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RESEARCH ARTICLE

Contextualizing cannabis water demand and potential for streamflow impacts relative to residential and agricultural users in Northern California

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Abstract

This study examines the relative water demand and potential streamflow impacts of cannabis cultivation, residential use, and non-cannabis agriculture in rural northern California watersheds. While cannabis has received much attention for its potential impact on sensitive aquatic species, the relative contribution to overall water demand in watersheds where cannabis is farmed remains poorly understood. Using spatial and temporal analyses across multiple watersheds, this study assesses how water use for cannabis cultivation compares to other major water users in terms of total demand, spatial distribution, and interannual fluctuations. Cannabis was more rarely the top water user in a given catchment (1.6% of observations) than were residential users (34.6%) or non-cannabis agriculture (29.8%). Cannabis water demand was more seasonal, with greater interannual variability, and more evenly spread among catchments than other water use types. Residential and non-cannabis agriculture had the potential to impair streamflow at annual timescales, while cannabis water use impacts was only evident at the monthly scale. Overall, findings suggest that water demand for residential and non-cannabis agriculture has a greater impact on streamflow than cannabis, but that demands from cannabis may cause additive impacts when all uses are considered. Additionally, the potential for cannabis demand to cause streamflow alteration varied year-to-year, with greater potential for impairment during dry years. Given these dynamics, we recommend adoption of holistic approaches that manage all human water uses to protect sensitive natural resources in cannabis-producing watersheds.

Introduction

The complex landscape of competing water users in California (USA) creates challenges for the management of freshwater resources [1,2]. Balancing the needs

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of diverse stakeholders, including residential users, agriculture, and environmental needs, is further complicated by the frequency and severity of drought and increasingly unpredictable water availability [3,4,5]. Managing water in rural areas presents particular challenges because users generally do not have access to large water storage systems and instead rely on local sources of water, including streams and groundwater, to meet their needs [6]. Increasing pressures from anthropogenic activities, both residential and agricultural, have been shown to significantly reduce streamflows [7,8], causing ecological stress and threatening aquatic species [9,10]. In recent decades, cannabis farming has entered the existing network of water users in many rural areas of California, further intensifying competition for water resources [11].

Cannabis farming in California has a distinct history in which decades of legal prohibition led to the concentration of siting and production in remote watersheds in the northern part of the state [12]. For the past 40 years, California has been an epicenter of cultivation supplying substantial proportions of national and even international markets [13]. While the amount of land area needed for such production is orders of magnitude smaller than that of non-cannabis agriculture, the location of cannabis farms not only tends to overlap areas of high environmental sensitivity [14] [8,15,16], farms rarely have access to municipal or otherwise reservoir-fed irrigation infrastructure.

Like most water users in California's rural watersheds, cannabis farming (both licensed and unlicensed) is heavily reliant on local water supplies to supply irrigation demand [17]. Because irrigation demands for cannabis occur during the dry season [18], water withdrawals have the potential to deplete the naturally low surface flows that exist in streams and are critical to sustaining sensitive freshwater species [19]. Furthermore, many cannabis farms draw water from small headwater streams where the potential for significant flow reductions is substantially higher that withdrawals from larger water courses [20].

To fully understand the risks that cannabis poses to streams and sensitive aquatic species, it is also important to consider other types of water uses. Many of California's rural watersheds support residential development at varying densities, as well as other forms of agriculture, including vineyards, fruit orchards, and ranching. These other water users also tend to rely on local water supplies and contribute to streamflow impacts [Deitch et al. 2009b], yet have not received the same public or regulatory attention as cannabis [21]. Previous research suggests that residential water demand in some California watersheds greatly exceeds that of cannabis farming [11], as may the demand of non-cannabis agriculture. However, a complete accounting of demands among water users and across cannabis-producing watersheds has yet to be performed. Further, the relative contribution of different water-use types to potential streamflow impairment (i.e., flow reductions) remains poorly understood. In particular, recent work has raised questions about the appropriate scale of measurement for identifying potential streamflow impairments by cannabis farming [20] and this question remains open for residential use and non-cannabis agricultural use in these areas as well.

Understanding how the water demands of cannabis cultivation compare to those of the other dominant water users is crucial for the development of effective water management strategies that can accommodate competing interests while safeguarding the long-term sustainability of shared freshwater resources. This study seeks to fill this gap by investigating the relative spatiotemporal water demands of three major water user types in rural California watersheds: cannabis cultivation, residential use, and non-cannabis agriculture. We specifically address the following research questions:

1. How does cannabis compare to other water users in terms of overall demand, seasonal demand, and spatial and inter-annual uniformity of demand across the landscape?
2. What are the most effective spatial and temporal scales to assess potential streamflow impairments of each water user type
3. Are there differences between water user types with respect to how their impacts could manifest in response to interannual fluctuations in streamflow?

Methods

Study area

The study area consists of 14 watersheds (Hydrologic Unit Code 12 or HUC12) across 10 counties throughout Northern California (Fig 1). Watersheds were randomly selected from the California Department of Fish and Wildlife (CDFW) Bay Delta Region and North Central Region using Balanced Acceptance Sampling (BAS) with post-stratification. The BAS design is a spatially balanced sampling procedure that ensures spatial diversity of sites and allows for sampling with replacement when selected locations cannot be observed due to study design constraints [22]. Watersheds were selected in concurrence with on-the-ground monitoring, and watersheds that were highly urbanized, inaccessible, or incompatible with field methods were not included in the study. We additionally did not include low-lying, valley watersheds with underlying groundwater basins because of the challenges of estimating streamflow depletion from groundwater use (but see [11]). Instead, we focused exclusively on upper watersheds where water users (including residential, cannabis agriculture, and non-cannabis agriculture) are known to rely primarily on streams, and shallow groundwater sources near streams, to meet their needs [17].

Due to the lack of data on exact diversion locations and subsurface properties, we did not distinguish between the effects of direct surface water diversions versus groundwater pumping.

We used post-stratification of the BAS ordered watersheds to ensure that 50% of the selected watersheds had at least one cannabis farm with an active California Department of Cannabis Control (DCC) license. Watersheds without any DCC licenses may still have unlicensed cultivation, but total cultivation area tended to be lower than in watersheds with permitted cultivation. Additionally, one of the 14 watersheds (Redwood Creek) was not part of the random BAS selection process and was included in the study because it is a priority watershed for conservation and restoration actions and has a legacy of licensed and unlicensed cannabis cultivation.

