

1 **Abbreviated title: Hypoxia in temperate headwaters**
2 **Title: Hypoxia is common in temperate headwaters and driven by hydrological extremes**
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12 **Abstract**

13 Hypoxia, or dissolved oxygen (DO) at low enough levels to impair organisms, is a
14 particularly useful indicator of the health of freshwater ecosystems. However, due to limited
15 sampling in headwater networks, the degree, distribution, and timing of hypoxia events are
16 not known across the vast majority of most river networks. We thus sought to clarify the
17 extent of hypoxia in headwater networks through three years of instrumentation of 78 sites
18 across eight temperate, agricultural watersheds. We observed broadly distributed hypoxia,
19 occurring 4% of the time across 51 of the 78 sites over 20 months. The hypoxia was driven by
20 three mechanisms: storm events, drying, and rewetting, with drying as the most common
21 driver of hypoxia (55% of all hypoxic event types). Drying induced hypoxia was most severe
22 in smaller streams (Strahler orders ≤ 3), whereas storm events preferentially induced hypoxia
23 in the larger streams (Strahler orders 3–5). A large diversity in DO trajectories towards
24 hypoxia depended on hydrologic event type, with subsequent expected differences in
25 mortality profiles of a sensitive species. Predictive models showed the most vulnerable sites
26 to hypoxia were small streams with low slope, particularly during hot, low discharge periods.
27 Despite variation among hypoxic events, there was remarkable similarity in the rate of DO
28 drawdown during hypoxia events (ca. $1 \text{ mg O}_2 \text{ L}^{-1} \text{ d}^{-1}$). This drawdown similarity may be a
29 useful rule-of-thumb for managers, and we hypothesize that it is a signal of increasing
30 downstream network-scale oxygen demand. Overall, we posit that hypoxia is likely a
31 common feature of most headwater networks that often goes undetected. Headwater hypoxia
32 may become more common under increasingly dry conditions associated with climate and
33 water resource management changes, with important implications for biological communities
34 and biogeochemical processes.

35 **keywords:** drought, hypoxic, drying, storms, rewetting, dissolved oxygen, temperature

36 **Introduction**

37 Low oxygen concentrations in fresh and salt waters are common and increasing in both
38 spatial and temporal extent around the world (Breitburg et al., 2018; Jenny et al., 2016). While
39 mechanisms driving low oxygen concentrations, or hypoxia, are well documented in lakes and
40 coastal areas, it is less well documented or understood in river networks that are often assumed
41 to be oxic. Hypoxia is known to lead to mortality (Rabalais et al., 2010 and references therein),
42 mobilize chemically reduced contaminants into the water column (Saup et al., 2017), and
43 exacerbate greenhouse gas emissions (Bastviken et al., 2004). Sparked both by these growing
44 environmental concerns and by a proliferation of rather inexpensive, accurate, and rugged
45 dissolved oxygen sensor technology (Rode et al., 2016), interest is mounting to understand the
46 spatiotemporal distributions of hypoxia in river waters (Dutton et al., 2018; Garvey et al., 2007).
47 Yet, of these river systems, headwater stream hypoxia dynamics are still the least understood
48 (Blaszcak et al., 2019; Carter et al., 2021; Gómez-Gener et al., 2020; Pardo and García, 2016).

49 Hypoxia in river systems can arise from a number of interacting processes linked to high
50 levels of respiratory or reductive processes somewhere in the hydrologic network. Broadly
51 speaking, we can define five underlying drivers of hypoxia, each of which is associated with
52 amplified respiratory processes. In no particular order, there are: 1) excess N and P input leading
53 to eutrophication, particularly in lakes/estuaries (Breitburg et al., 2018; Smith and Schindler,
54 2009), 2) point source pollution (Mallin et al., 2006; McConnell, 1980), 3) storms, which can
55 bring in low O₂ groundwater (Carter et al., 2021) or oxygen demanding substances (Dutton et al.,
56 2018; Kerr et al., 2013; Whitworth et al., 2012), 4) drying (Pardo and García, 2016; Tramer,
57 1977), and 5) rewetting, which may stimulate microbial activity (Acuña et al., 2005). These
58 varied drivers, in particular storms, drying, and rewetting, may have distinct hypoxic signatures
59 that are important for the survival of biota.

60 The low primary productivity relative to respiratory processes (Diamond et al., 2021;
61 Vannote et al., 1980) and increased likelihood for drying of headwater streams (Godsey and
62 Kirchner, 2014) suggests their trends towards longer and more frequent hypoxia events. Still,
63 most studies on stream hypoxia focus on humid climate streams and rivers larger than Strahler
64 order 2; less is known regarding the smaller order streams of headwater networks (Bishop et al.,
65 2008) that typically experience greater flow intermittence (Gómez-Gener et al., 2020). These
66 headwaters are the network capillaries connecting land to the river network and they physically
67 dominate total stream length and benthic area of river networks (Benstead and Leigh, 2012;
68 Strahler, 1957). By not studying this dominant portion of river networks, there may be a large
69 underestimation of the total extent of freshwater hypoxia.

70 Hypoxic episodes may become more common in headwaters under increased climate-
71 driven drought frequency and intensity (Dai, 2013; Samaniego et al., 2018), especially in
72 agricultural areas already experiencing irrigation-induced water deficits (Elliott et al., 2014). The
73 link between hydrologic extremes and hypoxia further suggests that headwaters may exhibit
74 disproportionately more hypoxia than downstream reaches, as they typically have greater
75 hydrologic responses to climate and land use change. Moreover, small stream drying patterns
76 typically lead to the formation of pools and hydrologic disconnection, i.e., “pooling” (Godsey
77 and Kirchner, 2014; Stanley et al., 1997) with understudied effects on subsequent heterogeneity
78 in oxygen and community physiological effects.

79 We addressed these research gaps by studying the oxygen regimes in agricultural
80 headwater rivers to assess the environmental conditions leading to headwater hypoxia, and the
81 subsequent degree of hypoxia throughout the networks. We hypothesized that hypoxic events
82 would arise under drying, storm, and rewetting conditions, but that hypoxia would be greatest

83 and most common in the smallest streams due to their increased risk for drying and pooling. We
84 further evaluated the potential impact of hypoxia on aquatic animal communities using the
85 modeled mortality response of the amphipod *Gammarus fossarum*, a sentinel organism of water
86 quality in stream ecosystems (Chaumot et al., 2015; Kunz et al., 2010) known for its sensitivity
87 to dissolved oxygen (Hervant and Mathieu, 1995; Maltby, 1995; Meijering, 1991). We
88 hypothesized that the model organisms would exhibit a mortality threshold response to lower
89 DO, which we could use as a way to set an ecologically relevant definition of hypoxia in our
90 stream networks.

91 **Methods**

92 *Study area*

93 We instrumented 78 sites, spanning Strahler orders 1–5 across eight catchments in
94 France: 1) Coise, 2) Loise, 3) Toranche, 4) Mare, 5) Lignon, 6) Ardières, 7) Vauxonne, and 8)
95 Yzeron (Figure 1, Table 1). These catchments were monitored for hypoxia between 3 July 2019
96 to 15 October 2021 (except winters from November 1–February 28) The first five catchments
97 (Coise–Lignon) are primarily agricultural headwater catchments of the Loire River basin, and
98 were instrumented from July 2019–October 2020, with 4, 11, 16, 8, and 3 sites in orders 1–5,
99 respectively. In these catchments, granite and gneiss lithology at upper catchment boundaries
100 gradually gives way to thick alluvium with clay and sand at catchment outlets in a flat basin
101 known as the Forez plain. The geology in the upper reaches prevents substantial aquifer storage
102 leading to regular drying. Topography is characterised by rolling hills with successions of
103 plateaus separated by steep slopes. Climate in these catchments is continental, with mean annual
104 temperature of 11°C (range during measurement period = 0.0–34.3°C) and mean annual
105 precipitation of 800 mm.

106 The Ardières and Vauxonne catchments are adjacent, but just across the regional
 107 drainage divide and are tributaries of the Sâone River, which itself is a tributary of the Rhône
 108 River. From 8 March 2021 to 14 October 2021, we instrumented 2, 6, 8, and 3 sites of Strahler
 109 order 2, 3, 4, and 5 respectively. These two catchments drain a hilly landscape of vineyards (32%
 110 land cover) exposed to pesticides (Montuelle et al., 2010). Soil is sandy loam on a shallow
 111 Hercynian crystalline bedrock. Climate is temperate with a mean annual air temperature of
 112 17.1°C (-2.1–35.2°C) and mean annual precipitation is 940 mm, with intense summer
 113 thunderstorms. The combination of climate, soil and steep slopes (up to >30%) is conducive to
 114 infiltration and sub-surface lateral flow (Gouy et al., 2021).

115 The last catchment, the Yzeron is a direct tributary of the Rhône River, draining a steep
 116 agricultural and forested landscape composed of magmatic and metamorphic (granite, gneiss,
 117 schist) bedrock that leads downstream to a semi-urban/urban zone with Quaternary fluvio-glacial
 118 and glacial deposits. From 08 March 2021 to 15 October 2021, we instrumented 2, 3, 6, 6, and 1
 119 sites from Strahler orders 1–5, respectively. The climate is a mix of continental/Mediterranean
 120 with mean annual temperature 13.8°C (-5.5–28.1°C) and mean annual rainfall 800 mm
 121 (Gnouma, 2006), which predominately occurs in spring and autumn. The hydrological regime is
 122 pluvial with low flows in summer and floods in autumn and spring. Road and storm sewages
 123 designed for flood mitigation allow rapid transport of urban runoff to downstream channels of
 124 the Yzeron.

Table 1. Characteristics of the Loire and Rhône tributaries' catchments and summary of their hydrochemistry from grab samples, mean±sd (n).

