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► **To cite this version:**

Albert Ruhi, Mathis Messenger, Julian Olden. Tracking the pulse of the Earth's fresh waters. *Nature Sustainability*, 2018, 1 (4), pp.198-203. 10.1038/s41893-018-0047-7 . hal-04151149

HAL Id: hal-04151149

<https://hal.science/hal-04151149>

Submitted on 4 Jul 2023

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1 **Title: Tracking the pulse of the Earth’s fresh waters**

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3

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11

12 **Article type:** Analysis

13 **Key words:** Freshwater scarcity, environmental monitoring, shifting baselines, streamflow,
14 water resources.

15 **Abstract:**

16 Reliable accounting of freshwater resources is key to managing hydrologic risk and
17 balancing freshwater allocations for ecosystems and society. However, recent claims have
18 argued that the global hydrometric network is not keeping pace with monitoring needs. Here we
19 examine this question globally and reveal that over the past four decades the number of
20 streamgaging stations reporting to global, open datasets has been declining. In the U.S., a
21 declining trend was reversed by the turn of the century, but high volatility at the river basin scale
22 threatens continued monitoring in over a quarter of the river basins of the conterminous U.S. We
23 propose to prioritize streamgaging rescue by identifying watersheds that heavily rely on
24 hydrologic data to support freshwater biodiversity conservation, and to manage flood or water
25 scarcity risk to human populations. We contend that actions at different institutional levels are
26 needed to secure the accumulation of long-term data needed for sustainable water management.

27 **Main text:**

28 Humans have long recognized the importance of tracking the pulse of the Earth’s water
29 resources, dating at least five millennia ago when Ancient Egyptians started monitoring peak
30 river stage to anticipate agricultural yield and risk to floodplain infrastructure ¹. Streamgaging
31 technology has improved dramatically since then, and networks of stations obtaining continuous
32 records of stage and discharge are now fundamental to water information systems (WIS) ². These
33 hydrometric networks are critical for allocating resources to support human and ecosystem water
34 needs (often via diversions or flow releases below dams), and for forecasting flood and drought
35 risk to societies ². In particular, the accumulation of long-term hydrologic data is needed to
36 evaluate hydroclimatic trends, to quantify flow regime alteration and associated flow-ecology
37 relationships, and to decrease statistical uncertainty in flood and drought predictions. For
38 instance, insufficient WIS may hinder effective implementation of environmental flows during
39 extended periods of suprasonal drought ³. Similarly, flood risk management also depends on
40 WIS. Since 1980, extreme flood events worldwide have claimed over 215,000 human lives, and
41 in North America alone, 215 lives have been lost and \$4.1 billion in property damages have been
42 caused annually by inland flooding ⁴. Without advanced WIS and high-precision forecasting,
43 these figures would be even larger—the U.S. Advanced Hydrologic Prediction Service,
44 supported by satellite data and by >8,000 streamgaging stations across the nation, saves an
45 estimated \$240 million per year in reduced flood losses ⁵. More recently, streamgages were
46 instrumental in reducing life and property losses during the exceptional 2017 Atlantic hurricane
47 season (with storm surge associated with Hurricanes Harvey, Irma, and Maria); as well as during
48 California’s recent floods for managing the Oroville Dam crisis in real time ⁶. As climate change
49 forces water managers and policy makers to grapple with increasing hydrologic uncertainty and

50 magnitude of extreme weather events ^{7,8}, WIS will become increasingly important for supporting
51 adaptive local decisions and environmental policy objectives.

52 Nevertheless, there is some evidence that the global hydrometric network has been
53 shrinking over the last three decades ^{9,10}. Global streamgaging efforts are difficult to evaluate
54 because most national water authorities do not make data on hydrometric infrastructure publicly
55 available ⁹. However, initiatives like the Global Runoff Data Centre, which under the auspices of
56 the World Meteorological Organization curates the largest international repository of
57 streamgaging data, provide the opportunity to appraise trends in data availability over time. As a
58 national-scale example, the United States Geological Survey (USGS) National Water
59 Information System (NWISWeb) is the primary online database for stream discharge and water
60 level observations ^{11,12}, a centralized system that allows for quantifying temporal trends in the
61 number of active streamgaging stations, and the types and quality of data being recorded in the
62 country. Here we combined analyses on the data reported by the Global Runoff Data Centre and
63 the USGS National Water Information System to examine the evidence for the deteriorating state
64 of WIS. Based on our findings, we make policy recommendations to strengthen WIS
65 strategically, globally and in the United States.

66 Trends in streamgaging data availability

67 The data set from the WMO Global Runoff Data Centre comprises 9,472 past and active
68 stations in 158 countries, of which 7,238 stations in 133 countries reported daily discharge data.
69 Temporal variation in the number of reporting stations in a given country may be caused by
70 changes in the hydrometric network, changes in data sharing policies, and/or lags in data
71 reporting—indicating variation in access to streamgaging data regardless of the cause. We found
72 that the total number of reporting stations peaked in 1979 and sharply declined thereafter (Fig.

73 1). After classifying stations by age class (length of the discharge record, in years), we observed
74 that the decline was expressed largely by stations with records shorter than 30 years (Fig. 1).
75 From 1979 to 2010 (selected to allow for lags in country reporting), 3,119 gages with <15 years
76 of discharge record and 2,055 gages with 15-30 years of data ceased reporting streamflow (Fig.
77 1). Aging of the ‘surviving’ stations explained the slight increase in the older age classes (777
78 stations over 30 years old); however, the overall trend showed a negative balance between new
79 and non-reporting stations.