Land use mapping

Cannabis farms within the study watersheds were mapped using high-resolution aerial imagery from Planet Labs 15 cm SkySat satellite imagery, Hexagon 15 cm aerial imagery, and Google Earth, building on established methods [23]. Briefly, a human mapper reviewed imagery captured during peak cannabis growing season (typically July-August) in ArcGIS [24] and delineated the footprint of cannabis cultivation areas, including greenhouses. As a quality control measure, a second human mapper then re-mapped 20% or 100% of the watershed. Watersheds (HUC12) were only included in this study if agreement in the total number of cannabis features identified between the two mappers in 20% re-mapped watersheds was > 70%. In the 100% re-mapped watersheds, both mappers conferred to reconcile all features that were not in

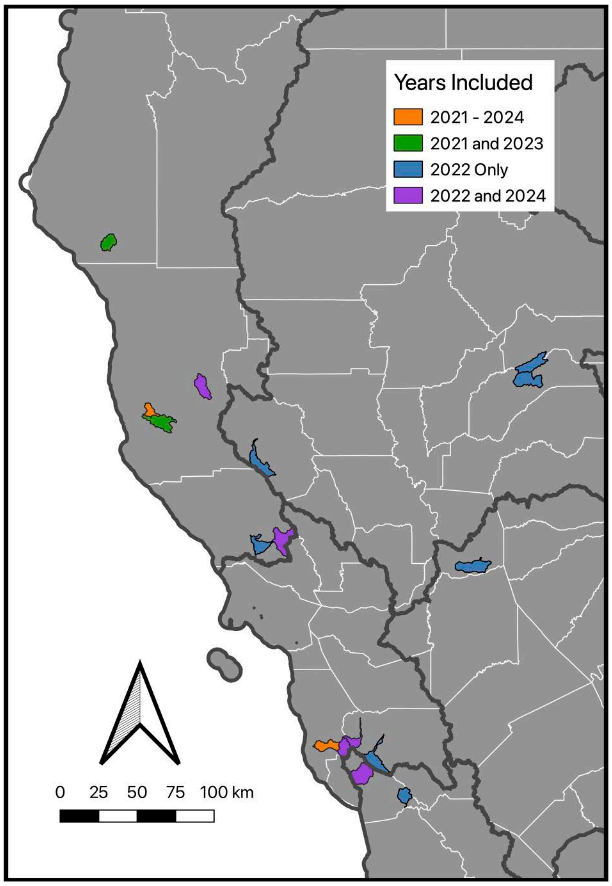

Fig 1. Study area map. All study watersheds sampled across Northern California are depicted in colors that correspond to the years in which they were included in analyses. County boundaries are depicted in white. HUC4 Watershed boundaries are depicted in dark gray. The basemap of county lines was obtained from the US Census Bureau 2025 TIGER/Line Shapefile of Counties (https://www.census.gov/cgi-bin/geo/shapefiles/index.php?year=2025&layergroup=Counties+%28and+equivalent%29).

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agreement between the two. Mapping agreement statistics are provided in S1 Table. Cannabis cultivation polygons were then aggregated at the parcel level to represent individual farms, using parcel data sourced from the National Parcelmap Data Portal [25]). Cannabis farms were identified as "regulated" or "unregulated" based on whether parcels had an active Lake and Streambed Alteration Agreement for cannabis from CDFW and/or a cultivation license from the DCC.

To map residential demand, all parcels within the study watersheds were designated as either occupied or unoccupied, based on the presence or absence of a building footprint, respectively. Building footprints were obtained from Dao [26], who generated a California-specific shapefile from the opensource Microsoft National Building Footprint. The footprint of non-cannabis agriculture in study catchments was established using the Cropland Data Layer raster provided annually by the United States Department of Agriculture [27]. Raster cells (900 m^2) were converted to area and each crop type was summed in each catchment.

Water demand and availability

Water demands for cannabis farms were estimated using established models, described in detail by Dillis et al. [20]. Briefly, the methodology aggregates cannabis grow sites to parcels as "farms" and characterizes the farms based on variables such as cultivation area, operation type (full outdoor or mixed-light), reference evapotranspiration, and expected water storage capacity. These variables are used to fit an annual water demand model and a monthly extraction model to parse demand into monthly estimates. The full composite model therefore provides monthly water demand estimates by combining annual predictions with storage-based extraction likelihoods (see S1 Text). Monthly cannabis farm-level irrigation estimates were then aggregated to the catchment scale.

Residential water demand was estimated at the parcel level as well. For occupied parcels, estimates of monthly water demand were generated based on uniform estimates of household water use produced by the California Single Family Water Use Efficiency Study [28]. Estimated residential water use for these parcels was then aggregated to the catchment scale on a monthly time step.

Water demand for non-cannabis agriculture was estimated by applying a formula for the Theoretical Irrigation Requirement (TIR,[28] for each crop type (by area) within each catchment:

$$TIR = 0.624 * RefET * \Sigma_c \left((A_c / E_c) * K_c \right) \quad \text{Eq 1}$$

Where 0.624 is a constant to convert inches of RefET to gallons per ft^2, RefET is average monthly reference evapotranspiration within the catchment's watershed [29], A_c is the area (m^2) of each crop type, E_c is crop irrigation efficiency, and K_c is the crop coefficient. Crop coefficients were provided by the California Crop and Soil Evapotranspiration Report produced by the California Department of Water Resources [30] and applied to the area of individual crop types identified in each catchment. Estimated TIR for all mapped crops was then aggregated to the catchment level on a monthly time step.

All analyses were conducted at the sub-watershed scale using polygons outlined by the National Hydrography Dataset [NHDPlusV2,31], hereafter referred to as "catchments". The HUC12 watersheds in our study area contained, on average, 33 (range 6–90) individual catchments (mean = 1.87 km^2, range 0.06 - 15.04 km^2). Catchment-level analyses were divided into monthly timesteps, such that the universal unit of measurement across all analyses were so-called *catchment-months*, unless otherwise specified. For instance, an annual sample of 10 catchments would yield 120 (10x12) catchment-month observations.

Monthly streamflow availability for each catchment was estimated using a natural flow model [32] that applies many variables, including monthly precipitation, air temperature, and runoff estimates to produce monthly flow estimates. Mean monthly natural flow estimates were converted from cubic feet per second to cubic meters per month for each catchment for the current study year (2022) and each of the preceding 30 years to produce an historical dataset. The 30 years of flow data were used to establish the likely range of available flows; water demand from the study year (2022) remained constant in each comparison with historical flow data. Because streamflow estimates for each catchment-month included inflow from upstream catchments, water demand of each water user type was similarly calculated by aggregating these demands from contributing upstream catchments. The total sample of catchment-months (n = 5508; n = 459 catchments) was restricted to only those with streamflow predicted to be greater than zero (n = 4367). The full water budget dataset [33] is hosted at the following location (https://doi.org/10.5061/dryad.k3j9kd5q4).

Water user demand and uniformity

The water demand of each water user type was tabulated on a monthly basis for each study watershed and compared using descriptive statistics in R Statistical Software [34,35]. We estimated the relative average differences in monthly and annual demands for each water use type and calculated the number of catchment-months during which each user type (cannabis, residential, and non-cannabis agriculture) accounted for the highest share of water demand across the study area and between the 14 study watersheds.

To compare the spatial uniformity of these water user types, the number of catchments in which each type was present and their relative water demand recorded for each catchment. Variability among catchments was analyzed by calculating and comparing the coefficient of variation (CV; standard deviation/mean) for each user type across the catchments in which each type occurred. To compare these non-parametrically distributed data, a permutation test was conducted (n = 1000 samples) of the water user type CV values across catchments. The CV (μ_i) was modeled using an inverse link function with user type (T_i) as the sole predictor variable.

$$1/\mu_i = \alpha + T_i\beta_t \quad \text{Eq 2}$$

where the coefficient of user type (β_t) is added to the intercept (α) to produce an estimate (inverse scale) of effects of user types, with cannabis as the reference level. Estimates in which 95% confidence intervals (constructed from standard errors) of the mean estimate did not overlap zero were considered statistically reliable. Additionally, p-values were calculated using Wald tests.

