

1

2 The threat of wildfire to cannabis agriculture in California

3

4 Christopher Dillis^{1*}, Van Butsic¹, Diana Moanga¹, Phoebe Parker-Shames¹, Ariani
5 Wartenberg¹, Theodore Grantham¹

6

7 ¹University of California Berkeley, Berkeley, California, United States of America

8

9

10 *Corresponding author

11 Email: cdillis@berkeley.edu

12

13

14

15

16 NOTE: This manuscript is a non-peer reviewed preprint, submitted to EarthArXiv

17

18

19

20

21

22 **Keywords: Marijuana, Fire Hazard Severity, Land Use Planning, Rural Agriculture**

23 **Abstract**

24 At the intersection of climate change and rural development, wildfire has emerged as a threat to
25 agriculture in the western United States. This nexus is particularly problematic for the rapidly developing
26 cannabis industry in California, which includes farms located outside of traditional agricultural zones and
27 within landscapes potentially more prone to wildfire. Using fire hazard severity metrics, current and
28 historical wildfire perimeter data, and future burn regime projections, we compared the location of
29 licensed cannabis farms in California to other agricultural types, to determine if cannabis is uniquely
30 vulnerable to wildfire. We found that cannabis farming was located closer to wildfire perimeters and
31 more often in high fire hazard severity zones than other agriculture. Over the last 50 years, the distance
32 between cannabis farm locations and fire perimeters decreased significantly, and projected burn
33 regimes for the remainder of the century place cannabis farms at greater risk than other agricultural
34 types. Our findings highlight cannabis' particular vulnerability to wildfire in California. In light of the
35 sector's growing importance in the state, and given potentially direct and indirect consequences (e.g.,
36 human health risks, socioeconomic impacts), these risks should be considered for the development of
37 future cannabis and rural development policies.

38

39 **1. Introduction**

40 Wildfire is becoming a global threat, compounded by climate change (Westerling et al, 2006)
41 and the expansion of human development in fire prone areas (Radeloff et al., 2018). The threat of
42 wildfire is particularly prominent in California, where the combination of prolonged drought, arid
43 vegetation, climate change, historical fire suppression, and development in the wild-urban interface
44 (WUI) is leading to more frequent and severe wildfires statewide (van Wagtendonk et al, 2021, Williams
45 et al, 2019; Keeley & Syphard, 2018; Kramer et al., 2018; Parks et al., 2015; Radeloff et al., 2018; Syphard

46 et al., 2007; Norgaard, 2014). Over the last five years, California has experienced its seven largest
47 wildfires on record (CAL FIRE, 2020a) and current projections for the state suggest an increase in
48 frequency and intensity of wildfires in the future (Westerling, 2018; Goss et al., 2020). As a result,
49 wildfire is expected to continue to generate large social, economic, and ecological costs in the state (Jin
50 et al., 2015; Kelly et al., 2020).

51 Wildfire has the strongest impacts on rural and agricultural communities that occupy fire-prone
52 areas of the landscape. This is especially true for California's ranching communities that rely on arid
53 rangelands, where wildfires disrupt operations and cause livestock losses each year (Bell 2015;
54 Herskovitz 2017). Other agricultural activities, such as wine grape cultivation, also occur in areas of the
55 landscape where wildfire may directly threaten vineyards, negatively impact wine quality through
56 smoke damage, and discourage tourism (Thach and Eyler, 2017; Bauman et al., 2020). Cannabis
57 cultivation, which is a rapidly growing segment of California's agricultural sector (Hudock 2019), may
58 face similar risks as rangelands and vineyards. Cannabis has historically been grown in rugged terrain, in
59 remote parts of the state away from population centers, as a result of its historical prohibition (Corva,
60 2014; Butsic et al., 2018). Additionally, the recent rapid expansion of cannabis in rural areas has
61 followed patterns of low-density development in the WUI known to exacerbate fire risk (Butsch et al.,
62 2018; Radeloff et al., 2018). Despite the potential for cannabis agriculture to be uniquely vulnerable to
63 wildfire, to date, there has been no analysis of the spatial distribution of cannabis farms in relation to
64 wildfire risk and no analysis of how the threat of wildfire to cannabis differs from other agriculture
65 sectors.

66 The implementation of a regulated California cannabis industry in 2018 has created a pathway
67 for small-scale legacy farms (i.e., previously unregulated), primarily located in the historical cannabis-
68 farming epicenter of Northern California, to transition to licensed production (Dillis et al., 2021).
69 Statewide expansion in production has led to the establishment of new, larger farms outside of this

70 region, especially along California’s Central Coast, yet cannabis cultivation in the irrigated and less fire-
71 prone agricultural lands of California’s Central Valley remains largely prohibited under local ordinances
72 (Dillis et al., 2021). Little attention has been given to how state and local policy is shaping the geography
73 of the cannabis industry in relation to wildfire risk. Furthermore, the consequences of growing wildfire
74 severity on cannabis agriculture from climate change has not been considered. To fill these information
75 gaps, we addressed the following questions:

- 76 1) Does wildfire pose a greater threat to licensed cannabis than to other forms of
77 agriculture on a statewide and county-level basis?
- 78 2) How does the threat of wildfire vary among licensed cannabis producing counties and
79 has the threat increased in recent years?
- 80 3) What is the projected wildfire risk to cannabis agriculture under climate change and how
81 does it compare to other agricultural sectors?

82 **2. Methods**

83 **2.1. Data**

84 License data for outdoor cannabis farms were obtained from the California Department of Food
85 and Agriculture (CFDA) via a listserv distribution on May 27, 2020. License data included parcel numbers,
86 which were matched to a county parcel layer obtained from the National Parcelmap Data Portal
87 (Boundary Solutions, 2020). Multiple licenses on a single parcel were consolidated into a single
88 observation and parcel centroids were used for all analyses. The locations of three other classes of
89 agriculture were collected from the 2019 USDA Cropland Data Layer and the 2016 National Land Cover
90 Database (USDA, 2019; Dewitz, 2019): pasture (excluding cultivated hay crops), grapes, and an
91 aggregate of remaining crop types (referred to hereafter as *general crops*). Both the USDA Cropland
92 Data Layer and the National Land Cover Database datasets feature nearly comprehensive mapping of
93 agriculture in California at 30 meter resolution. For our statewide analysis, we took a random sample of

94 points from within each agricultural class of interest from across the state, using an equal number of
95 points for each crop (n=2228, the number of licensed cannabis farms in our dataset) in order to provide
96 a balanced sample. For subsequent analyses restricted to cannabis producing counties, non-cannabis
97 agricultural points were resampled to once again balance those of cannabis (n= 2228) with each
98 agricultural type. Because agriculture is clustered in select counties statewide, and potentially clustered
99 within these counties as well, we used county and subwatershed (HUC12) locations as predictors in
100 mixed-effects models. County boundaries were downloaded from the California State Geoportal (State
101 of California, 2019) and subwatershed boundaries were obtained from the National Hydrography
102 Dataset (USGS 2019).

103 We assessed fire risk on the landscape by Fire Hazard Severity Zones (FHSZ), as well as historical
104 fire perimeters, obtained from the California State Geoportal on December 7, 2020. FHSZs established
105 by CAL FIRE classify terrain as moderate, high, or very high hazard severity based on factors including
106 slope, fuel, and fire weather (CAL FIRE, 2020b). Although there is a small amount of missing data in
107 Federal Responsibility Areas (e.g. National Forest) and Local Responsibility Areas (e.g. incorporated
108 townships), zones with no data are most commonly those in areas of urban development or intensive
109 irrigated agriculture, such as the Central Valley, in which wildfire is extremely unlikely. Fire perimeter
110 data for the years 1950-2020 (CAL FIRE, 2020c; 2020d) were used as an additional risk metric and were
111 screened for a minimum size of 400 ha, following Westerling (2018), to filter out small fires included in
112 the database.