80 Evidence from the United States suggests a bimodal trend in the number of gaging
81 stations, surpassing the threshold of 8,000 active stations in the late-1960s and again in the
82 mid-2010s (Fig. 2). This pattern mimicked fluctuations in the number of relatively young
83 stations (i.e. those with discharge record lengths ranging between 15 and 30 years; Fig. 2), and is
84 likely explained by shifts in USGS funding. Around 1970, the USGS Cooperative Water
85 Program (now the Cooperative Matching Funds) was not able to keep up with inflation, leaving
86 an increasing percentage of funding responsibility to the cooperating agencies (R. Mason, *pers.*
87 *comm.*). In 2000, the USGS National Streamflow Information Program (now Federal Priority
88 Streamgages) was started, providing increased funding for the streamgaging network and
89 explaining the inflection point in the net number of active stations. In addition, the total number
90 of stations with records >50 years has more than doubled since 1980 (from 1247 to 2638
91 stations), and has kept increasing at a stable rate over the last two decades. However, analyses at
92 the river basin scale (Hydrological Unit Code 6) delivered a more nuanced perspective.
93 Time-series models on 70 years of streamgaging data (1947-2016) show decreasing trends in the
94 number of active streamgages for 21% of the analyzed river basins, and even river basins with
95 non-negative trends present important fluctuations in streamgaging over time due to station

96 turnover (Supplementary Figure 1; see changes in active and deactivated streamgages over time
97 in shiny.sesync.org/apps/gages). As a consequence, over one-quarter (29%) of the analyzed river
98 basins in the conterminous U.S. have >50% probability of having their gage network density
99 halved by 2022 (Fig. 3), that is, by the end of the current USGS Water Science strategic plan.
100 Importantly, these ‘imperiled’ river basins are widely distributed across major hydrologic
101 regions, and overlap spatially with areas of high water scarcity risk (48 %), high flood risk (31
102 %), and high fish diversity (38 %) (Fig. 3). Water scarcity and flood risk overlap in 9 imperiled
103 river basins dispersed throughout most of the U.S., from the Southwest (Upper Colorado-
104 Dolores) to the Mid Atlantic (Long Island) (Fig. 4). Three of these critical river basins
105 (Albemarle-Chowan, Lower Ohio, Yazoo) also support highly diverse fish faunas (measured as
106 endemism weighted richness/unit) (Fig. 3). This indicates that declines in flow monitoring may
107 compromise human responsiveness to water challenges and the ability to manage freshwater
108 biodiversity simultaneously.

109 Declining funding, shifting priorities

110 The trends observed in the GRDC data set are likely caused by a combination of
111 weakening infrastructure and data sharing policies, two threats that make global water data ‘a
112 newly endangered species’¹⁰. Although hydrometric networks continue to be relatively dense
113 and largely operative in Europe, North America, Japan, South Africa, and Australasia, important
114 monitoring gaps remain in areas such as central Asia, the Arctic, and large swaths of Africa^{9,13}.
115 Substantial decreases (>25%) in operational capacity have been reported from Russia and the
116 former Soviet states over the last three decades¹⁰. In many countries, stations tend to be spatially
117 clustered and short-lived because data collection is contingent on development projects. Limited
118 funding and shifting government priorities also limit streamgaging capacity in developing and

119 developed countries alike ^{9,14,15}. For example, almost one-third of gages in Zimbabwe provide
120 unreliable data due to decreasing funding for streamgage monitoring and maintenance ¹⁶.
121 Similarly, budgetary reductions in the 1990s led to a substantial shrinking of the gaging network
122 in Canada ¹⁷. Although some countries exclusively fund and operate their WIS at the national
123 level, many others depend on co-funding from regional and local partners ¹⁵. This collaborative
124 approach expands agency over hydrometric infrastructure and monitoring, but may increase
125 vulnerability to economic recessions and shifting priorities if there is little strategic oversight and
126 commitment to long-term gage operation.

127 The United States exemplifies the challenge of volatile funding for hydrometric
128 networks. Two decades ago, the U.S. Congress warned in a report of the declining number of
129 gages despite increased demand for basic streamflow information. Subsequent investigations
130 repeatedly called for an upgrade of the network ^{14,15}, but years later long-term stations are still
131 being lost and the number of gages with ≥ 30 years of data has not increased since the 1990s
132 (Fig. 2). Moreover, budgetary cuts now faced by the U.S. Geological Survey (USGS) will further
133 burden the nation's WIS. The FY 2019 U.S. federal budget request ¹⁸ would cut USGS funding
134 by 20% (from \$1.08 billion to \$860 million), and would affect several Water Resources
135 programs (-23% funding), including the Groundwater and Streamflow Information Program that
136 oversees the country's streamgaging network. This would further diminish the agency's ability to
137 strengthen the hydrometric network and apply cost-effective monitoring and record maintenance.
138 The truncation of valuable, long-term data may increase the vulnerability of socio-environmental
139 systems to hydroclimatic extremes (floods and droughts). Additionally, a weaker WIS may limit
140 the government's ability to meet its responsibilities under several federal laws. For instance,
141 discharge data are instrumental for setting instream-flow requirements to conserve species listed

142 under the Endangered Species Act ^{19,20}, and for estimating pollutant loads to waterbodies to
143 comply with the Clean Water Act ^{21,22}.

