Tracking the pulse of the Earth's fresh waters

Albert Ruhi, Mathis Messager, Julian Olden

Title: Tracking the pulse of the Earth's fresh waters

Authors: Albert Ruhi[1,2*], Mathis L. Messager[3], Julian D. Olden[3]

Affiliations:

[1] National Socio-Environmental Synthesis Center (SESYNC), University of Maryland, Annapolis, MD 21401, USA.

[2] Department of Environmental Science, Policy, and Management, University of California, Berkeley, CA 94720-3114, USA.

[3] School of Aquatic and Fishery Sciences, University of Washington, Seattle, WA 98105, USA.

*Correspondence to: albert.ruhi@berkeley.edu

Article type: Analysis

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

Abstract:

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

Main text:

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

magnitude of extreme weather events [7,8], WIS will become increasingly important for supporting adaptive local decisions and environmental policy objectives.

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

Trends in streamgaging data availability

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

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

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

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

Declining funding, shifting priorities

The trends observed in the GRDC data set are likely caused by a combination of weakening infrastructure and data sharing policies, two threats that make global water data 'a newly endangered species' [10]. Although hydrometric networks continue to be relatively dense and largely operative in Europe, North America, Japan, South Africa, and Australasia, important monitoring gaps remain in areas such as central Asia, the Arctic, and large swaths of Africa [9,13]. Substantial decreases (>25%) in operational capacity have been reported from Russia and the former Soviet states over the last three decades [10]. In many countries, stations tend to be spatially clustered and short-lived because data collection is contingent on development projects. Limited 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

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

Design modular systems that can be readily scaled. When facing the question of decreasing gage 'mortality' (by securing imperiled gages) *vs.* rescuing old or installing new gages, agencies should generally choose gage protection, as truncated time series and station turnover limit statistical inference even when gage numbers remain constant. However, in some cases it may be desirable to support a complementary, temporary monitoring infrastructure that accrues little maintenance costs and can be activated at will [26]. In regions like the U.S. sunbelt, where water allocations for human use and ecosystems are increasingly at odds [27], drought-activated stations would allow for more accurate tracking and enforcement of water allocations during periods of acute water stress, when human and ecosystem water needs are 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 habitat[3]. In countries such as Spain and
190 Australia, where a single state office administers surface and groundwater rights [3], 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 WMO [2]. 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 data [10].
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 future [28]. Yet, streams are highly dynamic over time, and remote
208 sensing products need to be validated with field measurements [13]. 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

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

Concluding remarks

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

Methods:

Streamgaging historical data

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

Historical streamflow data for all streamgage stations of the United States were compiled from the USGS National Water Information System (NWIS) using the 'dataRetrieval' R package [29] on January 10, 2018. Mean daily discharge data were downloaded for the period January 1854 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 to 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

$$NDC_{HUC6} = \frac{1}{\bar{R}_{HUC6}} \times \sum_{County=1}^{\substack{N\ county \\ in\ HUC6}} NDC_{County} \times \bar{R}_{County} \times \frac{Area_{HUC6-County\ intersection}}{Total\ area_{County}}$$

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 1949-2010 [31].
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 km^2), this metric adequately reflects relative water scarcity
275 patterns among regions in the United States.
276 Flood risk

We calculated flood risk in the conterminous United States as the percentage of the total human population that lives within the 100-year flood zone. To compute flood risk, 2010 census block level population data were intersected with 100-year flood zone polygons from the National Flood Hazard Layer (NFHL), a digital database containing all flood hazard mapping data from the Federal Emergency Management Agency's National Flood Insurance Program (FEMA NFIP). Census-block population data was used because of its high resolution (average and median area of a census block: 0.74 km^2 and 0.02 km^2, respectively), and its ability to spatially discriminate between settled areas and waterways or uninhabited floodplains. Despite its high resolution, the section of census blocks overlapping flood zones often did not include any housing. Therefore, we calculated the number of people living in a flood zone as the product of the census-block population size and the percentage of the census block urbanized area (calculated from 2011 National Land Cover Data) overlapping the 100-year flood zone (Zone A from the NFHL). When a census block did not contain any urban land cover (LC), we computed the product of census block population and percentage of census block total area intersecting a flood zone. The population in each census block living in an area for which a flood hazard study exists was computed the same way. Finally, the percentage of the population in each river basin living in a 100-year flood zone equals to the total population living in a 100-year flood zone across all census blocks of a river basin divided by the total population living in an area for which a flood hazard study exists. When a census block straddled the boundary between two river basins, the population living in a flood zone within each basin was proportional to the area of the census block overlapping the basin. For each HUC6, flood risk was therefore computed as follows:

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

, where:

Flood risk$_{\text{HUC6}}$ =

$$\frac{\sum_{C=1}^{N\ blocks\ with\ urban\ LC} \frac{Total\ area\ within\ HUC6_C}{Total\ area_C} \times \frac{Population_C \times Urban\ area\ within\ flood\ zone_C}{Total\ urban\ area_C}}{\sum_{C=1}^{N\ blocks\ with\ urban\ LC} \frac{Total\ area\ within\ HUC6_C}{Total\ area_C} \times \frac{Population_C \times Urban\ area\ with\ FEMA\ status_C}{Total\ urban\ area_C}} +$$

$$\frac{\sum_{C=1}^{N\ blocks\ with\ no\ urban\ LC} \frac{Total\ area\ within\ HUC6_C}{Total\ area_C} \times \frac{Population_C \times Area\ within\ flood\ zone_C}{Total\ area_C}}{\sum_{C=1}^{N\ blocks\ with\ no\ urban\ LC} \frac{Total\ area\ within\ HUC6_C}{Total\ area_C} \times \frac{Population_C \times Area\ with\ FEMA\ status_C}{Total\ area_C}}$$

Fish biodiversity metrics

We compiled a dataset of the distribution of freshwater fish at the subbasin level (HUC8) throughout the conterminous United States based on the NatureServ and ancillary local and regional sources, and then computed the endemism weighted richness/unit (EWU) for each river sub-basin, following (*2*):

EWU_{HUC8} = *Sum of each species' Endemism Unit* , where:

Endemism Unit = 1 / Number of HUC8s where the species is present

Accordingly, the most endemic species in a HUC8 has an Endemism Unit = 1. EWU_{HUC8} were then aggregated at the river basin level (HUC6) by averaging sub-basin level EWU within each river basin.

Time-series analysis of gage 'population' dynamics

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

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

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

We estimated *u* and *q* based on observed streamgaging data over the last 70 years (1947-2016), and we then used these coefficients to compute the probability that a gage population would hit a 50% decline threshold within the following 6 years ('decline risk') [after [32]]. Model residuals were examined via the autocorrelation function. Only the 228 river basins (HUC6) with a median number >10 gages over the period 1947-2012 were considered for this analysis. Because the relative influence of losing a gage in low-density basins is higher than in high-density basins, this approach provides a conservative estimate of gaging decline risks. We

chose the forecast to be 6 years long because that time horizon coincides with the end of the current USGS Water Science strategic plan 2012-2022 [34].

Data availability

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

Correspondence:

Please address correspondence and requests for materials to: Albert Ruhi (albert.ruhi@berkeley.edu), Department of Environmental Science, Policy, and Management, University of California, Berkeley.

Acknowledgments:

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

Author contributions:

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

References:

1. Bell, B. The oldest records of the Nile floods. *Geogr. J.* **136,** 569–573 (1970).
2. WMO 168. *Guide to hydrological practices Volume I: Hydrology – from measurement to hydrological information*. (World Meteorological Organization, 2008).
3. Escriva-Bou, A., McCann, H., Hanak, E., Lund, J. & Gray, B. Accounting for California's water. *Calif. J. Polit. Policy* **8,** 1–26 (2016).
4. Munich RE. Natural Catastrophes. (2017). Available at: http//natcatservice.munichre.com.
5. National Oceanic and Atmospheric Administration. Advanced Hydrologic Prediction Service (AHPS) for Water Resources and Emergency Management. (2017). Available at: http://www.nws.noaa.gov/ohd/ahps/ahps.htm.
6. Vahedifard, F., AghaKouchak, A., Ragno, E., Shahrokhabadi, S. & Mallakpour, I. Lessons from the Oroville dam. *Science* **355,** 1139–1140 (2017).
7. Milly, P. C. D. *et al.* Stationarity is dead: whither water management? *Science* **319,** 573–574 (2008).
8. Willner, S. N., Levermann, A., Zhao, F. & Frieler, K. Adaptation required to preserve future high-end river flood risk at present levels. *Sci. Adv.* **4,** eaao1914 (2018).
9. Hannah, D. M. *et al.* Large□scale river flow archives: importance, current status and future needs. *Hydrol. Process.* **25,** 1191–1200 (2011).
10. Vörösmarty, C. *et al.* Global water data: A newly endangered species. *Eos, Trans. Am. Geophys. Union* **82,** 54–58 (2001).
11. Granato, G. E. *Computer programs for obtaining and analyzing daily mean streamflow data from the U.S. Geological Survey National Water Information System website*. (US Geological Survey, 2009).