Variable	Loire					Rhône		
	Coise	Loise	Toranche	Mare	Lignon	Ardières	Vauxonne	Yzeron
N sites	11	20	3	4	4	15	3	18
Area (km ²)	6.1–350	0.8–132	54.7–76.1	61.9–233	62.1–664	3.6–142	6.6–46.0	0.8–59.4
Alt. [†] (m)	344–619	337–627	338–377	352–422	330–360	199–389	227–228	197–731
Q* (m ³ s ⁻¹)	0.17	0.13	0.06	0.34	1.11	0.59	0.19	0.10

pH	7.8±0.2 (40)	7.5±0.4 (123)	7.7±0.4 (27)	7.8±0.2 (35)	7.6±0.3 (43)	7.5±0.1 (91)	7.8±0.1 (17)	7.6±0.3 (107)
SpC** (μ S cm ⁻¹)	296±129 (71)	315±255 (156)	320±82 (33)	193±79 (49)	136±57 (59)	145±45 (166)	238±59 (32)	322±124 (195)
DOC ^{††} (mg L ⁻¹)	4.6±1.1 (24)	4.3±1.6 (73)	7.0±1.4 (13)	7.0±1.6 (20)	5.1±1.6 (26)	3.3±0.9 (125)	ND	6.7±2.9 (78)
NO ₃ -N (mg L ⁻¹)	2.3±1.9 (24)	2.2±2.1 (73)	2.4±2.3 (13)	1.2±0.6 (20)	0.9±0.6 (26)	2.2±1.8 (88)	2.0±1.6 (17)	2.1±1.3 (78)
PO ₄ ³⁻ -P (mg L ⁻¹)	0.12±0.12 (24)	0.07±0.07 (73)	0.11±0.1 (13)	0.08±0.05 (20)	0.08±0.06 (26)	0.1±0.1 [‡] (45)	ND	0.08±0.07 (78)

[†]altitude in meters above NGF IGN69 datum

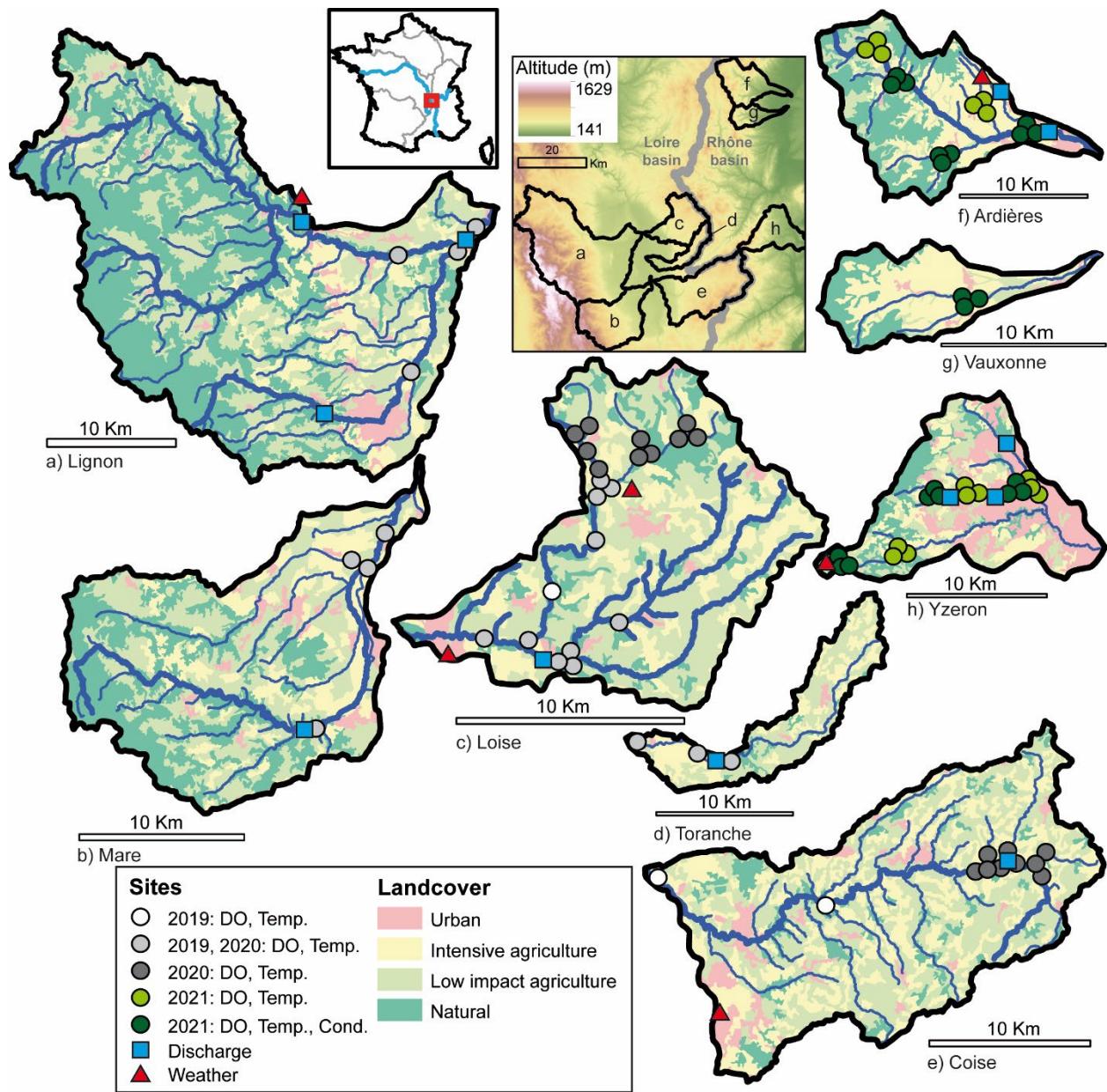
^{*}interannual median at the outlet during sampling period

^{**}specific conductance at 25°C

^{††}dissolved organic carbon

[‡]estimated from Montuelle et al. (2010)

ND = no data



126

127 **Figure 1.** Map of instrumented study sites with points indicating sensor placement and
128 monitoring duration.

129 *Data collection and processing*

130 We monitored the sites for dissolved oxygen (DO; mg L^{-1}) and stream temperature ($^{\circ}\text{C}$)
131 for variable periods between July 2019 and October 2021, but not during winter (November–
132 February; Figure 1). At each site, DO and stream temperature were measured every 15 minutes
133 with an in-situ sensor (HOBO U26-001, Onset Computer Corporation, Massachusetts, USA)

134 instrumented with a copper anti-biofouling guard. At 12 sites in 2020 and 18 sites in 2021, we
135 installed conductivity sensors (HOBO U24-001, Onset Computer Corporation, Massachusetts,
136 USA). We cleaned DO and conductivity sensors with a toothbrush every two weeks to remove
137 biofouling. Prior to deployment, we lab-calibrated DO sensors with both 100% water-saturated
138 air and with sodium sulphite for 0% saturation. Conductivity sensors were calibrated based on
139 field measurements obtained with a calibrated handheld probe (Pro Plus, YSI Inc., Ohio, USA) at
140 the beginning and end of each two-week measurement period per manufacturer instructions. We
141 also measured DO and temperature with the calibrated handheld probe at each field visit to check
142 for sensor drift and develop corrections as needed. We placed sensors in the middle of the water
143 column, and as close to the thalweg as possible. As streams began to dry, we vertically
144 repositioned sensors to keep them submerged and continuously capture stream DO and prevent
145 loss of data.

146 Across all sites, we measured DO and stream temperature at 15-minute intervals for a
147 total of 1,687,776 measurements. The quality controls applied to all DO data prior to analysis are
148 described in detail in Diamond et al. (2021). Briefly, we 1) averaged 15-minute data to hourly
149 resolution to reduce file sizes and processing time, 2) removed data that were extremely noisy,
150 collected in dry conditions, or otherwise of suspect quality, and 3) corrected for minimal sensor
151 drift. For data that passed quality control (nDO=380,161), we calculated hourly DO saturation
152 (DO_{sat}) and specific conductance.

153 *Storm, drying, and rewetting events*

154 We observed three environmental events conducive to hypoxia across our sites: 1)
155 storms, 2) drying, and 3) rewetting. Each of these environmental events were identified
156 according to the following definitions. First, we classified storm events as a doubling of baseflow
157 (Carter et al., 2021), with storms at least 24 hours apart counting as separate events. We used the

158 functions *high.spells* and *baseflow* (based on a Lyne-Hollick recursive digital filter) from the
159 *hydrostats* R package (Bond, 2022) to determine these events. Through sensitivity analyses, we
160 determined these criteria to accurately and reproducibly capture each distinct event in the
161 observed discharge time series. To determine storm effects on DO, we examined the three days
162 before the storm peak flow and the week following the peak flow (Carter et al., 2021).

163 Second, to classify distinct drying events, we relied on a combination of sensor data, field
164 observations, and discharge data. Ideally, accurate local discharge or stage data should
165 characterize these events, but the large number of sites precluded continuous measurement at
166 each location, and there is a well-known problem with low-flow accuracy from local stream
167 network gages (Zimmer et al., 2020). Hence, to indicate dry periods, we used the observation
168 that DO sensors read near-saturation and experience air-temperature-like fluctuations when they
169 are out of the water. These dry-period DO sensor observations are directly supported by 1)
170 concurrent conductivity measurements (reading near $0 \mu\text{S cm}^{-1}$), 2) field observations of dry
171 stream beds, and 3) near-zero or zero-flow measurements of discharge at local discharge stations.
172 Therefore, these moments (i.e., when sensors are out-of-water) represent the end-points of our
173 drying periods. We then determined the beginning points of our drying periods by extending the
174 end-point backwards in time to a point when specific discharge measurements exceeded the 10%
175 percentile, using the *low.spell.lengths* function from *hydrostats*.

176 Third, rewetting events were demarcated by typically rapid and large reductions in
177 temperature, and increases in conductivity of stream water after dry periods. These moments
178 were also associated with measured rainfall events and concomitant discharge responses, so we
179 have high confidence in the start time of rewetting events. The length of a rewetting event lasted
180 either until the stream dried again (see above), or until discharge exceeded the 10% percentile.

181 To avoid over-counting drying events, we did not consider the drying after rewetting to be a
182 drying event as defined above unless the discharge exceeded the 10% percentile before re-drying
183 after rewetting.

184 *Hypoxia evaluation*

185 In this study, we defined instantaneous hypoxia conditions to occur in the stream water
186 when DO is less than $3 \text{ mg O}_2 \text{ L}^{-1}$. This instantaneous hypoxia level was selected for three
187 primary reasons: 1) it is national threshold value for “bad” ecological potential of water quality
188 in France (Ministère chargé de l’écologie, 2019), 2) it appears to be a threshold for mortality in
189 the biological indicator species, *Gammarus fossarum* (Fig. S1), and 3) measurements of DO
190 concentrations are less uncertain and require fewer assumptions than estimates of DO percentage
191 saturation, although this metric is still commonly used (e.g. 50%, Carter et al., 2021). Some
192 regulatory agencies define coastal hypoxia as $< 2 \text{ mg L}^{-1}$ (NSTC, 2003) though evidence
193 suggests freshwater biota experience chronic toxicity below 5 mg L^{-1} (Saari et al., 2018).
194 Overall, there is no single definition for hypoxia, and different numeric thresholds may be
195 appropriate for the regulation or study of specific impacts (in mg L^{-1} or % saturation).