144 Creative solutions

145 Here, we propose a set of measures at the political, institutional, and technological levels
146 to increase the coverage, reliability, and accessibility of the global WIS:

147 *Protect and rescue gages strategically, at the river basin scale.* The marginal benefit of
148 ensuring the survival of a gage depends on the value of the monitoring data it provides, but also
149 on the number, and ultimately the fate, of other gages operating in the same river basin.

150 However, such factors are rarely considered in strategic plans such as the U.S. Geological
151 Survey's Federal Priority Streamgages program. We performed this forward-looking exercise in
152 the U.S., and demonstrate with an interactive map (shiny.sesync.org/apps/gages) how dynamic
153 visualization of monitoring efforts and needs can support strategic prioritization at the river basin
154 scale (i.e., the prioritization of streamgaging in river basins with high flood risk, water scarcity,
155 biodiversity value, and gage loss probability). Because flow monitoring is likely to decline in
156 areas with high monitoring needs, this compromises human responsiveness to future water
157 challenges. Therefore, funding for gages in these basins should be prioritized over other basins.
158 We recommend performing similar 'Population Viability Analyses' of monitoring infrastructure
159 wherever data allows, further evaluating gages based on their representation of the stream
160 network ²³.

161 *Create non-traditional funding opportunities.* A wide range of public agencies contribute
162 to funding national hydrometric networks, but involvement of non-governmental partners is both
163 sporadic and largely negligible. For example, 850 partner agencies contribute to monitoring flow
164 in the United States, but 'other partners' (including NGOs and the private sector) only funded

165 8% of the stations in FY 2016 (D. Yeskis, USGS, *pers. comm.*). Given the relatively modest cost
166 of maintaining a gage (estimated at \$16,310/year; D. Yeskis, USGS, *pers. comm.*), local
167 partnerships with cities, small and midsize businesses, homeowner associations, or non-for-profit
168 organizations, could be emphasized via Cooperative Matching Funds to protect important gages
169 from going offline. At a larger scale, cooperation with counties and regional insurance
170 companies could be established with the goal of maintaining or increasing gage density in flood-
171 and drought-prone areas. In the U.S. alone, the federally-run National Flood Insurance Program
172 has close to 5 million individual policies totaling \$1.23 trillion under coverage. If only one-tenth
173 of one percent of the \$3.52 billion generated in premiums was invested in monitoring, 215 gages
174 could be saved annually; a number exceeding the 206 stations that have been discontinued
175 recently due to funding shortfall. This investment would increase the accuracy of flood zones
176 and Flood Insurance Rate Maps, decreasing in turn the cost of risk-based insurance premiums for
177 homeowners^{24,25}.

178 *Design modular systems that can be readily scaled.* When facing the question of
179 decreasing gage ‘mortality’ (by securing imperiled gages) vs. rescuing old or installing new
180 gages, agencies should generally choose gage protection, as truncated time series and station
181 turnover limit statistical inference even when gage numbers remain constant. However, in some
182 cases it may be desirable to support a complementary, temporary monitoring infrastructure that
183 accrues little maintenance costs and can be activated at will²⁶. In regions like the U.S. sunbelt,
184 where water allocations for human use and ecosystems are increasingly at odds²⁷,
185 drought-activated stations would allow for more accurate tracking and enforcement of water
186 allocations during periods of acute water stress, when human and ecosystem water needs are
187 greatest. Such a system would have benefited California during its recent multi-year drought,

188 when freshwater ecosystem impacts were exacerbated by the absence of gages in approximately
189 half of the state’s watersheds containing critical aquatic habitat³. In countries such as Spain and
190 Australia, where a single state office administers surface and groundwater rights³, temporary
191 systems could supplement the existing WIS to account for surface-groundwater interactions (e.g.,
192 return flows from groundwater pumping) during periods of extreme low flows.

193 *Build capacity in developing countries.* International development agencies should fund
194 projects aimed at meeting streamgaging density levels recommended by the WMO². In May
195 2017, the World Bank approved funding for the ‘National Hydrology Project for India’, a \$350M
196 endeavor that will finance a new WIS for India, including streamflow and groundwater
197 monitoring infrastructure to enable a web-based, real-time flood forecast system. This
198 nationwide project builds on two successful basin-scale projects previously funded by the World
199 Bank, which decreased flood early warnings from hours to days and saved lives and minimized
200 flood damages valued in \$17-65M/year. Increasing streamgaging density in developing countries
201 entails challenges related to the size, remoteness, and political context of many under-monitored
202 areas. However, similar initiatives could benefit many African countries—directly, via improved
203 water resource management; and indirectly, by reducing the systematic over-design of water
204 projects due to missing or unreliable hydrologic data¹⁰.

205 *Leverage technological progress.* Space-based methods like radar altimetry for large
206 river stage, and mass-conserved flow law inversion (McFLI) techniques, may transform the
207 hydrologic sciences in the future²⁸. Yet, streams are highly dynamic over time, and remote
208 sensing products need to be validated with field measurements¹³. Therefore, initiatives that
209 promote global hydrologic data collection, curation, and sharing will be increasingly valuable as
210 they enable an expanding range of basic research questions and hydrological applications. For

211 example, the Consortium of Universities for the Advancement of Hydrologic Science integrates
212 global data from diverse sources (government, universities, citizen science) and makes it publicly
213 available under a universal format ('HydroClient'). We expect that financial incentives will
214 continue to be an effective way of encouraging participants to follow open data guidelines ^{9,10},
215 particularly when data commercialization hinders agencies from providing unrestricted access to
216 water information.