12. Goodall, J. L., Horsburgh, J. S., Whiteaker, T. L., Maidment, D. R. & Zaslavsky, I. A first approach to web services for the National Water Information System. *Environ. Model. Softw.* **23,** 404–411 (2008).

13. Fekete, B. M., Looser, U., Pietroniro, A. & Robarts, R. D. Rationale for monitoring discharge on the ground. *J. Hydrometeorol.* **13,** 1977–1986 (2012).

14. Lanfear, K. J. & Hirsch, R. M. USGS Study reveals a decline in long□record streamgages. *Eos, Trans. Am. Geophys. Union* **80,** 605–607 (1999).

15. Hirsch, R. M. & Costa, J. E. U.S. stream flow measurement and data dissemination improve. *Eos, Trans. Am. Geophys. Union* **85,** 197–203 (2004).

16. Nyabeze, W. R. Calibrating a distributed model to estimate runoff for ungauged catchments in Zimbabwe. *Phys. Chem. Earth, Parts A/B/C* **30,** 625–633 (2005).

17. Mishra, A. K. & Coulibaly, P. Developments in hydrometric network design: A review. *Rev. Geophys.* **47,** 1–24 (2009).

18. U.S. Geological Survey. U.S. Geological Survey 2019 Budget Justification. (2018).

19. Poff, N. L. *et al.* River flows and water wars: emerging science for environmental decision making. *Front. Ecol. Environ.* **1,** 298–306 (2003).

20. Ward, F. A. & Booker, J. F. Economic costs and benefits of instream flow protection for endangered species in an international basin. *JAWRA J. Am. Water Resour. Assoc.* **39,** 427–440 (2003).

21. Benson, R. D. Pollution without solution: flow impairment problems under Clean Water Act Section 303. *Stan. Envtl. LJ* **24,** 199–267 (2005).

22. Van Putten, M. C. & Jackson, B. D. The dilution of the Clean Water Act. *U. Mich. JL Reform* **19,** 863–901 (1985).

23. Deweber, J. T. *et al.* Importance of understanding landscape biases in USGS gage locations: implications and solutions for managers. *Fisheries* **39,** 155–163 (2014).

24. Anderson, D. R. The national flood insurance program. Problems and potential. *J. Risk Insur.* **41,** 579–599 (1974).

25. Michel-Kerjan, E., Czajkowski, J. & Kunreuther, H. Could flood insurance be privatised in the United States? A primer. *Geneva Pap. Risk Insur. Issues Pract.* **40,** 179–208 (2015).

26. Caldwell, A. W., Conrads, P. A., Mason Jr, R. R. & Berenbrock, C. USGS hurricane storm-surge monitoring networks: An example from Hurricane Rita. (2010).

27. Arumugam, S. *et al.* Synthesis of public water supply use in the US: spatio□temporal patterns and socio□economic controls. *Earth's Futur.* **5,** 771–788 (2017).

28. Alsdorf, D. E. & Lettenmaier, D. P. Tracking fresh water from space. *Science* **301,** 1491–1494 (2003).

29. Hirsch, R. M. & De Cicco, L. A. *User guide to Exploration and Graphics for RivEr Trends (EGRET) and dataRetrieval: R packages for hydrologic data*. (US Geological Survey, 2015).

30. Devineni, N., Lall, U., Etienne, E., Shi, D. & Xi, C. America's water risk: Current demand and climate variability. *Geophys. Res. Lett.* **42,** 2285–2293 (2015).

31. Maurer, E. P., Wood, A. W., Adam, J. C., Lettenmaier, D. P. & Nijssen, B. A long-term hydrologically based dataset of land surface fluxes and states for the conterminous United States. *J. Clim.* **15,** 3237–3251 (2002).

32. Holmes, E. R., Ward, E. & Wills, K. Package 'MARSS'. (2014).

33. Ruhi, A., Olden, J. D. & Sabo, J. L. Declining streamflow induces collapse and replacement of native fishes in the American Southwest. *Front. Ecol. Environ.* **14,** 1–8

(2016).