196 As there is no single assessment of hypoxia and its impacts, we evaluated the degree of
197 hypoxia in several ways. Apart from simply calculating total hours and percentage of hypoxia
198 within and across sites, we also delineated continuous hypoxic events (with up to a 2-hour gap of
199 $\text{DO} > 3 \text{ mg L}^{-1}$), taking into account their lengths, and periodicity, and the diel distributions of
200 hypoxia. We further calculated rates of DO drawdown leading to hypoxia during storm, drying,
201 and rewetting events by fitting linear regressions through daily minima (Carter et al. 2020).
202 Finally, we attempted to identify simple predictors of hourly hypoxia (i.e., binary: hypoxic or
203 oxic) with logistic regression and classification trees (R package rpart; Therneau and Atkinson,
204 2022). Potential predictors of DO conditions measured included stream habitat of the DO sensor

205 (pool, riffle, or run; visually assessed), hourly stream temperature, daily specific discharge of the
206 catchment, reach slope, Strahler order, distance from the source, and altitude. Data were highly
207 skewed towards oxic conditions, so we balanced the data with combined over- and under-
208 sampling using the R package *ROSE* (Lunardon et al., 2014). We split the dataset into training
209 (70%) and testing (30%) data for model building and validation, respectively.

210 *Prediction of gammarid mortality during hypoxic events*

211 To connect observed hypoxia events with hypoxia physiological response for stream
212 biota, we modeled *Gammarus fossarum* (“gammarid”) mortality using measured DO
213 concentrations from contrasting hypoxic event types as input to a General Unified Threshold
214 model of Survival (GUTS) (Jager et al., 2011). The GUTS toxicokinetic-toxicodynamic model,
215 based on bioassay survival data, is regularly used in prospective hazard assessment of pesticides
216 and fluctuating concentrations of toxic chemicals (Ockleford et al., 2018). GUTS quantifies
217 mortality rate evolution based on the internal concentrations of hazardous compounds in
218 organisms, which are controlled both by uptake rates and internal contaminant elimination rates
219 (Baudrot et al., 2018). We adapted GUTS to include hypoxic stress instead of toxic stress by
220 considering the DO deficit below an arbitrary value of 12 mg L^{-1} as the stressor input metric
221 (instead of contaminant concentration). Using the web-interface MOSAIC (<https://mosaic.univ-lyon1.fr/guts>) (Charles et al., 2018), we calibrated the GUTS model with an experimental dataset
222 of gammarid mortality in laboratory conditions under different constant levels of DO deficit
223 (Recoura-Massaquant et al., 2022). We used the reduced individual tolerance version of the
224 model (GUTS-RED-IT), which assumes a log-logistic distribution of sensitivity threshold among
225 individuals. The calibration experiment consisted of monitoring mortality over a five-day
226 laboratory exposure of 300 male organisms of homogenous body size ($\sim 10 \text{ mm}$) to 10 constant
227 nominal DO concentration conditions ($8, 6, 5, 4, 3.5, 3, 2.5, 2, 1.5$ and 1 mg L^{-1} , respectively),

229 with three replicates of 10 individuals per concentration condition (Fig. S1). DO deficits were
230 obtained by bubbling N₂ gas through water columns. All detailed experimental data are available
231 from the open access data repository Recherche Data Gouv (Recoura-Massaquant et al. 2022).
232 We then used the calibrated GUTS-RED-IT model to estimate potential mortality responses
233 under observed hypoxic scenarios from three storm events and five drying events.

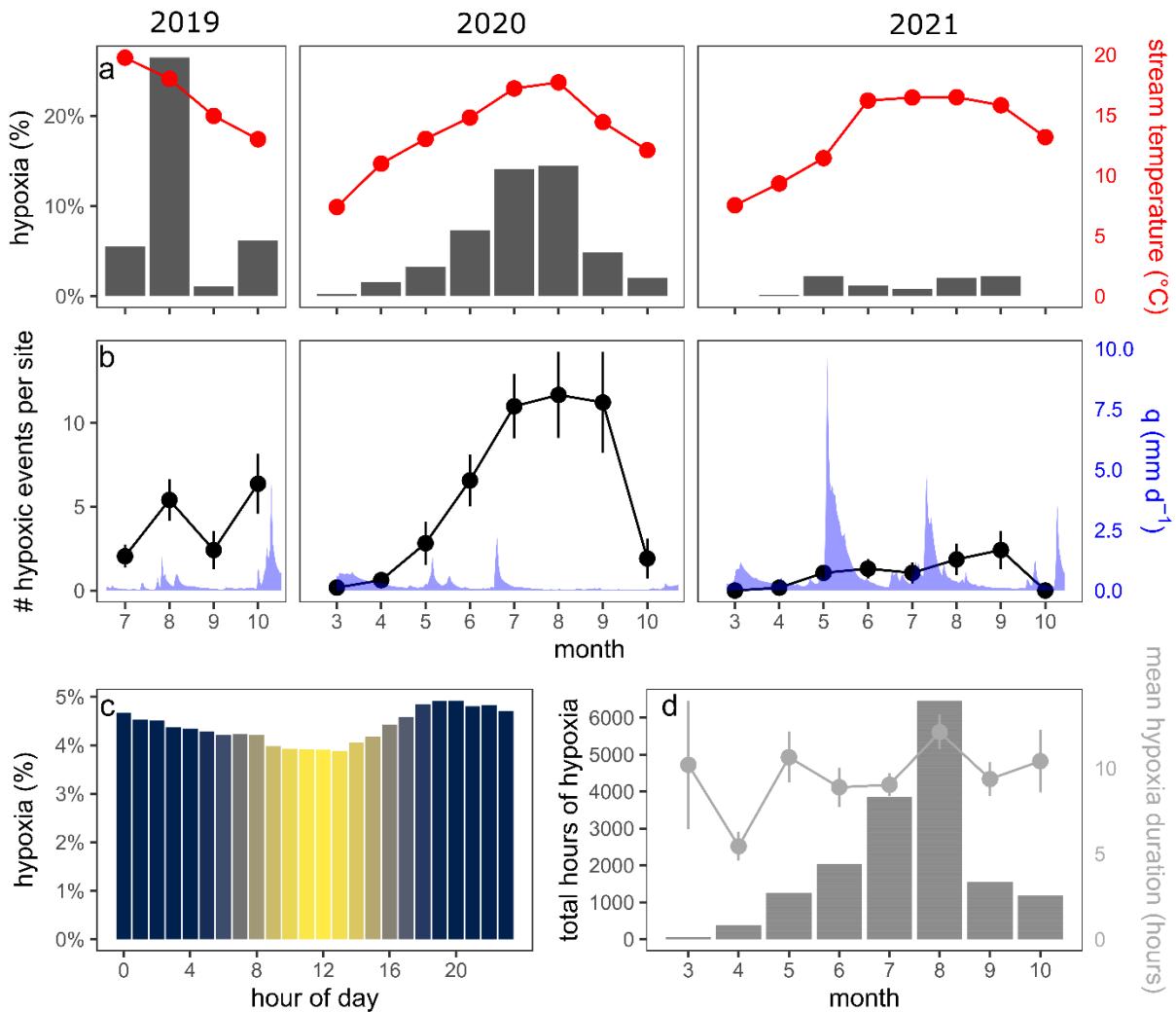
234 **Results**

235 *Degree of hypoxia across sites*

236 Overall, we observed 16,781 hours of hypoxia (DO < 3 mg L⁻¹), an average of 4.4% of all
237 site hourly measurements from 2019–2021. Hypoxia occurred at 51 of 78 sites for at least one
238 hour of hypoxia, and at 37 sites for at least 1% of the time. The greatest degree of hypoxia was in
239 2019, accounting for 9.2% of all measurements that year, followed by 2020 with 6.2%, and 2021
240 with 1.3%. Note that in 2021, in addition to being a wetter year (Fig 2b), the sites changed from
241 the Loire to the Rhône basin (Fig. 1). Among catchments, the Toranche experienced the most
242 hypoxia (12.9% or 2,335 hours), and the Vauxonne the least (0.3% or 57 hours; Table S1). In
243 general, hypoxia was spatially heterogeneous, but drying tended to synchronize hypoxia within
244 catchments. For example, in late July 20, when most sites in the Loise catchment were almost
245 dry, sites ranging 4.2–31.4 km² (7 out of 16 sites) exhibited hypoxia at the same time before
246 drying.

247 Across our sites, we observed correlations between the degree of monthly hypoxia and
248 stream temperature (Fig. 2a) and specific discharge (Fig. 2b). Hence, hypoxia was greatest in
249 summer months (Fig. 2d) when temperatures were greatest and discharge was lowest. There
250 were negligible differences in hypoxia rates between night and day, although solar noon was the
251 least likely time to observe hypoxia (Fig. 2c). Mean hypoxic duration was 10 hours, and while
252 this did not vary over time (Fig. 2d), there was two orders of magnitude variation across events

253 (range=1–210 hours). In general, differences in degree of hypoxia among Strahler orders were
 254 marginal (Table 2), and did not correspond to downstream trends ($p > 0.05$ for all linear fits).
 255 Still, Strahler order 1 exhibited the lowest degree of hypoxia for all metrics.



256
 257 **Figure 2.** Time series of hypoxia metrics. a) Monthly percentage of measurements that were
 258 hypoxic (bars) with mean monthly across-site stream temperature (red) for 2019–2021 (columns
 259 for a and b). b) Mean monthly number of unique hypoxic events across sites (black, vertical bars
 260 are standard errors) and mean daily specific discharge (blue) across gaging stations. c) Hourly
 261 percentage of measurements that were hypoxic across sites and years, with lighter colors

262 indicating daylight hours. d) Total hours of hypoxia (bars) and the mean duration of hypoxia
 263 (grey, vertical bars are standard errors) across sites and years by month.

Table 2. Hypoxia summary statistics by Strahler order, mean \pm sd when given.