113 To analyze future projections of fire regimes we used a dataset from Moanga et al. (2020),
114 which was derived from Westerling (2018) projections. The estimated number of hectares burned were
115 calculated under the RCP4.5 greenhouse gas concentration pathway (a scenario in which emission levels
116 peak around 2040 and then gradually decline; CalAdapt, 2018). The statewide modeled wildfire activity
117 was analyzed using the ESRI space-time mining capabilities (Space-Time Cube and Emerging Hot Spot

118 Analysis functions). Areas likely to experience high levels of wildfire activity in both space and time were
119 identified and classified into several different hot and cold spot categories based on the spatial and
120 temporal progression of modeled wildfire activity (Table 1). The Space-Time Cube and Emerging Hot
121 Spot Analysis functions were used to analyze the data in 3D across both space and time by aggregating
122 the predicted number of hectares burned into space-time bins. Modeled wildfire data provided
123 estimates of the number of hectares burned for each year between 2020 and 2100 across California
124 (area divided into 10688 grid cells - one grid cell extending approximately 6 km²). The initial wildfire
125 projection data was aggregated into space time bins so that each bin incorporated one grid cell and
126 contained modeled data for one time slice (temporal interval was set on a yearly basis to capture the
127 gradual progression of wildfire activity). In total, our analysis included 4,950,973 hectares of hot-spots
128 (76.90% of the study area) and 149,981 hectares of cold-spots (2.32% of the study area), which
129 represent predicted fire dynamics for the period analyzed (2020-2100).

130 ***2.2. Does wildfire pose a greater threat to legal cannabis than to other forms of agriculture*** 131 ***on a statewide basis?***

132 To understand if cannabis farms were on average located closer to wildfires than other
133 agricultural types across California, we compared distance to wildfires between agricultural types, using
134 aggregated fire perimeters dating back to 1950. We used distance to fire perimeters as our main metric
135 of comparison, because neither FHSZ data nor burn probability data (from Westerling, 2018) are
136 comprehensive statewide. For each agricultural type, the distance was calculated between each data
137 point and the nearest fire perimeter. Although the majority of agricultural data points (especially those
138 of cannabis) were not contemporary with many of these fires, the perimeters instead are used herein as
139 a proxy for measuring geospatial susceptibility to wildfire.

140 We fit a multilevel model, using the lme4 package in R Statistical Computing Software (Bates et
141 al 2015, R Core Team, 2018), to establish whether there was a statistically reliable difference between

142 cannabis and other agricultural types in terms of proximity to fire. Random effects were used for county
143 and subwatershed to account for nested spatial clustering of data points. Because the distribution of
144 distances was right-skewed and overdispersed, we opted to use a negative binomial model. Rather than
145 log transforming the distances prior to model fitting, the generalized linear model (GLM) used a log link
146 function, predicting the distance (D_i) of each agricultural data point to the nearest wildfire perimeter,
147 using the following equation:

148 Eq. 1

$$149 \log(D_i) = \alpha + \alpha_c + \alpha_{wc} + \beta_d d + \epsilon$$

150 A fixed-effects term for *Agricultural Type* (β_d) is added to random intercepts for *County* (α_c) and
151 *Watershed* (nested within County; α_{wc}) as well as the overall intercept (α). Cannabis was designated as
152 the reference level for *Agricultural Type*, therefore producing coefficient estimates of the remaining
153 agricultural types relative to cannabis (as the overall intercept). Model coefficients were considered
154 reliable if 95% confidence intervals, constructed from the standard errors, did not overlap zero.

155 **2.3. How does the threat of wildfire vary among legal cannabis producing counties and is the** 156 **threat increasing?**

157 We conducted a similar analysis focusing only on cannabis producing counties, restricted to
158 those counties comprising at least 1% of all CDFA outdoor cultivation licenses statewide. These included:
159 Humboldt, Lake, Mendocino, Monterey, Nevada, San Luis Obispo, Santa Barbara, Santa Cruz, Sonoma,
160 Trinity, and Yolo Counties (Figure 1). In these counties, we compared the threat of wildfire to cannabis
161 against the remaining agricultural types (pasture, grapes, general crops) using Fire Hazard Severity Zone
162 (FHSZ) data. We also compared cannabis wildfire risk between counties using fire perimeter data.

163 In order to address whether the threat of wildfire to cannabis has changed over the preceding
164 decade, we measured the distance of licensed cannabis farms to historic perimeters of wildfires that
165 occurred between 1970 and 2020. We compared the proximity of cannabis farms to historic fire

166 perimeters in two time periods, 1970-2015 (*Period: early*) and 2016-2020 (*Period: recent*), again using a
167 multilevel negative binomial model. The model used a log link function, predicting the distance (D_i) of
168 each cannabis data point to the nearest wildfire perimeter, using the following equation:

169 Eq. 2

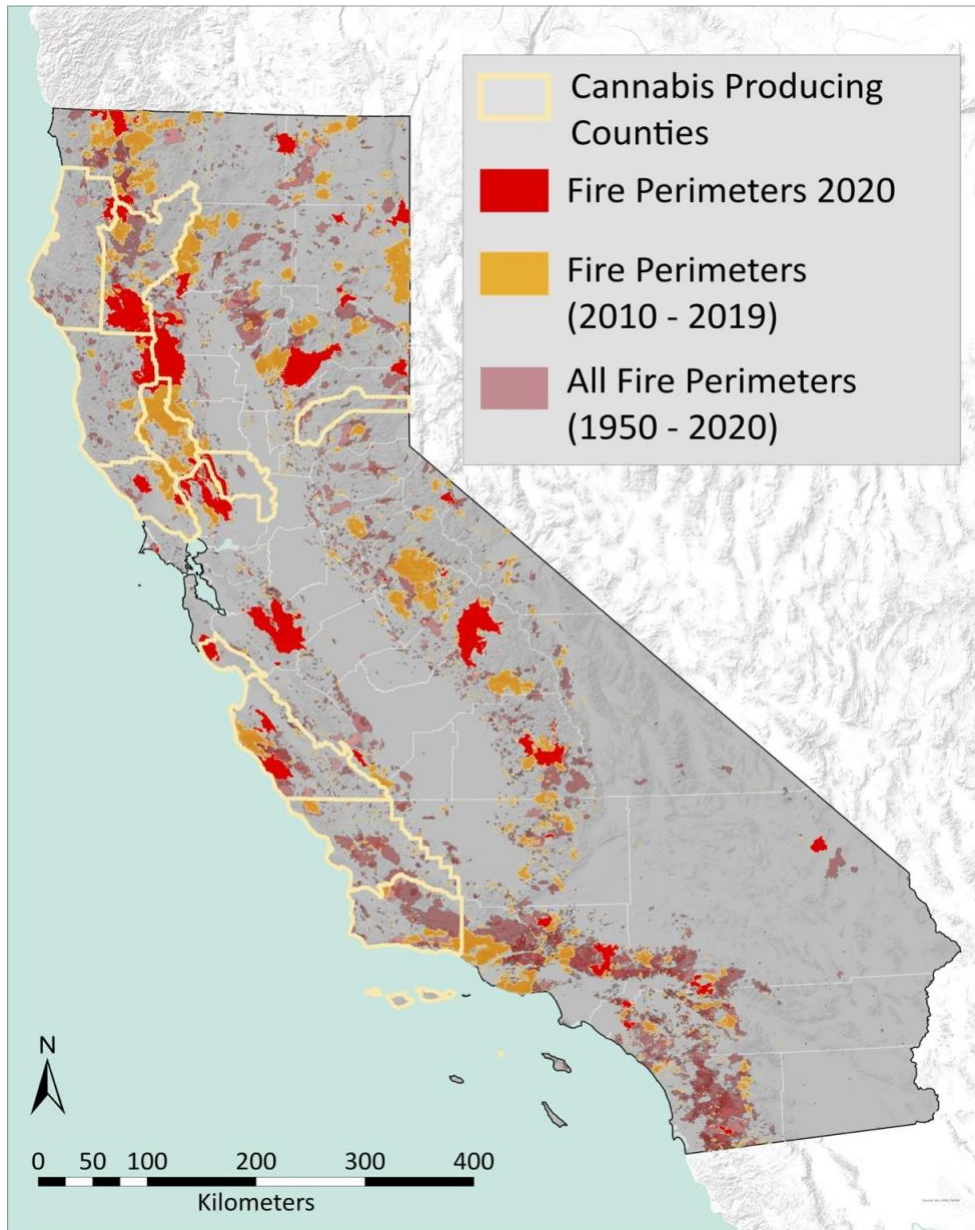
$$170 \log(D_i) = \alpha + \alpha_c + \alpha_{wc} + \beta_p p + \epsilon$$