34. Evenson, E. J. *et al. Strategic directions for US Geological Survey water science, 2012-2022-Observing, understanding, predicting, and delivering water science to the Nation*. (US Geological Survey, 2012).

Figure legends

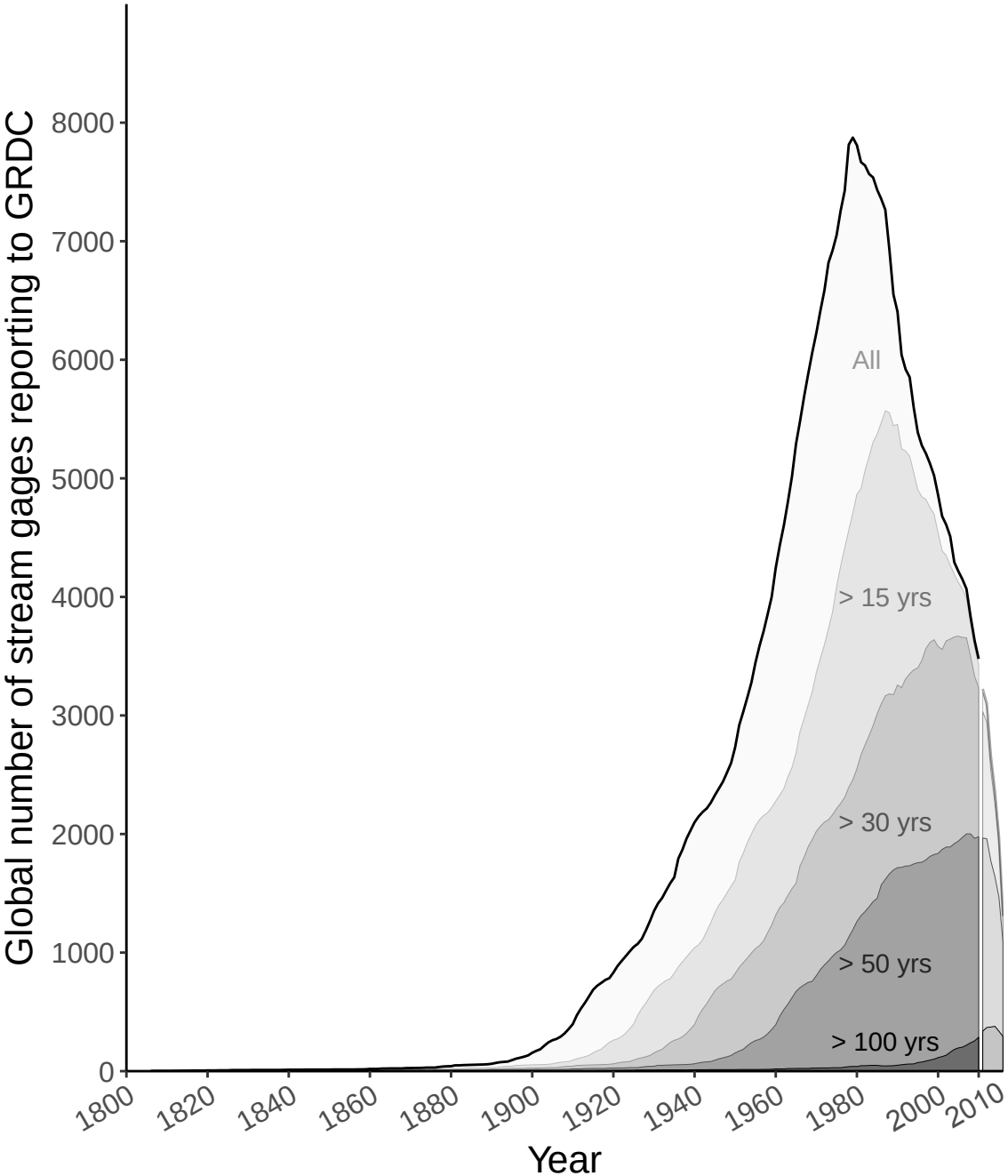
Fig. 1. Global trends in streamgaging stations reporting to the World Meteorological Organization's Global Runoff Data Centre. We classified stations by age class (length of the discharge record, in years). The number of reporting stations peaked in 1979 and decreased sharply thereafter. Comparisons to 2010 (white vertical line) accounts for lags in data reporting, but trends to present-day are shown.