Strahler order	Total hypoxia (hours)	Percentage of time hypoxic* (%)	Unique hypoxia events** (n)	Event length† (hours)	Time between events†† (days)	Night hypoxia‡ (%)
1	786	3.1	34	8 \pm 6	3.0 \pm 11.3	51%
2	3180	4.9	44	9 \pm 11	5.5 \pm 18.8	49%
3	7778	5.1	73	10 \pm 13	9.3 \pm 43.1	48%
4	3015	3.0	37	10 \pm 10	13.7 \pm 45	49%
5	2022	5.6	27	14 \pm 17	9.9 \pm 31.5	50%

*Total hours of hypoxia divided by total hours of DO measurements \times 100

** Event defined as at least one hour of DO $< 3 \text{ mg L}^{-1}$; events continue with up to 2-hour gap in hypoxia

†Event length begins at time of first hypoxia and continues until hypoxia ends, with up to 2-hour gap in hypoxia

‡The time between hypoxic events

††The percentage of total hypoxia that was measured at night, where night is defined as $<200 \mu\text{mol m}^{-2} \text{ s}^{-1}$ PAR

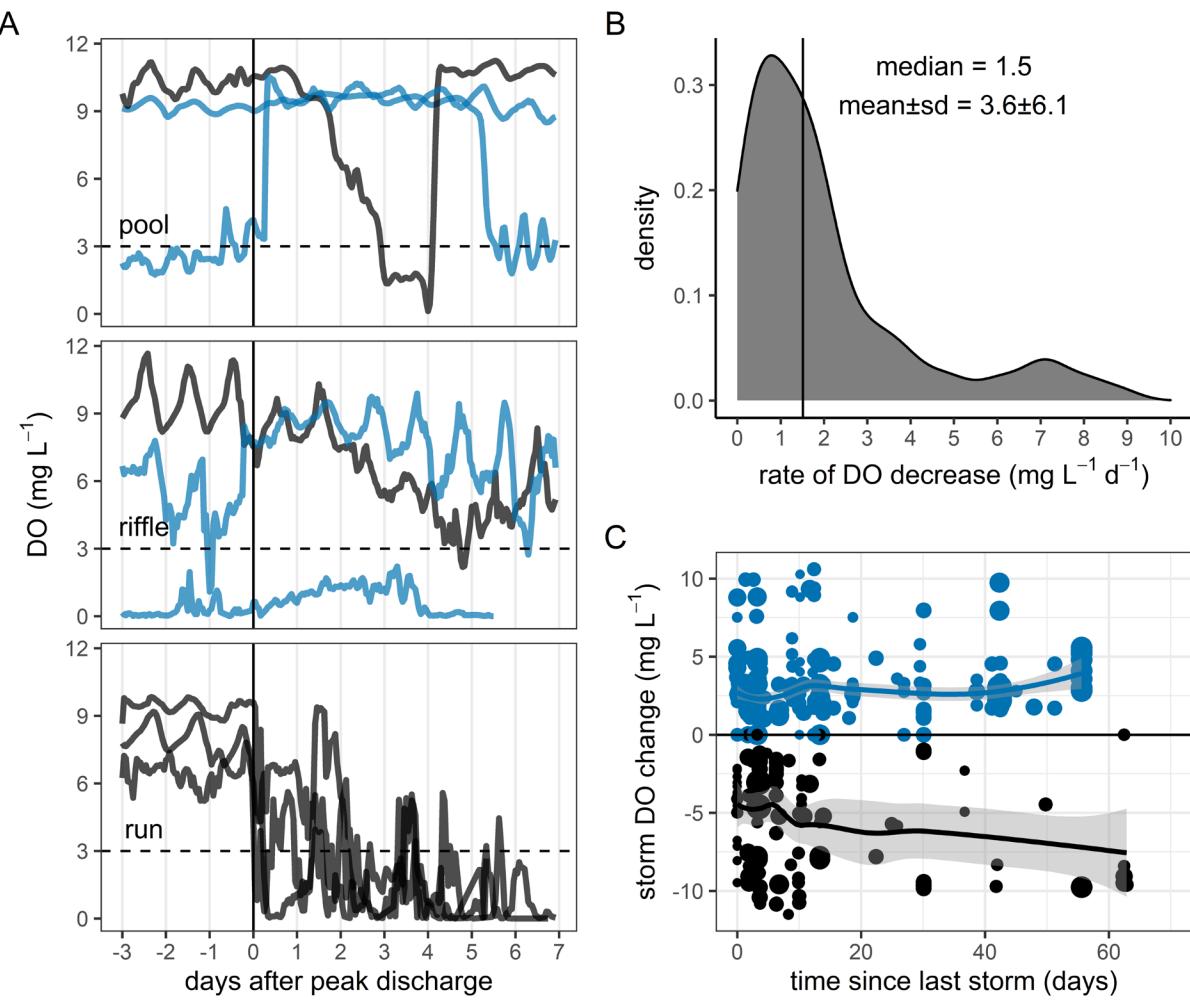
264

265 *Storm events*

266 We recorded 152 storm events across the 13 discharge gages with an average storm pulse
 267 length of 2.6 ± 4.2 days (mean \pm sd; range = 1 hour–22.1 days), leading to 776 site-events. Of those
 268 site-events, 107 resulted in at least one hour of hypoxia. For 131 of the 669 site-events without
 269 hypoxia, there was no change in DO mean or variance after the storm peak (ANOVA and t-tests
 270 of 5 days before and after; $p > 0.01$), whereas 414 of them exhibited an increase in DO, but no
 271 change in DO diel range. Storm events resulting in hypoxia occurred predominately in higher
 272 order sites, with 87% in orders 3–5, and 62% in orders 4–5.

273 DO trajectories following storm events were highly variable (Fig. S2). Of the storms that
 274 induced hypoxia, it took a median of 41 hours (53 ± 48 hours) after peak discharge to become
 275 hypoxic, ignoring sites that were hypoxic prior to the storm. This is the amount of time for DO to
 276 drop between 8.0 and 3.3 mg L^{-1} when using the median and mean rates of DO decrease (Fig.
 277 3b). Sites stayed hypoxic for a median of 7 hours (20 ± 32 hours) after first becoming hypoxic.

278 There were 48 events where peak discharge rapidly induced oxic conditions to previously
 279 hypoxic sites, but oxic conditions rarely lasted for more than a few days (Fig. 3a). These event
 280 types were spread across 25 sites and every Strahler order and habitat. There were few obvious
 281 predictors of the effect of a particular storm event on changes to DO, with time since last storm
 282 event, baseflow before storm event, and storm pulse magnitude having no predictive power (Fig.
 283 3c).



284
 285 **Figure 3.** Summary of storm event effects on DO. A) three different storm events for each
 286 of three different habitat types (pool, riffle, run) with colors indicating whether DO increased
 287 (blue) or decreased (black) after the storm event. Dashed line indicates hypoxia and vertical line

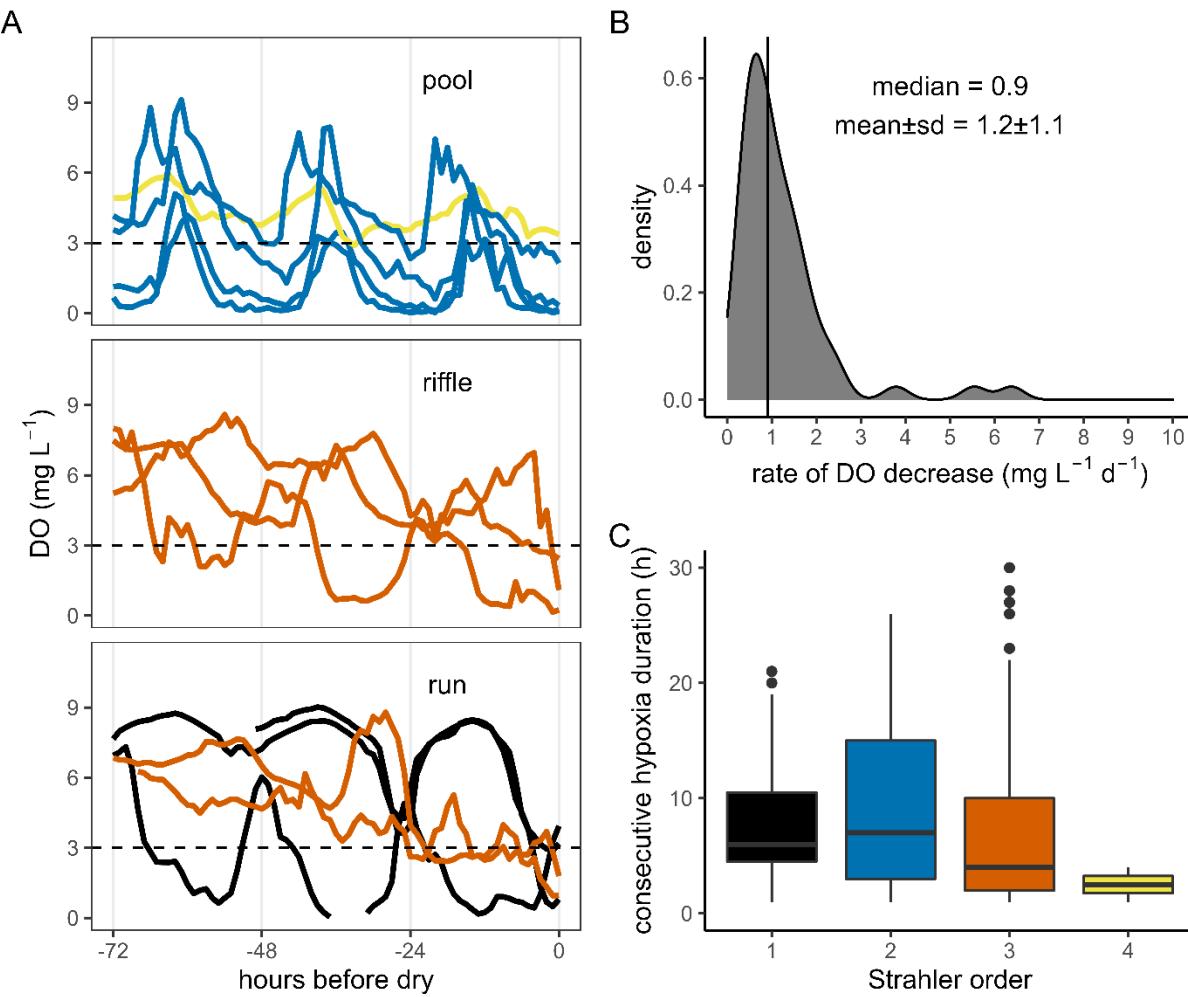
288 indicates peak discharge. B) Distribution of DO decreases (black events in panel A) across all
289 events that led to a decrease in DO. C) Comparison of change in DO (colors as in A) as a
290 function of time since the last storm, with the point size indicating the magnitude of the storm
291 pulse. LOESS lines with 95% confidence intervals are shown.

292 *Drying*

293 Across all 13 stream gages in the study area, dry conditions were recorded 86 times with
294 a mean dry duration of 6.7 ± 11.2 days (range = 8 hours – 86 days). Flow was lowest in 2019 and
295 2020 (Fig. 2b). In the Loire basin, the Loise, Coise, and Toranche catchments experienced zero-
296 flow for 2%, 2%, and 24% of days in 2019, and 11%, 11%, 29% in 2020. Average dry durations
297 for those catchments were 1, 1, and 4.5 days in 2019, and 1, 1, and 80 days in 2020. In the Rhône
298 basin, sites in the Yzeron catchment in 2021 also experienced drying 1.5–4.6% of the time, with
299 average site dry durations of 4.9–11.8 days. Using our criteria to determine if a sampling site was
300 dry, we estimate that 23 of 78 sites became dry at least once. Within those 23 sites, we observed
301 60 distinct drying events (2.6 ± 1.5 events per site). The remaining results refer to these hypoxic
302 drying events (Fig. 2a).