171 Fixed-effects terms for *Period* (β_p) were added to random intercepts for *County* (α_c) and *Watershed*
172 (nested within County; α_{wc}) as well as the overall intercept (α). *Recent* was designated as the reference
173 level for *Period*, therefore interpreting the coefficient estimate of *Period* as the difference observed in
174 *Period: early* relative to *recent* (as the overall intercept). Model coefficients were exponentiated to
175 produce estimates on the original scale of the response variable (km). The difference was considered
176 reliable if 95% confidence intervals, constructed from the standard errors, did not overlap zero.

177

178

179



213 Figure 1. Study Area Map. Wildfire perimeters from 2020 are depicted, with the perimeters of the
214 preceding decade and historical perimeters (since 1950) included for context. Cannabis producing
215 counties included in this analysis are restricted to those comprising at least 1% of CDFA outdoor
216 cannabis licenses.

217

218 **2.4. What is the projected wildfire risk to cannabis agriculture under climate change and how**
219 **does it compare to other agricultural sectors?**

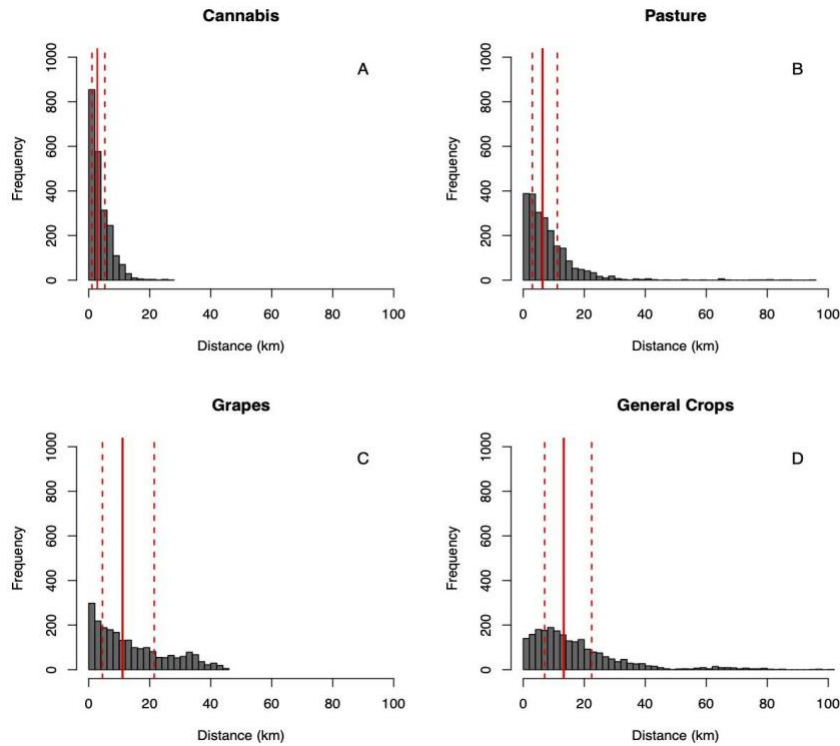
220 To assess the future threat of wildfire to licensed cannabis farms, we recorded the spatio-
221 temporal burn pattern projections summarized by Moanga et al. (2020) for each agricultural data point
222 from 2020-2100. Each point location was classified based on its projected burn pattern as:
223 New/Intensifying Hot Spot, Historical/Persistent Hot Spot, Sporadic/Oscillating Hot Spot, Diminishing
224 Hot Spot, No Pattern Detected, Diminishing Cold Spot, Sporadic/Oscillating Cold Spot,
225 Historical/Persistent Cold Spot, New/Intensifying Cold Spot, or No Data (Table 1). Projected burn
226 patterns were summarized between agricultural types in cannabis producing counties, as well as
227 between cannabis producing counties, focusing exclusively on cannabis data points. Using a space-time
228 approach in analyzing modeled wildfire activity throughout the twenty-first century allowed us to take
229 into account not only the spatial, but also the temporal dynamic of predicted wildfire activity and helped
230 identify areas likely to experience different wildfire threats through time. These distinctions are
231 important in assessing not only the current wildfire risk of cannabis farms, but also evaluating how this
232 risk is predicted to evolve in the future.

233 As a final metric of the threat to cannabis posed by wildfire, we calculated the proportion of
234 cannabis farms within fire perimeters of the 2020 fire season. The proportion of cannabis farms within
235 fire perimeters was calculated for each cannabis producing county. Cannabis was also compared to the
236 remaining agricultural types, focused specifically within cannabis producing counties.

237 **3. Results**

238 **3.1. Does wildfire pose a greater threat to legal cannabis than to other forms of agriculture**
239 **on a statewide basis?**

240 Cannabis farms were located closer to known wildfire perimeters than were any other type of
241 agriculture (Figure 2), with a median distance of 2.81 km (IQR = 1.06,5.27) for cannabis, compared to
242 6.31 km for pasture (IQR= 2.96, 11.16), 11.10 km for grapes (IQR= 4.50, 21.48), and 13.28 km (IQR =



255 Figure 2. Farm Proximities to Known Wildfires. Perimeters for fires since 1950 are compared against the
 256 geospatial locations of (A) cannabis and sampled data points for (B) pasture, (C) grapes, and (D) general
 257 crops. Median distances for each agricultural type are indicated by a red line, with the interquartile
 258 range (IQR) represented with dashed lines on either side of the median.

259

260 7.00, 22.43) for general crops. Results of the negative binomial model confirmed that the distance for
 261 cannabis was significantly smaller than all other agricultural types, even after accounting for clustering
 262 of types within counties (Table 2). Coefficient estimates for *grapes* (MLE= 0.11; SE= 0.03, OSE= 4.82 km),
 263 *pasture* (MLE= 0.14, SE= 0.03, OSE= 4.96 km), and *general crops* (MLE= 0.14, SE= 0.03, OSE= 4.95 km)
 264 were all reliably positive, indicating larger distances than those of cannabis (Intercept MLE=1.46 ,
 265 SE=0.11 , OSE= 4.30 km). Additionally, the percentage of cannabis farms that were located within

266 historical fire perimeters (9.89%) was higher than grapes (2.91%), pasture (1.75%), and general crops
267 (0.89%).