Interannual uniformity of demand was considered by comparing year-to-year changes in demand among user types within catchments. This analysis was restricted to cannabis and non-cannabis agriculture, as they were expected to vary more than residential demands. Although yearly watershed mapping was conducted from 2021 to 2024, the specific watersheds mapped alternated biannually so that 2021 mapping was compared to 2023 and 2022 mapping was compared to 2024. Differences in these two-year intervals were aggregated into a single dataset and comparisons were made between cannabis and non-cannabis agriculture using a hurdle model, in which a binomial component was used to separate catchments in which no agriculture of either kind occurred in either timestep. The non-zero component of the hurdle model used a beta regression [36] to compare the effect of water user type (T_i) on the absolute difference in demand between timesteps (μ_i), normalized by calculating as the percentage of total demand of each user type. That is, the estimated difference was that of the overall percentage of a water user type's demand in a single catchment. The beta model used a logit link function to fit the following equation:

$$\text{logit}(\mu_i) = \alpha + T_i\beta_t \quad \text{Eq 3}$$

where the coefficient of user type (β_t) is added to the intercept (β) to produce a log-odds estimate of the change between time periods. Estimates in which 95% confidence intervals (constructed from standard errors) of the mean estimate did not overlap zero were considered statistically reliable. Additionally, p-values were calculated using Wald tests.

Identification of streamflow impairments

We first evaluated the potential magnitude of streamflow impairment by different water use types varied at different spatial and temporal scales of measurement. Dillis et al. [20] suggested that analyses at the HUC12 watershed scale may be too coarse to identify potential streamflow impairments from cannabis farming, given that farms tend to represent a small fraction (generally less than 1%) of the average HUC12 watershed area. We therefore compared estimates of water demand with natural supplies (from streamflow) at the smaller, catchment scale, and then gradually increased the scale of analysis by increasing the number of catchments evaluated. Temporal granularity was also analyzed to determine whether monthly timescales were needed in order to detect potential streamflow impairment. Impairments were calculated as the estimated water demand of each user type relative to modeled available streamflow at one of three timesteps for each catchment: annual, seasonal (cannabis growing season April-October), and monthly. For this analysis specifically, the units of observation were thus catchment-years, catchment-seasons, and catchment-months respectively. To simplify our analysis, we evaluated streamflow impairment at three levels of severity (>1%, > 5%, and >10%). Impairments were assessed as water budget deficits within the time period evaluated, assuming water withdrawal from instream flows or near-channel wells, and do not account for the potential time lag between groundwater extraction and streamflow depletion.

Poisson models were fit using the number of upstream catchments (C_i) to predict the number of estimated impairments (μ_i) for each catchment. Sample size (S_i) for each number of upstream catchments was included as a predictor to control for the fact that sample size decreased as the number of upstream catchments increased:

$$\log(\mu_i) = \alpha + C_i\beta_C + S_i\beta_s \quad \text{Eq 4}$$

where β_u and β_s are added to the intercept α to produce a log estimate of the number of estimated impairments. Estimates in which 95% confidence intervals (constructed from standard errors) of the mean estimate did not overlap zero were considered statistically reliable. Additionally, p-values were calculated using Wald tests.

Temporal scale of measurement was considered at three levels: monthly, seasonal, and annual. Monthly and annual levels considered water budgets based on monthly and annual timesteps, respectively, while the seasonal scale aggregated monthly flow and demand of the dry season months of May through October. The Poisson models described above were used to determine whether these relationships were statistically reliable.

Impairments relative to interannual streamflow variation

We next assessed how flow impairments from water demands were expected to vary across a range of interannual streamflow variation, spanning wet to dry years. Static demand estimates based on 2022 data of cannabis farms, residences, and non-cannabis agriculture were compared against a long-term flow dataset to measure changes in impairment frequency in response to increasingly dry conditions. We assessed impacts at both annual and monthly timescales. Total aggregated streamflow (i.e., all monthly values in all study catchments) was calculated on an annual basis from 1992 to 2022 and the annual water year percentile of each year was calculated. Zero-flow catchment-months for each year were excluded. The number of catchment-months with estimated 1%, 5%, and 10% impairments for each water user type was then totaled for each year. Three OLS models (one for each impairment severity) were then used to predict the proportional increase in the number of impairments (μ_i) using the water year percentile (W_i):

$$\mu_i = \alpha + W_i\beta_w \quad \text{Eq 5}$$

where β_w is added to the intercept α to produce a predicted proportional increase in the number of impairments of each severity. Relationships were considered statistically reliable in cases where 95% confidence intervals did not overlap zero. Additionally, p-values were calculated using t-tests.

To test for differences between cannabis and the other two water users, individual comparisons were made by fitting additional OLS models in which number of impairments was replaced by the difference between cannabis proportional increase and residential proportional increase, and the difference between cannabis proportional increase and non-cannabis agriculture proportional increase. Differences were considered statistically reliable where 95% confidence intervals (constructed from the standard errors) of the mean estimate did not overlap zero.

Results

Water user demand and uniformity

The water demand of cannabis and non-cannabis agriculture were more concentrated in the dry season; however, the peak of cannabis water demand extended further into the late summer months when flows are continuing to recede (Table 1). Overall however, average cannabis water demand was substantially lower than residential use or non-cannabis agricultural demand on both an annual and monthly basis across all study catchments. Of all catchment-months sampled (n = 4367), there were only 71 (1.6%) in which cannabis was the top water user. In contrast, residential use (n = 1512; 34.6%) and non-cannabis agriculture (n = 1299; 29.8%) were more common as the top water user. The 71

Table 1. Average monthly and annual water demand of the three water user types across all study catchments. Standard deviations are provided in parentheses.

Month	Cannabis m^3	Residential Use m^3	Non-Cannabis Ag m^3
1	56 (118)	430 (2327)	3472 (21197)
2	58 (120)	388 (2101)	2747 (17972)
3	62 (126)	430 (2327)	4204 (26188)
4	53 (86)	416 (2252)	4447 (28017)
5	57 (61)	430 (2327)	7197 (45428)
6	88 (78)	416 (2252)	8528 (53007)
7	111 (101)	430 (2327)	14854 (87693)
8	122 (112)	430 (2327)	6978 (41548)
9	102 (93)	416 (2252)	6126 (38889)
10	58 (55)	430 (2327)	3769 (20938)
11	32 (63)	416 (2252	4882 (31731)
12	37 (78)	430 (2327)	2950 (18379)
Annual	1665 (7337)	80518 (502652)	901482 (3517444)

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catchment-months in which cannabis was the top water user were distributed among only 5 of the 14 study watersheds, whereas residential use and non-cannabis agriculture occurred as a top water user in every watershed (Fig 2). Seasonality of demand varied between water user types (Fig 3). Residential demand was relatively consistent across months, while cannabis and non-cannabis agriculture was more seasonal, with distinct peaks in August and July, respectively.

Residential use ($n = 275$; 59.9%) and non-cannabis agriculture ($n = 147$; 32.7%) were present in more catchments than was cannabis agriculture ($n = 86$; 18.7%) and had a greater proportion of their total demand across the study area concentrated in fewer catchments. More than half of the total demand of non-cannabis agriculture (56.5%) and more than a third of total demand of residential use (38.5%) was concentrated in five catchments (Fig 4A). In comparison, the five catchments with highest cannabis demands only represented about a quarter of total cannabis water demand (26.4%) across the study area. The results of the permutation test demonstrated that the coefficient of variation for cannabis water demand among catchments was reliably lower (Intercept MLE: 0.88; $SE = 0.02$) than the CVs of either residential use ($MLE = -0.56$; $SE = 0.02$; $p < 0.001$) or non-cannabis agriculture ($MLE = -0.57$; $SE = 0.02$; $p < 0.001$), further suggesting that there was less variation in demand among catchments with cannabis than other water users (Fig 4B).