303 Drying was the most common hydrologic driver of hypoxia, accounting for 55% of all
304 hypoxic events. The mean hypoxia duration during drying was 6.2 hours (range = 1–55 hours);
305 the greatest durations occurred in Strahler order 2 (mean = 9.3 ± 9.5 hours). The smaller Strahler
306 orders (1–3) were twice as likely to become hypoxic during drying than to remain oxic, and for
307 Strahler order 1 drying events always resulted in hypoxia. The mean decrease in daily DO
308 minima was $1.3 \text{ mg L}^{-1} \text{ d}^{-1}$ (Fig. 4b), with relatively little variation (IQR = 0.6 – $1.5 \text{ mg L}^{-1} \text{ d}^{-1}$).
309 This decrease in DO was not concomitant with increases in stream temperature, which did not
310 exhibit increasing trends with drying ($p > 0.05$). Once drying began, it took 3.8 ± 2.9 days for sites
311 to become hypoxic (IQR = 1.8–4.8 days). We observed increases ($p < 0.05$) in DO diel ranges

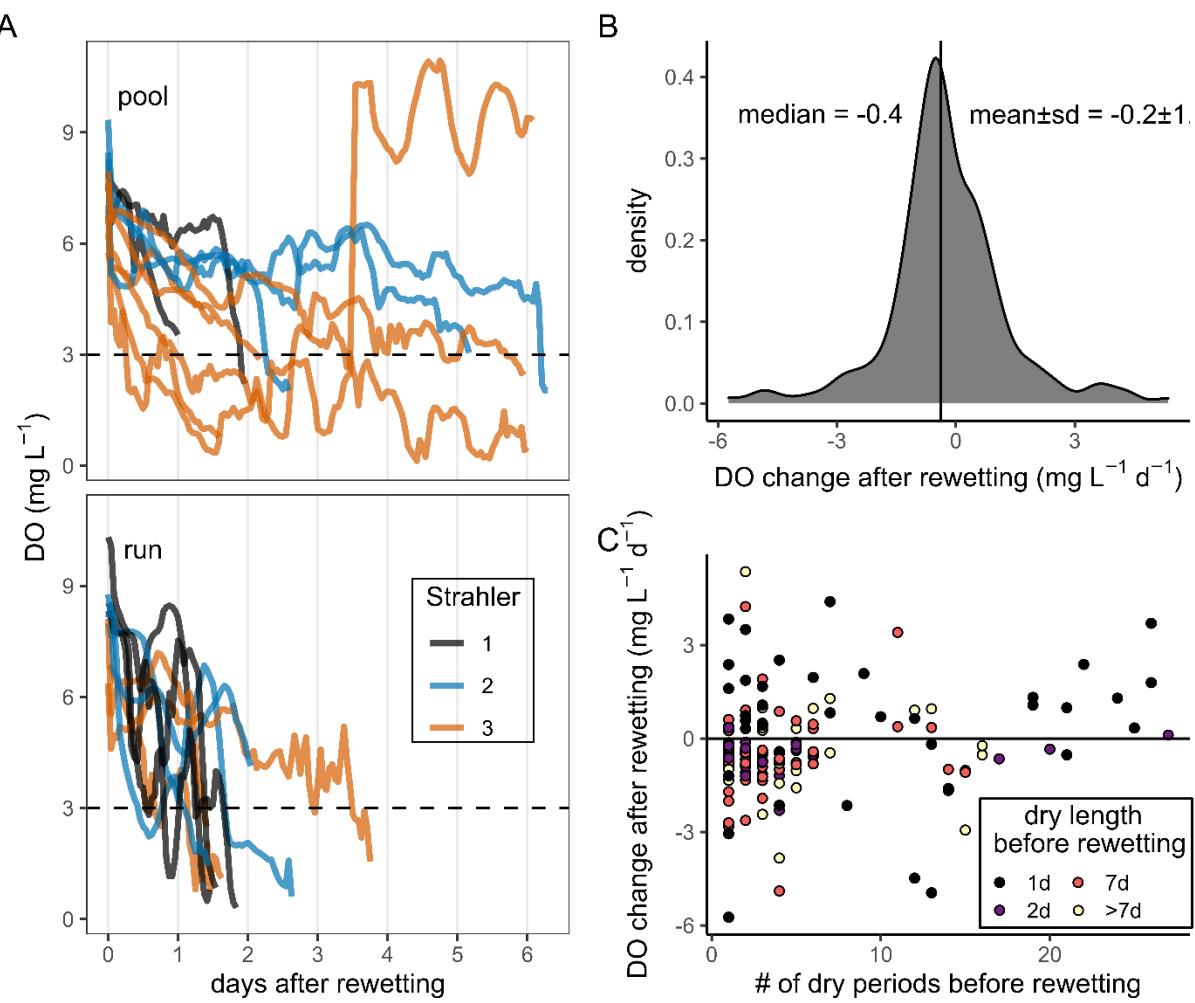
312 over drying periods in 12 instances (18% of hypoxic drying events), with a mean increase of
313 $0.7 \pm 0.5 \text{ mg L}^{-1} \text{ d}^{-1}$. Apart from Strahler order (Fig. 4c), there were no clear predictors of a site to
314 become hypoxic during drying or on how long it would stay hypoxic.



315
316 **Figure 4.** Summary of drying hypoxia events. A) Three-to-four different drying events for
317 each of three different habitat types (pool, riffle, run) with colors indicating Strahler order;
318 dashed line indicates hypoxia. B) Distribution of DO decreases across all events. C) Length of
319 consecutive hypoxia (colors as in A) as a function of Strahler order.

320 *Rewetting*

321 There were 314 rewetting events according to our criteria with 46 of these events leading
322 to at least one hour of hypoxia. These events occurred across 27 of 78 sampling sites. There was
323 a mean duration of 6 ± 13 days of dry conditions before rewetting, and sites went through an
324 average of 4.9 ± 4.7 drying and rewetting cycles. Rewetting led to more decreases than increases
325 in DO (Fig. 5b). When only considering negative changes, the mean decrease in DO was -1.0 ± 1
326 $\text{mg L}^{-1} \text{d}^{-1}$ (median = $-0.7 \text{ mg L}^{-1} \text{ d}^{-1}$). Apart from the fact that there were no riffle rewetting
327 events that led to hypoxia (Fig. 5a), there were no other obvious controls on DO changes after
328 rewetting, e.g. dry period duration or previous number of dry periods before rewetting (Fig. 5c).



329

330 **Figure 5.** Summary of rewetting event effects to DO. A) Different rewetting events leading
331 to hypoxia for each of two different habitat types (pool and run; riffles did not experience
332 rewetting hypoxia) with colors indicating Strahler order; dashed line indicates hypoxia. B)
333 Distribution of DO changes across all events, vertical line indicates median. C) DO change after
334 rewetting as a function of the number of dry periods before rewetting and the dry period duration
335 (colors).

336 *Predicting hypoxia*

337 A classification tree was able to predict instances of hypoxia across a training dataset
338 with an accuracy of 81% (c-statistic = 0.79, sensitivity = 0.67, specificity = 0.82). Notably, the
339 resulting 10-node tree predicted hypoxic events with probability = 0.79 for periods with stream
340 temperature $> 11^{\circ}\text{C}$, specific discharge $< 0.014 \text{ mm d}^{-1}$ (ca. 1-10 L s^{-1} for these catchments), and
341 Strahler order ≤ 3 (Fig. S3). The highest probability of hypoxia ($p=0.86$) was observed for the
342 same temperature conditions, but for discharge $> 0.014 \text{ mm d}^{-1}$, and reach slopes 0.042–0.054 m
343 m^{-1} . The lowest probabilities for hypoxia were under cold-water conditions (temperature < 11
344 $^{\circ}\text{C}$) and high slope conditions (slope $\geq 0.054 \text{ m m}^{-1}$). The variable importance for the
345 classification tree were temperature = 34, slope = 32, specific discharge = 18, Strahler = 10, and
346 habitat = 6. Similar variable importance was observed for a regression tree on DO (Fig. S4).

347 Given that discharge and temperature were the most important continuous variables in
348 predicting hypoxia and DO at our sites, we used them as predictors in a logistic regression for
349 hypoxia. The model (Table 3) performed relatively poorly (Fig. S5) with a pseudo $R^2=0.10$
350 (McFadden, 1987) and accuracy 63% (c-statistic = 0.66, sensitivity = 0.69, and specificity
351 =0.63), especially when compared with the classification tree. Holding temperature constant, the
352 odds of hypoxia decreased by 15% for each unit increase in $\ln(q)$, whereas by holding discharge
353 constant, the odds of hypoxia increased by 19% for each $^{\circ}\text{C}$ increase.

