

1           **Water storage and irrigation practices associated with**  
2           **cannabis production drive seasonal patterns of water**  
3           **extraction and use in Northern California watersheds**

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5           **Short title: Cannabis irrigation practices drive seasonal patterns of**  
6           **water extraction and use**

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8           **Christopher Dillis<sup>1\*</sup>, Connor McIntee<sup>1</sup>, Ted Grantham<sup>2</sup>, Van Butsic<sup>2</sup>, Lance Le<sup>1</sup>,**  
9           **Kason Grady<sup>1</sup>**

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11           <sup>1</sup>California State Water Resources Control Board, North Coast Region, Santa Rosa, California, United  
12           States of America

13           <sup>2</sup>University of California Berkeley, Berkeley, California, United States of America

14  
15           **\*Corresponding author**

16           **Email: [christopher.dillis@waterboards.ca.gov](mailto:christopher.dillis@waterboards.ca.gov)**

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## 25 **Abstract**

26           Concerns have been raised over the impacts of cannabis farms on the environment and  
27 water resources in particular, yet data on cultivation practices and water use patterns and have  
28 been limited. Estimates of water use for cannabis cultivation have previously relied on  
29 extrapolated values of plant water demand, which are unable to account for differences in  
30 cultivation practices, variation across the growing season, or the role of water storage in  
31 altering seasonal extraction patterns. The current study uses data reported by enrollees in  
32 California's North Coast Regional Water Quality Control Board (Regional Water Board) Cannabis  
33 Program to model how variation in cultivation practices and the use of stored water affect the  
34 timing and amount of water extracted from the environment. We found that the supplemental  
35 use of stored water resulted in a seasonal pattern of water extraction (i.e. water withdrawals  
36 from the environment) that was distinct from water demand (i.e. water applied to plants).  
37 Although water input to storage in the off-season months (November through March) reduced  
38 water extraction in the growing season (April through October), farms generally did not have  
39 sufficient storage to completely forbear from surface water extraction during the growing  
40 season. Beginning in 2019, forbearance will be required during this period for those in the  
41 regulated cannabis industry. The two most important predictors of storage sufficiency (type of  
42 storage infrastructure and seasonality of water source) also had reliable effects on seasonal  
43 extraction patterns, further emphasizing the link between water storage and extraction  
44 profiles. These findings suggest that resource managers and policy makers should consider the  
45 ways in which cultivation practices drive water extraction patterns and how these practices  
46 may be influenced by participation in the regulated cannabis industry.

## 47 **Introduction**

48 Northern California has long been the center of cannabis production in the United  
49 States [1-3]. Cannabis cultivation sites are distributed throughout the region and are generally  
50 located in remote, upper watersheds [4]. When the state voted to permit recreational cannabis  
51 use in 2016, a key argument for legalization was allowing the state to better address  
52 environmental harms caused by cannabis production [5]. In California, illegal cannabis farms  
53 have been shown to fragment forested landscapes [6], introduce pesticides, fertilizers, and  
54 rodenticides into the environment [5, 7-9], and are often located in sensitive habitats, including  
55 along streams that support endangered salmon species [4].

56 There has been particular concern over the impacts of cannabis cultivation on water  
57 resources in areas with seasonally dry conditions [5]. Because many cannabis farms in Northern  
58 California are located in rural landscapes with no access to municipal water supplies, cultivators  
59 generally obtain water directly from the environment, relying on local springs, streams, and  
60 groundwater wells [10]. Stream flow has been identified as an important limiting factor to  
61 salmon, and other sensitive aquatic species in the region, particularly given the seasonal  
62 drought of California's Mediterranean Climate [11-14]. Because cannabis water demands  
63 coincide with the summer dry season, agricultural water diversions in the North Coast Region  
64 have the potential to reduce stream flows [15-16], increase stream temperatures [17], or even  
65 dewater streams during critical life stages of aquatic species [18-19]. Although these streams  
66 are highly sensitive to variability in flow rates [20-21], there is a dearth of information  
67 surrounding cannabis water use practices, making it difficult to quantify potential  
68 environmental impacts.

69           An accurate baseline assessment of water use by cannabis cultivation is particularly  
70 important when considering the spatial and temporal distribution of cannabis water demands.  
71 Although cannabis cultivation has a relatively small geographic footprint, there is a high degree  
72 of spatial clustering among cultivation sites [6] at both local [22] and regional scales [4].  
73 Currently, there are very few data on the cumulative impacts of many, dispersed water users  
74 [23-24] or flow estimates for small, unnamed streams on which they occur [25]. Impacts from  
75 densely clustered cannabis farms may be exacerbated by temporal clustering of water demand,  
76 with cannabis plants requiring frequent watering in late summer drought months and thus  
77 causing concern for instream flows [5, 18]. A key assumption behind this concern has been that  
78 water demand of cannabis plants directly results in water extraction during this period;  
79 however, there has been no systematic analysis of when water is drawn from the watershed or  
80 the factors that contribute to extraction patterns.

81           To date, estimates of water use by cannabis cultivation have relied on scaling a static  
82 approximation of outdoor cannabis plant demands during the growing season for outdoor  
83 cultivation, June-October [26-27, 18]. Unfortunately, this approach cannot account for changing  
84 water demands over the course of the growing season or under different cultivation conditions.  
85 For instance, a substantial proportion of farms use mixed-light operations (whether in  
86 greenhouses or “hoophouses”) that alter light cycles to produce multiple harvests of smaller  
87 cannabis plants, potentially extending the growing season, yet resulting in much lower water  
88 demand per-plant relative to outdoor cultivation. Another significant shortcoming of plant-  
89 based estimates is that they do not account for the practice of using stored water. Although  
90 cannabis farms are known to often utilize water storage, to date, detailed data on capacities

91 have been sparse, given limited site access and the difficulty of obtaining these data from aerial  
92 imagery [28-29]. An improved estimation of the water demand of cannabis cultivation would  
93 account for water that is extracted and stored outside of the growing season, as well as how  
94 factors such as water sources shape both when and how much water is extracted and stored.  
95 These seasonal patterns of water extraction hold tremendous importance, given the potential  
96 for overlap between cannabis water demands and low summer water availability.

97 This study analyzed self-reported data from cannabis farmers that were enrolled for  
98 regulatory coverage under California's North Coast Regional Water Quality Control Board  
99 Cannabis Waste Discharge Regulatory Program [10]. The reports were filtered to reduce bias  
100 and then analyzed through the development of multiple models that related water use  
101 practices to farm characteristics, including cultivation area, the type of operation (i.e. outdoor  
102 vs. mixed-light), water storage capacity, type of storage, and water source, to address the  
103 following questions:

- 104 1) Are water extraction rates distinct from those of water use (i.e. based on plant  
105 demand) over the growing season and are these patterns influenced by operation  
106 types?
- 107 2) Do farms typically have sufficient capacity to maintain a positive water storage  
108 balance for the entirety of the dry season (April through October) and what are the  
109 most important predictors of sufficiency?
- 110 3) How do the factors that influence water storage in turn affect the timing and amount  
111 of water extraction?

112

## 113 **Methods**

### 114 **Data**

115           The data used in this study were collected from cannabis farms enrolled for regulatory  
116 coverage under the North Coast Regional Water Quality Control Board Cannabis Waste  
117 Discharge Regulatory Program (NCRWQCB Cannabis Program). This program was established in  
118 August 2015, with the majority of enrollees entering the program in late 2016 and early 2017.  
119 The data discussed herein were collected from annual reports submitted in 2018 (n=1,702) and  
120 were required to reflect site conditions during the 2017 cultivation year. These data, therefore,  
121 largely represent the first full season of cultivation regulated by the NCRWQCB for the majority  
122 of enrollees in the Cannabis Program. Parcels with cannabis cultivation (including multiple  
123 contiguous parcels under a single ownership) constituted a *farm*, and reporting was done at this  
124 scale. Although the spatial extent of the NCRWQCB Cannabis Program included all of  
125 California's North Coast Region, due to constraints placed on cultivation by local and county  
126 ordinances, reports from enrolled farms were limited to Humboldt, Trinity, Mendocino, and  
127 Sonoma Counties (Fig 1).

128

129 **Fig 1. Study Area Map.** The North Coast Region of California contains additional counties  
130 besides Humboldt, Trinity, Mendocino, and Sonoma; however, enrollments in the NCRWQCB  
131 Cannabis Program, and thus data included in the current study, were limited to these counties.

132

133           Given that data were self-reported, we screened reports for quality and excluded those  
134 that were not prepared by professional consultants. Additional criteria for excluding reports  
135 included: reported water applied from storage without any corresponding input to storage,  
136 substantial water input reported from “rain” during summer drought months, and failure to list  
137 a proper water source. Farms were not required to use water meters, and those without  
138 meters often made estimates based the frequency of filling and emptying of small temporary  
139 storage tanks (250 – 2500 gallons; 946 – 9,460 L) used for gravity feed systems and/or nutrient  
140 mixing. We attempted to identify and exclude farms with erroneous reporting by removing  
141 extreme water extraction outliers (more than 1.5 x Interquartile Range) and those with  
142 imprecise monthly estimates (e.g., 20,000, 25,000, and 30,000 L). Farms with total cultivation  
143 area over one acre (43,560 ft<sup>2</sup>; 4,046 m<sup>2</sup>) were also excluded, to minimize additional error  
144 inflation resulting from water use estimates at large (and infrequently occurring) scales. Farms  
145 that reported no water use for the entire season or no cultivation area were excluded from the  
146 analysis (reports were required from all enrollees regardless of whether cultivation occurred  
147 during 2017 season). Farms that reported a cultivation area of exactly 10,000 ft<sup>2</sup> or 9,999 ft<sup>2</sup>  
148 (929 or 928 m<sup>2</sup>, respectively) were determined to reflect regulatory thresholds for local  
149 cultivation ordinances rather than true cultivation area size. Aerial imagery from the National  
150 Agriculture Imagery Program (2016 NAIP) was reviewed to provide an improved estimate of the  
151 size of cultivation area for these farms. The final dataset included 608 reports.

152           The data reported for each farm included the size of cultivation area (*cultivation area*:  
153 ft<sup>2</sup>), volume of water applied to plants (*water applied*: gallons), volume of water input to  
154 storage (*water input*: gallons), type and volume of water storage infrastructure (*storage type*:

155 pond, other (i.e. tank or water bladder); *storage capacity*: gallons). Although the data were  
156 reported on the standard measurement system, for the purposes of data analysis and  
157 reporting, these measures were converted to SI units. Water data were reported on a monthly  
158 basis (*month*), specifying up to three sources of applied water (*application source*: delivery,  
159 municipal, pond, rain, springs, surface, tanks, water bladder, or well) and water input to storage  
160 (*input source*: delivery, municipal, rain, springs, surface, or well). An additional parameter  
161 (*source type*: seasonal, perennial) was created specifying whether farms relied exclusively on  
162 seasonal water sources (e.g. rain, springs, surface) or had at least one perennial source (i.e.  
163 incorporating well, delivery, or municipal water). Although farms may have perennial access to  
164 springs and surface water, these water sources are subject to pending regulatory restrictions,  
165 which will prohibit water diversions from April through October (i.e. “forbearance period”).  
166 However, for the 2017 cultivation year, farms that reported use of these sources during this  
167 period were not subject to regulatory violations or penalties, nor did the use of these sources  
168 make them ineligible for enrollment [10].