Cannabis demand was less consistent year to year compared to non-cannabis agriculture. Change in a catchment's water demand (relative to the user type's overall demand) was greater for cannabis (Median biannual change = 0.42%) than non-cannabis agriculture (Median = 0.03%). The difference was supported by the beta model, as cannabis had a reliably higher estimated change per catchment (Intercept $MLE = -4.89$; $SE = 0.08$; Estimate = 0.75%) than non-cannabis agriculture ($MLE = -9.47$; $SE = 0.09$; $p < 0.001$; Estimate = 0.29%).

Identification of streamflow impairments

We identified potential for streamflow impairment of all three severity levels (1%, 5%, 10%) from residential use (Fig 5) and non-cannabis agriculture (Fig 6) across all timesteps sampled (annual, monthly, seasonal). By contrast, there were no estimated impairments of any severity for cannabis at an annual timestep and only 1% severity impairments at a seasonal timestep (Fig 7). However, impairments of 5% and 10% from cannabis were identified at the monthly timestep.

For all water user types, increasing spatial scales reduced the number of estimated impairments across all severities, as confirmed by the Poisson models (S2 Table). That is, the number of upstream catchments (β_c) had a reliably negative

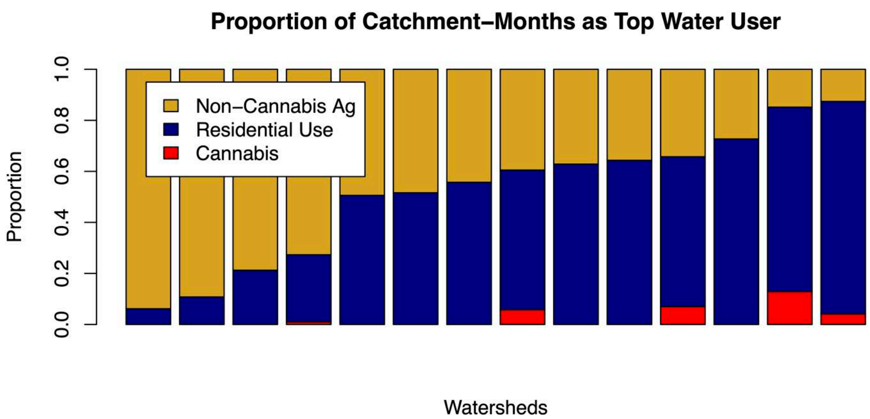

Fig 2. Top water user tenure. The proportion of catchment-months in which each water user type represented the top water demand is depicted in each of the 14 watersheds. Non-cannabis agriculture is depicted in goldenrod, residential use is depicted in blue, and cannabis cultivation is depicted in red. Watersheds are sorted by proportion of catchment-months in which non-cannabis agriculture was estimated to be the top water user, as it was the most common of the three user types to hold this position.

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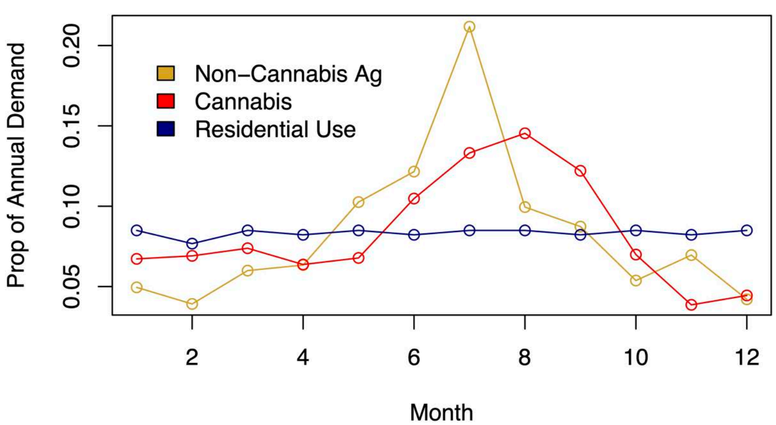

Fig 3. Seasonal water user demand. Monthly proportions of total annual demand are depicted for each water user type. Non-cannabis agriculture is depicted in goldenrod, residential use is depicted in blue, and cannabis cultivation is depicted in red.

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effect on the number of estimated catchment-month impairments for all nine relationships for all user types. For instance, at a monthly time step there were reliably negative relationships between the number of upstream catchments and the estimated number of 1% (MLE = -0.13, SE = 0.01; $p < 0.001$), 5% (MLE = -0.15, SE = 0.01; $p < 0.001$), and 10% streamflow impairments (MLE = -0.15, SE = 0.01; $p < 0.001$) from cannabis. Qualitatively identical results were found for the detection of impairments from residential use and non-cannabis agriculture. For cannabis agriculture, 90% of all 1% streamflow impairments were estimated to occur in focal catchments with fewer than 20 upstream catchments and no impairments were estimated to occur for focal catchments with more than 33 upstream catchments. The mean number of catchments in a watershed was 32.85 (SD = 23.67).

The number of catchment-months in which cannabis alone (i.e., cannabis versus total estimated unimpaired flow) was estimated to have at least a 1% impairment (n = 101, 2.3% of catchment-months) was far less than residential use alone (n = 1154; 26.4% of catchment-months) or non-cannabis agriculture alone (n = 1563; 35.8%; Table 2). The frequency of cannabis impairments of at least 1% nearly tripled (n = 282; 6.5%) when considering remaining flow (i.e., simultaneously

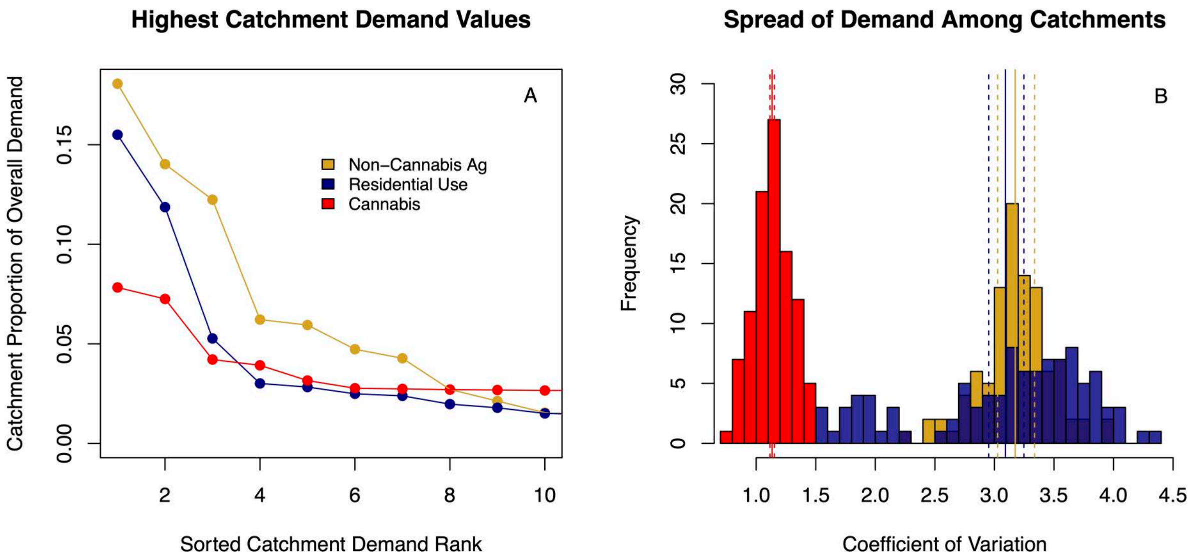

Fig 4. Variation of water user demand across catchments. The highest-demand catchments are depicted for each water user type, based on the highest proportional demand of total user type demand **(A)**. Non-cannabis agriculture is depicted in goldenrod, residential use is depicted in blue, and cannabis cultivation is depicted in red. Results of the permutation test are depicted as histograms, with solid lines representing maximum likelihood estimates and dashed lines depicting the 95% confidence interval of the estimate **(B)**.