Table 3. Logistic regression results for probability of hypoxia^{*}

Coefficients	Estimate	SE	z-value	p-value
Intercept	-3.0	0.02	-151	<0.0001
ln(q)**	-0.16	0.00	-71	<0.0001
temperature	0.17	0.00	-131	<0.0001

$$^* \hat{p} = \frac{\exp(b_0 + b_1 \ln(q) + b_2 \text{temp})}{\exp(1 + b_0 + b_1 \ln(q) + b_2 \text{temp})} = \log \frac{p(\text{hypoxia})}{1 - p(\text{hypoxia})}$$

** daily specific discharge [mm d⁻¹]

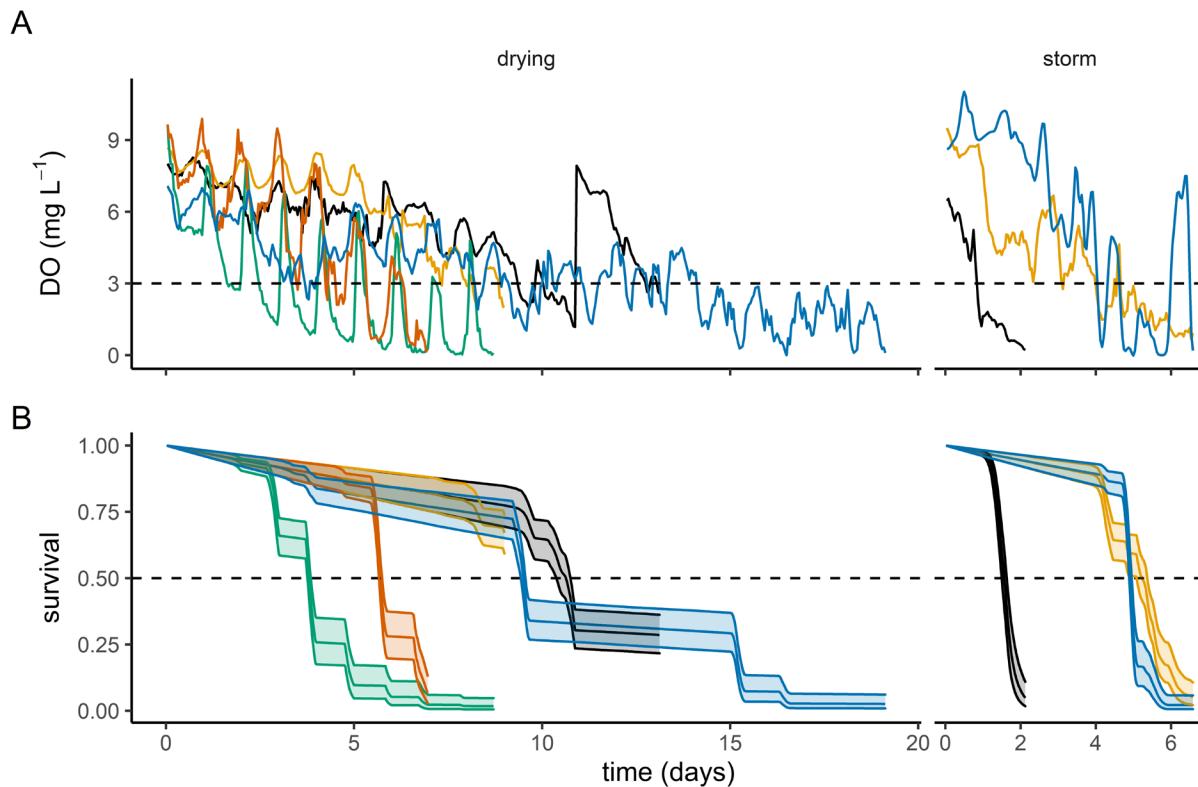
354

355 *Gammarid mortality patterns*

356 The laboratory experiments revealed a gammarid mortality threshold response to DO at 3
 357 mg L⁻¹ (Fig. S1). The predictions of the calibrated GUTS model based on our field data for storm
 358 and drying events thus follow this threshold, with mortality occurring when DO < 3 mg L⁻¹ (Fig.
 359 6). There was a clear difference in mortality profiles between drying and storm hypoxic events,
 360 with a staircase shape for the drying, and a more continuous and abrupt shape for storms. The
 361 staircase mortality under drying is due to the marked diel DO oscillations that allow oxic
 362 recovery periods during the day. Hence, the time between the start of hypoxia and the quasi-
 363 extinction of the population of individuals (e.g. 95% dead) is much shorter for storms than for
 364 drying events. Specifically, storm events achieved quasi-extinction in less than two days for the
 365 three storm events considered, whereas it took at least three days for the drying events, with one
 366 drying event not crossing 50% mortality (Fig. 6b).

367 During drying, successive mortality events were triggered for successively lower DO
 368 thresholds. This is explained by the Individual Tolerance assumption in GUTS model, where the
 369 population loses the most sensitive individuals first, but only the most tolerant ones when the
 370 stress conditions worsen. This is most apparent for the longer drying event (blue line on Fig. 6b)
 371 with a first large event of mortality at day 9 when DO concentrations reach 3 mg L⁻¹, followed

372 by a phase without mortality between days 10–15 while DO still fluctuates in the same
373 concentration range. A second event of mortality occurs only when DO < 2 mg L⁻¹.



374

375 **Figure 6.** Summary of GUTS model results for gammarid survival under hypoxia driven by
376 drying and storms. A) Time series of DO concentrations for eight different hypoxic events (five
377 drying and three storms), colored by individual event. B) Time series of gammarid survival
378 (1=100% population survives, 0 = complete mortality) with 95% confidence intervals in shade.
379 Dashed lines indicate hypoxia and 50% mortality in A and B, respectively. Note different x-axis
380 lengths for storms and drying.

381 **Discussion**

382 *Hypoxia is abundant in space and time in headwaters*

383 Hypoxia was temporally common over the growing season across our study area, with a
384 surprisingly even spatial distribution across watersheds and Strahler orders. This ran counter to

385 our hypothesis that hypoxia would occur preferentially in the smallest streams (e.g., Strahler
386 order < 3), and there was moreover little difference in degree of hypoxia among sites (Table 2).
387 Equally surprising was that there were marginal differences between night and day hypoxia at
388 the study- or Strahler order-level (Fig. 1, Table 2; cf. Carter et al. 2021), suggesting that when it
389 occurs, it spans full night and day periods. Still, hypoxia was slightly more common in the early
390 evening, suggesting most grab-sample monitoring approaches are underestimating its extent.
391 Spatially, although we sampled Strahler order 3 (n=29) at twice the rate of order 2 (n=14) and
392 five times the rate of order 1 (n=6), normalized hypoxia metrics (Table 2) still indicate parity
393 among these smallest orders with the larger orders 4 (n=21) and 5 (n=8). Although common
394 across Strahler orders, hypoxia occurrence was spatially stochastic and created patches of oxic
395 and hypoxic areas that were separated as a function of local characteristics unquantified here
396 (Fig. S3, Table 3). This is an important nuance to consider when modeling at larger scales: e.g.,
397 drying does not uniformly induce hypoxia.

398 The unexpected commonality of hypoxic conditions in this study supports growing
399 observations of apparent non-eutrophication related hypoxia across watersheds of varying size,
400 climate, geology, and land use (Blaszcak et al., 2019; Carter et al., 2021; Gómez-Gener et al.,
401 2020). Thus, hypoxia may be an overlooked aspect of catchment hydrochemistry, with
402 implications for nutrient processing and community dynamics (Pardo and García, 2016).

403 *Hydrologic events induce variable hypoxia trajectories*

404 Hypoxia events exhibited distinct characteristics—from initiation to recovery—that
405 depended on hydrologic event type. The most rapid hypoxia trajectories evolved under storm
406 events (Fig. 3a) and rewetting (Fig. 5a). Both storm and rewetting events exhibited dynamic DO
407 changes (Fig. 3b, Fig. S2, Fig. 4b), which were not explained by several common sense factors
408 such as size of the storm pulse, time since last storm or last rewetting cycle (Fig. 3c, Fig. 4c),

409 stream habitat, or Strahler order. However, we note that pools were generally slower to reach
410 hypoxia than runs under rewetting events (Fig. 4a), likely due to their greater water volume and
411 oxygen mass. Overall, we noted the emergence of several archetypal storm pulse DO behaviors,
412 including no changes, immediate drops, slow drops, and a peak of high DO aligning with the
413 storm peak followed by gradual drawdown to hypoxia. Point source inflows of low DO or high
414 oxygen-demanding substances may explain the rapid DO drop storm archetype observed here
415 (Dutton et al., 2018). The latter archetype of a DO peak followed by drawdown was the most
416 commonly observed in a low-gradient, humid catchment with an order of magnitude higher
417 discharge (Carter et al., 2021), hinting at a common driver. We suggest this could be a
418 hydrologic mechanism.

419 Storm peaks likely drive high gas exchange, leading to rapid oxygenation, but afterwards
420 we hypothesize that increased soil respiration after storm events (Lee et al., 2004; Sponseller,
421 2007) entails low DO water to the stream after the storm peak. Soil respiratory processes may
422 reduce the DO in hillslope or nearby riparian groundwater, especially as rising groundwater
423 intercepts greater proportions of soil carbon (Li et al., 2021; McGuire and McDonnell, 2010) as
424 noted in dissolved organic carbon export patterns (e.g., Diamond and Cohen, 2018; Zarnetske et
425 al., 2018). Such soil respiration pulses typically last less than 48 hours (Lee et al., 2004) and
426 would likely arrive in baseflow after the peak, roughly aligning with the timeframe of our
427 observations. Thus, the slower DO drawdown archetype may be explained by mobilization of
428 “old” water lateral inflows during storm events that push low DO water into the stream channel
429 at a volume that replaces any pre-storm in-channel DO (Brown et al., 1999; Buttle, 1994; Klaus
430 and McDonnell, 2013).

431 In contrast to storms and rewetting, drying events consistently exhibited a gradual DO
432 drawdown towards hypoxia. These drawdowns were often associated with large diel swings in
433 DO, particularly for pools and runs (Fig. 3a). Such swings would often lead to temporary relief
434 from hypoxia during daylight hours, unless primary productivity and gas exchange were too low
435 to match respiratory demand. It was during drying periods that the stream network as a whole
436 was the most likely to undergo synchronous hypoxia (cf. Diamond et al. 2022), although
437 individual site trajectories towards hypoxia were highly heterogeneous. Dry periods thus
438 compound hydrologic stress on organisms with low oxygen stress, and likely represent critical
439 periods for metacommunity development (Sarremejane et al., 2017).

440 *Hypoxia induced potential mortality of an indicator species*

441 The combination of hypoxia mode, magnitude, and temporal characteristics controlled
442 the extent of organismal mortality or survival. Storm (or rewetting) events induced classic pulse
443 disturbances with rapid mortality, whereas drying was more akin to a stress disturbance with
444 gradual mortality (Fig. 6) (Bender et al., 1984). As such, drying press disturbances may leave
445 possibilities for gammarids to find modes of survival during daytime hypoxia alleviations due to
446 DO increases from primary productivity. This is in contrast to storms, which cause more intense
447 and rapid crashes in DO. Hence, it is not just the presence of hypoxia, but the trajectory into and
448 out of it that likely matters to biota.

449 We note here that the coupling of seasonal population phenology and hypoxia is likely a
450 strong control of subsequent drops in gammarid densities. For instance, we observed most
451 hypoxia during summer, but population models demonstrate that this is the least sensitive period
452 of gammarid adult mortality (Coulaud et al., 2014), suggesting some inherent population-level
453 resilience. Conversely, while there is limited evidence on embryo or egg response to hypoxia, it

454 seems plausible that these life phases may be more sensitive than the adults tested here, implying
455 major demographic consequences in summer (Geffard et al 2010; Coulaud et al 2014).