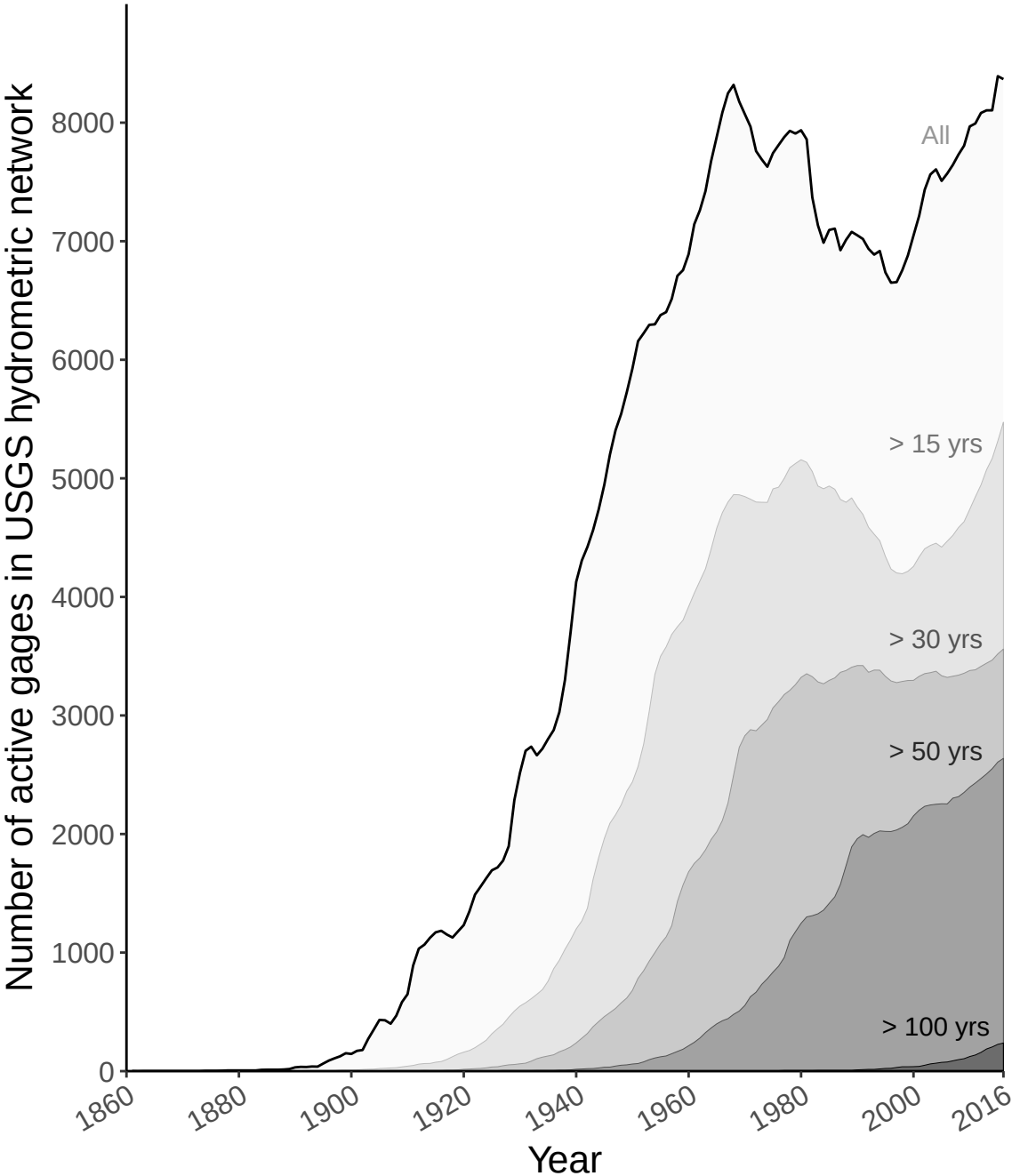
Fig. 2. Trends in the number of active streamgaging stations in the USGS hydrometric network. We classified stations by age class (length of the daily discharge record, in years). The total number of active streamgages peaked twice, in the late-1960s and in the mid-2010s.