169 Cultivation area was reported as the footprint of mixed-light infrastructure and outdoor  
170 gardens, incorporating both canopy area and the space between plants. Aerial imagery (2016  
171 NAIP) was used to distinguish which farms had outdoor gardens, mixed-light infrastructure, or  
172 both, and an additional model parameter was created (*operation type*: outdoor, mixed-light,  
173 combination). The purpose of identifying *operation type* was to control for variation in plant  
174 spacing (plants under mixed-light cultivation are smaller and more tightly spaced), ambient  
175 temperature and humidity (mixed-light cultivation occurs underneath a canopy covering), and



176 length of cultivation season (mixed-light operations tend to produce multiple harvests,  
177 although on shorter intervals).

178

## 179 **Seasonality of Water Use and Water Extraction**

180 Water use and water extraction totals for each month were created using combinations  
181 of reported water applied to plants and water input to storage and these served as response  
182 variables for model fitting. *Water use* was defined as water applied either from storage or  
183 directly applied from the original source, thus reflecting plant demand. *Water extraction* was  
184 defined as water either input to storage or directly applied from the original source, thus  
185 reflecting withdrawal from the watershed.

186 As an additional check of these self-reported data, we sought to compare the reported  
187 rates of *water use* against the commonly adopted figure of 22 L/plant/day [26-27, 18] for  
188 outdoor plants during the growing season. This was done using aerial imagery data from an  
189 existing study in which the number of mature cannabis plants were counted within a cultivation  
190 area of a known size to determine the size of cultivation area representative of a single,  
191 outdoor, cannabis plant. This number was determined to be 15 m<sup>2</sup> of cultivation area,  
192 accounting for both the canopy of the plant and spacing between individuals. The rate of 22 L/  
193 15 m<sup>2</sup>/day was converted to 22 L/ 15 m<sup>2</sup>/month and depicted where appropriate (Figs 2 and 4)  
194 to provide context.

195 Simultaneously estimating the factors influencing *water use* (and *water extraction*)  
196 required model fitting to account for zero-inflated, over-dispersed data. Two hurdle models  
197 were fit to produce monthly estimates of the response variables *water use* and *water*

198 *extraction*, respectively, using R statistical programming software [30]. Traditionally used for  
199 count data, hurdle models are two-component (binary and continuous) models applied to data  
200 with excessive zero values, with the assumption that zero values arise from a process separate  
201 from the non-zero values [31-32]. In this context we assume that *water use* is zero only when  
202 cannabis cultivation is not occurring and *water extraction* is zero only when cannabis cultivation  
203 is not occurring, or when water is being applied only from storage. Non-zero observations are  
204 qualitatively distinct from observations of zero, given that if water use or extraction occurs (i.e.  
205 non-zero), there is a large minimum amount (~3,000 L) instead of observations declining  
206 linearly to zero. The binary component model of the hurdle model (predicting zero vs non-zero)  
207 produces a likelihood of *water use* (and *water extraction*), while the continuous component  
208 model produces values for strictly non-zero estimates. The product of the binary and  
209 continuous components' estimates are the full hurdle model predictions for *water use* and  
210 *water extraction*, conditional on the likelihood of an observation being non-zero. Using this  
211 approach, the hurdle model is able to simultaneously account for monthly observations in  
212 which some farms did not use or extract water, while not allowing these observations to  
213 artificially reduce the estimates for farms, overall, during said month.

214         The first (binary) component (referred to hereafter as *binomial model*) of the hurdle  
215 models fit a multilevel logistic regression to the binomial response  $p_{m,t}$  indicating whether  
216 *water use* or *water extraction* were zero. The predictors included scaled (to standard Z-score)  
217 *cultivation area* ( $Z$ ), *month* ( $m$ ), and *operation type* ( $t$ ), and interactions for *cultivation area* and  
218 *month*, as well as *cultivation area* and *operation type*. The form of this logistic regression is a

219 generalized linear model (GLM) with a logit link function and  $p$  being drawn from the binomial  
220 distribution:

$$\begin{aligned} \text{Eq. 1a-c} \quad \text{logit}(p_{m,t}) &= \beta_{0,m,t} + Z + \beta_{1,m,t}Z + \varepsilon \\ \beta_{0,m,t} &= \gamma_{m,0} + \gamma_{t,0} \\ \beta_{1,m,t} &= \gamma_{m,1} + \gamma_{t,1} \end{aligned}$$

222  $\gamma_{m,0}$  and  $\gamma_{t,0}$  sum up to the intercept  $\beta_{0,m,t}$  for a given month and operation type, respectively.

223  $\gamma_{m,1}$  and  $\gamma_{t,1}$  sum up to the slope  $\beta_{1,m,t}$  for a given month and operation type, respectively. Given

224 twelve months and three operation types, the logistic model contained 36 levels. With the

225 same predictors as the binomial model, the second (continuous) component model fits a GLM

226 with a Gamma distributed response variable  $\mu$  using an inverse link function:

$$\text{Eq. 2} \quad \mu^{-1} = \beta_{0,m,t} + Z + \beta_{1,m,t}Z + \varepsilon$$

228 Intercepts and slopes were as described in Eq. 1a-c. The continuous component excluded data

229 with zero *water use* or zero *water extraction*. Hurdle model estimates ( $W$ ) were calculated as

230 the product of the two estimated responses for the binomial model and continuous component

231 model:

$$\text{Eq. 3} \quad W = \hat{\mu} \cdot \frac{1}{1 + e^{\hat{p}}}$$

233 Because model fitting required the use of a link function to account for non-normally

234 distributed data, estimated relationships between continuous variables (i.e. *cultivation area*

235 and *water use*, *cultivation area* and *water extraction*) were non-linear. For the purposes of

236 model interpretation, predictions (liters of *water use* and *water extraction*) were made for each

237 level of the categorical variables (*month* and *operation type*) at the median value of the

238 continuous variable, *cultivation area* (1,098 m<sup>2</sup>). These results can be interpreted as the

239 predicted *water use* or *water extraction* on the median sized farm. Responses in GLMs at the

240 level of the linear predictors are asymptotically normal, and confidence intervals for model  
241 responses were calculated with the t-distribution and standard errors. Standard errors for  
242 GLMs are the square root of the diagonal elements of the model covariance matrix, estimated  
243 via maximum likelihood estimation.

244

## 245 **Storage Capacity Sufficiency**

246 For each farm, the total amount of reported *water use* from April through October was  
247 subtracted from the reported storage capacity of the farm to create the response variable  
248 *storage balance* (i.e. positive values indicate sufficiency while negative values indicate  
249 insufficiency). Extreme outliers of *storage balance* were identified (6 x Interquartile Range) and  
250 excluded (n=17). To simultaneously estimate the factors influencing *storage balance* ( $S$ ), a  
251 multilevel linear model was fit using the predictors: *cultivation area* ( $A$ ), *operation type* ( $t$ ),  
252 *storage type* ( $g$ ), *source type* ( $r$ ) and an interaction between *cultivation area* and *operation type*:

253 Eq. 4a-b

$$\begin{aligned} S &= \beta_{0,t,g,r} + A + \beta_{1,t}A + \epsilon \\ \beta_{0,t,g,r} &= \gamma_t + \gamma_g + \gamma_r \end{aligned}$$

254  $\gamma_t$ ,  $\gamma_g$ , and  $\gamma_r$  are components summing to the intercept  $\beta_{0,t,g,r}$  for a given combination of  
255 *operation type*, *storage type*, and *source type*, respectively, resulting in 12 levels total in the  
256 model.

257

## 258 **Water Storage, Sources, and Extraction Patterns**

259 An additional hurdle model was fit to determine if predictors of *storage balance* also  
260 had reliable effects on seasonal patterns of *water extraction*. The original hurdle model for

261 water extraction was supplemented using two additional predictors of *storage balance* (i.e.  
262 *source type* and *storage type*) along with their interactions with *month*. The intercept defined in  
263 Eq. 1b was thus revised accordingly:

264 Eq. 5 
$$\beta_{0,m,t,g,r} = \gamma_m + \gamma_t + \gamma_g + \gamma_r + \gamma_{m,g} + \gamma_{m,r}$$

265  $\gamma_{m,g}$  and  $\gamma_{m,r}$  are terms for the interactions of *storage type* and *source type*, respectively, with  
266 *month*. The slope term  $\beta_{1,m,t}$  remained the same. Adding two categorical predictors, with two  
267 categories each, resulted in 144 levels in the hurdle models. AIC comparison was used to  
268 determine if addition of these parameters was justified [33].

269 For the purposes of model interpretation, predictions of *water extraction* (liters) were  
270 made for each level of the categorical variables (*month*, *operation type*, *source type*, and  
271 *storage type*) at the median value of the continuous variable, *cultivation area* (1,098 m<sup>2</sup>).

272

## 273 Results

274 The sample of reported data analyzed included outdoor and mixed-light operations, and  
275 those with combinations of the two cultivation types (Table 1). Average farm size varied  
276 between operation types, with outdoor farms smaller than mixed-light farms and combination  
277 farms larger than both. Average reported annual water use and extraction totals were much  
278 less for outdoor farms, relative to mixed-light and combination farms; however, there was a  
279 notable amount of variation within levels. Average annual water extraction was higher for  
280 farms with seasonal water sources than perennial sources, and for farms with ponds relative to  
281 those without; although average water storage balances for the forbearance period were  
282 greater for these farms with seasonal water sources and ponds.

283

**Table 1. Summary Statistics.**

	Sample size	Mean Cultivation Area (Std Dev)	Mean Annual Water Use (Std Dev)	Mean Annual Water Extraction (Std Dev)	Mean Forbearance Storage Balance (Std Dev)
<b>Operation Type</b>					
Outdoor	n = 179	1,185 m <sup>2</sup> (575)	358,854 L (303,389)	371,579 L (322,659)	-72,655 L (279,560)
Mixed-light	n = 206	1,301 m <sup>2</sup> (896)	533,981 L (458,686)	602,295 L (508,742)	-38,136 L (522,637)
Combination	n = 130	1,521 m <sup>2</sup> (894)	500,513 L (344,295)	531,692 L (370,372)	-54,056 L (428,964)
<b>Source Type</b>					
Seasonal	n = 237	1,301 m <sup>2</sup> (812)	-	556,275 L (456,227)	-62,178 L (592,885)
Perennial	n = 371	1,296 m <sup>2</sup> (823)	-	449,183 L (390,923)	-285,354 L (338,389)
<b>Storage Type</b>					
Pond	n = 61	1,438 m <sup>2</sup> (807)	-	831,505 L (534,016)	+384,613 L (591,284)
Other	n = 477	1,282 m <sup>2</sup> (818)	-	452,254 L (387,702)	-253,927 L (359,426)

Summary statistics for categorical model parameters. Forbearance storage balance is defined as the reported amount of water used during the pending forbearance period (Apr-Oct) minus the reported storage capacity of the farm.