217 Concluding remarks

218 In this Analysis, we highlight recent declining trends in streamgaging data availability in
219 the U.S. and globally. We urge governments to strengthen hydrometric networks strategically, so
220 that anticipated declines in streamgaging capacities are averted, particularly where humans and
221 ecosystems require water data the most. We further encourage freshwater scientists,
222 practitioners, and decision makers to promote a global, open-access WIS that enables tracking
223 the pulse of the Earth's water resources into the future.

224

225 **Methods:**

226 Streamgaging historical data

227 Data from global streamgaging efforts was obtained from the Global Runoff Data Center
228 (GRDC) data set (<http://www.bafg.de/GRDC>, accessed on January 10, 2018). A gage was
229 considered active if its daily discharge records were reported to GRDC that year.

230 Historical streamflow data for all streamgage stations of the United States were compiled
231 from the USGS National Water Information System (NWIS) using the 'dataRetrieval' R package
232 ²⁹ on January 10, 2018. Mean daily discharge data were downloaded for the period January 1854
233 to December 2016. Periods for which river discharge records were estimated rather than

234 measured (e.g., due to gage malfunction) were excluded from the analysis. In total, discharge
235 data were compiled for nearly 23,000 stations. For each year, a streamgage was classified as
236 ‘active’ if it recorded discharge for at least 180 days during that year, and as ‘inactive’ if it did
237 not. This criterion did not include seasonally operated gages — which constitute ~5% of the total
238 number of gages in the USGS hydrometric network (*not shown*) — to allow for estimating the
239 potential shift from year-round data collection to seasonal operation. We then computed the
240 number of active stations in each of the 352 river basins (Hydrological Unit Code or HUC 6) of
241 the National Water Boundary Dataset (WBD), every year from 1854 to 2016, using the
242 geographic location of the gaging station reported in the NWIS.

243 Water scarcity

244 We represented water scarcity for each river basin of the conterminous United States using
245 the county-level Normalized Deficit Cumulated (NDC)³⁰. The NDC is equal to the maximum
246 cumulative deficit between average daily water demand in 2010 and local daily renewable
247 supply from 1949 to 2010, divided by the average annual rainfall volume (county area x
248 average depth of precipitation) in that county. This index does not include as renewable supply
249 exogenous sources of water such as rivers and canals flowing through each county, or water
250 transfers from outside. By only including endogenous sources of renewable water (i.e., runoff
251 and groundwater recharge from precipitation in that county), this metric reflects the reliance of
252 each county on outside sources (e.g., withdrawal from runoff originating outside the county) and
253 on non-renewable local sources of water (e.g., groundwater with slow recharge). Moreover, by
254 using the maximum cumulative deficit over the entire study period rather than the maximum
255 yearly deficit (which is reset at the beginning of each year), this index captures the potential
256 long-term impact of continued overconsumption of water and multiyear droughts. Finally, by

257 computing the ratio of water deficit to annual rainfall volume, NDC is normalized across climate
258 regions to relate each county's deficit to its available renewable endogenous water budget.

259 We computed the HUC6-specific NDC from county-level NDC by first intersecting
260 counties and river basins (HUC6), as administrative boundaries rarely follow watershed
261 boundaries. We then computed NDC for each HUC6, as:

262

$$NDC_{HUC6} = \frac{1}{\bar{R}_{HUC6}} \times \sum_{\text{County}=1}^{N \text{ county in HUC6}} NDC_{\text{County}} \times \bar{R}_{\text{County}} \times \frac{\text{Area}_{HUC6-\text{County intersection}}}{\text{Total area}_{\text{County}}}$$

263

264 , where \bar{R} is the average annual rainfall (mm) for each HUC 6 calculated using daily
265 gridded meteorological data for the period 1949-2010³¹.

266 By aggregating NDC across counties intersecting with a given river basin based on
267 proportional area located in that basin, our main assumptions were that water deficit is
268 distributed uniformly throughout each county, and that NDC is cumulative across counties (i.e.,
269 that maximum water deficit can be added up across county boundaries). Given that NDC is based
270 on the maximum daily water deficit in each county, the maximum water deficit in a given county
271 may not occur the same day in other counties in the same basin. In such a case, our NDC_{HUC6}
272 would overestimate the actual maximum water deficit for the basin. Nevertheless, because
273 agricultural patterns and climate are relatively homogenous within river basins across multiple
274 counties (average HUC6 area: 24,000 km²), this metric adequately reflects relative water scarcity
275 patterns among regions in the United States.

276 Flood risk

277 We calculated flood risk in the conterminous United States as the percentage of the total
278 human population that lives within the 100-year flood zone. To compute flood risk, 2010 census
279 block level population data were intersected with 100-year flood zone polygons from the
280 National Flood Hazard Layer (NFHL), a digital database containing all flood hazard mapping
281 data from the Federal Emergency Management Agency's National Flood Insurance Program
282 (FEMA NFIP). Census-block population data was used because of its high resolution (average
283 and median area of a census block: 0.74 km² and 0.02 km², respectively), and its ability to
284 spatially discriminate between settled areas and waterways or uninhabited floodplains. Despite
285 its high resolution, the section of census blocks overlapping flood zones often did not include
286 any housing. Therefore, we calculated the number of people living in a flood zone as the product
287 of the census-block population size and the percentage of the census block urbanized area
288 (calculated from 2011 National Land Cover Data) overlapping the 100-year flood zone (Zone A
289 from the NFHL). When a census block did not contain any urban land cover (LC), we computed
290 the product of census block population and percentage of census block total area intersecting a
291 flood zone. The population in each census block living in an area for which a flood hazard study
292 exists was computed the same way. Finally, the percentage of the population in each river basin
293 living in a 100-year flood zone equals to the total population living in a 100-year flood zone
294 across all census blocks of a river basin divided by the total population living in an area for
295 which a flood hazard study exists. When a census block straddled the boundary between two
296 river basins, the population living in a flood zone within each basin was proportional to the area
297 of the census block overlapping the basin. For each HUC6, flood risk was therefore computed as
298 follows:
299

