

Assessing streamflow depletion from agricultural groundwater use in headwater catchments using storage-discharge functions

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24 **Key Points:**

25 1. Streamflow depletion from groundwater extraction can be estimated using watershed
26 storage-discharge sensitivity functions.

27 2. Simulated water withdrawals from headwater catchments reduce streamflow and
28 accelerate stream drying, particularly in dry years.

29 3. Simulations suggest cannabis irrigation depletes streamflow; however, impacts are likely
30 localized and hard to detect at broad scales.

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32
33

34 **Abstract:**

35 Groundwater extraction can deplete streamflow in headwater catchments, but the complexity of
36 subsurface hydrological processes make impacts difficult to detect. Using hydrograph-inferred
37 hillslope groundwater storage and streamflow relationships, we propose a novel approach to
38 estimate streamflow depletion from groundwater pumping that is well-suited to areas with limited
39 groundwater monitoring infrastructure. We apply this method in two well-studied watersheds in
40 California's North Coast to quantify potential hydrologic impacts of cannabis agriculture, which is
41 concentrated in the region and has been identified as a potential threat to salmon-bearing
42 streams. We use a scenario-based approach to explore the relative effects of cannabis
43 cultivation area, irrigation water source (groundwater pumping vs. surface diversion), irrigation
44 efficiency, stream discharge at the onset of the growing season, and lithology on streamflow
45 depletion risk. Our models show that Elder Creek, a perennial stream, could be de-watered by
46 the late dry season with high levels (1% land cover) of cannabis irrigation from groundwater
47 when discharge at the start of the dry season is 1mm/day. In Dry Creek, a non-perennial
48 stream, dry season flow cessation could be advanced by five weeks from similar levels of
49 cannabis water demands. Streamflow impacts are more pronounced in drier years, and the
50 impacts from well-water extraction exhibit a muted effect relative to surface water diversion of
51 the same volume. Storage-discharge functions, such as those presented in our case study,
52 could be applied to estimate impacts of groundwater extraction for water use (e.g., for cannabis
53 agriculture) in headwater streams wherever streamflow data are available.

54 **Plain Text Summary:**

55 Nearly all streamflow originates as groundwater draining from hillslopes upstream. Groundwater
56 extraction for agriculture or household use can reduce streamflow by removing this water from

57 the landscape before it emerges into stream channels. While this effect is well-
58 understood, determining groundwater pumping's impact on streamflow is challenging due to
59 uncertainties in water use practices, difficulty measuring underground water movement, and
60 seasonal and yearly environmental water abundance changes. We developed a new method to
61 estimate groundwater pumping's impact on streamflow based on observed streamflow and
62 precipitation, which are easier to measure than groundwater levels. We tested this method in
63 two watersheds in Northern California to understand how water use by cannabis farms,
64 common to the region, could impact streamflow. Our results suggest in dry years, groundwater
65 pumping can de-water streams that typically flow year-round and cause seasonally dry streams
66 to dry sooner. In Elder Creek, a stream with year-round flows, pumping from wells could dry the
67 stream by late summer. In Dry Creek, which naturally dries in summer, pumping could cause
68 drying five weeks earlier. This new method can be used to estimate water use impacts in other
69 small streams and help communities manage their water in ways that limit environmental
70 impacts.

71 **Introduction:**

72 In headwater catchments without snowmelt, groundwater draining from hillslopes is a primary
73 source of streamflow that sustains both the ecological and human communities that inhabit
74 these upland areas (Salve et al. 2012, Lovill et al. 2018). Groundwater extraction from upland
75 catchments has the potential to deplete streamflow, yet quantifying the relationship between
76 hillslope hydrology and streamflow is challenging due to the difficulty of accessing remote,
77 rugged terrain and the complexity of subsurface hillslope hydrology (Rempe and Dietrich 2018).
78 Current methods for monitoring and calibrating groundwater models, such as borehole
79 observations, are expensive and offer only fixed points of reference across a hillslope.
80 Furthermore, methods commonly used to assess streamflow depletion from groundwater

81 extraction from large aquifers may not be well-suited for representing the hillslope hydrologic
82 processes that sustain streamflow, particularly in systems with more complex subsurface
83 structure (Rempe and Dietrich 2018, Fan et al. 2019, Zipper et al. 2022). Streamflow gauges in
84 headwater catchments, though uncommon (Andrews and Grantham 2024), offer an opportunity
85 to estimate depletion responses in these systems.

86 Given these challenges, new approaches are needed to assess streamflow depletion
87 risk from water withdrawals in headwater catchments. This is particularly true in regions such as
88 Northern California, USA, where the widespread distribution of small surface water diversions
89 and groundwater extraction in upland watersheds is a growing threat to salmon and other
90 sensitive aquatic species (Grantham et al. 2010, Carah et al. 2015, Dilis et al. 2021). Common
91 approaches for modeling the impacts of pumping on stream discharge include process-based
92 hydrological models (such as MODFLOW (Barlow and Harbaugh 2006)) and analytical
93 depletion functions (Zipper et al 2019b). However, these methods rely on processes and
94 parameters that are difficult to measure in upland settings, where groundwater commonly
95 resides below soil in fractured bedrock aquifers. Such models are also not designed for
96 groundwater systems defined by channels and ridge boundaries (Hahm et al 2018) and where
97 streams rapidly respond to active hillslope hydrology on the timescale of individual storms. Here
98 we present an alternative approach that takes advantage of storage-discharge functions
99 (Kirchner 2009, Ajami et al. 2011), which describe the relationship between stream discharge
100 and hillslope- or catchment-scale water storage. These functions have been applied to estimate
101 the dynamic storage capacity and groundwater recharge in headwater catchments (Dralle et al.
102 2018, Dralle et al. 2023a), but their application in assessing streamflow depletion risk from water
103 withdrawals has not yet been explored.

104 Here, we investigate how groundwater pumping potentially affects streamflow in
105 headwater catchments using storage-discharge functions. We specifically simulate the effects of
106 water withdrawals for cannabis agriculture, which occurs throughout northern California and is

107 concentrated in small, upland watersheds (Butsic et al. 2017). Cannabis cultivation in the region
108 relies heavily on streams and groundwater to meet irrigation needs (Dillis et al. 2020 and 2021).
109 As such, cannabis agriculture has been identified as a threat to stream ecosystems (Bauer et al
110 2014, Carah et al 2015), but the potential magnitude of diversion impacts on streamflow remain
111 poorly understood. In this study, we take a scenario-based approach to quantify how cannabis
112 cultivation area, irrigation water source (well or surface diversion), irrigation efficiency, water
113 year type, and watershed lithology affect streamflow depletion risk. Our primary goal is to
114 demonstrate how storage-discharge relationships can be used to calculate the impact of
115 groundwater extraction on stream discharge in headwater catchments, which face growing
116 water-use pressures in California and many regions of the world. Additionally we highlight the
117 relative effect of factors that may influence streamflow depletion risk from cannabis agriculture
118 in two well-studied watersheds in California's north coast.