284

285 Models were first developed for two continuous response variables: monthly *water use*  
 286 and monthly *water extraction*. Model parameters included *cultivation area* as a single  
 287 continuous predictor variable and two categorical variables: *operation type* and *month*. Model  
 288 interpretation is reported for both the full hurdle models and the binomial component models.  
 289 The binomial models estimate the likelihood for *water use* or *water extraction* to occur in a  
 290 given month, whereas the full hurdle models estimate the amount of monthly *water use* or  
 291 *water extraction*, conditional on the likelihood of *water use* or *water extraction* occurring for  
 292 that month (Table 2).

293

**Table 2. Binomial Component Models: Water Use and Extraction (Likelihood).**

Month	Outdoor (95% CI)	Mixed-light (95% CI)	Combination (95% CI)
<b>Water Use</b>			
January	0.25 (0.21, 0.29)	0.39 (0.35, 0.44)	0.39 (0.34, 0.44)
February	0.28 (0.24, 0.33)	0.43 (0.39, 0.48)	0.43 (0.38, 0.48)
March	0.37 (0.32, 0.41)	0.53 (0.48, 0.58)	0.53 (0.47, 0.58)
April	0.62 (0.58, 0.67)	0.76 (0.72, 0.80)	0.76 (0.72, 0.80)
May	0.86 (0.82, 0.89)	0.92 (0.90, 0.94)	0.92 (0.90, 0.94)
June	0.99 (0.97, 1.00)	0.99 (0.99, 1.00)	0.99 (0.99, 1.00)
July	1.00 (0.98, 1.00)	1.00 (0.99, 1.00)	1.00 (0.99, 1.00)
August	1.00 (0.98, 1.00)	1.00 (0.99, 1.00)	1.00 (0.99, 1.00)
September	0.98 (0.96, 0.99)	0.99 (0.98, 0.99)	0.99 (0.98, 0.99)
October	0.91 (0.88, 0.93)	0.95 (0.93, 0.96)	0.95 (0.93, 0.96)
November	0.38 (0.33, 0.42)	0.54 (0.49, 0.58)	0.53 (0.48, 0.59)
December	0.27 (0.23, 0.31)	0.42 (0.37, 0.47)	0.42 (0.36, 0.47)
<b>Water Extraction</b>			
January	0.45 (0.41, 0.50)	0.52 (0.48, 0.57)	0.53 (0.48, 0.58)
February	0.48 (0.44, 0.53)	0.56 (0.51, 0.60)	0.56 (0.52, 0.61)
March	0.55 (0.51, 0.60)	0.62 (0.58, 0.66)	0.63 (0.58, 0.68)
April	0.69 (0.64, 0.73)	0.75 (0.71, 0.78)	0.75 (0.71, 0.79)
May	0.77 (0.73, 0.81)	0.82 (0.78, 0.85)	0.82 (0.79, 0.85)
June	0.82 (0.78, 0.85)	0.86 (0.83, 0.88)	0.86 (0.83, 0.89)
July	0.80 (0.76, 0.84)	0.84 (0.81, 0.87)	0.85 (0.82, 0.88)
August	0.80 (0.76, 0.84)	0.84 (0.81, 0.87)	0.85 (0.82, 0.88)
September	0.81 (0.78, 0.85)	0.85 (0.82, 0.88)	0.86 (0.83, 0.89)
October	0.80 (0.76, 0.83)	0.84 (0.81, 0.87)	0.84 (0.81, 0.87)
November	0.50 (0.45, 0.54)	0.57 (0.53, 0.61)	0.57 (0.53, 0.63)
December	0.43 (0.39, 0.48)	0.50 (0.46, 0.55)	0.53 (0.46, 0.56)

Binomial model estimates of likelihood of water use and water extraction for median size cultivation area. Confidence intervals in parentheses.

295           The binomial models indicated that the likelihood of *water use* was greatest (>0.85) in  
296 the growing season (June – October) for all *operation types* (Table 2) and lowest (< 0.40) in the  
297 winter months (November – March). However, likelihood estimates were reliably higher for  
298 mixed-light and combination cultivation farms than for outdoor farms (November – March),  
299 reflecting *water use* extending further into these off-season months. Likelihood of *water*  
300 *extraction* was reliably higher than *water use* from November – March, indicating that water  
301 was more likely to be extracted, but not necessarily used, in the offseason. Correspondingly,  
302 although the likelihood of *water use* was at certainty (1.00) in the peak growing season (July  
303 and August), the likelihood of *water extraction* in these months was reliably lower (<0.85).

304           Predicted *water use* volumes from the hurdle models indicated strong seasonal  
305 patterns, peaking in the late growing season (Fig 2; S1 Table). *Water extraction* volumes were  
306 also greatest in the growing season, but showed less seasonal variation than *water use*. For  
307 both outdoor and mixed-light cultivation types, *water extraction* was greater than *water use*  
308 between November and April, but was less than *water use* from May to October. Overall, *water*  
309 *use* and *water extraction* totals were higher for mixed-light than for outdoor *operation type*  
310 farms of the same (median) size, likely resulting from greater density of plants per m<sup>2</sup> of  
311 *cultivation area*.

312

313 **Fig 2. Water Use versus Water Extraction.** Predicted monthly water use and water extraction  
314 for outdoor and mixed-light operation types. Model estimates are provided for median farm  
315 size (cultivation area = 1,098 m<sup>2</sup>). Dashed lines depict 95% confidence intervals for the mean



316 estimate. The rate of 22 L / plant (15 m<sup>2</sup>) / day, which equates to 51,020 L per month for the  
317 median farm size of 1,098 m<sup>2</sup> of cultivation area, is plotted to provide contextual comparison.

318  
319 Models were next developed for *storage balance* to address the necessity of *water*  
320 *extraction* during the growing season (April – October). Reliable predictors of *storage balance*  
321 included *cultivation area* (Estimate = -166.09 L; SE = 49.44), *source type* (Seasonal Estimate =  
322 114,945 L; SE = 35,246), and *storage type* (Pond Estimate = 599,763 L; SE = 15,420) (Table 3).  
323 The model predicted *storage balance* to be insufficient (-278,879 L) for the median size farm  
324 (*cultivation area* = 1,098 m<sup>2</sup>) that relied on perennial sources and used tanks or bladders  
325 (“Other”) for storage. Farms of this size relying on seasonal water sources were also predicted  
326 to have a negative *storage balance* (-163,930 L). Only farms relying on seasonal water sources  
327 that had ponds were predicted to have a positive *storage balance* (435,833 L) at the median  
328 size of *cultivation area*. In general, *storage balance* decreased with increasing size of *cultivation*  
329 *area* (Fig 3). Farms without ponds were predicted to have an increasingly negative storage  
330 balance, although farms with ponds were predicted to have sufficient *storage balance* for sizes  
331 up to nearly one acre of cultivation (3,718 m<sup>2</sup>).

332

**Table 3. Model estimates for water storage balance (Liters).**

Parameter	Estimate	SE
Intercept	-96,611	65,236*
Cultivation Area	-167	49*
Operation Type (Mixed-light)	-28,770	82,444
Operation Type (Combination)	-160,463	92,777
Storage Type Pond	599,763	58,371*
Seasonal Water Source	114,950	35,245*

OT Mixed-Light*Cultivation Area	28	62
OT Combination*Cultivation Area	131	68*

Estimates for the linear model of water storage balance. Asterisks indicate reliable estimates (95% CI does not overlap zero).

333

334 **Fig 3. Water Storage Sufficiency.** Water storage balance for the cultivation season (April -  
335 October) as predicted by cultivation area, source type, and storage type. Reported water use  
336 for the cultivation season is subtracted from reported storage capacity, with values of zero  
337 indicating storage sufficiency (boundary depicted by red line). Solid lines depict mean  
338 estimates, while dashed lines depict 95% confidence intervals.

339

340 Given the importance of *source type* and *storage type* as predictors of *storage balance*,  
341 these parameters were used to refine model estimates of *water extraction*. Both component  
342 models of the hurdle model fit with the additional parameters of *source type* and *storage type*  
343 were favored by AIC (Binomial AIC = 7,456; Gamma AIC = 119,974) over the original component  
344 models (Binomial AIC = 8,265; Gamma AIC = 120,352). The binomial model predicted a reliably  
345 higher likelihood of *water extraction* for farms relying on seasonal water sources in the months  
346 of January, February, and March relative to farms with at least one perennial water source  
347 (Table 4). The pattern was reversed in the summer months of July, August, and September,  
348 with farms extracting from seasonal water sources predicted to have a reliably smaller  
349 likelihood of *water extraction* than farms with a perennial *source type*. Similarly, the binomial  
350 model predicted a reliably higher likelihood of *water extraction* for farms with ponds in the  
351 months of January, February, and March, relative to farms without ponds (i.e. *storage type*:  
352 other; Table 4). The pattern was reversed in the summer months of July, August, and

353 September, with farms using ponds predicted to have a reliably smaller likelihood of extracting  
 354 water, relative to farms without ponds.

355 The volume of *water extraction* predicted by the full hurdle model followed the pattern  
 356 of the binomial model (Fig 4; S2 Table). *Water extraction* totals were reliably greater for farms  
 357 with seasonal water sources in the months of January (0.59), February (0.62), and March (0.65)  
 358 relative to farms with at least one perennial water source (0.31, 0.34, and 0.44, respectively;  
 359 Table 4). The pattern was reversed in the summer months of June, July, August, and  
 360 September, with predicted amount of *water extraction* from farms with a seasonal *source type*  
 361 lower than farms with a perennial *source type*. Farms with ponds demonstrated an even more  
 362 pronounced divergence from farms using perennial sources. *Water extraction* totals were  
 363 reliably higher for farms with pond *storage type* in the months of January (0.84), February  
 364 (0.82), and March (0.83) relative to other (tanks or water bladders) *storage type*, regardless of  
 365 *source type*. The pattern was reversed in the summer months of July, August, and September,  
 366 with predicted amount of *water extraction* from farms with ponds lower than from farms  
 367 without ponds, regardless of *source type*. However, this difference was only reliable between  
 368 farms with ponds and those without, in which the *source type* was perennial, as 95% confidence  
 369 intervals overlapped when comparing farms with and without ponds, in which *source type* was  
 370 seasonal.