$$\text{Flood risk}_{\text{HUC6}} = \sum_{C=\text{census blocks within HUC6}} \frac{\text{Population living within flood zone}_c}{\text{Population living in area with flood hazard study}_c}$$

300

301

, where:

302

303

Flood risk_{HUC6} =

304

$$\frac{\sum_{C=1}^N \text{blocks with urban LC} \frac{\text{Total area within HUC6}_C \times \text{Population}_C \times \text{Urban area within flood zone}_C}{\text{Total area}_C} \times \frac{\text{Population}_C \times \text{Urban area within flood zone}_C}{\text{Total urban area}_C}}{\sum_{C=1}^N \text{blocks with urban LC} \frac{\text{Total area within HUC6}_C \times \text{Population}_C \times \text{Urban area with FEMA status}_C}{\text{Total area}_C} \times \frac{\text{Population}_C \times \text{Urban area with FEMA status}_C}{\text{Total urban area}_C}} +$$

305

$$\frac{\sum_{C=1}^N \text{blocks with no urban LC} \frac{\text{Total area within HUC6}_C \times \text{Population}_C \times \text{Area within flood zone}_C}{\text{Total area}_C}}{\sum_{C=1}^N \text{blocks with no urban LC} \frac{\text{Total area within HUC6}_C \times \text{Population}_C \times \text{Area with FEMA status}_C}{\text{Total area}_C}}$$

306

307 Fish biodiversity metrics

308

We compiled a dataset of the distribution of freshwater fish at the subbasin level (HUC8)

309

throughout the conterminous United States based on the NatureServ and ancillary local and

310

regional sources, and then computed the endemism weighted richness/unit (EWU) for each river

311

sub-basin, following (2):

312

313

$$EWU_{\text{HUC8}} = \text{Sum of each species' Endemism Unit} \quad , \text{ where:}$$

314

315

$$\text{Endemism Unit} = 1 / \text{Number of HUC8s where the species is present}$$

316

317

Accordingly, the most endemic species in a HUC8 has an Endemism Unit = 1. EWU_{HUC8}

318

were then aggregated at the river basin level (HUC6) by averaging sub-basin level EWU within

319

each river basin.

320

321 Time-series analysis of gage ‘population’ dynamics

322 Finally, we analyzed streamgaging dynamics within each HUC6 using statistical
323 time-series models, namely univariate, first-order, autoregressive or AR(1) models, using the
324 ‘MARSS’ R package³². Autoregressive models are frequently used in Population Viability
325 Analysis to estimate probabilities of hitting critical decline thresholds, or ‘quasiextinction’^{32,33}.
326 Here we similarly applied this concept to streamgage ‘populations’ within each HUC6. In its
327 simplest form (i.e., without considering exogenous covariates or density-dependent effects), an
328 AR(1) model can be expressed as:

329

$$330 \quad x_{i,t} = x_{i,t-1} + u_i + w_{i,t}$$

331

332 , where $x_{i,t}$ is the number of gages active in HUC6 i at time step t , u represents their
333 long-term trend (akin to a species intrinsic growth rate), and $w_{i,t}$ represents the process error, or
334 the stochastic component that affects the gage population from one time step to the next one
335 (assumed to be drawn from a normal distribution with a mean of 0 and variance q).

336 We estimated u and q based on observed streamgaging data over the last 70 years (1947-
337 2016), and we then used these coefficients to compute the probability that a gage population
338 would hit a 50% decline threshold within the following 6 years (‘decline risk’) [after³²]. Model
339 residuals were examined via the autocorrelation function. Only the 228 river basins (HUC6) with
340 a median number >10 gages over the period 1947-2012 were considered for this analysis.
341 Because the relative influence of losing a gage in low-density basins is higher than in
342 high-density basins, this approach provides a conservative estimate of gaging decline risks. We

343 chose the forecast to be 6 years long because that time horizon coincides with the end of the
344 current USGS Water Science strategic plan 2012-2022³⁴.

345 Data availability

346 All data that support the findings of this study are available from the corresponding
347 author upon request. Data from the U.S. analyses can be directly downloaded from:
348 <https://shiny.sesync.org/apps/gages>. See Supplementary Table 1 for data sources.

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353 **Acknowledgments:**

354 We thank Douglas Yeskis, Brian Reece, and Robert Mason (USGS) for answering our
355 questions regarding U.S. streamgage monitoring. We also thank Margaret Palmer, Ted
356 Grantham, and three anonymous reviewers for their comments. Albert Ruhi was supported by
357 the National Socio-Environmental Synthesis Center (SESYNC), under funding received from
358 NSF DBI-1052875. Financial support was provided by a H. Mason Keeler Endowed
359 Professorship (School of Aquatic and Fishery Sciences, University of Washington) to Julian
360 Olden.