119 **Methods:**

120 **Storage-discharge sensitivity functions**

121 Runoff in forested headwater catchments is commonly driven by storage in hillslope
122 groundwater (the saturated zone). Storage-discharge functions use the recession behavior of
123 the stream itself to empirically quantify how changes in groundwater storage translate into
124 changes in flow. Such functions could be applied to estimate the effects of groundwater
125 pumping on streamflow depletion risk. The most straightforward approach to using storage-
126 discharge functions was well-described by Kirchner (2009), who assumed that stream discharge
127 (Q) is an unspecified, but uniquely-defined, function of catchment dynamic storage (S):

128

129
$$Q = f(S) \quad (1)$$

130

131 Dynamic storage is determined through a catchment-scale mass balance:

132

133 $dS/dt = P - Q - E$ (2)

134

135 Where P = precipitation and E = evapotranspiration

136

137 Kirchner (2009) introduced an additional representation of f , the catchment sensitivity function:

138

139 $g(Q) = f'(f^{-1}(Q)) = dQ/dS = \frac{dQ/dt}{ds/dt} = \frac{dQ/dt}{P - Q - E}$ (3)

140

141 The sensitivity function can be interpreted as the mathematical sensitivity of discharge to
142 changes in storage. That is, $g(Q)$ quantifies how much discharge will change for a given change
143 in catchment storage. In general, the sensitivity function is difficult to determine without
144 knowledge of all terms in the catchment mass balance. However, when P and E are small,
145 Equation 3 simplifies as:

146

147 $g(Q) = dQ/dS \approx -\frac{dQ/dt}{Q}$ when $P, E \ll Q$ (4)

148

149 That is, the sensitivity function can be empirically determined during periods of time when P and
150 E are small (e.g. on rain-free nights). Kirchner (2009) used this approach to successfully model
151 streamflow and storage in a pair of small, humid catchments in the UK. More generally, storage-
152 discharge functions have been applied in numerous hydrological modeling contexts (Teuling et
153 al. 2010, Rusjan et al. 2015, Adamovic et al. 2015).

154

155 However, Dralle et al. (2018) demonstrated a shortcoming of the approach; storage-discharge
156 functions inferred through this method cannot capture all aspects of dynamic storage in a
157 watershed. Instead, because $g(Q)$ is determined through flow recession only, it can only
158 “detect” changes in the storage that directly drive flow generation, i.e., groundwater. Other
159 reservoirs of dynamic storage in a watershed may exist, and may play a role in runoff
160 generation, but not **directly** affect Q . For example, near surface soil moisture may change due
161 to plant water use from the vadose zone, but this does not necessarily lead to changes in Q ,
162 since Q is driven by hydraulic pressure in the deeper groundwater zone. This leads to problems
163 in the interpretation of dQ/dS at the catchment scale, where not all storage changes actually
164 result in discharge changes. Consequently, the concepts outlined by Kirchner (2009) may be
165 easily interpretable in humid catchments, but in landscapes with significant unsaturated zone
166 storage dynamics, there may be large, dynamic reservoirs of water in the landscape that can
167 change without directly impacting flow. This would confound any simple interpretation of
168 hydrograph-inferred storage as including all storage in the watershed. Klaus et al. (2019)
169 resolved this ‘dual-storage’ issue, and discussed how it may lead to significant challenges
170 identifying a single sensitivity function that maps total dynamic storage (storage in the vadose
171 zone and groundwater) to streamflow.

172

173 Following Dralle et al. (2023a), we therefore refine the interpretation of the sensitivity function
174 as:

175

$$176 \quad g(Q) = dQ/dS_{gw} = \frac{dQ/dt}{R - Q - E_{gw}} \quad (5)$$

177

178 Where P has become R and is interpreted as a groundwater recharge term, and where E_{gw}
179 ($E_{gw} + E_{vz} = E$) is the portion of evapotranspiration that is sourced from the groundwater zone.

180

181 This formulation acknowledges that storage changes inferred through flow analysis only
182 concern the subsurface saturated reservoir that generates flow.

183 **Determining $g(Q)$**

184 We applied the modified storage-discharge function to determine $g(Q)$ in two focal watersheds:
185 Elder Creek and Dry Creek in northern California (see study area descriptions below). We
186 obtained daily streamflow timeseries for both streams and then imposed screening criteria to
187 select a subset of the data. Days were determined suitable for fitting the sensitivity function if (a)
188 there was no precipitation, (b) there was no precipitation in the preceding day, (c) discharge was
189 decreasing over the course of the day ($dQ/dt < 0$), and (d) the sample time was from November
190 - March. On days that satisfied these conditions, flow derivatives were calculated using forward
191 difference, and the binning and fitting procedure of Kirchner (2009), which results in a sensitivity
192 function that is quadratic on log scales.

193

194 $\ln(g(Q)) = \ln((-dQ/dt)/Q)$ (6)

195

196 Though the sensitivity functions were calculated from November - March, our analysis occurs
197 from May - September, which requires that the function be applied to some ranges of Q outside
198 those which were used to determine $g(Q)$. Despite this extrapolation, model fit was good (figure
199 2). For more detail see Dralle et al. 2023a and accompanying code.

200 **Assessing changes in streamflow from groundwater pumping**

201 The modified formulation (Eq 6) is particularly useful in the present context, where water
202 withdrawals for irrigation will come from the saturated zone of hillslopes. Indeed, we might

203 consider groundwater pumping (U) as a negative recharge from the groundwater reservoir, re-
204 writing mass balance as:

205

206 $dQ/dt = g(Q)(R - U - E_{gw} - Q)$ (7)

207

208 During the summer months when groundwater is pumped and plant water use is primarily
209 sourced from unsaturated soils and bedrock (Rempe and Dietrich 2018, Hahm et al. 2019),
210 Equation 7 can be simplified as:

211

212 $dQ/dt = -g(Q)(U + Q)$ (8)

213

214 This is a first order differential equation for Q , which can be solved under natural (i.e. $U = 0$) and
215 groundwater pumping (i.e. $U > 0$) scenarios.

216 **Case study: estimating streamflow depletion risk from cannabis
217 agriculture in northern California**

218 Study area (geographic setting, watershed characteristics, hydrology - as
219 represented by the models)

220 We focus on two intensively studied watersheds within the larger Eel River watershed, Elder
221 Creek and Dry Creek, which represent two dominant lithologies in this region. Elder Creek lies
222 entirely in the Franciscan Coastal Belt and Dry Creek in the Central Belt Melange. We provide a
223 brief overview of the physical and hydraulic properties of these watersheds below, but for more
224 details refer the reader to Hahm et al. (2019) and other studies (Dralle et al. 2017, Rempe et al.
225 2018, Lovil et al 2017, Hahm et al 2019, Dralle et al 2019, 2023a, 2023b). These watersheds

226 represent end members on the spectrum of dominant lithologies of the South Fork Eel River
227 (Dralle et al. 2023b). Despite differences in lithology and streamflow, these streams are only 20
228 km apart, and thus experience similar climate and weather. Storage-discharge sensitivity
229 functions have been calculated for both streams in previous work (Dralle et al 2018, 2023a)
230 using the methods described above.

