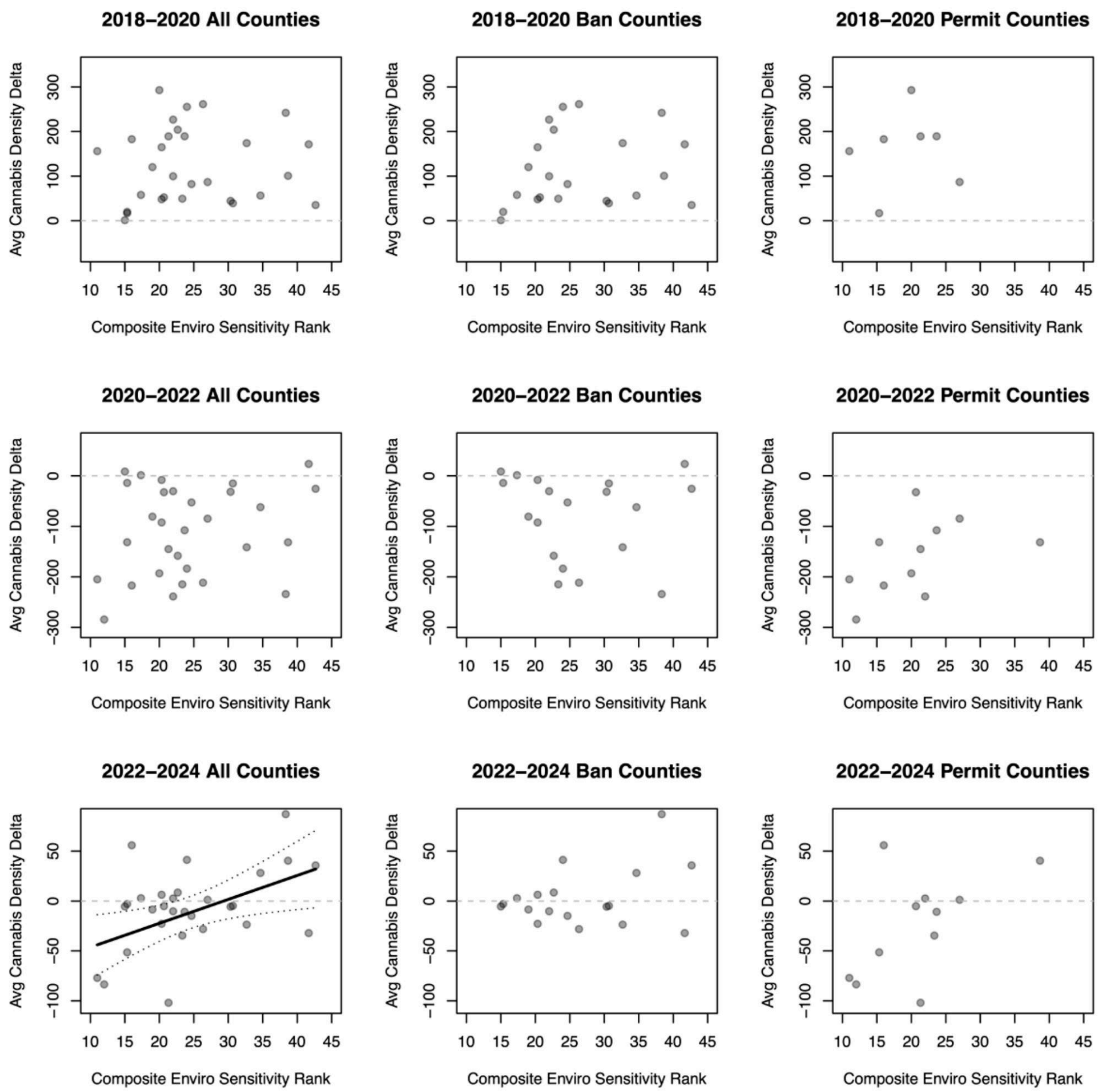

Cultivation Stability
Ban
No
Yes
Enforcement Rank (Ban County)
Landowner Liability for Tennants
Average Building Density
Average Proportion Forested
Proportion of Cells W Pub/Priv Boundary

Figure 8.