268 **3.2. How does the threat of wildfire vary among legal cannabis producing counties and is the**
269 **threat increasing?**

270 The percentage of cannabis farming in high (43.88%) or very high FHSZs (35.25%) was also larger
271 than any other type of agriculture found in cannabis producing counties (Figure 3). Grapes were the next
272 most common type to occur in high (24.53%) or very high FHSZs (5.09%), followed by pasture (12.43%;
273 0.76%, respectively). General crops almost never occurred in high (6.83%) or very high FHSZs (0.45%).
274 There was also a notable amount of variation in the percentage of cannabis farming within FHSZs
275 between counties (Figure 4). For instance, Trinity (93.44%) and Nevada (53.33%) had over half of their
276 cannabis farms in very high FHSZs, while Monterey and Yolo had almost no farms located in either high
277 (6.82%; 0.00%, respectively) or very high FHSZs (0.00%; 2.33%, respectively).

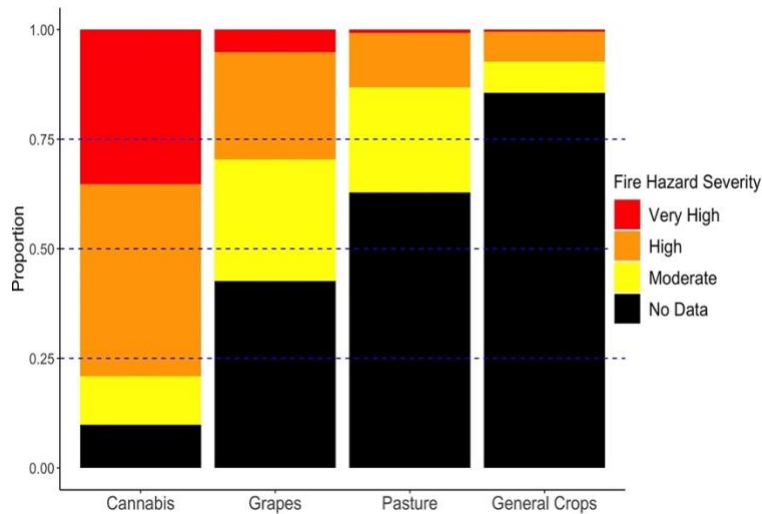
278 For all counties, the proximity of cannabis farms to historic fire perimeters has decreased over
279 time (Figure 5). The median reduction of average annual distance between early (1970-2015) and recent
280 (2016-2020) was smallest in Santa Barbara County (-3.19 km), whereas Lake County recorded the largest
281 median reduction in distance from (-43.81 km), and smallest average distance to (13.41km) wildfire
282 within the recent period. The results of the negative binomial model indicated that, overall, the
283 proximity cannabis farms to wildfire during the *recent* period has reliably decreased (Intercept MLE =
284 4.20, SE= 0.05; Coefficient MLE = -0.44, SE = 0.01), corresponding to a change in average annual distance
285 from 66.37 km (95% CI = [60.43, 72.89]) to 42.94 km (95% CI = [38.82,47.51]).

286

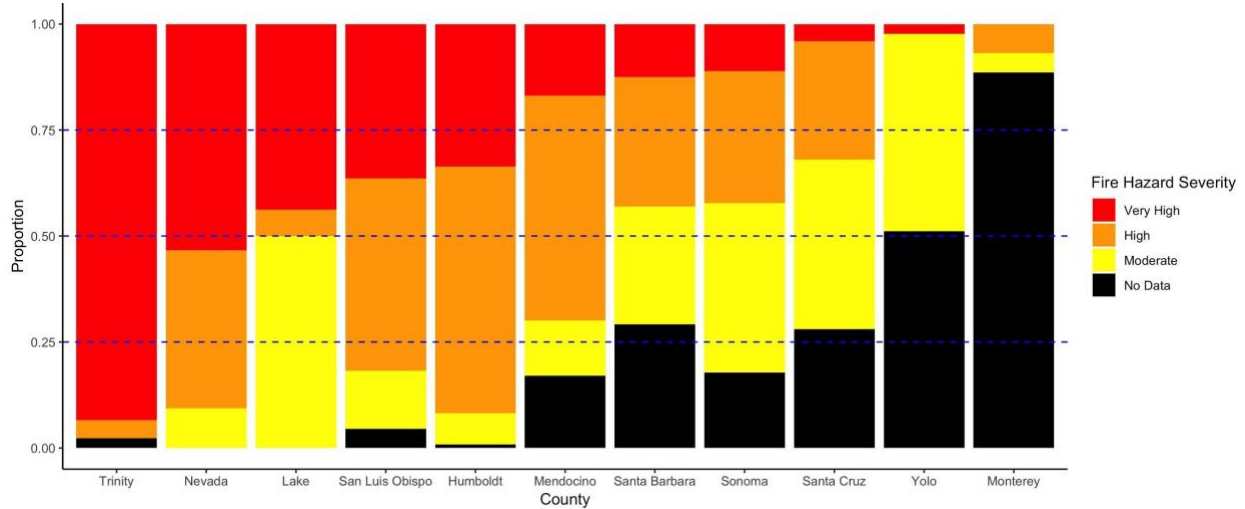
287

288

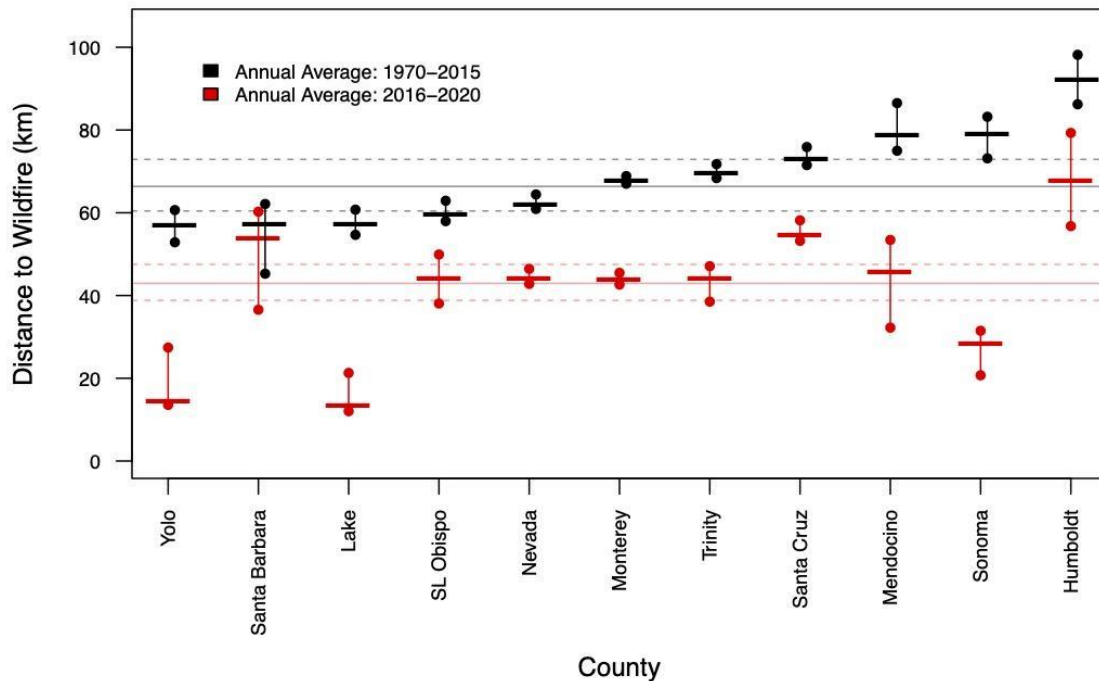
289



298 Figure 3. Fire Hazard Severity Zones by Agricultural Type. Proportions of farms of the four agricultural
 299 types within each FHSZ category are summarized, within cannabis producing counties only. FHSZs are
 300 categorized as moderate, high, and very high, with no data values resulting from areas not categorized
 301 either due to a lack of fire danger or Federal Fire Responsibility or Local Fire Responsibility zones.