371

**Table 4. Binomial Models: Additional Predictors of Water Extraction (Likelihood).**

Month	Source: Seasonal Storage: Other (95% CI)	Source: Perennial Storage: Other (95% CI)	Source: Seasonal Storage: Pond (95% CI)
January	0.59 (0.51, 0.66)	0.31 (0.26, 0.36)	0.84 (0.71, 0.91)

February	0.62 (0.54, 0.69)	0.34 (0.30, 0.40)	0.82 (0.69, 0.90)
March	0.65 (0.57, 0.72)	0.44 (0.38, 0.49)	0.84 (0.72, 0.92)
April	0.72 (0.64, 0.78)	0.63 (0.57, 0.68)	0.83 (0.70, 0.92)
May	0.71 (0.63, 0.78)	0.81 (0.76, 0.85)	0.53 (0.40, 0.66)
June	0.64 (0.56, 0.72)	0.96 (0.93, 0.97)	0.34 (0.23, 0.48)
July	0.60 (0.52, 0.68)	0.95 (0.92, 0.97)	0.36 (0.25, 0.50)
August	0.61 (0.53, 0.68)	0.95 (0.92, 0.97)	0.31 (0.20, 0.44)
September	0.62 (0.54, 0.70)	0.96 (0.93, 0.98)	0.34 (0.23, 0.48)
October	0.65 (0.57, 0.72)	0.89 (0.85, 0.92)	0.53 (0.39, 0.67)
November	0.50 (0.42, 0.57)	0.45 (0.40, 0.51)	0.60 (0.47, 0.72)
December	0.50 (0.42, 0.58)	0.32 (0.27, 0.38)	0.77 (0.63, 0.86)

Water extraction model estimates for median size cultivation area, with additional predictors of source type and storage type. Confidence intervals in parentheses.

372

373 **Fig 4. Additional Predictors of Water Extraction.** Monthly water extraction, based on source  
 374 type and storage type. Model estimates are provided for median farm size (cultivation area =  
 375 1,098 m<sup>2</sup>). Dashed lines depict 95% confidence intervals for the mean estimate. The rate of 22 L  
 376 / plant (15 m<sup>2</sup>) / day, which equates to 51,020 L per month for the median farm size of 1,098 m<sup>2</sup>  
 377 of cultivation area, is plotted to provide contextual comparison.

378

## 379 Discussion

380 Cannabis cultivation has been considered an emerging environmental threat to  
 381 Northern California watersheds [5]. While there is strong evidence that a large number of farms  
 382 are located in sensitive and remote locations [4], until now, there had been little data about

383 their actual water demand patterns. Applying newly available data, we modeled the  
384 characteristics of water extraction, storage, and use for over 600 cannabis farms in Northern  
385 California, providing policy relevant information on these patterns.

386 We found reliable variation between months in terms of both water use and water  
387 extraction. For all operation types, water extraction in offseason months exceeded water use,  
388 reflecting input to storage rather than immediate use for cultivation. This stored water likely  
389 reduced the need to withdraw water in summer months, as water extraction was less than  
390 water use during this period. However, farms did not generally have enough storage to  
391 completely refrain from extracting from April through October. The same useful predictors of  
392 storage sufficiency (type of storage infrastructure and seasonality of water sources) had reliable  
393 effects on extraction patterns, further emphasizing that patterns of input to storage are linked  
394 to storage capacity and whether a farm needs to store water. Farms relying on seasonal water  
395 sources, and especially those with ponds, weighted their annual extraction profile toward  
396 offseason months, whereas farms incorporating perennial sources had extraction profiles that  
397 more closely followed plant demand over the growing season. The results observed herein  
398 demonstrate that estimating the water demands of cannabis cultivation will require accounting  
399 for monthly extraction patterns, in addition to cultivation strategies and farm characteristics  
400 that influence them. Furthermore, given the link between water storage and extraction  
401 patterns, widespread storage insufficiency represents an important topic of discussion in light  
402 of future natural (e.g. drought) and regulatory (e.g. forbearance) restrictions on seasonal water  
403 sources.

404

## 405 **Storage Insufficiency**

406           The results suggest that many farms may need to expand water storage capacity if they  
407 are to eliminate the need for surface water extractions during the growing season. Beginning in  
408 2019, forbearance requirements will be implemented by the California State Water Resources  
409 Control Board that prohibit extraction from surface water (and springs that deliver to surface  
410 water) from April through October. Therefore, although farms included in the current study  
411 were not subject to these restrictions at the time data were collected, farms relying on surface  
412 water (and connected springs) will be required to either develop storage or seek an alternative  
413 water source, such as subsurface water. Furthermore, the data analyzed in the current study  
414 were collected after a particularly wet winter (2016-2017) [34] and many seasonal water  
415 sources reported, herein, may not be available during drought, or even normal years. While  
416 farms may have the options of developing storage for surface water and/or rain catchment,  
417 receiving water from offsite, or extracting subsurface water, previous work has suggested that  
418 drilling wells may be the method of choice to source water in a manner that will provide  
419 insurance against drought and comply with forbearance requirements [10]. The appeal of  
420 drilling a well may reflect difficulties associated with obtaining storage infrastructure, which  
421 could be partially responsible for this decision.

422           Although farms with ponds generally had sufficient water storage to comply with  
423 forbearance requirements, only approximately 10% of farms reported use of a pond for  
424 cannabis irrigation. There are logistical, financial, environmental, and regulatory concerns that  
425 are likely limiting this option for farms. Aside from the costs and engineering constraints for  
426 building ponds on rugged terrain, there may be difficulty in ensuring ponds are not situated on

427 seasonal watercourses, thus capturing streamflow and rendering them non-compliant with  
428 state and county regulations. Depending on where they are located, ponds may also serve as  
429 habitat for invasive species, such as bullfrogs, which are also of concern to regulatory agencies.  
430 Although water storage tanks could avoid these concerns, the costs of units themselves and the  
431 availability of appropriate terrain to site numerous large water tanks may pose complications  
432 for farms in rugged terrain. With increasingly larger farms in such areas, the likelihood of  
433 securing enough tanks to meet water needs becomes increasingly smaller. Under these  
434 circumstances, not all farms that rely on seasonal water may be able to meet forbearance  
435 requirements (or outlast drought conditions), due to a lack of water storage. In these cases,  
436 farmers may instead choose to bypass storage requirements by drilling wells, which emphasizes  
437 the need to account for extraction patterns of perennial versus seasonal water sources.

438

## 439 **Water Sources and Ecological Impacts**

440         Based on results observed in the current study, farms using wells would be expected to  
441 follow an extraction pattern that matches plant demand, overlapping with diminishing instream  
442 flow during summer dry months [35]. It is known that extraction of ground water may have a  
443 delayed impact on instream flow on the order of weeks, months, or years, depending on the  
444 depth of extraction, conductivity of the soil, and the recharge received from precipitation [36].  
445 As a result, understanding lagged effects on instream flow will be useful when assessing the  
446 potential benefits of shifting the instream flow impacts of cannabis water extraction out of the  
447 crucial summer drought months. An accurate assessment of the benefits and risks of well  
448 extraction will require a better understanding of the geology and hydrology in areas where

449 cannabis cultivation occurs and on the spatial and temporal dimensions of groundwater-surface  
450 water interactions [37-38]. While there may be benefits of lagged impacts of wells on instream  
451 flow, the possibility of wells instead being directly hydrologically connected to streams may  
452 result in additional concerns for instream flow [39].

453         Wells that are shallow and close to surface water have a high likelihood of directly  
454 capturing stream flow [40-41]. As a result, water extraction would have a minimal lag on  
455 instream impacts and the extraction pattern, matching plant demand, would directly overlap  
456 with the most crucial low instream flow period. Further work is needed to determine the  
457 propensity for wells servicing cannabis farms to be located near streams and the degree to  
458 which they are hydrologically connected. For wells that are determined to be capturing surface  
459 water, forbearance requirements will prohibit the use of these sources from April through  
460 October. The ability of these farms to switch to storing water or to drill a new well would then  
461 influence their ability to remain in compliance with regulations. For sites that are currently  
462 outside of the regulated industry, this may be a barrier to becoming permitted. Given the link  
463 between water sources and seasonal extraction patterns demonstrated in the current study, it  
464 will be useful to determine how unpermitted sites (i.e. those operating outside the regulated  
465 industry) may use water in order to develop a holistic understanding of the impact of cannabis  
466 cultivation in general on instream flow.

467         Although the current study demonstrated that summer water extraction is reduced for  
468 farms that use seasonal water sources, unpermitted sites frequently use seasonal sources  
469 opportunistically during the summer growing season [18]. In fact, illegal diversions are a major  
470 issue, given that the majority of cannabis cultivation in the North Coast of California is currently



471 unpermitted [42]. In those cases, plant demand (i.e. *water use*) estimates provided herein may  
472 be more appropriate predictors of water impacts, assuming little to no storage is being used.  
473 However, it is difficult to anticipate what proportion of these farmers incorporate water  
474 storage, either due to necessity or concern for environmental impacts. This simultaneously  
475 emphasizes the importance of these sites entering the regulated industry [43] and illustrates  
476 the limitations of trying to estimate collective impacts of cannabis cultivation without sufficient  
477 data on cultivation practices of unpermitted operations.

478

## 479 **Future Research Needs**

480 A lack of understanding of illicit (i.e., unpermitted) cannabis farming practices  
481 represents one of several limitations of this study and a need for additional data. Field  
482 observations from warrant inspections on unpermitted cannabis farms have revealed several  
483 cultivation practices that may affect how water is extracted, stored, and used for cannabis. For  
484 example, perennial springs that would otherwise feed small streams are often dammed by  
485 cannabis cultivators to store water for critical summer months. Alternatively, spring diversions  
486 often feed directly into storage tanks without overflow protections, thereby moving water out  
487 of its regular channel and dispersing it in upland areas. Empirical streamflow studies may be  
488 useful to assess the impact of these practices, comparing expected water extraction totals to  
489 instream flow reductions in a paired watershed design. These efforts would be aided by  
490 improving water extraction estimates themselves, using more detailed data to improve  
491 accuracy.

492 Data collection incorporating additional parameters that influence water use for  
493 cannabis cultivation would be beneficial to both regulators and farmers. The results of this  
494 study indicate significant differences in predicted water use and extraction amounts as a result  
495 of operation types known to differ in plant sizes, spatial arrangement, and evapotranspiration  
496 potential based on ambient temperature and humidity. However, the precise relationship  
497 between these variables remains unknown. Furthermore, there are certainly additional factors,  
498 such as the soil type, local climate, and cultivar that will influence water consumption [26]. A  
499 better understanding of these factors could potentially inform water conservation best  
500 practices targeted toward specific cultivation strategies and growing conditions, the variety of  
501 which are a hallmark of the cannabis industry in Northern California. Improved estimates that  
502 account for diverse cultivation practices may also help growers to know how their use  
503 compares with the expected range of water use and thus be able to identify and address  
504 operational inefficiencies.