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considering demand of the other two water user types) instead of total unimpaired flow. The other water user types only saw marginal increases in 1% impairment frequency when considering remaining flow instead of unimpaired flow. Estimates of more severe cannabis impairments were almost non-existent in the absence of other water users.

Impairments relative to interannual streamflow variation

Streamflow impairments were more common in drier water years for all water users; however, the increase in response to aridity was more pronounced for cannabis than the other water user types. Streamflow impairments decreased for all water user types (as measured by the proportional difference relative to the wettest year) as the water year percentile increased (Fig 8; Table 3). Cannabis demonstrated a reliably negative relationship (MLE = -0.01; SE = < 0.001) between water year percentile and the amount of 1% streamflow catchment-month impairments, as well as reliably negative effects for 5% (MLE = -0.01; SE = < 0.001; $p < 0.001$) and 10% impairments (MLE = -0.01; SE = < 0.001; $p < 0.001$). Residential use and non-cannabis agriculture exhibited the same trends.

The rate at which impairments decreased in response to higher flows was significantly greater for cannabis relative to residential use or non-cannabis agriculture (Table 4). The difference between the decrease in 1% impairments between cannabis and residential use reliably decreased with water year percentile (MLE = < -0.001; SE = < -0.0001; $p < 0.001$). The same was true for differences corresponding to 5% (MLE = < -0.001; SE = < -0.0001; $p < 0.001$) and 10% (MLE = < -0.001; SE = < -0.0001; $p < 0.001$) impairment severities. Similar differences were estimated between cannabis and non-cannabis agriculture at 1% (MLE = < -0.001; SE = < -0.0001; $p < 0.001$), 5% (MLE = < -0.001; SE = < -0.0001; $p < 0.001$), and 10% (MLE = < -0.001; SE = < -0.0001; $p < 0.001$) impairment severities.

Discussion

This study estimated the relative water demands of cannabis farming, residential use, and non-cannabis agriculture and their potential to impair streamflow at various spatial and temporal scales. Relative to the two other water user

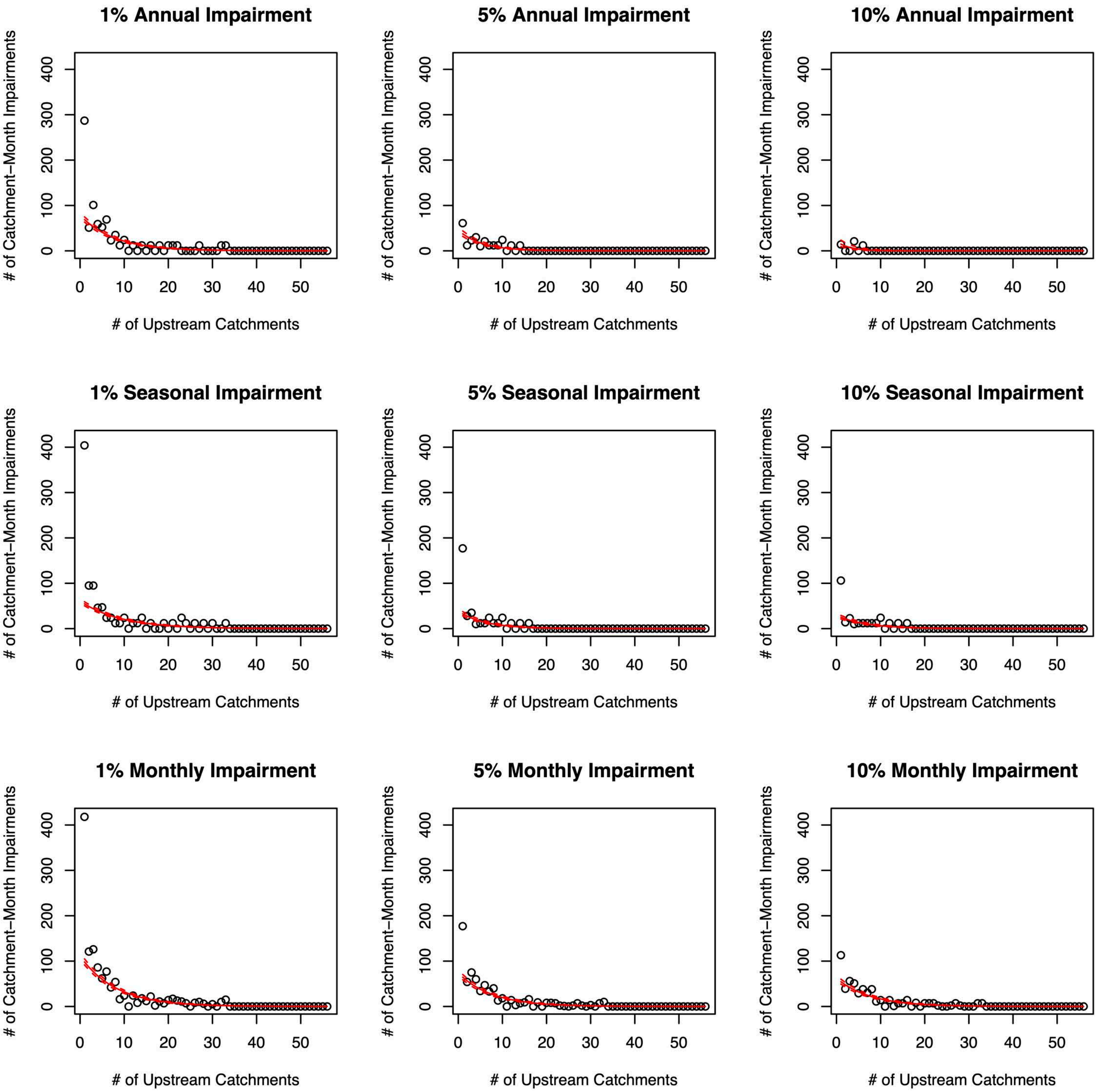

Fig 5. Detection of residential use impairments. Relationships between the number of upstream catchments for a focal catchment is plotted against the number of catchment-months in which impairments were observed for each number of upstreams catchments. The nine plots depict the three-by-three permutation of temporal granularity (annual, seasonal, monthly timestep) and impairment severity (1%, 5%, and 10%). Red lines are indicative of statistically reliable relationships, with solid lines depicting maximum likelihood mean estimates and dashed lines indicating 95% confidence intervals of the means.