231 Elder Creek

232 Elder Creek (16.9 km^2) cuts through deeply weathered, fractured shale and sandstone of the
233 Coastal Belt of the Franciscan Formation. Hillslopes in Elder have deep weathering profiles,
234 including fractured rock, saprolite, and soils, which contain large volumes (300 to 600 mm) of
235 dynamic storage in unsaturated soils, unsaturated weathered bedrock, and saturated weathered
236 bedrock. Dralle et al. (2018) estimate up to 100 mm of this dynamic water may be stored in the
237 saturated zone, with upwards of 500 mm stored in the unsaturated zone. Elder Creek receives
238 mean annual rainfall of roughly 2000mm/year. Over the course of the dry Mediterranean climate
239 summer, stream flow recedes, but cold perennial flow is supplied by the hillslope's large storage
240 capacity which flows from seeps and springs (Lovill 2018, Dralle et al. 2023b). Coastal Belt
241 landscapes tend to support mixed-conifer and conifer forests.

242 Dry Creek

243 Dry Creek (3.5 km^2) flows through Franciscan Coastal Belt Melange. This Melange is a mixture
244 of larger bedrock blocks of varying size and lithology suspended in a clay-like argillite matrix.
245 Melange landscape weathering profiles are thin, with a much smaller dynamic storage capacity
246 (200mm) compared to that of Coastal Belt hillslopes. Dry Creek receives mean annual rainfall of
247 roughly 1800mm. In the winter months, when precipitation exceeds this low storage capacity,
248 the water table rises until it intersects the ground surface, generating streamflow and producing
249 flashy peak flows in stream channels. The low storage capacity of melange landscapes cannot

250 support perennial summer flow; Dry Creek discharge usually ceases within 2 months of the final
251 storm of the wet season. Melange landscapes tend to support Oak-Savannah habitat, with
252 patches of more dense vegetation and springs near larger blocks of sandstone and shale
253 suspended in the melange matrix (Hahm et al. 2019).

254 Cannabis water use scenarios

255 We applied storage-discharge functions to estimate streamflow depletion risk in our two study
256 watersheds using a scenario-based streamflow modeling approach. We combined categorical
257 levels of irrigation source (groundwater or surface water), farm water-use efficiency, areal
258 coverage of cannabis cultivation on the landscape, lithology, and initial streamflow conditions
259 during the growing season as parameters to create hypothetical scenarios that represent the
260 wide range of potential impacts streams might experience on the landscape (Table 1). By
261 systematically designing and evaluating water use scenarios, we are able to isolate the effects
262 of each parameter, rather than attempting to detect effects through empirical measurements of
263 the environment. Using $g(Q)$ and each combination of parameter values described above, we
264 generated synthetic hydrographs which were then used to assess the effects of each parameter
265 on streamflow magnitude and duration of discharge during the growing season (see section
266 “Determining $g(Q)$ ”). By specifying all combinations of parameter values for the two watersheds,
267 we generated and evaluated 580 unique scenarios by predicting daily discharge and number of
268 days with zero flow ($Q = 0$) and comparing predicted values with expected, unimpaired
269 conditions during the growing season (May - September).

270 Initial flow

271 Initial flow values represent the discharge (mm/day) at the start of the spring irrigation season in
272 May, when streamflow is entirely fed by groundwater inflows and naturally begins to recede. Higher

273 values are representative of more subsurface storage and lower values representative of less.
274 Values were chosen to range from 0.1 to 10 mm/day for both streams, which includes the
275 natural range of variation at the end of the wet season for both streams, and conditions outside
276 of those currently observed. We chose a wider range than currently observed to encompass the
277 range of conditions that may occur with climate change.

278 Farm water-use

279 We define farm water-use as the area-normalized volume of cannabis farm irrigation demand.
280 Dillis et al. (2023) modeled the amount of water used by both permitted and unpermitted farms
281 to irrigate cannabis crops, and we use those estimates for farms in Mendocino and Humboldt
282 Counties. In our scenarios, we assumed farms did not use on-site storage and thus extracted
283 water from the environment for immediate irrigation use according to seasonal plant water
284 demands (figure S2). Using water-use estimates from farms without storage (N = 7115), we
285 area-normalized monthly-water use estimates (mm/day). There was substantial variation in
286 normalized water-use estimates and we selected median, 75th, 90th, and 95th percentiles as
287 categorical parameter values, reflecting variation in water-use, in our model scenarios (Figure
288 S2). Monthly water demand estimates were used to interpolate daily values.

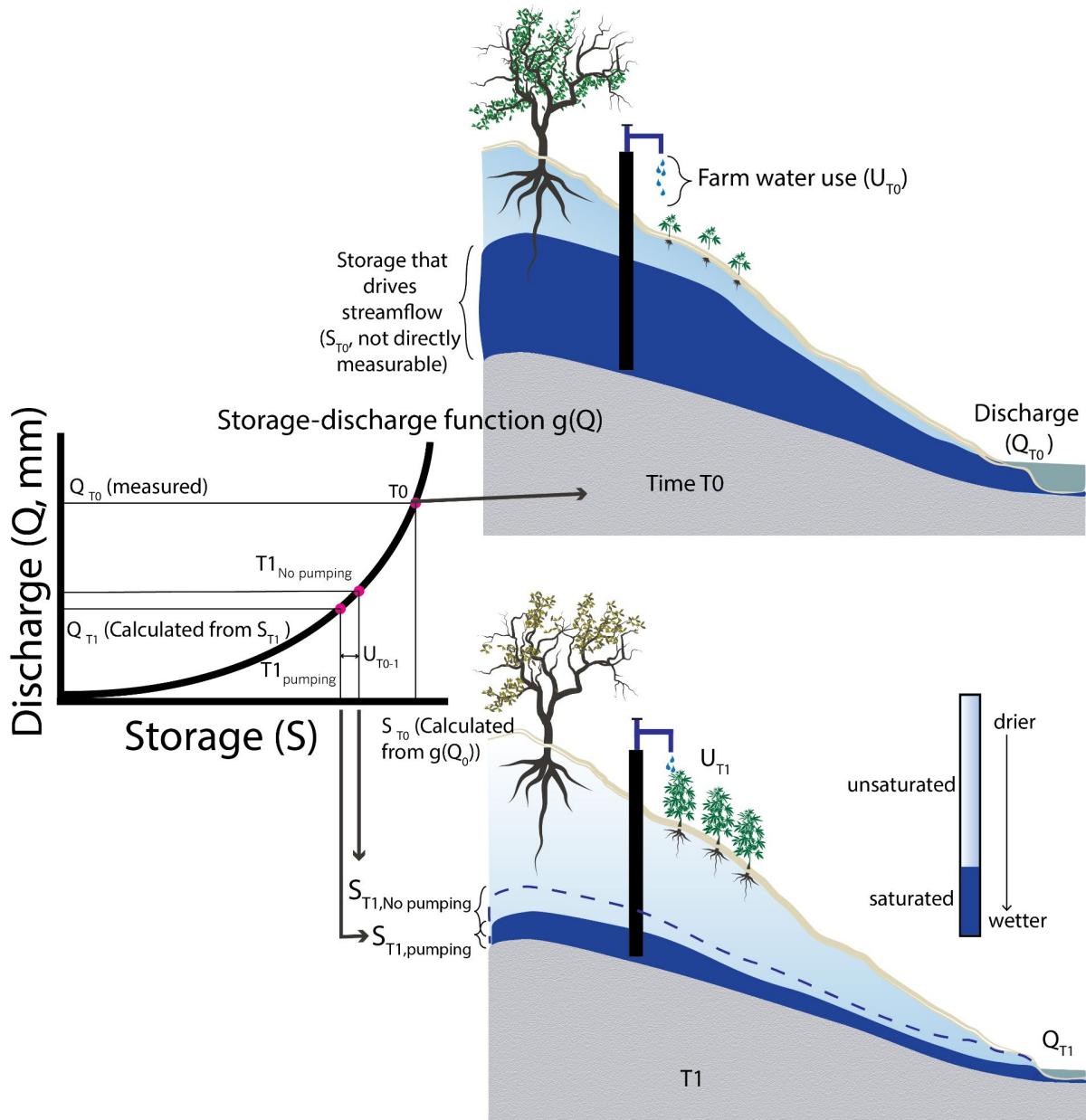
289 Areal coverage of cannabis agriculture