456 Despite our findings of a clear risk of hypoxia-induced mortality events for the gammarid
457 populations, these modeled outcomes need to be supported by empirical studies. For example,
458 additional lab manipulations with variable DO concentrations, and in-situ exposure studies will
459 allow more nuanced study of how DO dynamics affect populations. Moreover, such studies
460 would permit direct testing of the Individual Tolerance approach used in this work. Our choice
461 for using the Individual Tolerance model, which assumes that there are differences in sensitivity
462 among individuals, derives purely from its better fit with the lab data. The hypothesis of the
463 existence of tolerant and sensitive individuals could be tested in the lab by applying, for
464 example, two successive hypoxia events to evaluate if the mortality levels shift at the second
465 event. The likely existence of less sensitive individuals would imply inheritance of genetic
466 fortitude against hypoxia such that future generations may be more tolerant of increasingly lower
467 levels of DO.

468 *Difficulty predicting hypoxia*

469 We did not find a simple, robust way to predict hypoxic events based on site level habitat,
470 geomorphic, hydrologic, or thermal conditions. These are all relatively easy to measure attributes
471 of streams that are often incorporated as fundamental parts of many stream ecosystem and
472 hydrological models, so seeing no strong predictive power in them presents a challenge for easy
473 modeling of hypoxia in headwaters. Our best model suggests that hypoxia tends to occur under
474 high temperature, low slope, low discharge, and small Strahler order conditions, but this model
475 still had very limited predictive success (67% true positive rate). These best predictors tend to
476 align with other stream DO work, particularly the small slope (Carter et al., 2021) and low
477 discharge-small Strahler order conditions (Gómez-Gener et al., 2020). Within these conditions,

478 and under storm event conditions, we did not observe clear predictors of the degree of hypoxia
479 (e.g., hypoxia duration)—we could only assess the likelihood for some level of hypoxia to occur.
480 Hence, there are missing fundamental controls in our array of predictors that can distinguish
481 these hypoxic events. Perhaps the lack of geomorphologic complexity across sites limited the
482 gradient of predictors able to explain the variance in hypoxia, but the diversity of hypoxic
483 trajectories and responses even within a narrow range geographic area suggests the need for
484 alternative hypotheses on hypoxia controls. We surmise that local hydrology—especially lateral
485 inflows, point sources, and hyporheic exchange, which were poorly constrained here—is likely a
486 strong predictor of hypoxia dynamics at the scale of small headwater streams.

487 *Consistent oxygen drawdown under various conditions*

488 Despite the fact that we observed a range of hypoxic trajectories under storms, drying,
489 and rewetting events, the median rate of drawdown leading to hypoxia was remarkably similar
490 across events and sites—approximately $1 \text{ mg O}_2 \text{ L}^{-1} \text{ d}^{-1}$. We suggest that this may imply an
491 increasing downstream network-scale oxygen demand (i.e., “ecosystem respiration” [$\text{g O}_2 \text{ m}^{-2} \text{ d}^{-1}$]).
492 For this pattern to emerge, oxygen demand should increase downstream at roughly the same
493 rate as depth increases (e.g., in proportion to $d \approx Q^{0.3}$; Raymond et al. 2012). This is because
494 depth increases the volume of water and thus the mass of oxygen at a given concentration: mass
495 flux must therefore increase to reduce the concentration by a consistent magnitude at increasing
496 volumes. This downstream increase in demand may only become apparent when the balancing
497 DO controls of primary production and gas exchange are minimal. Indeed, under storm and
498 recession conditions, primary production is often reset to zero due to scouring and turbidity
499 (O’Donnell and Hotchkiss, 2022; Uehlinger, 2000; Uehlinger and Naegeli, 1998) leading to
500 respiration dominance. Under drying conditions, pool formation and low flow reduce gas
501 exchange (Stanley et al., 1997) and reduced replenishment of upstream nutrients for primary

502 production, lead to respiration dominance of the DO signal. Interestingly, previous efforts
503 observed weak-to-no longitudinal pattern of ecosystem respiration in this region, although DO
504 proxies for ecosystem respiration revealed strong downstream increases (Diamond et al., 2021).

505 The observation of similar DO drawdown under varying conditions is at the very least
506 useful as a rule-of-thumb for managers when wanting to estimate time-until-hypoxia. For
507 instance, assuming typical summer conditions with daily DO minima around 7 mg L^{-1} , one could
508 expect the first instances of hypoxia in about four days under drought conditions. Moreover, we
509 observed similar durations of hypoxia (ca. 7-hours) among drying and storm events, implying an
510 additional rule-of-thumb when estimating or modeling hypoxia-induced mortality of sensitive
511 species. Importantly, drying-induced hypoxia is likely to be exacerbated upon rewetting,
512 suggesting a compounded effect of drought on DO quality. Also useful to managers and
513 researchers is that our results demonstrate that low Strahler order streams, despite being
514 historically overlooked for hypoxia, will be the most likely to undergo hypoxia in drought
515 conditions. In other words, these river network capillaries should be hotspots for future
516 investigation of hypoxia and its biological effects.

517 **Conclusions**

518 We observed regular hypoxic conditions across eight temperature agricultural networks
519 with varying land use, geology, and hydrology. Although common, hypoxia occurrence was
520 spatially stochastic and created patches of oxic and hypoxic reaches. Hypoxia across 78 sites
521 spanning Strahler orders 1–5 was driven by storms, drying, and rewetting, with drying being the
522 dominant mechanism. Models based on our field data indicated that storms and drying events are
523 pulse- and press-disturbances, respectively, whose distinct hypoxia signals induce corresponding
524 mortality profiles in sensitive species. We conclude that the DO trajectory into and out of
525 hypoxia drives mortality patterns with implications for metacommunity structure and

526 development. Despite difficulty in predicting the degree and specific occurrences of hypoxia, we
527 showed that hypoxia is most likely to occur in small, low slope streams, under high temperature
528 and low discharge conditions, but that storm-induced hypoxia is preponderant to higher order
529 streams. Regardless of the hydrologic driver of hypoxia, we observed a remarkably consistent
530 daily drawdown in DO of 1 mg L^{-1} , suggesting a downstream increase in oxygen demand, and a
531 useful rule-of-thumb for managers. Overall, we conclude that hypoxia is a regular and
532 increasingly common occurrence in headwater networks with the potential to be a strong control
533 on biogeochemistry and biological communities, meriting its continued study.

534 **Author Contributions**

535 JD—conceptualization, design, sampling, analysis, writing
536 FM—conceptualization, design, analysis, writing
537 GP—conceptualization, design, sampling, analysis, writing
538 LV—sampling, analysis, writing
539 AC—sampling, analysis, writing
540 RR—sampling, analysis, writing
541 JZ—analysis, writing

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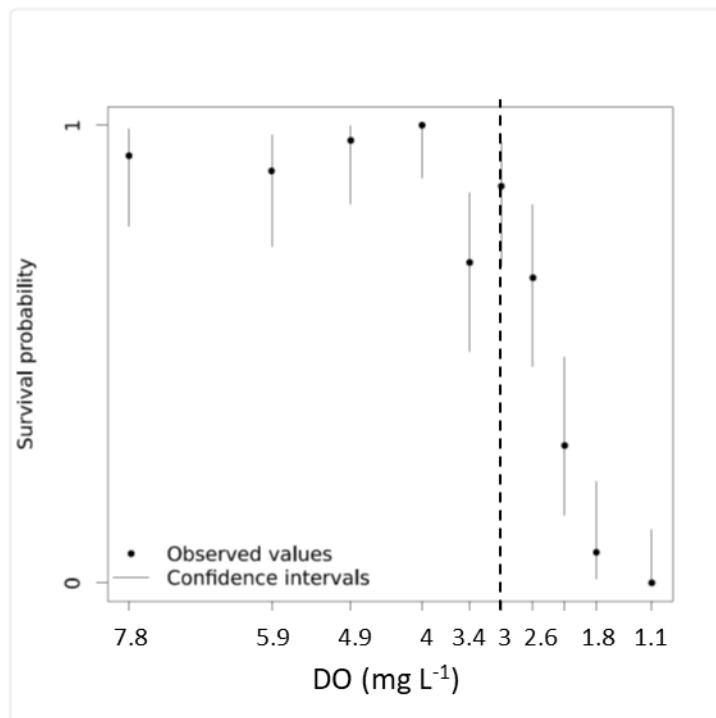
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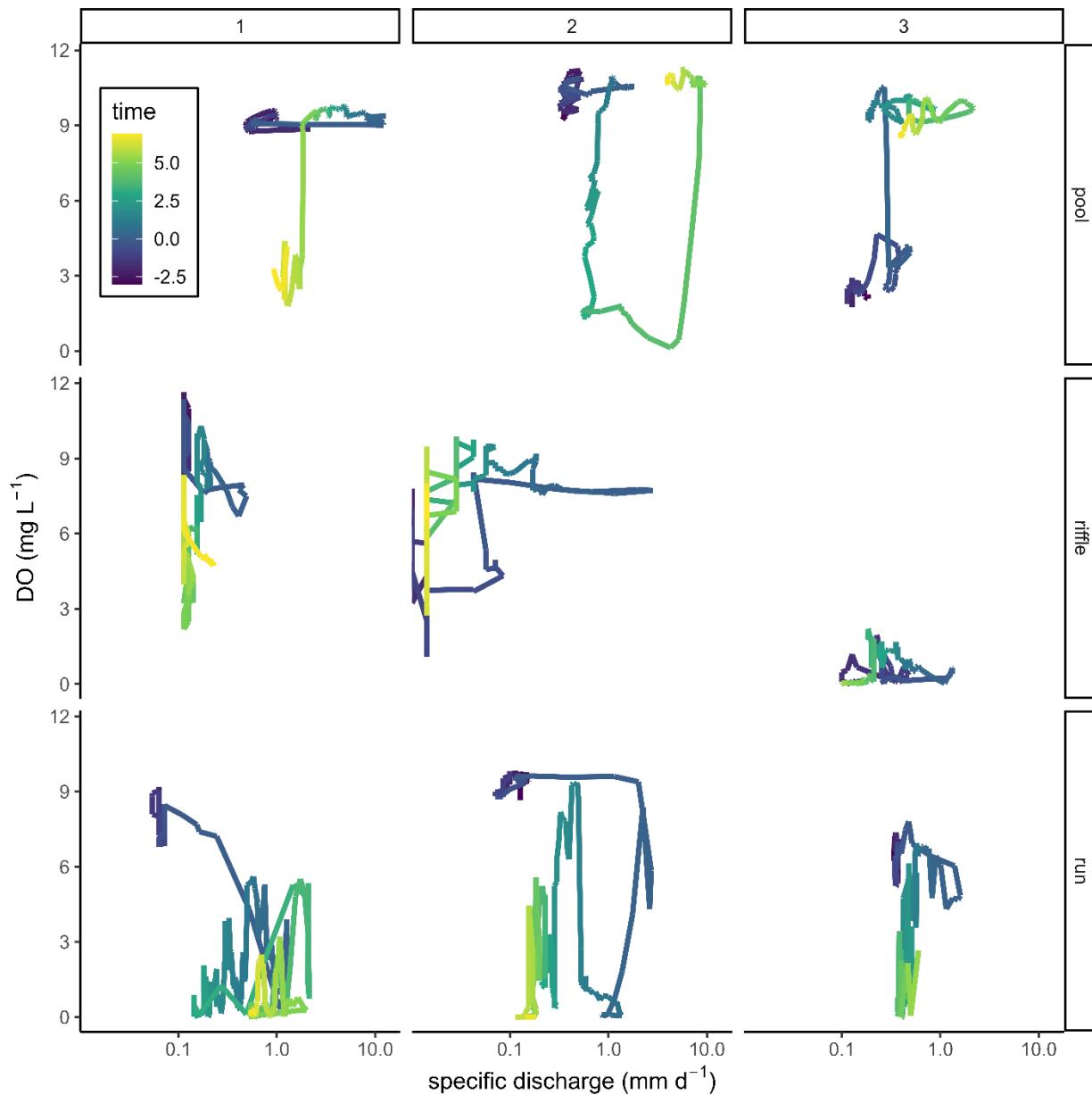
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767 **Figure S1.** Five-day survival in the lab for the gammarids at varying levels of DO. Note the
768 survival threshold at approximately 3 mg L⁻¹ (dashed vertical line). Experimental dataset:
769 doi.org/10.57745/KP9PO5