302
 303 Figure 4. Fire Hazard Severity Zones by County. Proportions of cannabis farms (only) within each FHSZ
 304 category are summarized by county. FHSZs are categorized as moderate, high, and very high, with no
 305 data values resulting from areas not categorized either due to a lack of fire danger or Federal Fire
 306 Responsibility or Local Fire Responsibility zones.



307 Figure 5. Annual Average Distance to Wildfire. The annual average distances between cannabis farms
 308 and wildfire perimeters recorded in each of the 11 cannabis producing counties in two five-year periods:
 309 *Early* (2010-2014) and *Recent* (2015-2019). Raw data are plotted as bars representing median values and
 310 dots representing the interquartile range. Results of the model predictions are overlaid in corresponding
 311 colors, with maximum likelihood estimates displayed as a horizontal line, bracketed by dashed lines
 312 depicting the 95% confidence interval of the MLE.

313

314 **3.3. What is the projected wildfire risk to cannabis agriculture under climate change and how**
 315 **does it compare to other agricultural sectors?**

316 Cannabis was the only agricultural type with over 75% of farms (84.67%) located in areas
 317 projected as New/Intensifying, Historical/Persistent, or Sporadic/Oscillating Hot Spots for the prediction
 318 period 2020-2100. The only other agricultural type to exceed 50% in these classifications was grapes
 319 (60.79%), while the occurrence of pasture (42.41%) and general crops (24.39%) in these areas was much

320 lower. Among cannabis producing counties, seven of 11 had 75% or more of cannabis farms located in
321 zones projected as New/Intensifying, Historical/Persistent, or Sporadic/Oscillating Hot Spots (Santa
322 Barbara: 97.22%, San Luis Obispo: 77.27%, Trinity: 100%, Mendocino: 98.55%, Monterey: 75%, Lake:
323 100%, and Nevada: 97.33%). There were three counties in which over half of the cannabis farms were
324 specifically within zones projected as New/Intensifying Hot Spots (Santa Barbara: 95.83%, Trinity:
325 61.64%, and San Luis Obispo: 63.64%).

326 The percentage of cannabis farms located within fire perimeters in 2020 was higher than those
327 of any other agricultural crop: (0.63%) or 14 out of 2,228 CDFA licensed farms. The number of sampled
328 grape data points was even lower (6 out of 2,228; 0.026%) and no sampled points for pasture or general
329 crops were located within fire perimeters in 2020. Of the cannabis farms within 2020 fire perimeters,
330 eight were in Mendocino County (1.29% of county farms), three were in Trinity County (0.98% of county
331 farms), two were in Sonoma County (4.44% of county farms), and one was in Santa Cruz County (4.00%
332 of farms).

333

334

335

336

337

338

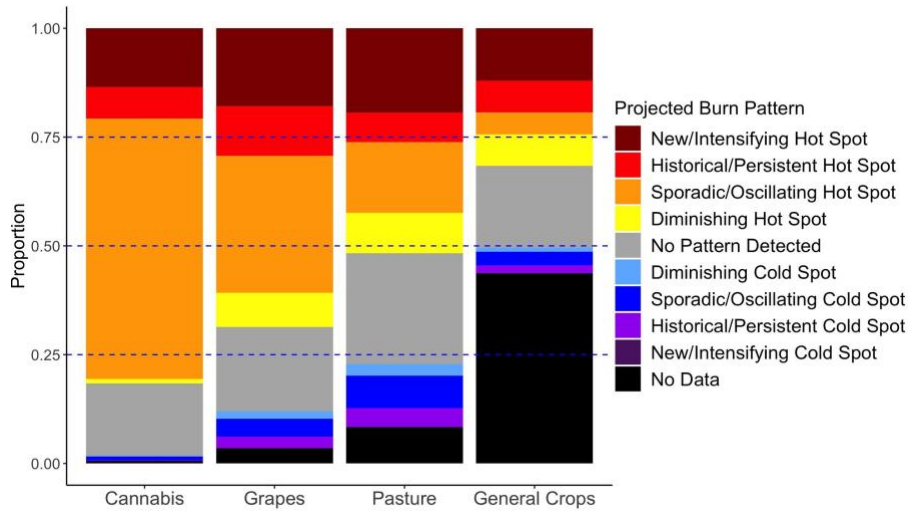
339

340

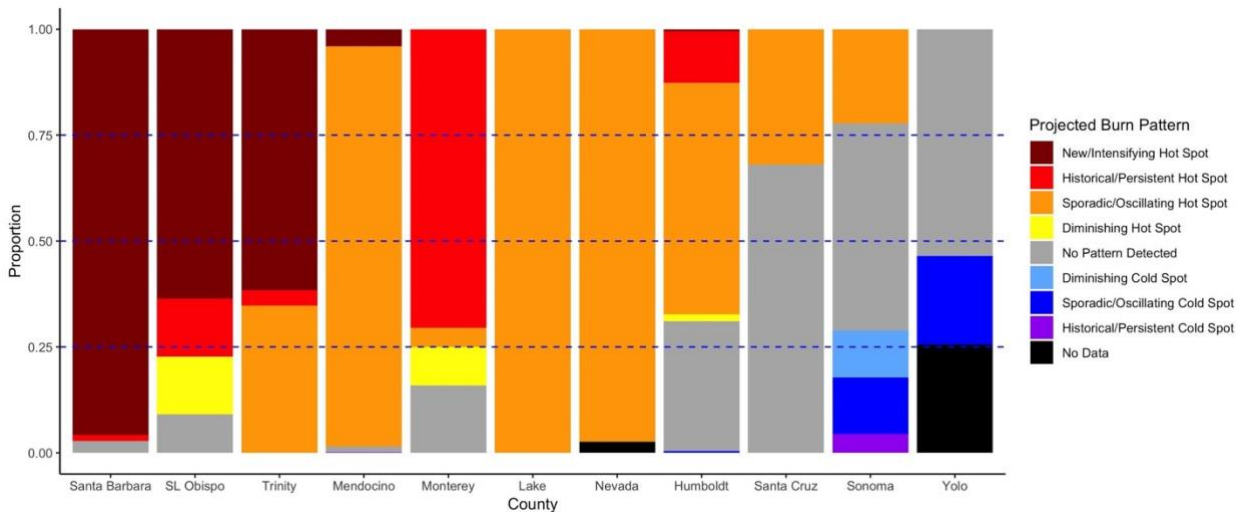
341

342

343



352 Figure 6. Projected Burn Regimes by Agricultural Type. Proportions of farms of the four agricultural
 353 types within each projected burn pattern category are summarized, within cannabis producing counties
 354 only. Categories are adapted from those used by Moanga et. al (2020). No data values result from areas
 355 for which burn probability data from Westerling (2018) were not produced due to extremely low
 356 likelihood of wildfire.



357 Figure 7. Projected Burn Regimes by County for Cannabis Agriculture. Proportions of cannabis farms
 358 (only) within each projected burn pattern category are summarized by county. Categories are adapted
 359 from those used by Moanga et. al (2020). No data values result from areas for which burn probability
 360 data from Westerling (2018) were not produced due to extremely low likelihood of wildfire.

361 **4. Discussion**

362 Global increases in the severity and occurrence of wildfires, driven by climate change and other
363 anthropogenic factors (Liu et al. 2010), are particularly evident in drought-stressed regions such as
364 California. Our spatial analysis of statewide wildfire risk in California suggests that cannabis agriculture is
365 uniquely vulnerable to wildfire impacts relative to other crops. At the statewide scale, cannabis farms
366 are on average located within 3km of a past wildfire, whereas pasture is located over twice as far,
367 grapes three times as far, and general crops are located over four times as far from wildfires.
368 Furthermore, although the statewide distribution of cannabis agriculture is largely confined to a handful
369 of relatively fire-prone counties, the distribution of cannabis farms within these counties is still closer to
370 historic wildfire perimeters, and more likely to be found in high fire hazard severity zones, than are all
371 other agricultural types. Our results further suggest an alarming trend of increasing fire risks to cannabis
372 in the future. The wildfire risk for cannabis increased markedly during the five year period from 2015-
373 2020 compared to the preceding 45 years. Overall, we estimated that the distance between cannabis
374 farms and fire perimeters has shrunk by 36% during this time period. Likewise, using data on projected
375 burn regimes, we found that a disproportionate number of cannabis farms are located in wildfire
376 hotspots under future climate scenarios.