290 To determine the extent of cannabis agriculture to use in our scenarios, we evaluated the spatial
291 coverage of cannabis farms in Mendocino and Humboldt counties reported by Butsic et al.
292 (2018). We calculated the total coverage of cannabis farms relative to the area of watersheds at
293 multiple scales, including hydrologic unit code (HUC) 12 watersheds, reported in the USGS
294 2019 National Hydrography Dataset (Figure S2), representative of our two focal watersheds.
295 We found that cannabis cover ranged from 0 - 13.059% (median = 0.078%, 95th percentile =

296 0.666%) coverage of watershed area and we chose to analyze coverage of 0.05, 0.1, 0.5, 1, 5,
297 and 10% for our scenario analyses.

298 **Water source**

299 We modeled two sources of water extraction by farms: surface water diversions and
300 groundwater pumping (wells). Wells are the most abundant source of extraction in the North
301 Coast, but surface water diversions also occur, particularly in wetter watersheds (Dillis et al.
302 2019a). To calculate total daily water use (U , mm/day) within each of our scenarios, we
303 multiplied the percent area of cannabis cultivation in the catchment by the farm water-use
304 percentile value. We solve for Q in both water source scenarios by integrating Equation 8 (with
305 $U=0$ in the solver for surface water diversions) through the growing season with the `solve_ivp`
306 function from Python's SciPy package. In our surface water diversion scenarios, the pump rate
307 (U) was subtracted from the modeled unimpaired hydrograph for that day, which resulted in the
308 impaired discharge from surface diversions on a given day. For the groundwater pumping
309 scenarios, $U>0$ in Equation 8 accounts for water used by cannabis agriculture that is removed
310 from the dynamic storage that contributes to streamflow (Figure 1). See section "Assessing
311 changes in discharge from groundwater pumping" for details of how groundwater extraction was
312 incorporated into storage-discharge functions.



313

314 Figure 1. Representation of the storage-discharge relationship within a hillslope at two
 315 timepoints (T0 and T1). At time T1, the dashed blue line represents where the saturated zone
 316 would be if there were no groundwater pumping on the hillslope.

317

318 Table 1. Parameter levels used to generate synthetic hydrographs and streamflow depletion
 319 scenarios.

Model parameter	Levels
Initial flow (mm/day)	0.1, 0.5, 1, 5, 10
Water source	Surface diversion, groundwater extraction
Areal coverage of cannabis on landscape (percent farm area relative to catchment area)	0.01, 0.05, 0.1, 0.5, 1, 5, 10
Farm water-use efficiency	Percentiles of monthly farm water use presented in Dillis et al. (2023) percentiles were 0.5, 0.75, 0.9, 0.95
Stream type	Elder Creek (Coastal Belt), Dry Creek (Melange)

320

321 **Responses of streamflow and categorizing depletion**

322 For each scenario, we calculated the percent reduction in total summer discharge and number
 323 of zero-flow days predicted to occur. These response variables were chosen for their ecological
 324 significance to fish and other species dependent upon streamflow. After calculating percent
 325 reduction in summer discharge and number of days without surface flow in each scenario, we
 326 used these responses to generate effect sizes of all independent variables using linear models.
 327 Four linear models were created, one for each catchment and one each for our response
 328 variables of summer discharge and number of days with zero flow. The parameter estimates
 329 from these linear models were reported as effect sizes.

330

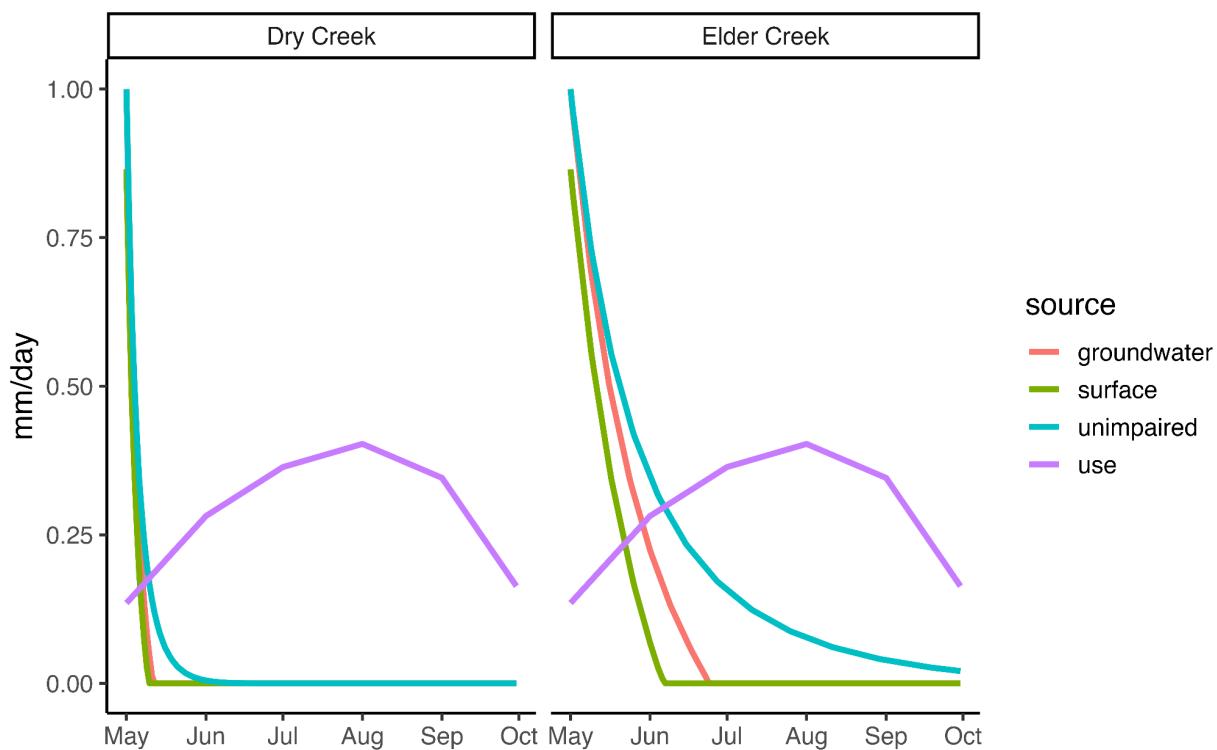
331 **Open Research and Data Accessibility**