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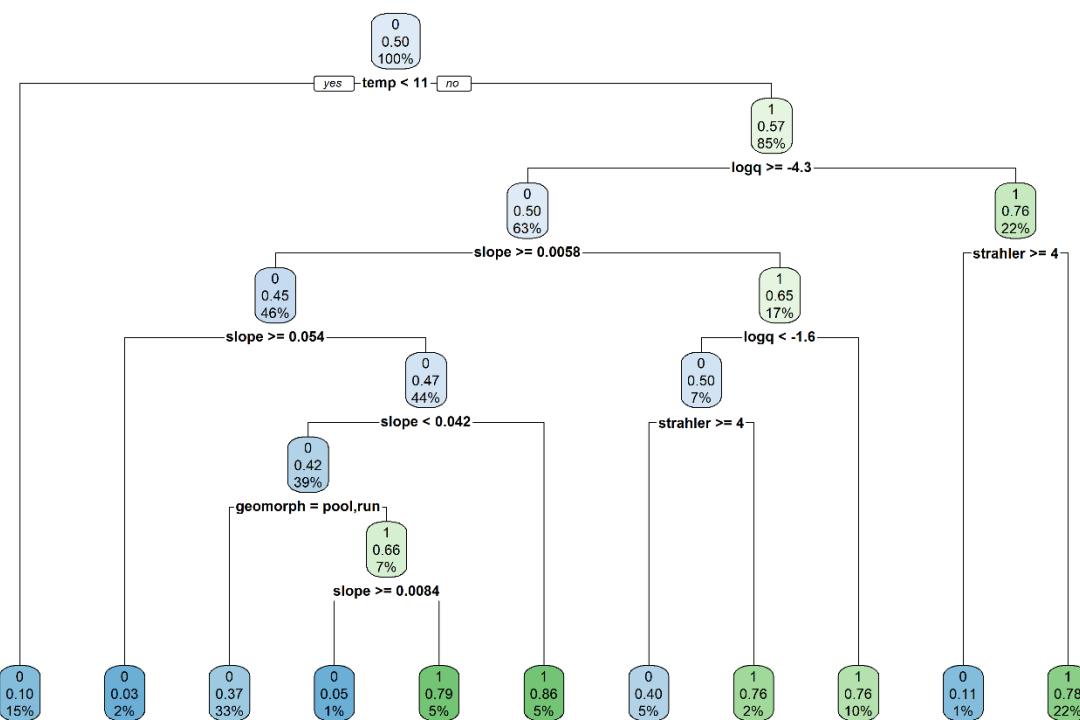
772 **Figure S2.** Hysteresis paths of DO versus q for the events shown in Figure 3 by unique storm
 773 events (columns) and geomorphic habitat setting (rows) with color indicating the time relative to
 774 peak storm discharge (days). Note the highly variable paths that DO takes across storm events.

Table S1. Hypoxia summary statistics by catchment, mean \pm sd when given.

Catchment	Hypoxia (hours)	Hypoxia (%)	Hypoxia (events)	Event length (hours)
Ardières	1844	2.5	31	18 \pm 28

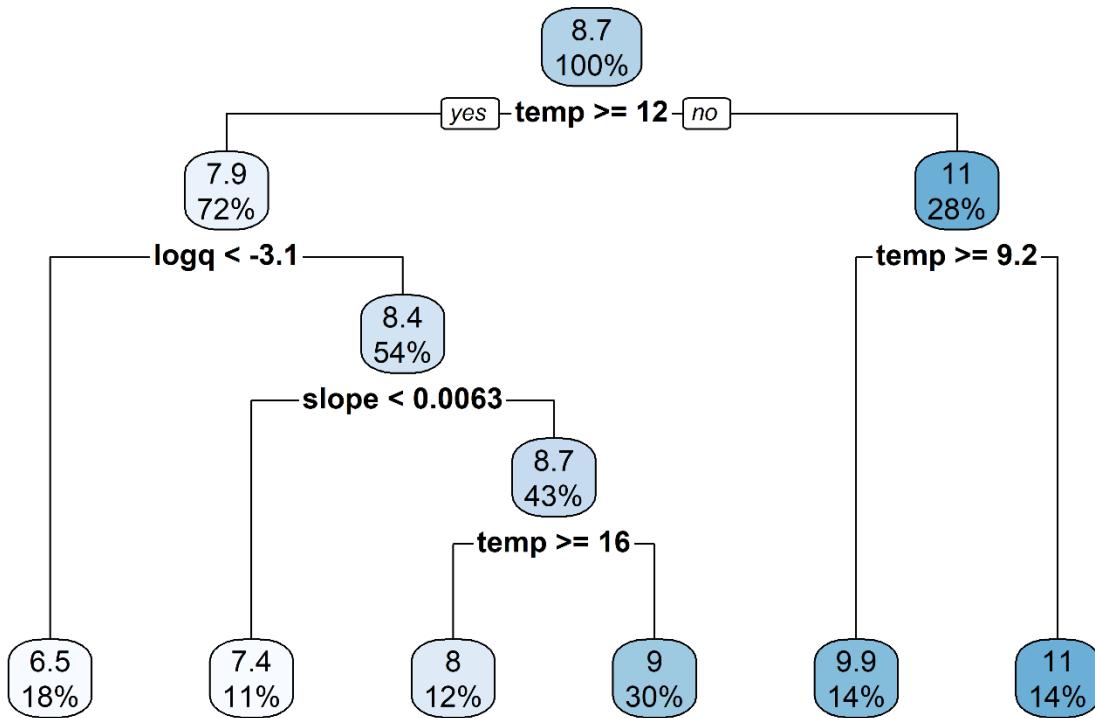
Coise	3555	8.1	44	15±31
Lignon	1067	5.4	23	17±39
Loise	6110	5.9	37	12±21
Mare	1517	7.9	37	20±33
Toranche	2335	12.9	73	19±35
Vauxonne	57	0.3	9	6±5
Yzeron	296	0.3	7	8±8

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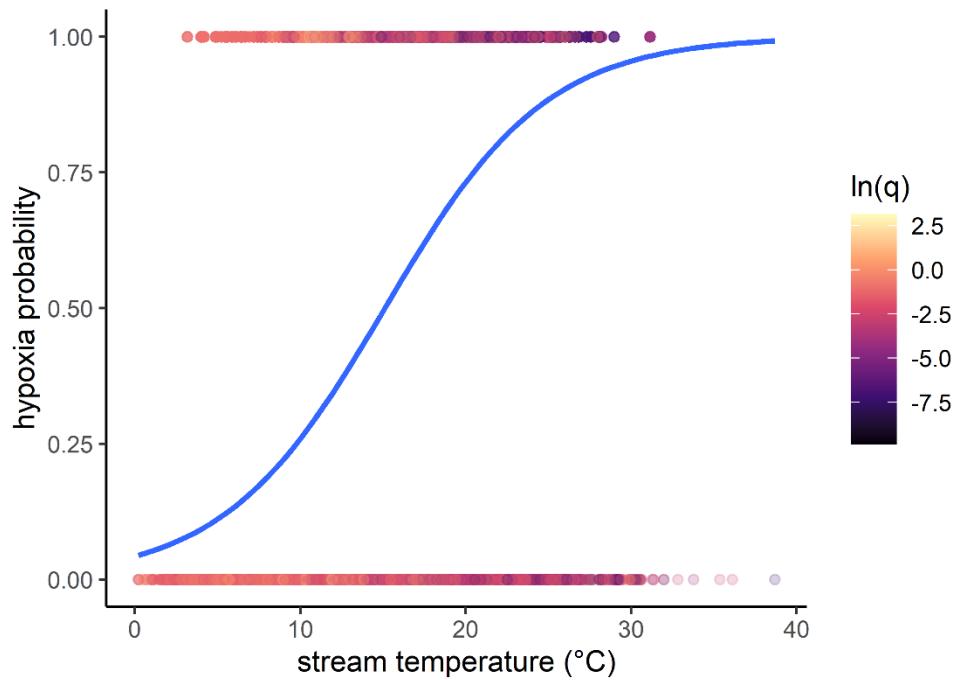
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777 **Figure S3.** Classification tree for hypoxia ($n = 266,079$ from a balanced dataset). Each node
 778 shows from top to bottom: the predicted class (0 = oxic [blue], 1 = hypoxic [green]), the
 779 predicted probability of hypoxia, the percentage of total observations in the node.



780

781 **Figure S4.** Regression tree for DO ($n = 266,080$ training data; 70%). Each node shows from
782 top to bottom: the predicted DO value (mg L^{-1}) and the percentage of total observations in the
783 node. Model details: based on testing data ($n = 114032$, 30%) $\text{RMSE} = 1.8 \text{ mg L}^{-1}$, $R^2 = 0.41$,
784 $\text{MAE} = 1.2 \text{ mg L}^{-1}$, bias = 0.0. Variable importances are temperature = 71, specific discharge =
785 21, slope = 7, Strahler order = 1, and light = 1.



786

787 **Figure S5.** Logistic regression (blue line) of hypoxia on a balanced dataset of hypoxic and
788 oxic conditions (n=266,079) with point colors indication $\ln(\text{specific discharge})$.