505

## 506 **Conclusion**

507 This study demonstrates that predicting water demands of cannabis farms requires  
508 consideration of the seasonal patterns of water extraction, cultivation practices, water sources,  
509 and storage availability. Pending decisions for farmers aiming to comply with regulations may  
510 influence these seasonal extraction patterns and in turn, inform relative impacts to instream  
511 flow. In general, more data are needed on cultivation practices to help determine additional  
512 factors that influence water demand by cannabis farms. Regulators and researchers may  
513 continue to explore the geographical, climatic, and operation-specific factors that influence

514 water demand and more specifically tailor regulations based on these factors. Cannabis farmers  
515 may benefit from an established understanding of what water use expectations are and should  
516 be. All stakeholders will benefit from determinations of environmental impacts, so that  
517 regulatory objectives can be effective, transparent, and achievable [44-45].

518

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523 Regional Water Quality Control Board Cannabis Waste Discharge Regulatory Program, which  
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525

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685

## 686 **Supporting Information**

687 **S1 Figure. Distributions of Summary Statistics.** Summary statistics for the continuous model  
688 parameters of *cultivation area* (predictor) and *storage balance* (response). Annual water use  
689 and annual water extraction are depicted for descriptive purposes only and are not included as  
690 model predictors or response variables.

691

692 **S2 Figure. Monthly Water Data Distributions.** Raw monthly water use and water extraction  
693 values. Distributions depict non-zero observations, used in the continuous (gamma) model  
694 component of the hurdle model. The proportion of monthly observations that were non-zeros  
695 is also provided, corresponding to binary input to the binomial model component of the hurdle  
696 model.

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**S1 Table. Full Hurdle Model Estimates (Liters).**

Month	Outdoor (95% CI)	Mixed-light (95% CI)	Combination (95% CI)
<b>Water Use</b>			
January	3964 (2984, 5320)	6720 (5180, 8827)	6664 (5061, 8857)
February	4193 (3207, 5529)	6897 (5407, 8887)	6843 (5290, 8917)
March	6278 (4950, 8000)	9857 (7965, 12288)	9746 (7780, 12261)
April	14926 (12573, 17705)	20729 (17792, 24235)	20284 (17302, 23815)
May	31419 (27656, 35622)	41482 (36788, 6957)	39882 (35221, 45328)
June	48163 (43557, 53090)	64492 (57992, 72061)	60895 (54388, 68615)
July	56529 (50950, 62368)	79827 (71485, 89513)	74403 (65954, 84505)
August	60890 (54845, 67400)	88827 (79399, 99965)	82161 (72532, 93934)
September	54050 (48590, 60022)	76064 (68021, 85574)	71090 (62988, 80903)
October	33900 (30139, 38048)	43854 (39125, 49361)	42107 (37428, 47578)
November	7404 (5859, 9395)	11738 (9504, 14602)	11571 (9258, 14523)
December	4369 (3325, 5794)	7305 (5693, 9476)	7239 (9561, 9498)
<b>Water Extraction</b>			
January	20092 (16302, 24861)	34932 (27787, 44527)	31408 (25028, 39786)
February	20314 (16622, 24908)	34010 (27366, 42778)	30850 (24860, 38587)
March	22727 (18892, 27399)	37038 (30346, 45657)	33501 (27495, 41083)
April	23882 (20410, 27963)	35070 (29649, 41771)	32215 (27320, 38159)
May	27660 (23999, 31881)	40341 (34560, 47397)	36611 (31495, 42755)
June	36022 (31494, 41204)	56753 (48657, 66744)	49482 (42612, 7840)
July	39602 (34473, 45513)	66701 (56779, 79112)	56693 (48424, 66911)
August	42264 (36735, 48660)	74263 (62977, 88517)	61973 (52726, 73514)
September	38898 (33941, 44596)	64136 (54737, 75862)	54901 (47041, 64578)
October	28833 (25143, 33064)	41876 (35976, 49080)	37881 (32691, 44121)
November	14877 (12204, 18194)	21815 (17699, 27162)	20787 (16885, 25755)
December	16404 (13240, 20413)	26623 (21133, 33988)	24716 (19656, 31349)

Water use and extraction model estimates for median size cultivation area, by operation type. Confidence intervals in parentheses.

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**S2 Table. Full Hurdle Model Estimates for Additional Predictors (Liters).**

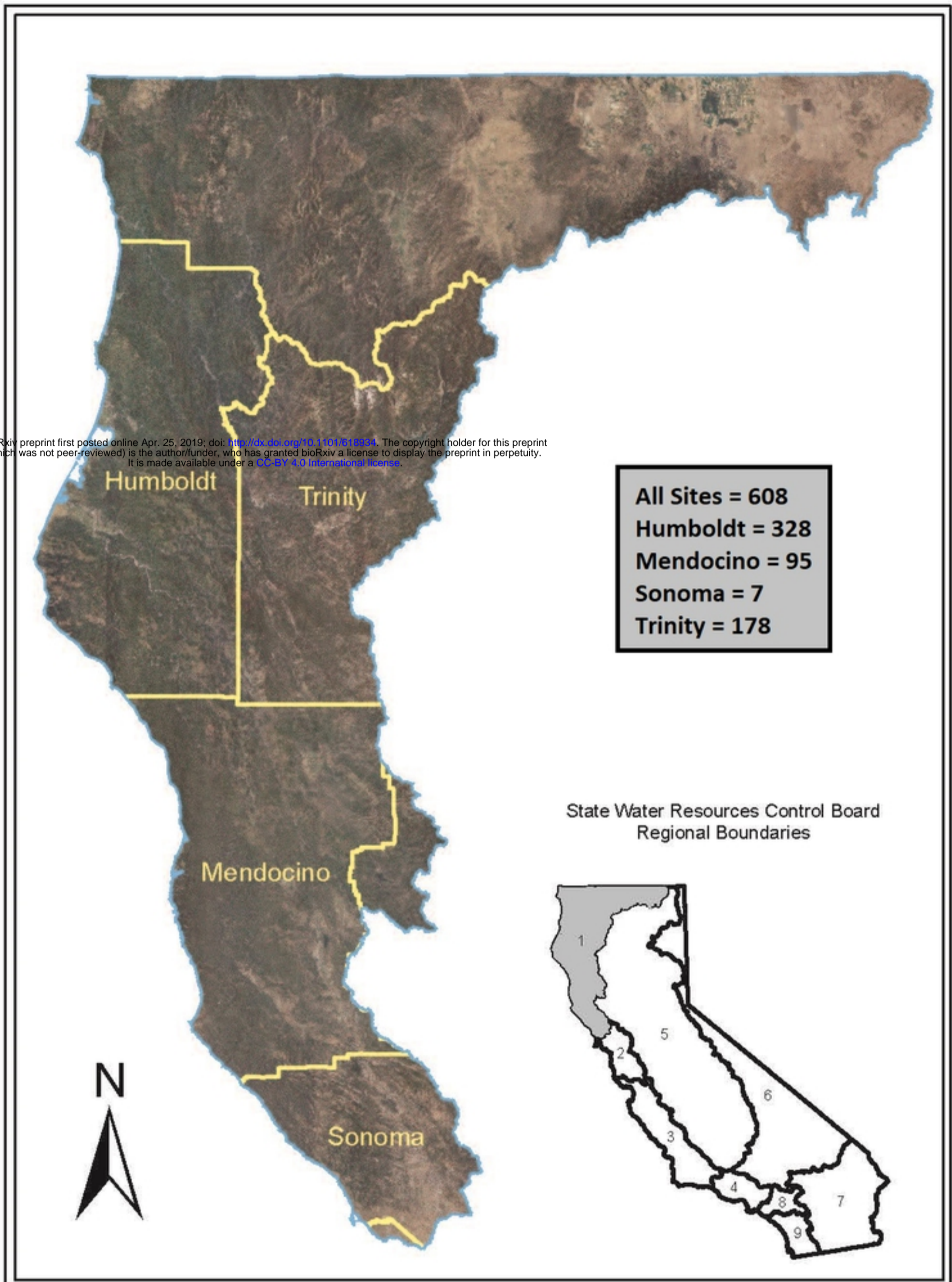
Month	Source: Perennial Storage: Other (95% CI)	Source: Seasonal Storage: Other (95% CI)	Source: Seasonal Storage: Pond (95% CI)
January	9991 (7386, 13640)	24482 (18514, 32237)	66754 (47181, 91822)
February	10158 (7628, 13630)	26205 (20010, 34149)	62758 (43894, 87217)
March	11896 (9226, 15410)	30162 (23227, 38946)	62561 (44305, 85627)
April	18956 (15565, 23061)	29052 (22858, 36603)	39124 (27504, 53266)
May	28877 (24634, 33778)	27256 (21542, 34154)	22268 (13672, 35255)
June	43182 (38113, 48807)	28963 (22447, 37013)	17684 (9649, 31735)
July	50087 (43948, 56981)	29316 (22418, 38029)	18167 (9971, 32552)
August	54027 (47448, 61430)	31459 (24057, 40821)	16770 (8851, 31444)
September	49173 (43291, 55747)	29136 (22355, 37667)	16331 (8804, 29828)
October	32524 (28173, 37455)	23488 (18112, 30224)	23193 (14003, 37241)
November	11730 (9154, 15092)	14812 (10840, 20250)	30554 (18948, 48788)
December	9431 (7035, 12745)	17312 (12715, 23548)	52948 (35952, 76012)

Water extraction model estimates for median size cultivation area, with additional predictors of source type and storage type. Confidence intervals in parentheses.