361 **Author contributions:**

362 AR, MM, and JDO designed the research; MM collated and visualized the data; AR and
363 MM analyzed the data; AR, MM, and JDO wrote the paper.

364

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438

439 **Figure legends**

440 **Fig. 1. Global trends in streamgaging stations reporting to the World Meteorological**

441 **Organization's Global Runoff Data Centre.** We classified stations by age class (length of the
442 discharge record, in years). The number of reporting stations peaked in 1979 and decreased
443 sharply thereafter. Comparisons to 2010 (white vertical line) accounts for lags in data reporting,
444 but trends to present-day are shown.

445 **Fig. 2. Trends in the number of active streamgaging stations in the USGS hydrometric**

446 **network.** We classified stations by age class (length of the daily discharge record, in years). The
447 total number of active streamgages peaked twice, in the late-1960s and in the mid-2010s.

448 **Fig. 3. Streamgaging decline risk and socio-environmental monitoring needs in the United**

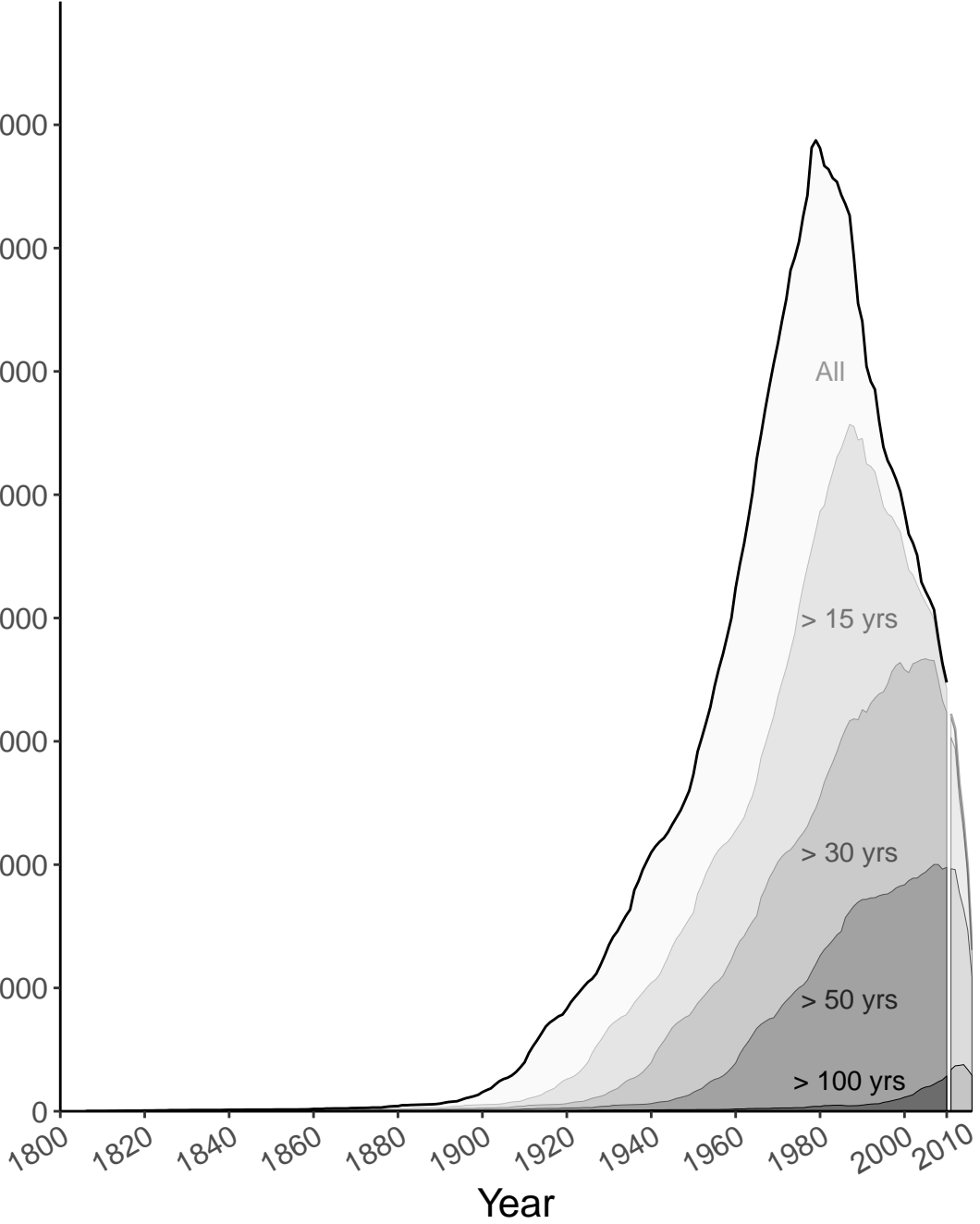
449 **States** (see interactive map here: shiny.sesync.org/apps/gages). We represent U.S. conterminous
450 river basins (Hydrological Unit Code 6) under streamgauge decline risk, inferred via time-series
451 analysis of USGS streamgaging history. Water scarcity was measured as Normalized Cumulative
452 Deficit, NDC; flood risk to human populations was measured as % of population living within a
453 100-year flood zone; and fish biodiversity was measured as endemism weighted richness. In the
454 inset maps, basins with >50% probability of having their gage network density halved by year
455 2022 are striped. Around 48% of the 'imperiled' river basins experience water scarcity, 31% of
456 them are under high flood risk, and 38% harbor high fish diversity (endemism weighted
457 richness/unit). See Methods for details.