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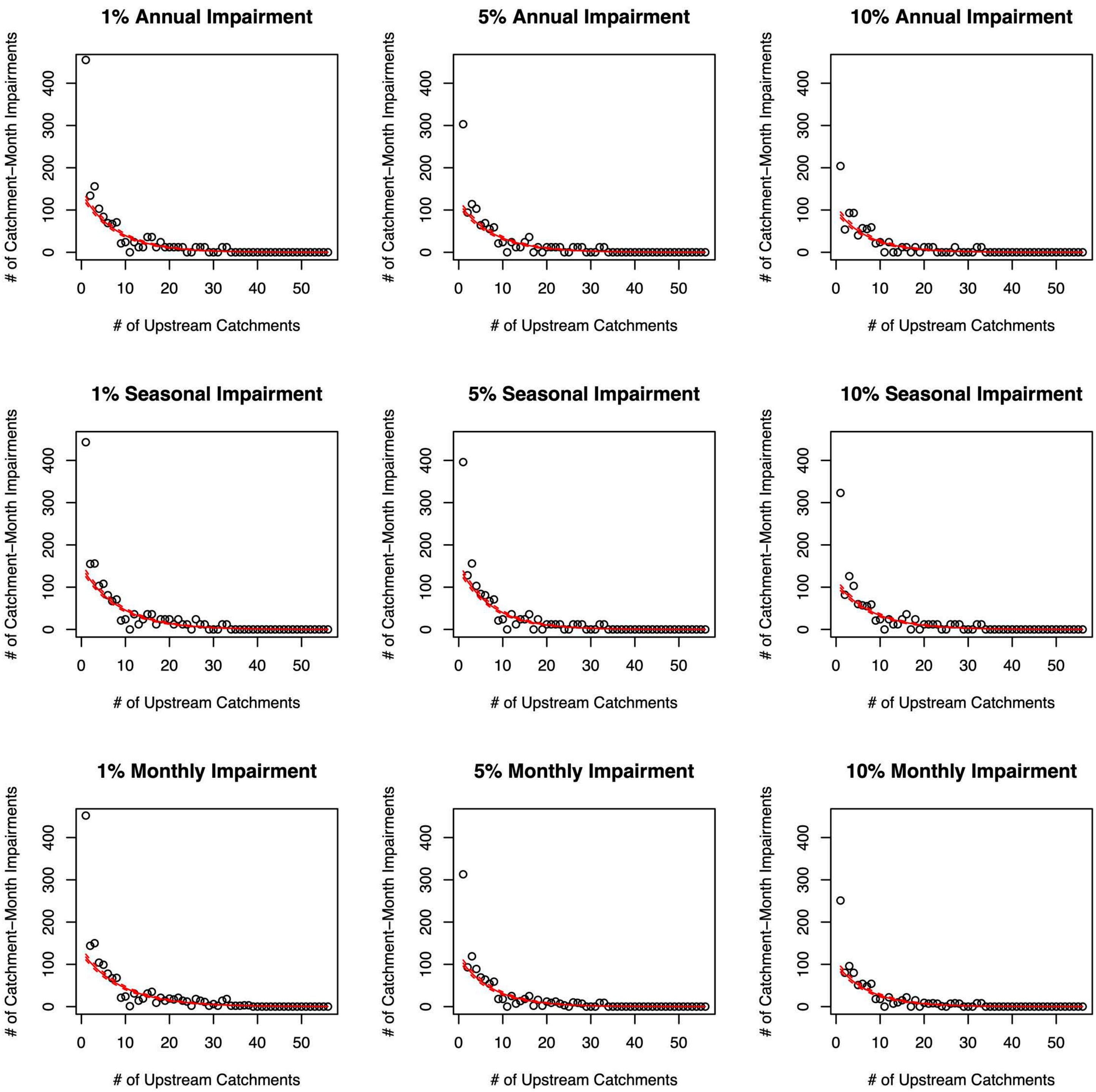

Fig 6. Detection of non-cannabis agriculture impairments. Relationships between the number of upstream catchments for a focal catchment is plotted against the number of catchment-months in which impairments were observed for each number of upstreams catchments. The nine plots depict the three-by-three permutation of temporal granularity (annual, seasonal, monthly timestep) and impairment severity (1%, 5%, and 10%). Red lines are indicative of statistically reliable relationships, with solid lines depicting maximum likelihood mean estimates and dashed lines indicating 95% confidence intervals of the means.

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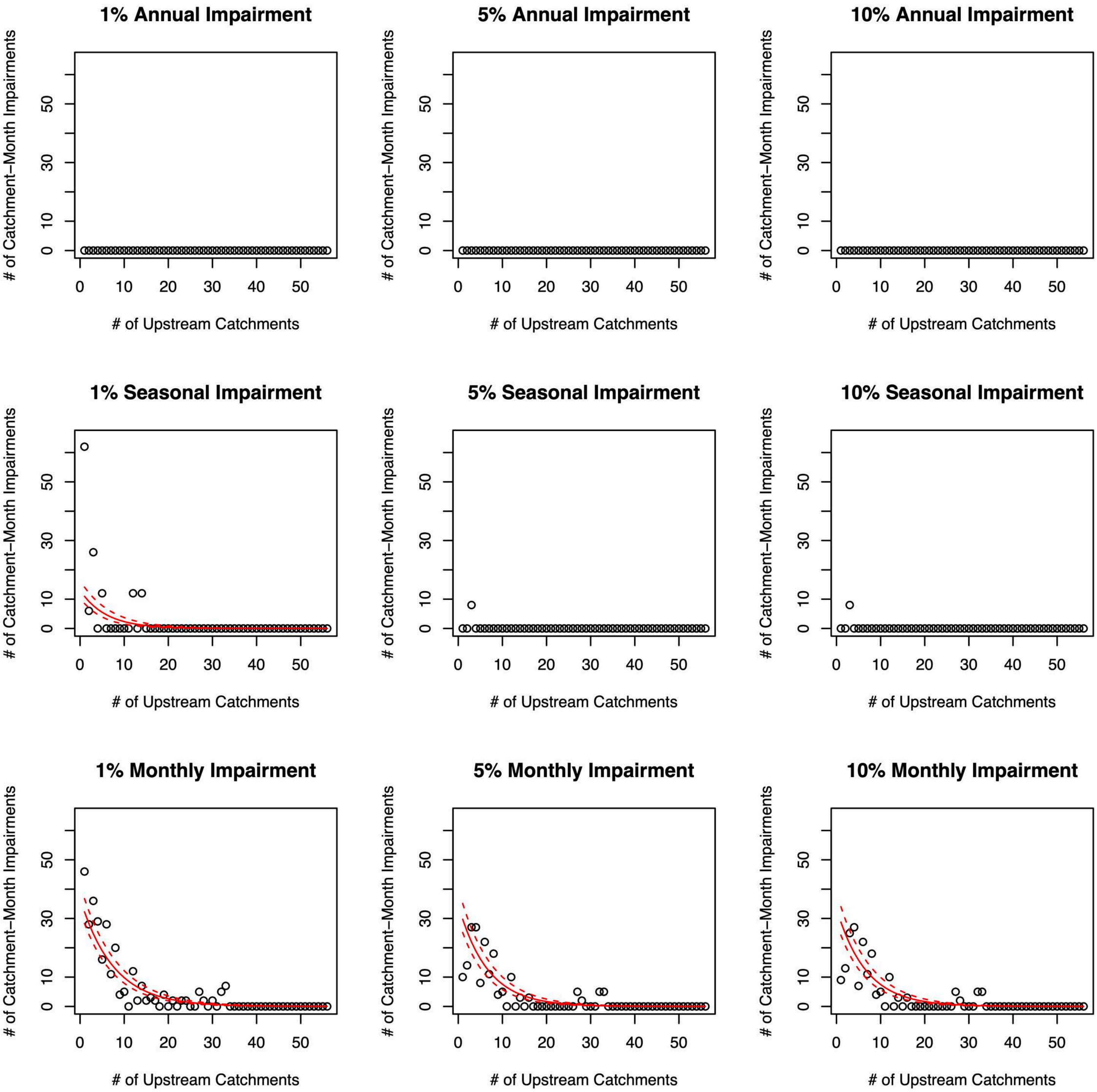

Fig 7. Detection of cannabis impairments. Relationships between the number of upstream catchments for a focal catchment is plotted against the number of catchment-months in which impairments were observed for each number of upstreams catchments. The nine plots depict the three-by-three permutation of temporal granularity (annual, seasonal, monthly timestep) and impairment severity (1%, 5%, and 10%). Red lines are indicative of statistically reliable relationships, with solid lines depicting maximum likelihood mean estimates and dashed lines indicating 95% confidence intervals of the means.