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# Study Area Map

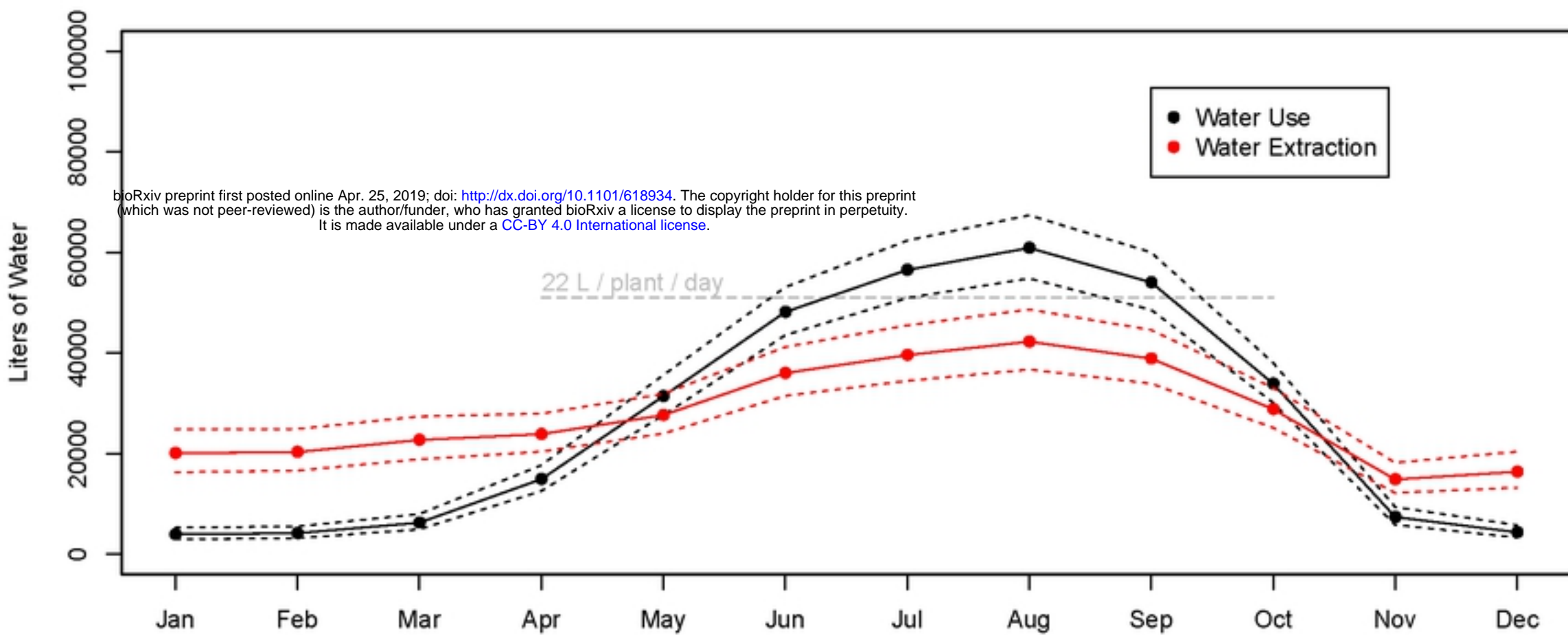
bioRxiv preprint first posted online Apr. 25, 2019; doi: <https://doi.org/10.1101/618934>. The copyright holder for this preprint (which was not peer-reviewed) is the author/funder, who has granted bioRxiv a license to display the preprint in perpetuity. It is made available under a [CC-BY 4.0 International license](https://creativecommons.org/licenses/by/4.0/).



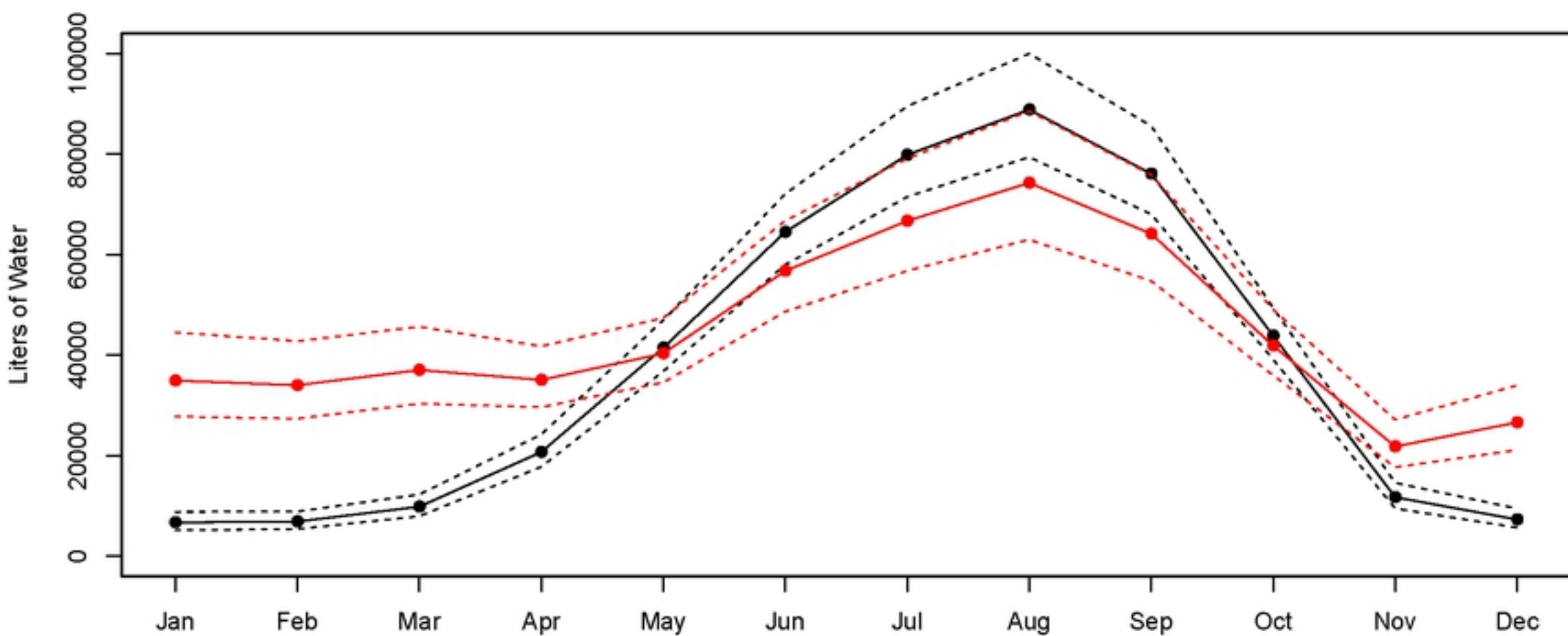
Figure

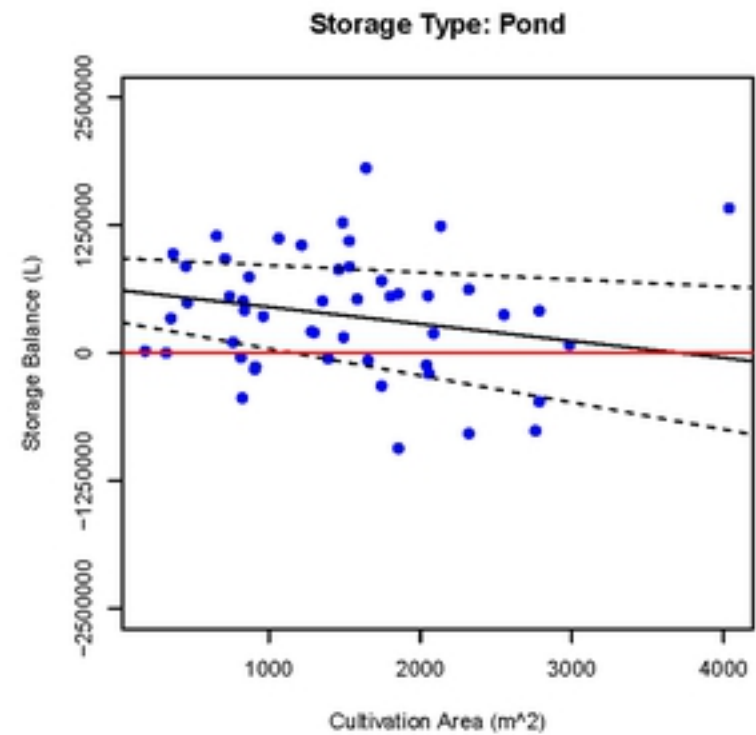
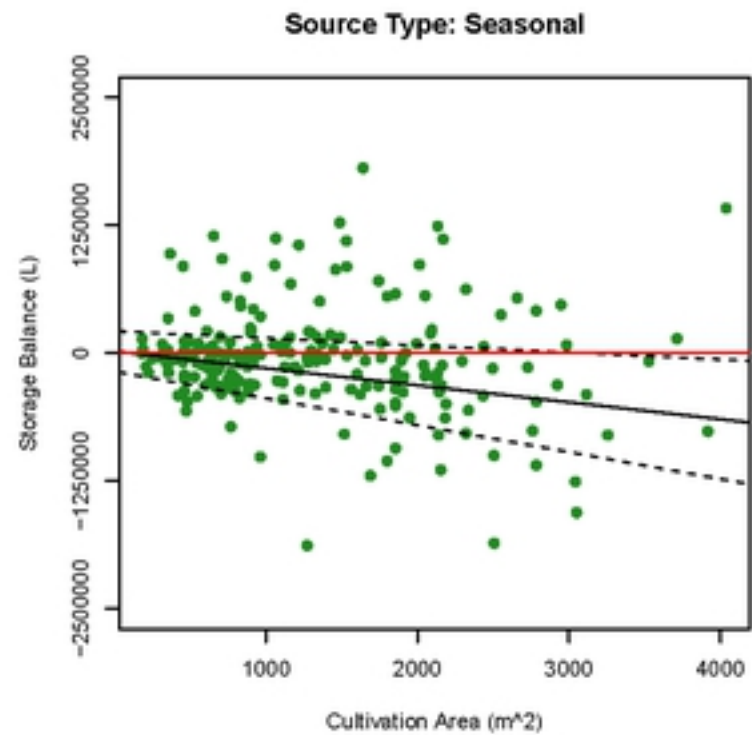
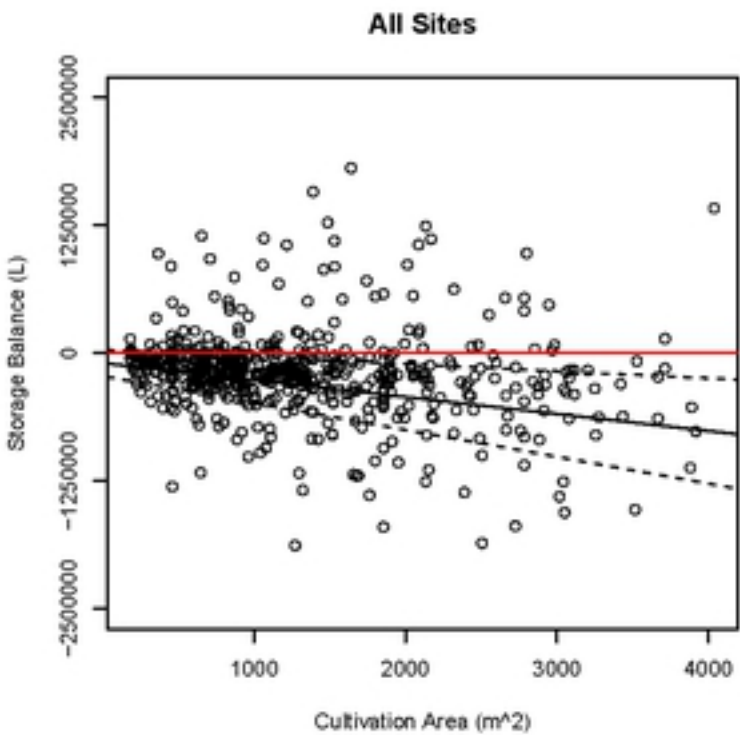