377 ***4.1. Geography of Cannabis in California May Exacerbate Threat from Wildfire***

378 The geography of cannabis farming is distinct from that of other agricultural types, as a result of
379 both variability in county-level regulations and the illicit history of the crop (Dillis et al., 2021). Although
380 the cannabis industry continues to expand in California, the current distribution of farms is still heavily
381 biased toward its historical origins in the northern part of the state. Establishment of the early cannabis
382 industry in this region was partially driven by the desire to grow undetected, leading growers to locate in
383 remote, hilly, fire prone areas (Corva, 2014; Butsic and Brenner, 2016). As farmers have entered the
384 legal market, many remain in these remote areas, given that their farms are already established. While

385 these small farms vastly outnumber their counterparts elsewhere in the state, the majority of legal
386 cannabis production has already shifted to the Central Coast, where farms are less numerous, but orders
387 of magnitude larger (Dillis et al., 2021). Unfortunately, the future wildfire outlook for the Central Coast
388 also poses a concern in that all three top cannabis producing counties in this region have more than half
389 of their farms in zones projected as persistent, new, or intensifying wildfire hotspots. In fact, over 95%
390 of its cannabis farms in Santa Barbara County, which is now the top cannabis producing county in the
391 state, are located in new or intensifying hot spot zones.

392 It is worth noting the counties that produce the vast majority of the state’s irrigated agricultural
393 crops are located in the Central Valley and are generally considered to have very low wildfire risk.
394 However, aside from Yolo County, every county in the valley has continued to prohibit cannabis
395 agriculture through local ordinances. As a consequence, many areas suitable for cannabis cultivation
396 that have lower fire risk are currently inaccessible. Future changes in policy that allow for cultivation
397 within these counties may significantly lower the overall wildfire risk to cannabis in the state. Within
398 current cannabis producing counties, many land use policies have encouraged production on lands
399 already used for agriculture. To the extent that these lands have less exposure to wildfire, it is possible
400 that newly establishing farms may have lower fire risk. As an example, Monterey and Trinity Counties
401 have both experienced an exceptional amount of wildfire since 2015 (covering 16% and 33% of their
402 land areas, respectively), yet the latter has over 90% of its cannabis farms in very high fire hazard
403 severity zones, while the former has none. This is largely because cannabis farming in Monterey County
404 is new and confined to agricultural zones, while production in Trinity County is still located in remote
405 legacy areas and there is relatively little agricultural land throughout the county in general.

406 ***4.2. Cascading impacts of wildfire on the cannabis industry***

407 Although the number of cannabis farms that were directly damaged by wildfire in 2020 (i.e.,
408 inside fire perimeters) is small (0.63%), a much larger proportion of farms were likely affected by their

409 close proximity to fire, and experienced impacts from smoke exposure or infrastructure damage (e.g.,
410 power and water systems). It is unknown what proportion of farms experienced crop damage or losses
411 from wildfire smoke. While the adverse effects of wildfire smoke on the chemical composition and
412 quality of wine grapes (“smoke taint”) is well documented and known to cause significant economic
413 impacts (e.g., (e.g., Krstic et al., 2015), the effects of smoke on the quality of cannabis products is less
414 well understood (but see Kukura, 2020; Schiller, 2020).

415 Wildfire smoke may also have additional implications for human health. Outdoor farm workers,
416 including for cannabis, may be particularly vulnerable to smoke exposure and health risks from the
417 inhalation of particulate matter from wildfire smoke (Riden et al., 2021), including severe respiratory
418 and cardiovascular damage (Cascio et al., 2018). Farmworker health and safety may also be impacted by
419 additional exposure to toxic particles from combusted building structures or chemicals found on site,
420 including pesticides, as well as flame retardants used to suppress wildfires (e.g., Riden et al. 2021). There
421 are also no publicly available data on the capacity for these chemical compounds, or the natural
422 byproducts of wildfire smoke, to impact the safety of cannabis licensed for human consumption. Given
423 California’s stringent testing requirements for cannabis flower, the effects of wildfire smoke add further
424 uncertainty to newly established testing protocols and there is no publicly available guidance on
425 potential mitigation measures. Finally, the federally illegal status of cannabis has made crop insurance
426 largely unavailable to cannabis farmers, thus increasing financial exposure should crops be either
427 burned or rendered unmarketable as a result of smoke damage.

428 An economic analysis of the potential impact of wildfire on the cannabis industry would be
429 helpful in understanding the scale of the risk and informing needed policy changes. With 2019 sales near
430 \$3 billion (McGreevy, 2019), cannabis is already one of the top five grossing agricultural sectors in
431 California (State of California, 2020), with rapid growth expected in the coming decade (Hudock, 2019).
432 In 2020, tax revenues from legal cannabis sales in the state amounted to over \$780 million (State of

433 California, 2021). Considering cannabis' increasing economic importance at state- and county-levels,
434 crop losses from wildfire are likely to have critical economic impacts, particularly in rural communities
435 with a higher direct social and economic dependence on cannabis agriculture (Kelly & Formosa 2020).
436 This could also disproportionately impact already marginalized small-scale cannabis farmers who may
437 not have resources to recover from wildfire-related losses.

438 **4.3. Conclusions**

439 Cannabis is unique among agricultural sectors both in the threat of exposure to wildfire and the
440 prospect of uninsurable crop losses. The geographic legacy of cannabis production in Northern California
441 and expansion of the regulated industry in the Central Coast has rendered it more vulnerable than other
442 types of agriculture, compounded by the regulatory exclusion of cannabis farms from traditional
443 agricultural regions in the Central Valley with relatively lower fire risk. If production is confined to
444 current counties, local regulations should encourage new farming in areas that are less prone to wildfire,
445 yet remain inclusive of existing cannabis farms. For instance, fire-safety programs for farms already
446 established in high-risk areas are needed to reduce the risks of wildfire to crops and human health. The
447 state should also pursue options for providing crop insurance to farmers that aren't eligible for federal
448 programs. Furthermore, given that the impacts of wildfire extend beyond fire perimeters, research on
449 smoke exposure risks for cannabis crops and farm workers is an urgent priority. Collectively, these steps
450 will help bolster the resilience of the developing regulated cannabis industry with respect to wildfire.
451 The impacts of wildfire on cannabis farming may be particularly severe, but serves more generally as an
452 example of the vulnerability of rural agriculture, and its dependent communities, in the face of climate
453 change and the consequent increase in natural disasters such as wildfire.

454 **Acknowledgements**

455 This work was made possible in part through funding from the Resources Legacy Fund and the Campbell
456 Foundation. Funding sources were not involved in the collection, analysis, or interpretation of the data,
457 writing of the report, or the decision to submit the article for publication.

458 **References**

459 Bates, D., Mächler, M., Bolker, B. and Walker, S. 2014. Fitting linear mixed-effects models using lme4.
460 *arXiv preprint arXiv:1406.5823*.

461
462 Bauman, M.J., Yuan, J. & Williams, H.A. 2020. Developing a measure for assessing tourists' empathy
463 towards natural disasters in the context of wine tourism and the 2017 California wildfires. *Curr. Issues*
464 *Tour.*, 23, 2476–2491.