332 All data management, plotting and statistical analysis were conducted Using R statistical
 333 software (Version 2023.12.0, R Development Core Team 2012) we used linear mixed-effects
 334 models (LMM, “lme4” package in R) to quantify the following parameters. Storage-discharge
 335 sensitivity functions and (un)impaired discharge time series were computed using Python. All

336 code and data can be found in the GitHub repository available on Zenodo [DOI:](#)
337 [10.5281/zenodo.14902190](https://doi.org/10.5281/zenodo.14902190)

338 **Results:**

339 Lower initial flow (discharge at the start of the growing season), higher percent coverage of
340 cannabis, higher pumping rates, and extraction from surface water all lead to lower summer
341 discharge and more days of zero flow (Figure 2, Figure 3, Figure 4 , Figure 5). Initial flow had
342 the greatest impact on summer discharge followed by extraction source, farm use efficiency,
343 and finally areal coverage of cannabis (Figure 5A). The number of zero-flow days was most
344 strongly influenced by water source, followed by areal coverage, use efficiency, and initial flow
345 (Figure 5B). Below, we highlight specific scenarios that illustrate the effects of each parameter,
346 which are summarized graphically (Figure 3 & Figure 4) and in effect-size calculation (Figure 5).



347

348 Figure 2: Example curves from modeled scenarios with lines for measured discharge (Q, blue),
 349 modeled unimpaired discharge using storage-discharge sensitivity function (dashed orange),
 350 Impaired hydrograph resulting from surface water withdrawal (red), modeled impaired
 351 hydrograph resulting from groundwater pumping (green), and the modeled water use or
 352 irrigation rate (purple). Both hydrographs show the scenario for parameter values Initial
 353 discharge = 1 mm/day, 90th percentile farm use efficiency, 5% areal coverage of cannabis.

354

355 Table 2. Selected scenario runs which showcase the impacts of each parameter on response
 356 variables of cumulative summer flow and number of zero flow days

357

Catchment	Extraction source	Initial flow (mm/day)	% areal coverage cannabis agriculture	Farm use efficiency percentile in summer	Percent reduction of zero flow	Number of days with zero flow	Additional zero-flow days
Dry	surface	0.5	1	0.5	12.95	133	30
Elder	surface	0.5	1	0.5	19.43	22	22
Dry	surface	10	1	0.5	1.7	124	31
Elder	surface	10	1	0.5	2.6	0	0
Dry	groundwater	10	1	0.5	1.35	123	30
Elder	groundwater	10	1	0.5	1.89	0	0
Dry	groundwater	10	0.1	0.5	0.21	111	18
Elder	groundwater	10	0.1	0.5	0.19	0	0
Dry	groundwater	10	1	0.95	3.2	129	36
Elder	groundwater	10	1	0.95	5.85	30	30
Elder	groundwater	10	10	0.5	6.9	68	68
Dry	groundwater	10	10	0.5	12.58	135	42

358

359 **Water source**

360 Using $g(Q)$ (equation 5) to estimate streamflow depletion from groundwater pumping, we were
361 able to compare the impacts of extracting similar volumes of water from surface water versus
362 groundwater on discharge. Water extraction from wells had a muted impact on discharge
363 relative to direct surface water diversions (Figure 2). Water extraction from wells also resulted in
364 less streamflow depletion over the course of the summer (Figure 2, Figure 3A, Figure 4) and
365 fewer zero flow days (Figure 3B). There were also significant differences in the responses of the
366 two study watersheds to water extraction. In Elder Creek (with median water use, initial
367 discharge of 10mm/day, and 1% cannabis on the landscape), surface water diversions resulted
368 in a 2.6% decrease in cumulative summer discharge no (0) zero-flow days occurred. In contrast,
369 when all diversions were from groundwater, Elder had a 1.9% decrease in summer flow (and
370 also no zero-flow days). In Dry Creek, surface water diversions resulted in 1.7% decrease in
371 cumulative summer discharge and 124 zero-flow days (Table 2). When all diversions were from
372 groundwater, Dry Creek had a 1.35% decrease in summer flow and 123 zero-flow days (Table
373 2).

374 **Initial flow**

375 Initial flow greatly impacted the amount of summer discharge (Figure 4) and number of zero-
376 flow days in both of our study streams, but had a greater impact on Elder Creek than Dry Creek
377 (Figure 5B). Initial flow also modulated the sensitivity of the streams to flow depletion from
378 cannabis irrigation (Figure 5). For example, when total volume of water extracted was held
379 constant (at 1% areal coverage of cannabis, median water use, and surface water extraction),
380 the percent reduction in summer discharge at 0.5mm/day and 10mm/day initial flow in Elder