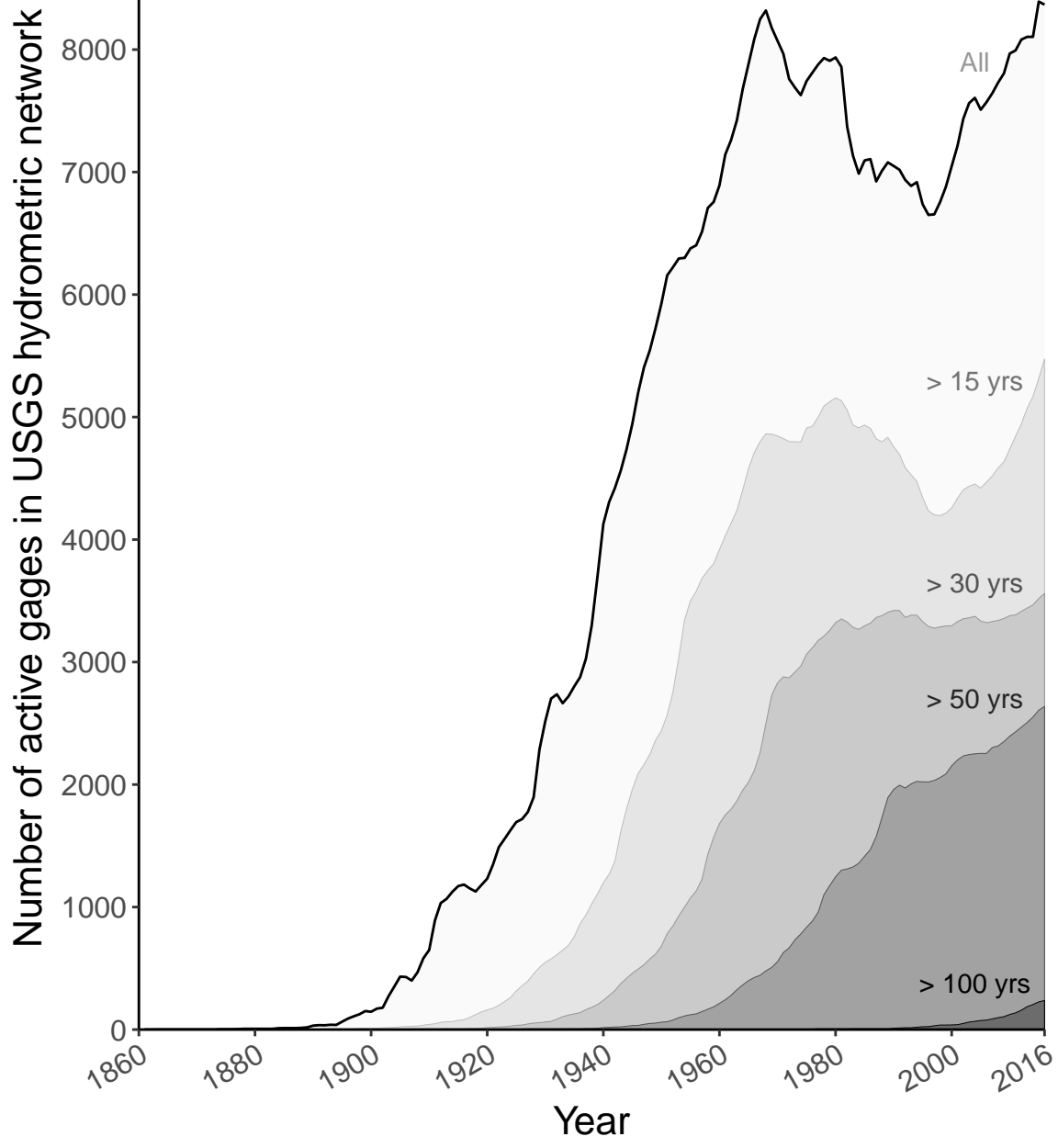
458 **Fig. 4. Spatial distribution of streamgaging decline risk in the United States** (see interactive

459 map here: shiny.sesync.org/apps/gages). We represent the U.S. conterminous river basins
460 (Hydrological Unit Code 6) under streamgauge decline risk ('imperiled' basins), inferred via
461 time-series analysis of USGS streamgaging history; under flood risk to human populations (% of