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Table 2. Estimated impairments across all severities comparing unimpaired flow with remaining flow (demand of other water users subtracted). Percent of all catchment months for observations are provided in parentheses.

Water user type	1% Impairment		5% Impairment		10% Impairment	
	Unimpaired flow	Remaining Flow	Unimpaired flow	Remaining Flow	Unimpaired flow	Remaining Flow
Cannabis	101 (2.3%)	282 (6.5%)	3 (0.1%)	179 (4.1%)	0 (0.0%)	174 (4.0%)
Residential Use	1154 (26.4%)	1246 (28.5%)	455 (10.4%)	666 (15.3%)	267 (6.2%)	518 (11.9%)
Non-Cannabis Ag	1563 (35.8%)	1564 (35.8%)	1087 (24.5%)	1091 (25.0%)	906 (20.8%)	911 (20.9%)

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types, cannabis farming represented a small fraction of total water demand within the study watersheds. Water use for residential and non-cannabis agricultural purposes accounted for most of the demand. As a result, these uses also had the greatest potential to cause streamflow impairment. This is in agreement with prior research demonstrating greater water demands (and streamflow depletion potential) from residential use than from cannabis agriculture from another northern California watershed [11]. Although we found that cannabis rarely caused streamflow impairment in the absence of other uses in a catchment, there was evidence that cannabis water demands contributed to elevated levels of impairment when other water users were present. These findings, in part, reflected that cannabis was less common across all catchments relative to the other water user types. However, the disproportionate impacts of residential use and non-cannabis agricultural demand on streamflow impairment also relates to the fact that they were often concentrated among the catchments in which they occurred. While prior research demonstrated that cannabis farms tend to be clustered on the landscape [37], the current study suggests that concentration of demand may be even greater for residential and non-cannabis agriculture in northern California watersheds. In terms of temporal uniformity however, cannabis water use was more variable year-to-year comparisons relative to other water user types.

Spatial clustering of all water user types helps to explain the fact that streamflow impairments are most likely to be identified at smaller (e.g., catchment) than larger (e.g., HUC12 watershed) spatial scales. We found that increasing the scale of analysis beyond a single catchment resulted in increasingly fewer estimates of streamflow impairments. Varying the analysis from annual to seasonal to monthly timesteps also demonstrated the sensitivity of our results to temporal scale. In particular, we found that cannabis water demand is notably more temporally clustered within a calendar year, whereas residential use and non-cannabis agriculture are more evenly spread throughout the year. Thus, we failed to detect streamflow impairments from cannabis when analyzing impacts at the annual timescale, but did find significant impacts at finer timesteps. We therefore suggest that future assessments of streamflow impairment consider be conducted at least monthly timesteps, if not finer (e.g., daily).

Results suggested that stream impairments from cannabis water demand had greater interannual variability than residential use or non-cannabis agriculture. In particular, the capacity for cannabis to manifest additional streamflow impairments in dry years was greater than other water user types. This is likely due to the significantly greater landscape-level demand from residential use and non-cannabis agriculture having already led to impairments in the most susceptible catchments even in the wettest water years. By contrast, cannabis has more opportunities to push catchments over 1% (or 5%, or 10%) impairment in response to drying conditions.

Cannabis in context

Recent work has emphasized that cannabis can have localized impacts on small headwater streams, given that it is particularly clustered on the landscape [37,18,17,20]). Yet, residential users and non-cannabis agriculture appear to be equally, if not more, concentrated in fewer catchments. To assess where cannabis may have streamflow impacts therefore first requires knowing where streams are likely already impacted. The current study demonstrates that cannabis is far more likely to exacerbate existing impairments than it is to manifest meaningful streamflow impairments on its own. Despite the fact the water demand of cannabis was only a fraction of that of residential use and non-cannabis agricultural