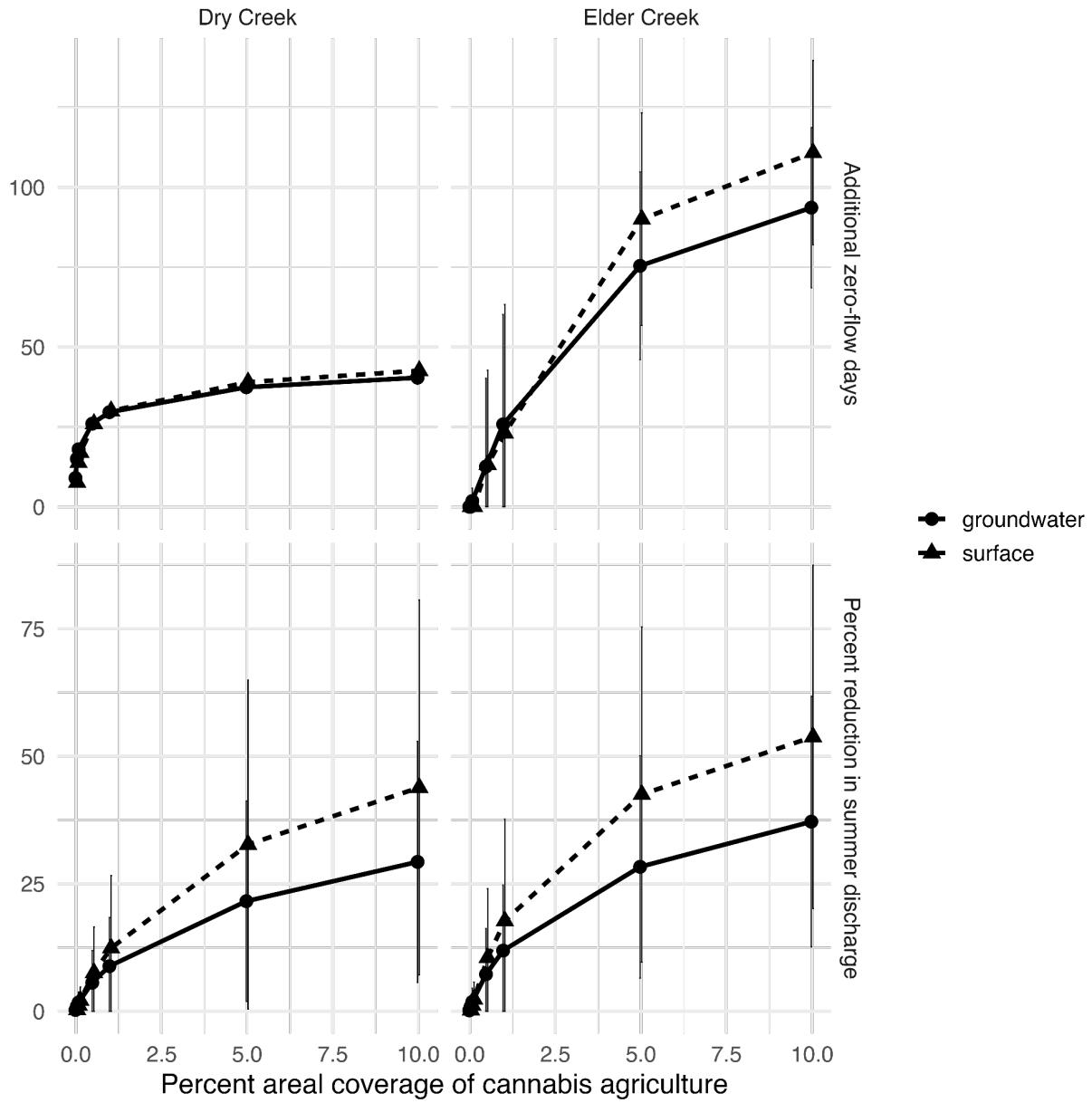
381 Creek's summer discharge was 19.4% (3.66 mm decrease from unpaired) and 2.6% (3.67 mm
382 decrease from unpaired), respectively. Dry Creek's total summer discharge decreased 13.0%
383 (0.39 mm decrease from unpaired) when initial discharge was 0.5mm/day, but only a 1.7%
384 (0.59 mm decrease from unpaired) with 10mm/day of initial discharge (Tabel 1). In the 0.5
385 mm/day initial condition scenarios (corresponding to a wet season with low precipitation and
386 storage), Elder Creek was predicted to experience 22 days additional of zero-flow (22 total) and
387 Dry Creek, 30 (130 total). When initial flows were increased to 10mm/day (corresponding to a
388 wet season with high precipitation and storage), Elder Creek's predicted number of additional
389 zero-flow days were 0 and Dry Creek 31 (124 total, Tabel 1).

390 Cannabis farm water use

391 Higher area-normalized water use by farms decreased cumulative summer discharge and
392 increased the number of zero-flow days. Comparing two similar scenarios (groundwater
393 pumping, initial flow of 10mm/day discharge, and 1% areal coverage of cannabis), median water
394 use in Elder Creek was predicted to have a 1.9% decrease in total summer discharge and no
395 zero-flow days. However, when farms were less efficient and used more water, estimated from
396 the 95th percentile of observed area-normalized water use, percent reduction in summer
397 discharge increased to 5.9% and zero-flow days increased to 30. In Dry Creek, similar
398 scenarios with the same parameter levels and median water use produced a 1.35% decrease in
399 cumulative summer discharge and 30 additional zero-flow days (123 total), while 95th percentile
400 use resulted in 3.2% reduction in summer discharge and 36 additional zero-flow days (129 total)
401 (Table 2).

402 Areal coverage of cannabis agriculture

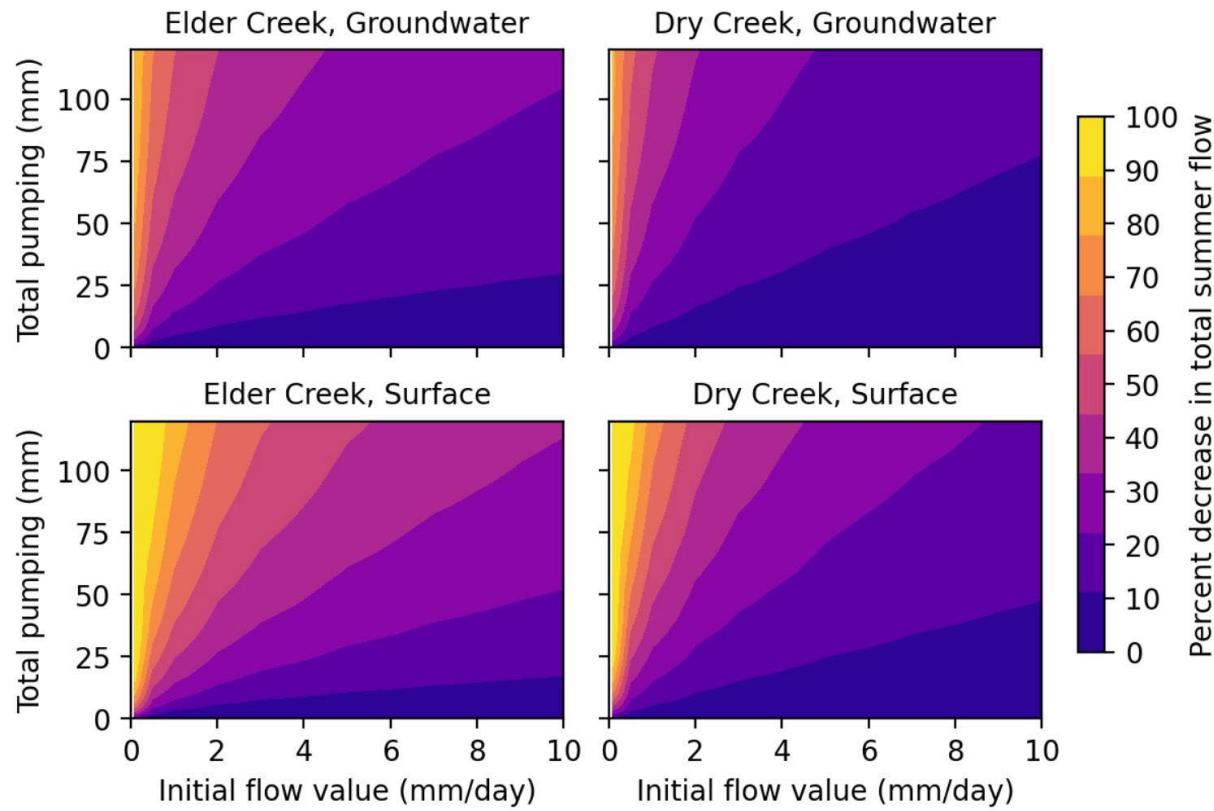
403 With greater area of cannabis agriculture in our scenarios, cumulative summer discharge
404 decreased and the number of zero-flow days increased. At 0.1% cannabis coverage, (holding
405 groundwater pumping, initial flow of 10 mm/day, and median water use constant), Elder Creek
406 had a predicted percent loss of cumulative summer discharge of 0.19% and 0 zero-flow days.
407 Under the highest level of aerial coverage observed in the region (10%), however, summer
408 discharge losses increased to 12.6% and zero-flow days increased to 68. Dry Creek in these
409 same scenarios had a predicted percent loss of cumulative summer discharge of 0.21% and 18
410 additional zero-flow days (111 total) at 0.1% cover and 6.9% loss of summer discharge and 42
411 additional zero-flow days (135 total) at 10% cover (Table 2).