465
466 Bell R. 2015. What happens when livestock are in the path of a wildfire. National Geographic.
467 [https://www.nationalgeographic.com/culture/food/the-plate/2015/09/03/what-happens-when-](https://www.nationalgeographic.com/culture/food/the-plate/2015/09/03/what-happens-when-livestock-are-in-the-path-of-a-wildfire/)
468 [livestock-are-in-the-path-of-a-wildfire/](https://www.nationalgeographic.com/culture/food/the-plate/2015/09/03/what-happens-when-livestock-are-in-the-path-of-a-wildfire/)

469
470 Bodwitch, H., Carah, J., Daane, K., Getz, C., Grantham, T., Hickey, G. and Wilson, H., 2019. Growers say
471 cannabis legalization excludes small growers, supports illicit markets, undermines local economies.
472 *California Agriculture*, 73(3), pp.177-184.

473
474 Boundary Solutions. 2020. National Parcelmap Data Portal.
475 <https://www.boundarysolutions.com/BSI/page1.php>.

476

477 Butsic, V. and Brenner, J.C. 2016. Cannabis (*Cannabis sativa* or *C. indica*) agriculture and the
478 environment: a systematic, spatially-explicit survey and potential impacts. *Environmental Research*
479 *Letters*, 11(4), p.044023.

480

481 Butsic, V., Schwab, B., Baumann, M. and Brenner, J.C. 2017. Inside the Emerald Triangle: Modeling the
482 placement and size of cannabis production in Humboldt County, CA USA. *Ecological Economics*, 142,
483 pp.70-80.

484

485 Butsic V, Carah JK, Baumann M, Stephens C, Brenner JC. 2018. The emergence of cannabis agriculture
486 frontiers as environmental threats. *Environmental Research Letters*, Dec 4;13(12):124017.

487 CalAdapt. 2018. Wildfire: explore projected changes in average area burned by wildfires for California.
488 Verified 22 October 2020 at <https://cal-adapt.org/tools/wildfire/>.

489 CAL FIRE. 2020a. Top 20 Largest California Wildfires. Accessed January 27, 2021 at
490 https://www.fire.ca.gov/media/4jandlhh/top20_acres.pdf

491

492 CAL FIRE. 2020b. Fire Hazard Severity Zones. Accessed September 1, 2020 at
493 <https://gis.data.ca.gov/datasets/789d5286736248f69c4515c04f58f414>

494

495 CAL FIRE. 2020c. Fire Perimeter Data (1900-2019). Accessed September 1, 2020 at
496 [https://gis.data.ca.gov/datasets/CALFIRE-Forestry::california-fire-perimeters-all?geometry=-](https://gis.data.ca.gov/datasets/CALFIRE-Forestry::california-fire-perimeters-all?geometry=-149.872%2C31.410%2C-88.349%2C43.564)
497 [149.872%2C31.410%2C-88.349%2C43.564](https://gis.data.ca.gov/datasets/CALFIRE-Forestry::california-fire-perimeters-all?geometry=-149.872%2C31.410%2C-88.349%2C43.564)

498

499 CAL FIRE. 2020d. Fire Perimeter Data (2020). Accessed December 7, 2020 at

500 [https://gis.data.ca.gov/datasets/CALFIRE-Forestry::wildfire-perimeters/data?geometry=-](https://gis.data.ca.gov/datasets/CALFIRE-Forestry::wildfire-perimeters/data?geometry=-56.778%2C24.076%2C-170.685%2C65.012)

501 [56.778%2C24.076%2C-170.685%2C65.012](https://gis.data.ca.gov/datasets/CALFIRE-Forestry::wildfire-perimeters/data?geometry=-56.778%2C24.076%2C-170.685%2C65.012)

502

503 Cascio, Wayne E. 2018. Wildland fire smoke and human health. *Science of the total environment*. 624:

504 586-595.

505

506 Corva, D., 2014. Requiem for a CAMP: The life and death of a domestic US drug war institution.

507 *International Journal of Drug Policy*, 25(1), pp.71-80.

508 Dillis, C., Biber, E., Bodwitch, H., Butsic, V., Carah, J., Parker-Shames, P., Polson, M., and Grantham, T.

509 2021. Shifting geographies of legal cannabis production in California. *Land Use Policy*. 105: 105369

510 Dewitz, J., 2019, National Land Cover Database (NLCD) 2016 Products: U.S. Geological Survey data

511 release, <https://doi.org/10.5066/P96HHBIE>.

512 ESRI. 2016. Space time pattern mining concepts: how emerging hot spot analysis works. Available at

513 <https://pro.arcgis.com/en/pro-app/tool-reference/space-time-pattern-mining/learnmoreemerging.htm>

514 Goss, M., Swain, D.L., Abatzoglou, J.T., Sarhadi, A., Kolden, C.A., Williams, A.P. and Diffenbaugh, N.S.,

515 2020. Climate change is increasing the likelihood of extreme autumn wildfire conditions across

516 California. *Environmental Research Letters*. 15(9), p.094016.

517 Herskovitz, J. 2017. US Plains wildfires leave thousands of cattle dead. Reuters.

518 [https://www.reuters.com/article/us-usa-wildfires/u-s-plains-wildfires-leave-thousands-of-cattle-dead-](https://www.reuters.com/article/us-usa-wildfires/u-s-plains-wildfires-leave-thousands-of-cattle-dead-idUSKBN16G2XG)

519 [idUSKBN16G2XG](https://www.reuters.com/article/us-usa-wildfires/u-s-plains-wildfires-leave-thousands-of-cattle-dead-idUSKBN16G2XG)

520 Hudock, C. 2019. US Cannabis Cultivation in California. New Frontier Data.

521 <https://newfrontierdata.com/cannabis-insights/u-s-cannabis-cultivation-in-california/>.

522 Jin, Y., Goulden, M.L., Faivre, N., Veraverbeke, S., Sun, F., Hall, A., Hand, M.S., Hook, S. & Randerson, J.T.
523 2015. Identification of two distinct fire regimes in Southern California: Implications for economic impact
524 and future change. *Environmental Research Letters*, 10, 094005.

525 Keeley, J.E. and Syphard, A.D., 2018. Historical patterns of wildfire ignition sources in California
526 ecosystems. *International journal of wildland fire*, 27(12), pp.781-799.

527 Kelly, E.C. and Formosa, M.L., 2020. The economic and cultural importance of cannabis production to a
528 rural place. *Journal of Rural Studies*, 75, pp.1-8.

529 Kelly, L.T., Giljohann, K.M., Duane, A., Aquilué, N., Archibald, S., Batllori, E., Bennett, A.F., Buckland, S.T.,
530 Canelles, Q., Clarke, M.F. and Fortin, M.J., 2020. Fire and biodiversity in the Anthropocene. *Science*,
531 370(6519).

532 Kramer, H.A., Mockrin, M.H., Alexandre, P.M. and Radeloff, V.C., 2019. High wildfire damage in interface
533 communities in California. *International journal of wildland fire*, 28(9), pp.641-650.

534 Krstic, M. P., D. L. Johnson, and M. J. Herderich. 2015. Review of smoke taint in wine: smoke-derived
535 volatile phenols and their glycosidic metabolites in grapes and vines as biomarkers for smoke exposure
536 and their role in the sensory perception of smoke taint. *Australian journal of grape and wine research*.
537 21:537-553.

538 Kukura, J. 2020. Entire West Coast marijuana crop threatened by fire, smoke, and ash. SFist.com.
539 <https://sfist.com/2020/10/06/entire-west-coast-marijuana-crop-threatened-by-fire-smoke-and-ash/>

540 Liu, Yongqiang, John Stanturf, and Scott Goodrick. 2010. Trends in global wildfire potential in a changing
541 climate. *Forest ecology and management*. 259: 685-697.