## Outdoor



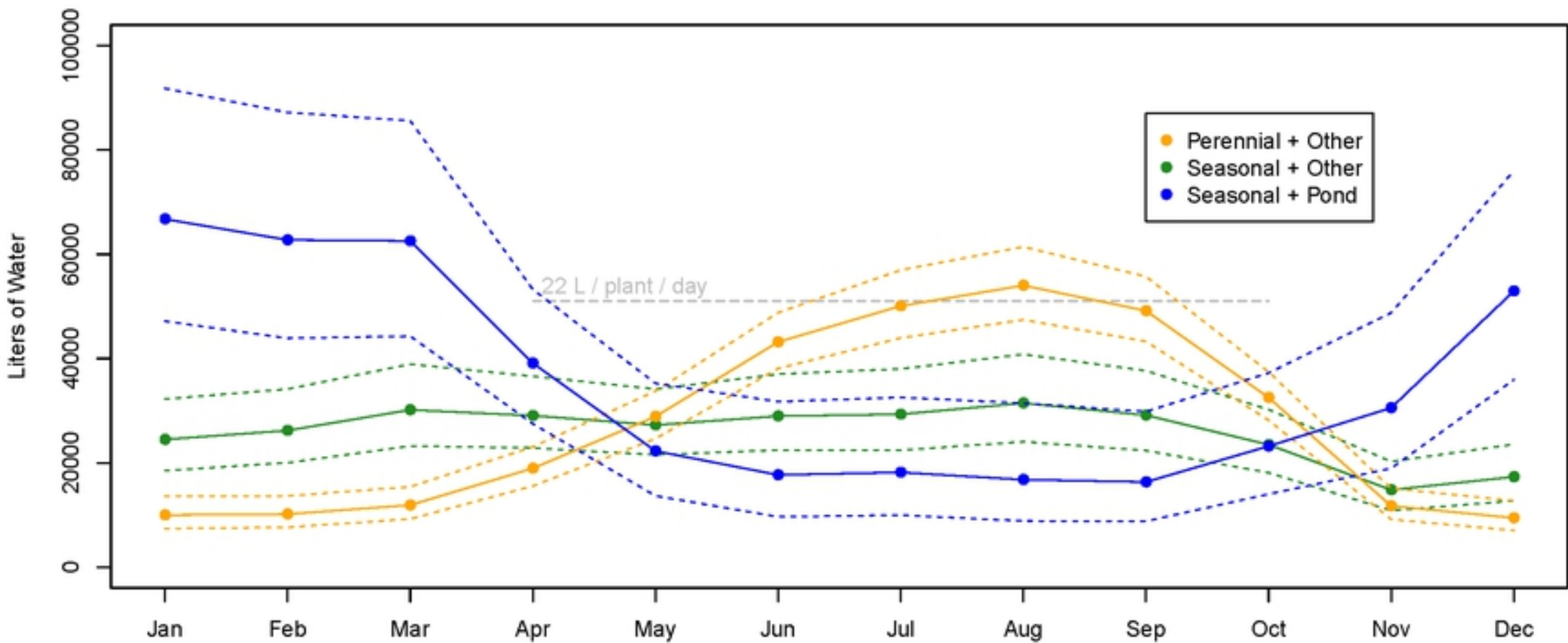
## Mixed-Light





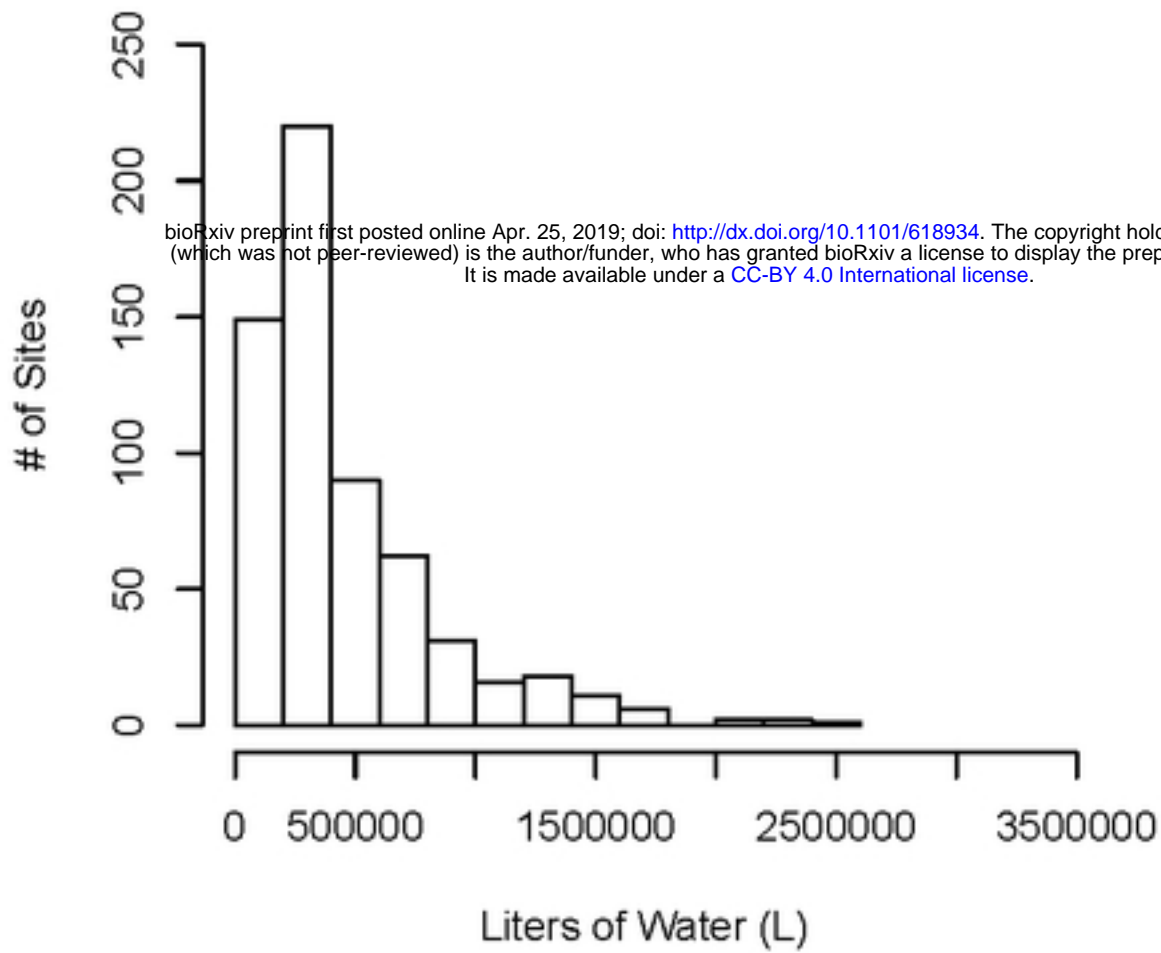
Figure

## Water Extraction Patterns

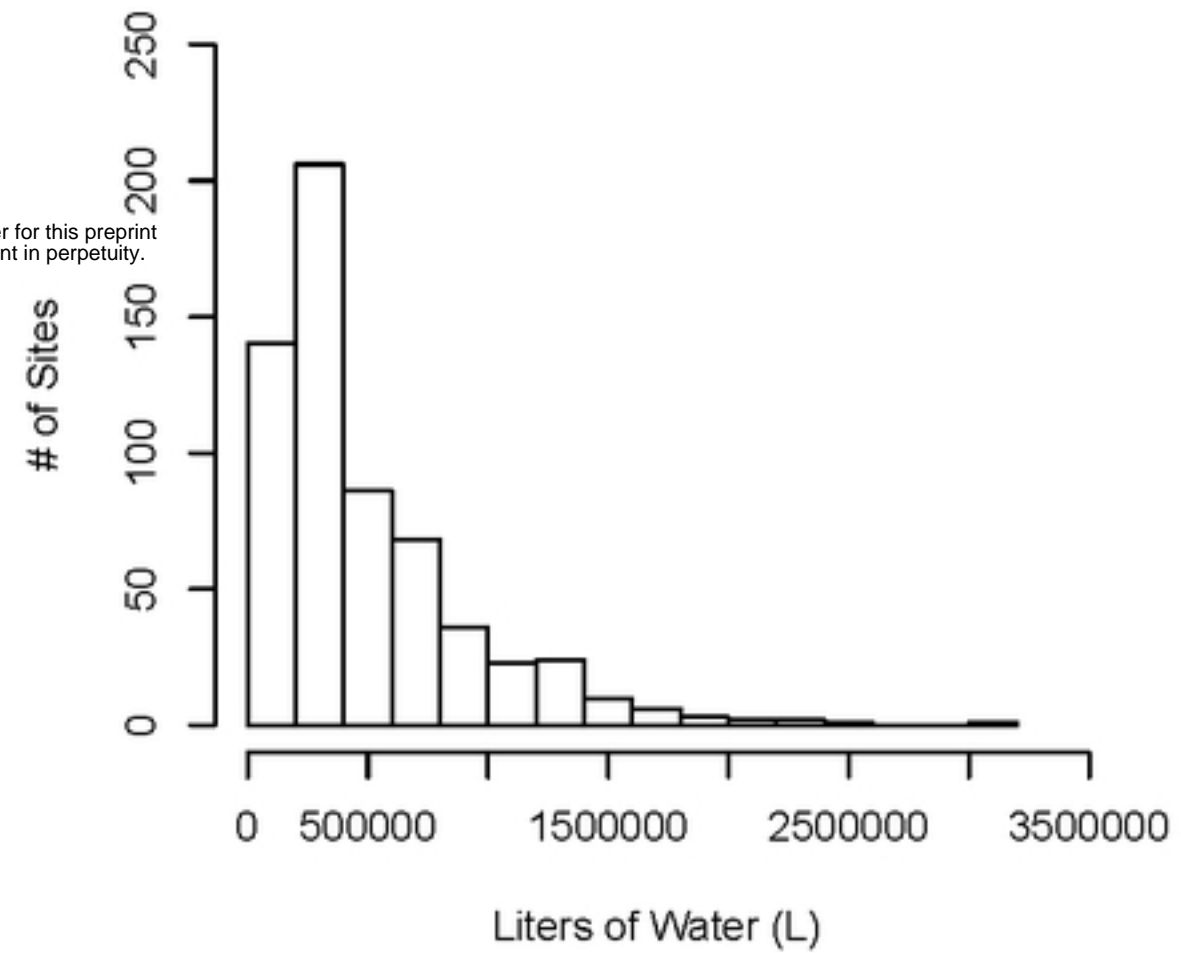


Figure