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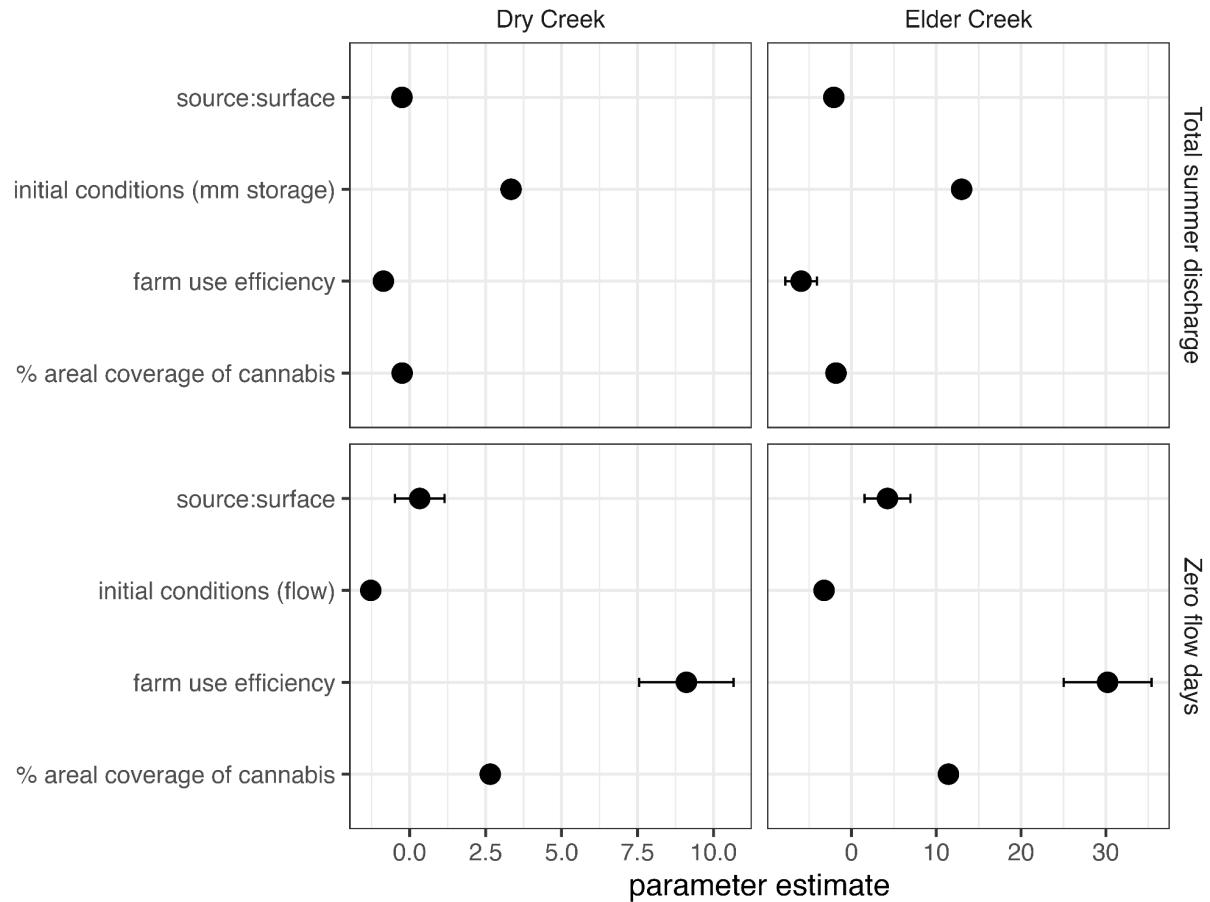
414 Figure 3: Summaries of number of additional days of no flow (top row) and reduction in summer
 415 discharge (bottom row) for median farm water use. Dashed lines represent surface water
 416 withdrawals, solid lines groundwater withdrawals. Dry Creek is shown on the left panels and
 417 Elder Creek on the right. Error bars show standard deviation around estimates.



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420 Figure 4: Heatmaps showing the proportional reduction in summer flow resulting from
 421 combinations of different initial discharges that represent water year type and a composite water
 422 use axis (areal coverage x pumping rate). Cooler colors represent lower reductions in summer
 423 flow compared to warmer colors.



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427 Figure 5: Effect size plots for each of our parameters of interest that were included in the
 428 modeled scenarios, note the difference in scale of x-axis between streams. Effect sizes are
 429 parameters estimates extracted from Linear models with A. total Summer discharge, and B.
 430 number of days with zero surface for both our study streams. Error bars are standard error.

431 Discussion:

432 Storage-discharge relationships have previously been used to predict streamflow patterns
 433 (Kirchner 2009), estimate the amount of hillslope storage that does not directly contribute to
 434 streamflow (Dralle et al. 2018), and infer groundwater recharge (Ajami et al. 2011, Dralle et al.

435 2023). In this novel application, we remove water from storage that represents an agricultural
436 demand on the landscape, and use this to calculate changes in discharge throughout the
437 summer streamflow recession period. This application of storage-discharge relationships fills a
438 much-needed gap in simulating groundwater dynamics in upland headwater catchments and
439 potentially improves our ability to manage water resources for both human and environmental
440 use in these systems. Though our case study focused on cannabis cultivation, which is a major
441 agricultural crop in headwater catchments in Northern California's (Butsic 2018), these methods
442 can readily be applied to estimate the impacts of other uses of groundwater and surface water
443 in headwater streams.