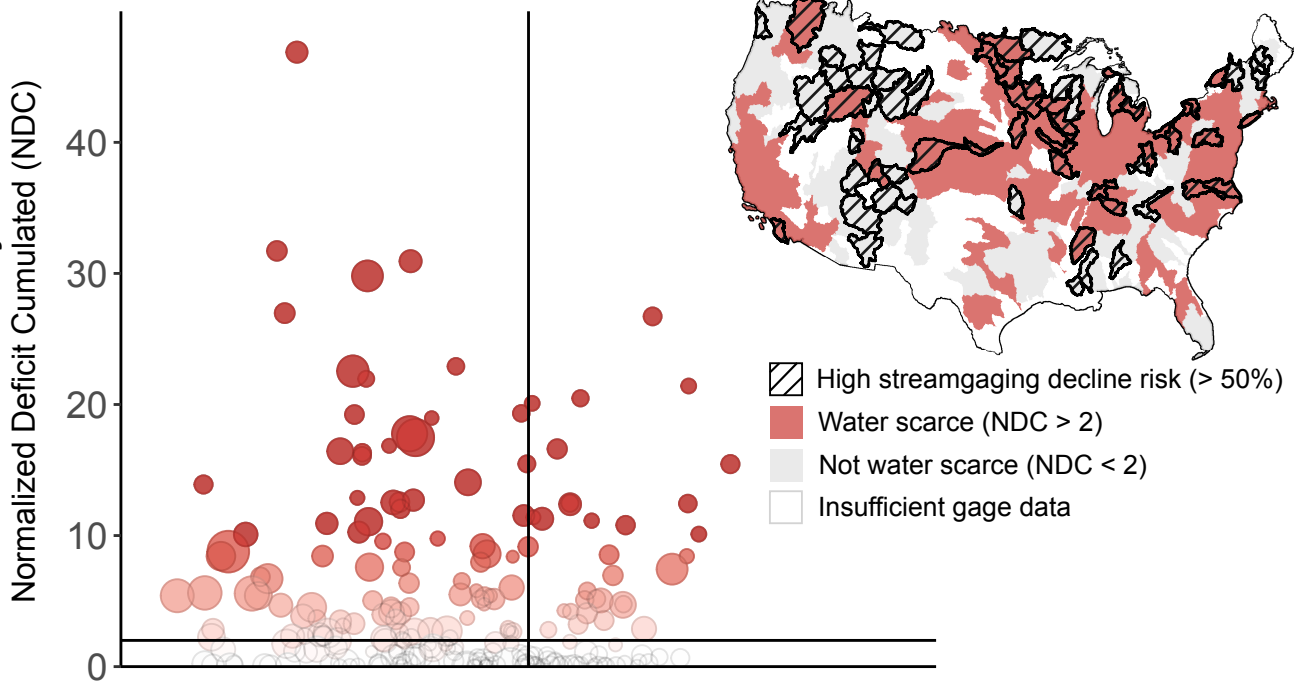
462 population living within a 100-year flood zone); and under water scarcity risk (measured as the
463 maximum long-term imbalance between water demand and endogenous supply or Normalized
464 Cumulative Deficit, NDC). See Methods for details, and Supplementary Figure 2 for raw decline
465 risk values.

Global number of stream gages reporting to GRDC

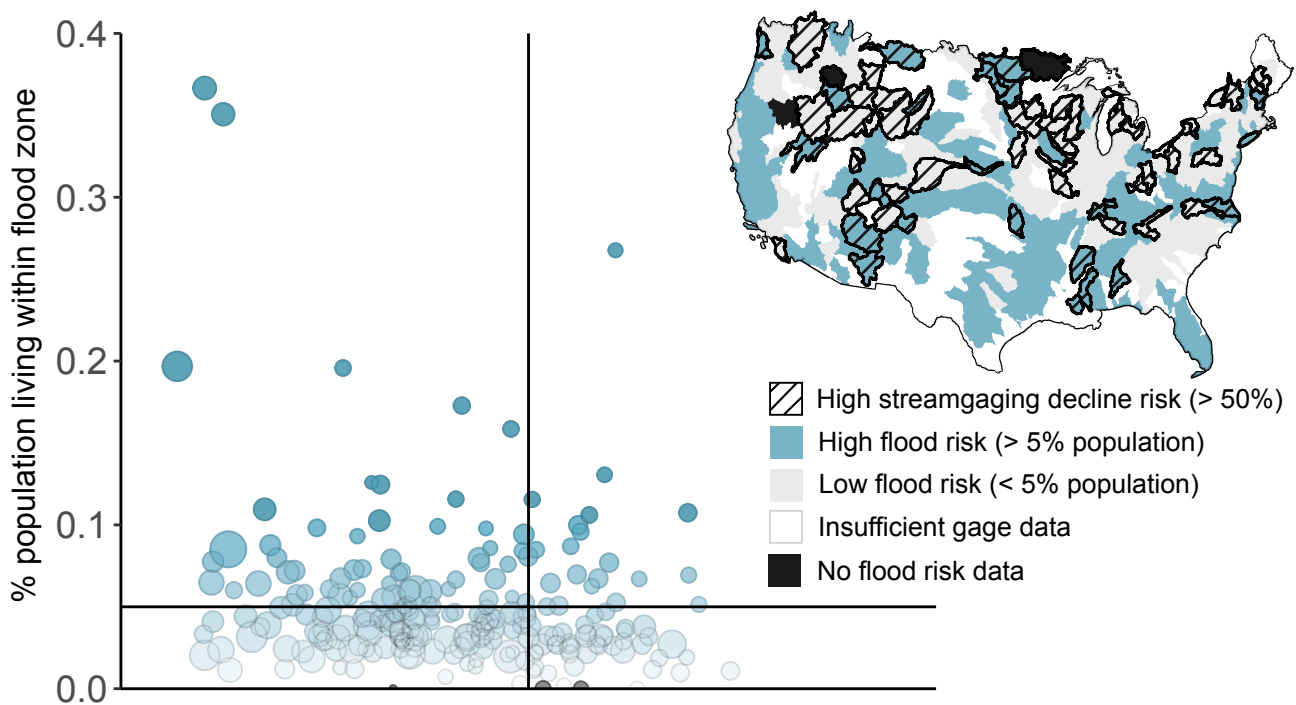




Water scarcity



Flood risk



Fish diversity