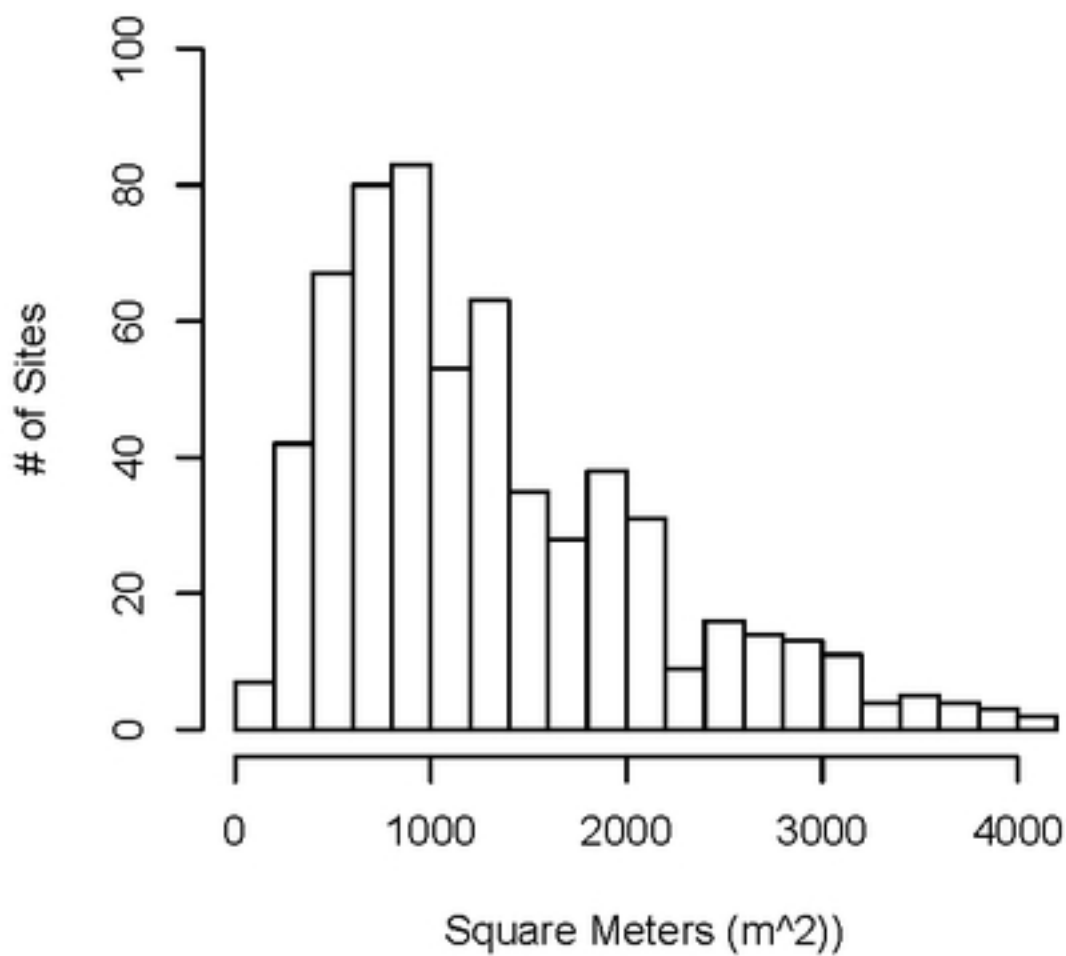
### Annual Water Use



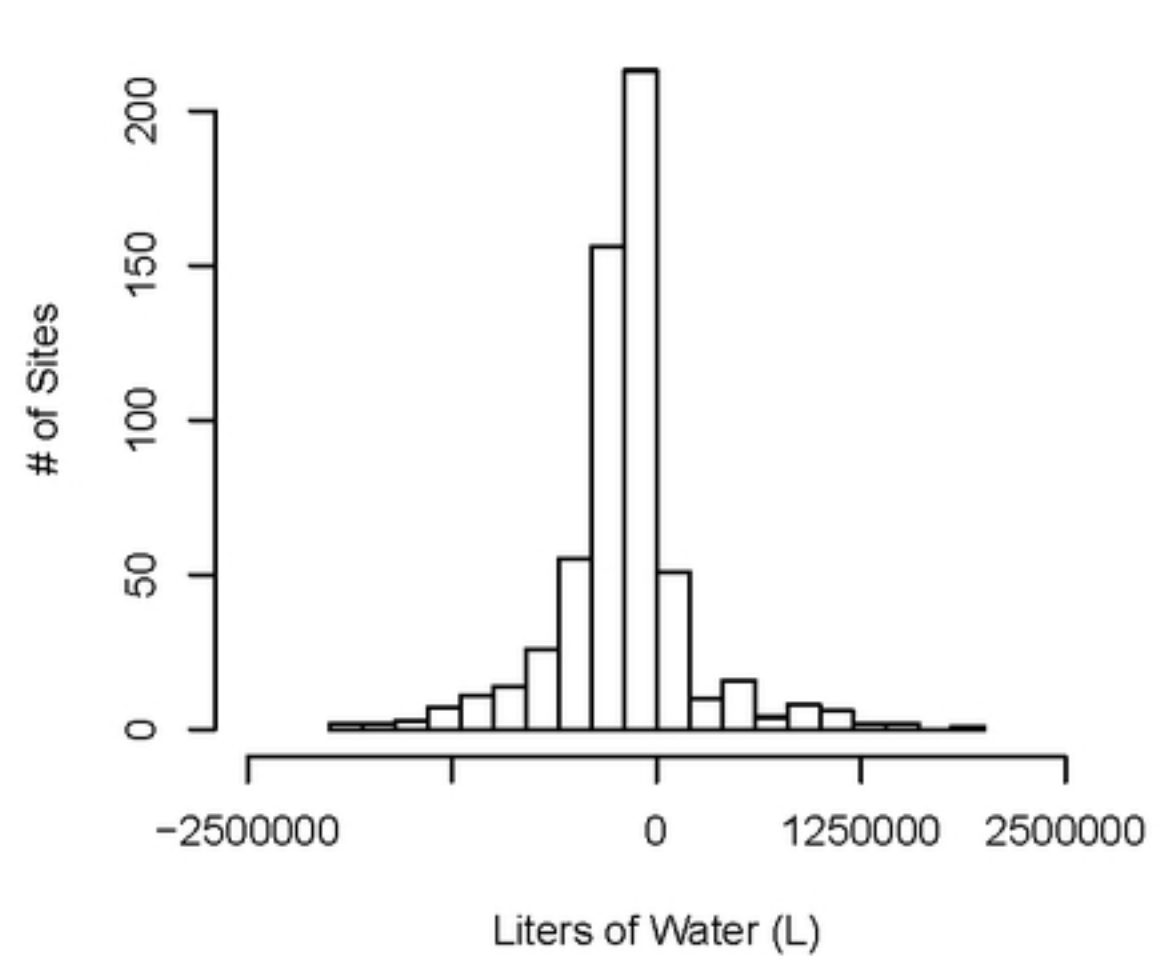
### Annual Water Extraction

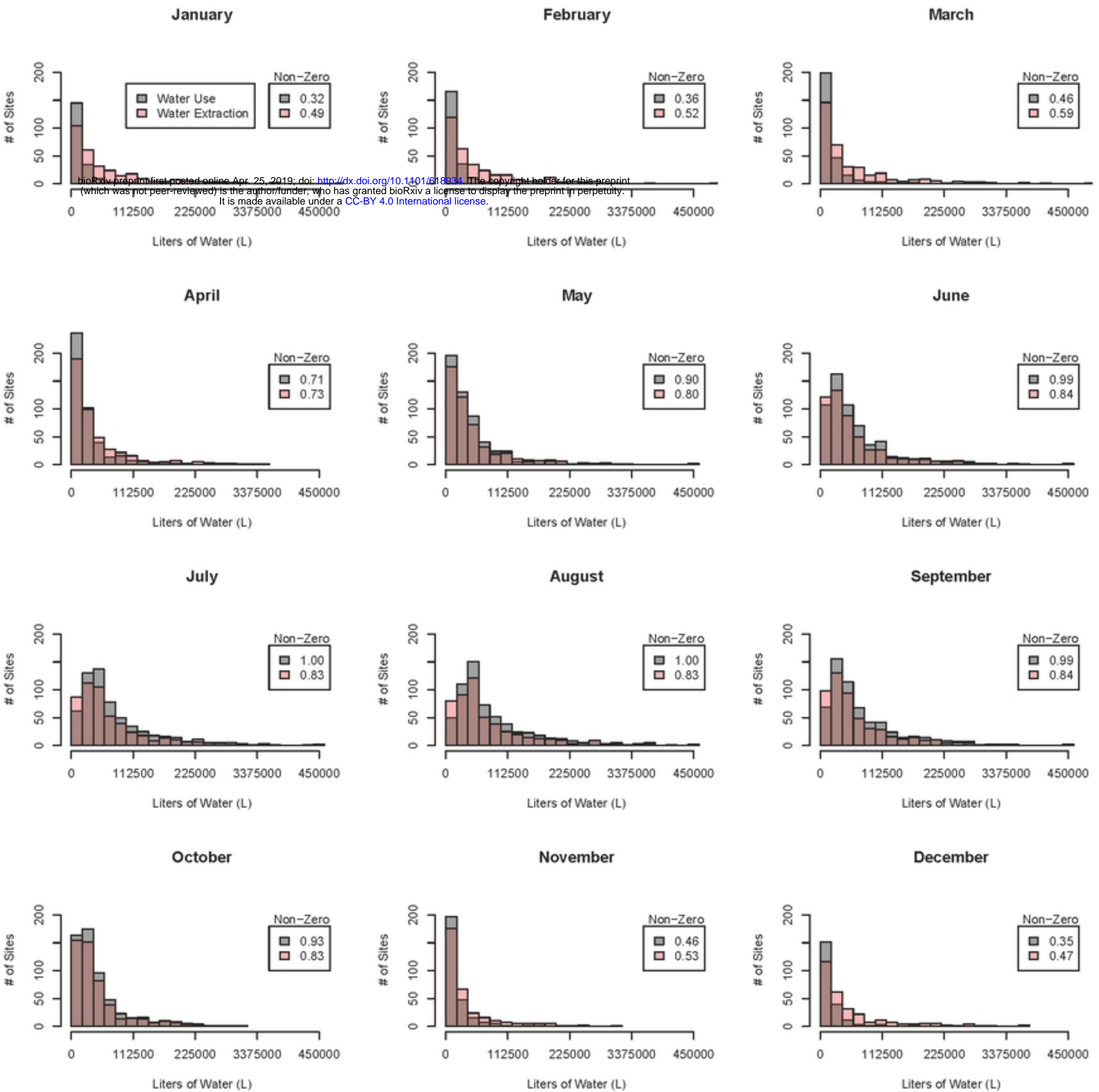


### Cultivation Area



### Storage Balance





Figure