444 Storage-discharge functions can be powerful tools for simulating headwater stream
445 dynamics, but data inputs and the resulting inferences must be scaled appropriately. Storage-
446 discharge relationships are most relevant for *catchment*-scale assessments. In particular,
447 diversions are not represented as discrete points on the landscape, but are considered as an
448 aggregated flux of water out from catchment storage (e.g., conceptually analogous to a uniform
449 drawdown of groundwater storage across all points in the landscape). However, in reality,
450 cannabis farms are often clustered on landscapes and hillslopes, and this clustering likely
451 concentrates impacts at smaller scales (Butsic et al. 2019). In addition, wells are often
452 positioned immediately adjacent to water sources. Particularly in melange landscapes (such as
453 the Dry Creek watershed), sandstone blocks are often associated with perennial water sources
454 that provide unique local habitats for aquatic and terrestrial species. Extraction from these
455 sources could have an outsized impact on the organisms that rely on these wet refuges in
456 otherwise dry landscapes. Wells positioned close to stream channels may approach surface
457 water extraction. In other circumstances, the spatial configuration of diversions could buffer
458 impacts. Because adjacent hillslopes that feed streamflow in the same catchment act
459 independently (Hahm et al. 2019), the absence of cannabis cultivation on some of these
460 contributing hillslopes should prevent complete stream dewatering. Additionally, our analysis

461 does not consider the case of groundwater pumping locally lowering the water table below the
462 stream channel, reversing head gradients and resulting in losing stream conditions. Overall, our
463 methods are useful for understanding the impacts at the catchment scale and allow for isolation
464 of the effects of different parameters on streamflow. However, on scales smaller than the
465 catchment level, future studies are needed to understand how storage-discharge methods can
466 be used to explore how the spatial distribution of extraction networks within catchments
467 differentially affect streamflow.

468 Here we demonstrate that cannabis agriculture in California's North Coast has the
469 potential to substantially reduce streamflow. However, our results also suggest that farms could
470 substantially decrease their impact by using more efficient irrigation practices. There is wide
471 variation in modeled area-normalized irrigation rates of farms (Figure S1, Dillis et al. 2023).
472 Users withdrawing the largest amounts of water per unit area have an outsized impact. Drip
473 irrigation, soil moisture sensors, and further understanding of plant water demand could
474 potentially decrease the volume of water being applied to plants without reducing yield.
475 Additionally, on-site storage in the form of ponds or tanks can decouple plant demand from
476 water extraction so that the late-summer overlap of high demand and low streamflow is
477 minimized (Dillis et al. 2020). Economic incentives for farmers to implement otherwise cost-
478 prohibitive storage options could reduce the impacts of irrigation during the summer months,
479 which coincide with the most stressful periods for many aquatic organisms. Finally, it is worth
480 noting that most catchments in Mendocino and Humboldt have relatively small areal coverages
481 of cannabis (median 0.078%, Figure s2). This suggests widespread impacts in these systems
482 are likely to be limited. Nevertheless, the high coverage of cannabis in some catchments, and
483 the propensity of cannabis to cluster in concentrated areas of the landscape (Butsic et al.,
484 2017), indicate that the potential for local impacts is still significant and warrants attention from
485 natural resource managers.

486 In our study streams, groundwater pumping is predicted to have a muted effect on
487 streamflow relative to surface water withdrawals of comparable magnitude. However,
488 groundwater extraction still has the capacity to greatly influence the amount and timing of
489 streamflow (Figures 2, 3, 4, 5). Groundwater pumping might result in a marginally smaller
490 reduction in discharge and also fewer zero-flow days over the course of the growing season,
491 relative to direct surface water diversions, (Table 2, Figure 3, 4), but still has the potential to
492 substantially decrease streamflow. In catchment systems where subsurface storage is greater
493 than annual precipitation, pumping could have multi-year impacts by reducing groundwater
494 reserves with resulting time-lagged impacts on streamflow (Zipper et al. 2019a). Additionally,
495 extracting water from groundwater may disproportionately influence certain organisms,
496 particularly phreatophytic vegetation, that could have used water on its path through the
497 hillslope to the stream channel. Farmers and resource managers should therefore carefully
498 consider potential impacts, location of wells, and groundwater storage capacity of the catchment
499 of interest in designing farm water systems.

500 The underlying lithology, and thus hydrogeology, of our study streams influenced how
501 streamflow responded to water extraction. Melange landscapes such as Dry Creek have less
502 storage capacity relative to those dominated by coastal belt lithology (Hahm et al. 2019).
503 Because of this, similar volumes of water extraction impact melange landscapes, and the
504 streams that flow through them, more intensely, particularly at low extraction volumes. In our
505 simulations, we saw substantially earlier de-watering of Dry Creek at cannabis coverages that
506 are represented on the landscape (Table 1, Figure 3, 4). This earlier drying could
507 catastrophically impact stream dependent organisms that live near their physiological limits in
508 these seasonally dry systems. In contrast, the potential impact to coastal belt streams is
509 particularly intense at high extraction volumes (cannabis area x extraction rate). While the
510 impacts on intermittent melange streams tend to plateau, perennial coastal belt streams can be

511 completely de-watered, removing key habitat for cool water organisms that rely on these
512 habitats.

513 The hydrologic impacts of water withdrawals in turn have consequences for the ecology
514 of the stream and riparian communities in these systems. Earlier drying of naturally intermittent
515 streams, such as Dry Creek, can impact aquatic organisms by disrupting phenology, or the
516 timing of life history events, and create mismatches between organisms and their environment.
517 For example, a more rapid onset of intermittency may lead juvenile salmonids to outmigrate
518 from streams before they can take advantage of seasonal peaks in food production (Dralle et al.
519 2023b). Fish that are unable to migrate are often confined to isolated pools, where they
520 experience high mortality from elevated water temperatures, low dissolved oxygen, increased
521 predation risk, and/or desiccation (Rossi et al. 2023; Obedzinski et al., 2018). Any reduction in
522 water availability from withdrawals could be expected to intensify these effects. Despite their
523 seemingly harsh conditions, in wet years, intermittent streams are heavily used by native
524 aquatic species (Wigington et al., 2006; Obedzinski et al., 2018). The reduction or loss of these
525 important habitats from water withdrawals could therefore be particularly detrimental to salmon
526 populations (Wigington et al. 2006). The reduction of streamflow in perennial streams, such as
527 Elder Creek, can also have significant ecological effects. Under very large extraction volumes,
528 even historically perennial streams like Elder Creek could experience a state change to
529 intermittency (Figure 2, 3, 4, 5). For organisms in these streams that are adapted to cool
530 perennial flows, a shift to intermittent conditions would represent a significant disturbance
531 (Bogan and Lytle 2011).

532 **Conclusions:**

533 In this study, we advance the application of storage-discharge relationships to predict
534 how groundwater extraction influences streamflow in headwater catchments. Subsurface water
535 dynamics are inherently difficult to observe in hillslopes, and storage discharge relationships

536 can help predict impacts to streamflow in moderate- to high-gradient catchments affected by
537 human land- and water-use pressures. We demonstrate the application of these methods with
538 cannabis agriculture in northern California, but the same approach could be used to investigate
539 the impacts of any human activity that extracts groundwater from the landscape in similar
540 mountainous regions of the world.

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