2018–2020 All Counties
2018–2020 Ban Counties
2018–2020 Permit Counties
2020–2022 All Counties
2020–2022 Ban Counties
2020–2022 Permit Counties
2022–2024 All Counties
2022–2024 Ban Counties
2022–2024 Permit Counties
Avg Cannabis Density Delta
Composite Enviro Sensitivity Rank

Supplementary Information

Table S1. County Environmental Sensitivity Rankings							
County	Proportion Watersheds Critical Habitat	Proportion Watersheds Critical Habitat Rank	Proportion Undeveloped	Proportion Undeveloped Rank	Stream Network Density	Stream Network Density Ran	Composite Rank
Alameda	0.2173913	25	55.5725054	44	1.28E-07	34	34.3333333
Alpine	0	41	98.5872881	2	5.43E-07	5	16
Amador	0	41	93.6773374	12	3.06E-07	19	24
Butte	0.2826087	22	66.4727527	37	3.04E-07	20	26.3333333
Calaveras	0.02777778	37	95.1506811	9	2.55E-07	24	23.3333333
Colusa	0.03703704	34	49.9524691	46	1.81E-07	31	37
Contra Costa	0.3	21	46.9480296	47	1.05E-07	39	35.6666667
Del Norte	0.05128205	33	76.1172645	27	6.72E-07	2	20.6666667
El Dorado	0	41	91.1063778	18	5.16E-07	7	22
Fresno	0	41	59.3530882	41	2.03E-07	30	37.3333333
Glenn	0.2	26	62.2635119	40	1.45E-07	32	32.6666667
Humboldt	0.73469388	7	81.3159784	25	5.71E-07	4	12
Imperial	0	41	72.9904264	31	3.03E-08	53	41.6666667
Inyo	0	41	99.0371167	1	4.93E-08	50	30.6666667
Kern	0	41	72.8102033	32	2.06E-08	55	42.6666667
Kings	0	41	19.1767607	56	4.15E-08	52	49.6666667
Lake	0.06666667	31	88.0226149	20	3.74E-07	13	21.3333333
Lassen	0	41	94.9035241	11	9.78E-08	40	30.6666667
Los Angeles	0.03539823	35	56.0480804	43	5.54E-08	47	41.6666667
Madera	0	41	69.0686602	35	2.35E-07	26	34
Marin	0.80769231	6	53.5777556	45	3.48E-07	17	22.6666667
Mariposa	0	41	98.1187705	3	2.70E-07	22	22
Mendocino	0.91964286	2	84.8287767	21	4.86E-07	10	11
Merced	0.05769231	32	46.4490696	49	9.30E-08	41	40.6666667
Modoc	0	41	91.4843163	17	1.35E-07	33	30.3333333
Mono	0	41	95.6847739	7	2.55E-07	23	23.6666667
Monterey	0.54081633	10	73.87251	30	1.19E-07	36	25.3333333
Napa	0.38095238	16	82.3277847	23	2.21E-07	27	22
Nevada	0.03333333	36	93.3305812	13	4.09E-07	11	20
Orange	0.13636364	28	32.8737624	54	1.14E-08	56	46
Placer	0.17391304	27	79.6971785	26	5.13E-07	8	20.3333333
Plumas	0	41	95.6203937	8	3.91E-07	12	20.3333333
Riverside	0.00534759	40	84.2739892	22	2.62E-08	54	38.6666667
Sacramento	0.38461539	15	33.3165615	53	1.07E-07	38	35.3333333
San Benito	0.34146342	17	92.7524013	14	4.71E-08	51	27.3333333
San Bernardino	0	41	95.9538228	6	9.80E-09	57	34.6666667

San Diego	0.0078125	39	75.7184225	28	5.52E-08	48	38.3333333
San Francisco	0.33333333	18	1.6786859	58	3.41E-09	58	44.6666667
San Joaquin	0.61538462	9	19.5839433	55	8.09E-08	43	35.6666667
San Luis Obispo	0.40625	13	81.8717369	24	7.54E-08	44	27
San Mateo	0.86666667	5	41.7544378	51	3.62E-07	15	23.6666667
Santa Barbara	0.38636364	14	64.6245848	39	1.19E-07	37	30
Santa Clara	0.5	11	70.9217807	33	2.05E-07	29	24.3333333
Santa Cruz	0.91666667	3	57.8880395	42	5.77E-07	3	16
Shasta	0.26446281	24	92.5531516	15	3.41E-07	18	19
Sierra	0	41	97.6859738	4	6.72E-07	1	15.3333333
Siskiyou	0	41	90.560436	19	3.67E-07	14	24.6666667
Solano	0.33333333	18	44.0072519	50	2.06E-07	28	32
Sonoma	0.90909091	4	73.875733	29	3.60E-07	16	16.3333333
Stanislaus	0.275	23	46.7938079	48	7.44E-08	45	38.6666667
Sutter	1	1	12.8474228	57	5.12E-08	49	35.6666667
Tehama	0.61797753	8	91.5232416	16	3.02E-07	21	15
Trinity	0.08791209	30	94.9060229	10	5.30E-07	6	15.3333333
Tulare	0	41	70.7532386	34	2.51E-07	25	33.3333333
Tuolumne	0.01492537	38	96.9286358	5	5.06E-07	9	17.3333333
Ventura	0.43396226	12	68.1610797	36	1.24E-07	35	27.6666667
Yolo	0.0952381	29	34.4782865	52	5.96E-08	46	42.3333333
Yuba	0.33333333	18	64.8648383	38	8.42E-08	42	32.6666667