542 McGreevy, P. 2019. California now has the largest legal marijuana market in the world. Los Angeles
543 Times. [https://www.latimes.com/california/story/2019-08-14/californias-biggest-legal-marijuana-
545 market](https://www.latimes.com/california/story/2019-08-14/californias-biggest-legal-marijuana-
544 market)

545 Moanga, D., Biging, G., Radke, J. and Butsic, V., 2021. The space–time cube as an approach to
546 quantifying future wildfires in California. *International Journal of Wildland Fire*, 30(2), pp.139-153.

547 Norgaard, K.M., 2014. The Politics of Fire and the Social Impacts of Fire Exclusion on the Klamath.
548 *Humboldt Journal of Social Relations*, 36(1).

549 Parks, S.A., Miller, C., Parisien, M.A., Holsinger, L.M., Dobrowski, S.Z. and Abatzoglou, J., 2015. Wildland
550 fire deficit and surplus in the western United States, 1984–2012. *Ecosphere*, 6(12), pp.1-13.

551 Radeloff, V.C.V.C., Helmers, D.P.D.P., Kramer, H.A., Mockrin, M.H.M.H., Alexandre, P.M.P.M., Bar-
552 Massada, A., Butsic, V., Hawbaker, T.J.T.J., Martinuzzi, S., Syphard, A.D.A.D., Stewart, S.I.S.I., Anu
553 Kramer, H., Mockrin, M.H.M.H., Alexandre, P.M.P.M., Bar-Massada, A., Butsic, V., Hawbaker, T.J.T.J.,
554 Martinuzzi, S., Syphard, A.D.A.D. & Stewart, S.I.S.I. 2018. Rapid growth of the US wildland-urban
555 interface raises wildfire risk. *Proc. Natl. Acad. Sci. U. S. A.*, 115, 3314–3319.

556 R Core Development Team. 2018. R: A language and environment for statistical computing. R
557 Foundation for Statistical Computing. Vienna, Austria, <https://www.r-project.org>.

558 Riden, H., Felt, E., and Pinkerton, K. 2021. The Impact of Climate Change and Extreme Weather
559 Conditions on Agricultural Health and Safety in California. *Climate Change and Global Public Health*.
560 *Humana, Cham*. 353-368.

561 Schiller, M. 2020. Can wildfires impact cannabis quality and test results? Cannabis Business Times.
562 <https://www.cannabisbusinesstimes.com/article/can-wildfires-impact-cannabis-quality-test-results/>

563 State of California. 2019. Department of Forestry and Fire Protection. Accessed September 1, 2020 at
564 <https://gis.data.ca.gov/datasets/CALFIRE-Forestry::california-county-boundaries>
565

566 State of California. 2020. Department of Food and Agriculture. California Agricultural Production
567 Statistics. Accessed February 10, 2021 at <https://www.cdfa.ca.gov/Statistics/>
568

569 State of California. 2021. California Department of Tax and Fee Administration. Accessed January 28,
570 2021 at <https://www.cdtfa.ca.gov/dataportal/dataset.htm?url=CannabisTaxRevenues>
571

572 Syphard, A.D., Radeloff, V.C., Keeley, J.E., Hawbaker, T.J., Clayton, M.K., Stewart, S.I. and Hammer, R.B.,
573 2007. Human influence on California fire regimes. *Ecological applications*, 17(5), pp.1388-1402.
574

575 Thach, L. and Eyler, R. 2017. Up in smoke: Will wildfires leave lasting economic scars on California's vital
576 wine country? *Australian and New Zealand Grapegrower and Winemaker*
577 [https://theconversation.com/will-wildfires-leave-lasting-economic-scars-on-californias-vital-wine-](https://theconversation.com/will-wildfires-leave-lasting-economic-scars-on-californias-vital-wine-country-86174)
578 [country-86174](https://theconversation.com/will-wildfires-leave-lasting-economic-scars-on-californias-vital-wine-country-86174).
579

580 USDA National Agricultural Statistics Service Cropland Data Layer. 2019. Published crop-specific data
581 layer [Online]. USDA-NASS, Washington, DC. Accessed September 1, 2020 at
582 <https://nassgeodata.gmu.edu/CropScape>.
583

584 U.S. Geological Survey, 2019, USGS TNM Hydrography (NHD), accessed March 1, 2020 at
585 <https://viewer.nationalmap.gov/basic/>.

586 van Wagtendonk, J., Sugihara, N., Stephens, S., Thode, A. 2021. Fire in California's Ecosystems.
587 University of California Press. [https://www.ucpress.edu/book/9780520286832/fire-in-californias-](https://www.ucpress.edu/book/9780520286832/fire-in-californias-ecosystems)
588 [ecosystems](https://www.ucpress.edu/book/9780520286832/fire-in-californias-ecosystems).

589 Westerling, A.L., Hidalgo, H.G., Cayan, D.R. and Swetnam, T.W., 2006. Warming and earlier spring
590 increase western US forest wildfire activity. *science*, 313(5789), pp.940-943.

591 Westerling, A.L. 2018. *Wildfire Simulations for California's Fourth Climate Change Assessment: Projecting*
592 *Changes in Extreme Wildfire Events with a Warming Climate: a Report for California's Fourth Climate*
593 *Change Assessment*. Sacramento, CA: California Energy Commission.

594 Williams, A.P., Abatzoglou, J.T., Gershunov, A., Guzman-Morales, J., Bishop, D.A., Balch, J.K. and
595 Lettenmaier, D.P., 2019. Observed impacts of anthropogenic climate change on wildfire in California.
596 *Earth's Future*, 7(8), pp.892-910.

597
598
599
600
601
602
603
604
605
606
607
608
609

610 **Tables**

Table 1. Descriptions of projected burn patterns adapted from ESRI (2016). Aggregates of individual burn patterns are indicated by horizontal lines. Each description of a hot spot pattern also applies to an equivalent description of a cold spot pattern.

Burn Pattern	Description
New Hot Spot	A location that is a statistically significant hot spot for the final time step and has never been a statistically significant hot spot before.
Intensifying Hot Spot	A location that has been a statistically significant hot spot for 90% of the time-step intervals, with the intensity of clustering increasing overall and that increase is statistically significant.
Historical Hot Spot	The most recent time period is not hot, but at least 90% of the time-step intervals have been statistically significant hot spots.
Persistent Hot Spot	A location that has been a statistically significant hot spot for 90% of the time-step intervals with no discernible trend indicating an increase or decrease in the intensity of clustering over time.
Sporadic Hot Spot	A location that is an on-again then off-again hot spot. Less than 90% of the time-step intervals have been statistically significant hot spots and none of the time-step intervals have been statistically significant cold spots.
Oscillating Hot Spot	A statistically significant hot spot for the final time-step interval that has a history of also being a statistically significant cold spot during a prior time step. Less than 90% of the time-step intervals have been statistically significant hot spots.
Diminishing Hot Spot	A location that has been a statistically significant hot spot for 90% of the time-step intervals, with the intensity of clustering decreasing overall and that decrease is statistically significant.
No Pattern Detected	Does not fall into any of the hot or cold spot patterns.

611
612
613
614

Table 2. Model coefficients. Results of negative binomial model predicting distance to known wildfire perimeter. Maximum Likelihood Estimates (MLE) and standard errors are provided along with the predicted estimate on the original scale (OSE).

Coefficient	MLE	Std. Error	OSE
Intercept (Cannabis)	1.46	0.11	4.30 km
Grapes	0.11	0.03	4.82 km
Pasture	0.14	0.03	4.96 km
General Crops	0.14	0.03	4.95 km

615
616
617
618
619
620
621
622
623
624

625

626

627

628

629

630