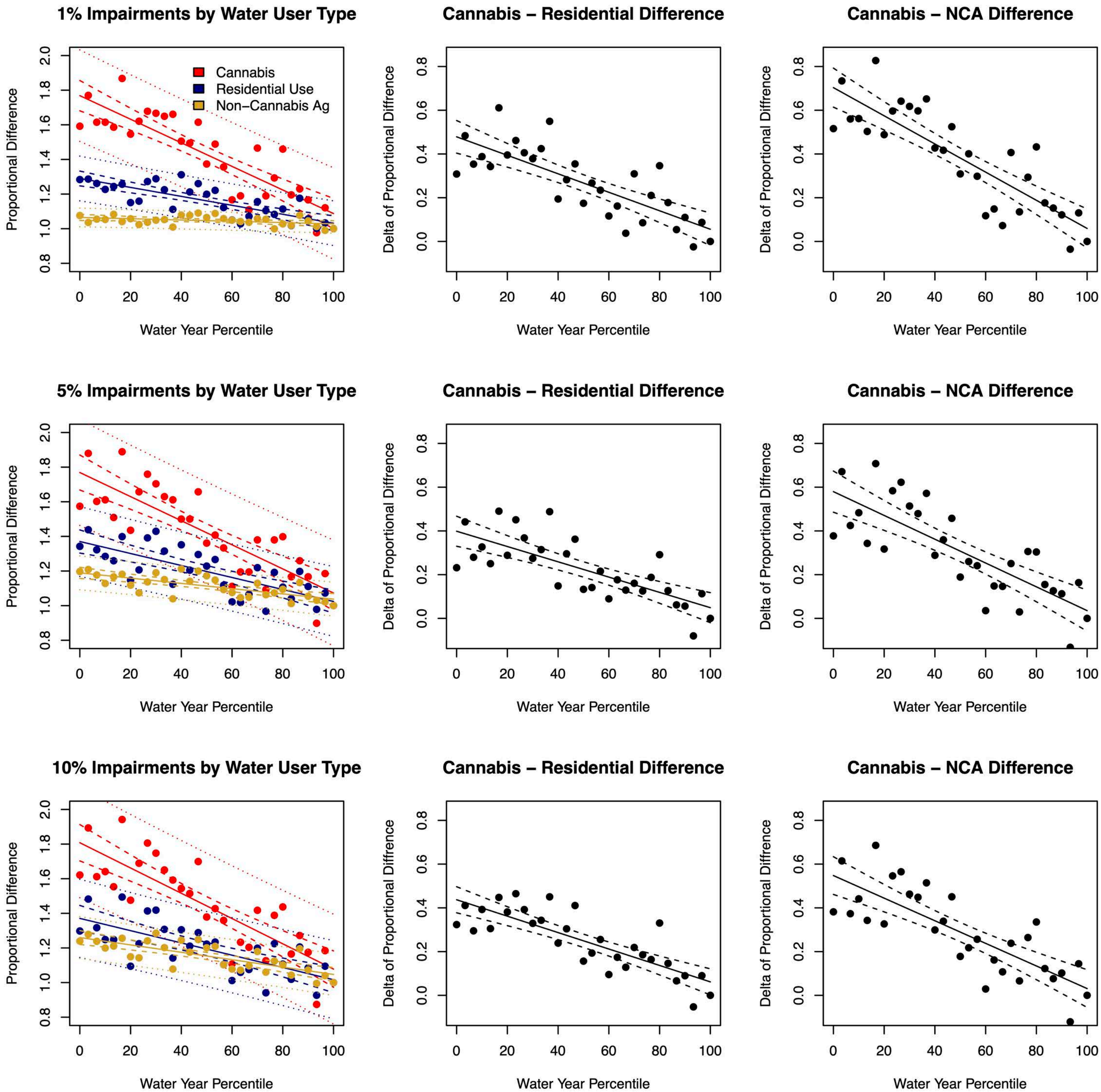

Fig 8. Response to streamflow fluctuation. The cumulative proportional increase in estimated impairment occurrence, relative to decreasing yearly flow rank (i.e., increasing aridity) is plotted for each water user type in the left-hand column. The range of sampled impairment severities are arranged within ascending order (1%, 5%, 10%, respectively). Non-cannabis agriculture is depicted in goldenrod, residential use is depicted in blue, and cannabis cultivation is depicted in red. Solid lines depict maximum likelihood mean estimates, dashed lines indicate 95% confidence intervals, and dotted lines indicate 95% prediction intervals. Accompanying each figure from the lefthand column are individual comparisons between cannabis and the other two water user types. Solid lines depict maximum likelihood mean estimates, while dashed lines indicate 95% confidence intervals of the mean.

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Table 3. Model estimates for the effect of water year percentile on the proportional difference (from 100th percentile) in the occurrence of streamflow impairments. All estimates were statistically reliable.

Cannabis		
Impairment Severity	**Intercept (SE)**	**Water Year Percentile (SE; p)**
1%	1.77 (0.04)	-0.01 (<0.001; p < 0.001)
5%	1.77 (0.05)	-0.01 (<0.001; p < 0.001)
10%	1.81 (0.05)	-0.01 (<0.001; p < 0.001)
Residential Use		
1%	1.29 (0.02)	<-0.01 (<0.001; p < 0.001)
5%	1.37 (0.03)	<-0.01 (<0.001; p < 0.001)
10%	1.37 (0.04)	<-0.01 (<0.001; p < 0.001)
Non-Cannabis Agriculture		
1%	1.06 (0.01)	<-0.01 (<0.001; p = 0.019)
5%	1.19 (0.02)	<-0.01 (<0.001; p < 0.001)
10%	1.26 (0.02)	<-0.01 (<0.001; p < 0.001)

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Table 4. Model estimates for the delta between cannabis and other water use types in the decrease of impairments relative to increasing water year percentile.

Cannabis vs Residential Use		
Impairment Severity	**Intercept (SE)**	**Water Year Percentile (SE; p)**
1%	0.48 (0.04)	<-0.001 (<0.0001; p < 0.001)
5%	0.40 (0.03)	<-0.001 (<0.0001; p < 0.001)
10%	0.44 (0.03)	<-0.001 (<0.0001; p < 0.001)
Cannabis vs Non-Cannabis Agriculture		
Impairment Severity	**Intercept (SE)**	**Water Year Percentile (SE; p)**
1%	0.70 (0.04)	<-0.001 (<0.0001; p < 0.001)
5%	0.58 (0.05)	<-0.001 (<0.0001; p < 0.001)
10%	0.55 (0.04)	<-0.001 (<0.0001; p < 0.001)

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demand, we found it may still be a meaningful contributor to streamflow depletion. Thus, efforts to mitigate these impacts appear warranted.

Previous work has shown that small-scale storage, relying on water diverted in the wet season, may be particularly effective for off-setting the impacts of cannabis diversions in the dry season, when supplies are most limited [20]. Preliminary assessments have shown that even a small increase in storage could have significant environmental benefits for aquatic species in some of California's most sensitive watersheds [20]. Because cannabis farms that licensed by the state are already prohibited from diverting water in the dry season, expanding off-stream storage to reduce streamflow impacts would require outreach and engagement with unlicensed cannabis farmers. While the willingness of these farmers to install storage is unknown, a recent survey by [38] indicated that many unlicensed cannabis farmers care about the environmental effects of their practices and suggests they may be receptive to increasing their local storage capacity.

Sensitivity to drought and importance of monitoring

The current study demonstrated that manifestation of new streamflow impairments in response to drought is likely to occur more quickly as a result of cannabis demand than the demand of other water users. This is likely due to impairment saturation by the other water user types, in that their impairments are already much more abundant and have begun to exhaust the most vulnerable catchments. This is supported by increasing frequency of impairment estimates for residential and non-cannabis agricultural demand at 5% and 10% severities (Table 1). Even at these higher impairment severities however, cannabis still has more potential to expand its impact as aridity increases. Additionally, the irregular spacing of cannabis and catchment-specific variation in streamflow manifestations of aridity complicate prediction of where these impairments may occur. That is, regional-scale drought will not necessarily affect all catchments uniformly.

Because cannabis farms, and unlicensed farms in particular, are more likely to move around on the landscape than other water users year to year [39], the task of predicting where cannabis-related impairments may occur is made even more difficult. Accurate prediction would require having a sense of 1) which catchments may see expansion or contraction of cannabis cultivation, 2) the competing demands of additional water user types, and 3) the likely range of unimpaired flow values of those catchments. The first two of these factors in particular are highly variable in space and time. Therefore, frequent monitoring of catchments across broad regional scales would be highly beneficial for two reasons: first, presently, mapping cannabis by itself is not necessarily indicative of where streamflow impairments are most likely to occur and second, generally, a rich dataset of year-to-year shifts in cannabis cultivation would provide a much-needed understanding of how precipitously and ephemerally this tipping-point source of demand operates on a landscape-scale.

Conclusions

This study situates cannabis farming within an established landscape dominated by non-cannabis agriculture and residential wate uses. We found that cannabis water demand is notably lower than these other user types, but that cannabis water use can still increase the risk of stream flow impairment, particularly in drier years when its impact is more pronounced. As water availability becomes further altered by climate change [5], the need for effective coordination among diverse water users will become increasingly important. Bringing cannabis farmers into productive conversations with residential and agricultural water users will require overcoming social stigmas against cannabis and acknowledging that even if cannabis were not to be farmed in the region, the risks to ecologically sensitive resources from other water users would persist. Accurate and frequent monitoring, alongside a more nuanced understanding of the spatial and temporal dynamics of water demand, will also be key to mitigating potential environmental impacts and ensuring sustainable water use across all sectors. Broader exploration of the relative contribution of cannabis to water demands in other rural catchments is also needed, particularly in the western US, where competition for water between cannabis and other stakeholders is common [40]. The findings of this study underscore the importance of considering cannabis farming within holistic water management strategies that account the complexities of competing water demands in sensitive watersheds.

Supporting information

S1 Text. Description of Water Extraction Modeling.
(DOCX)

S1 Table. Watersheds included in study.
(DOCX)

S2 Table. Model estimates for the effect of spatial scale for identification of streamflow impairments by water user type, temporal granularity, and impairment severity. Values presented in italics were not statistically reliable.
(DOCX)

S3 Table. Annual flow estimates aggregated over all study catchments.
(DOCX)

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Supervision: Christopher Dillis, Ethan Baruch, Theodore Grantham.

Validation: Christopher Dillis.

Visualization: Christopher Dillis.

Writing – original draft: Christopher Dillis.

Writing – review & editing: Christopher Dillis, Ethan Baruch, Theodore Grantham.

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