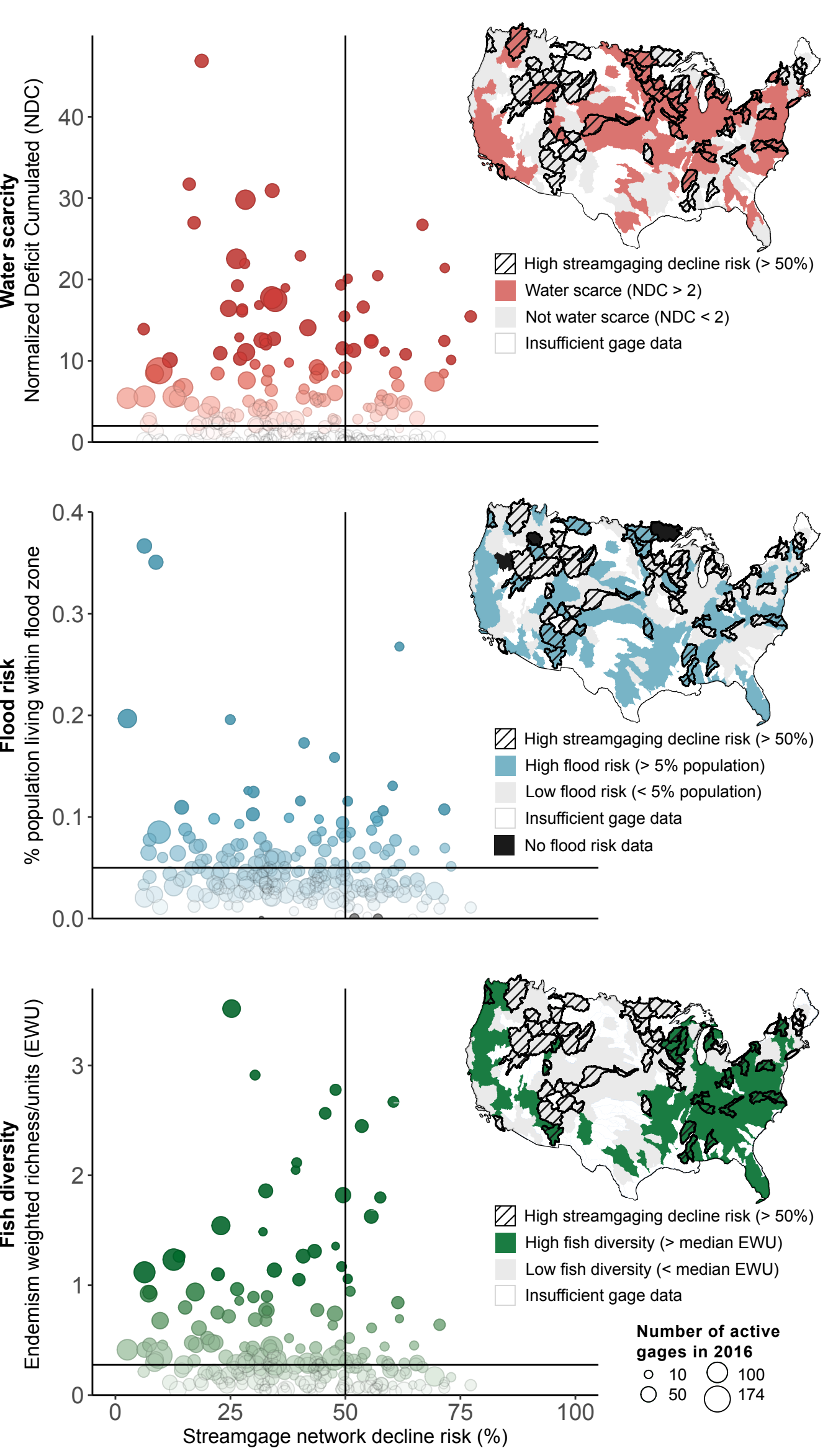
Fig. 3. Streamgaging decline risk and socio-environmental monitoring needs in the United States (see interactive map here: shiny.sesync.org/apps/gages). We represent U.S. conterminous river basins (Hydrological Unit Code 6) under streamgage decline risk, inferred via time-series analysis of USGS streamgaging history. Water scarcity was measured as Normalized Cumulative Deficit, NDC; flood risk to human populations was measured as % of population living within a 100-year flood zone; and fish biodiversity was measured as endemism weighted richness. In the inset maps, basins with >50% probability of having their gage network density halved by year 2022 are striped. Around 48% of the 'imperiled' river basins experience water scarcity, 31% of them are under high flood risk, and 38% harbor high fish diversity (endemism weighted richness/unit). See Methods for details.

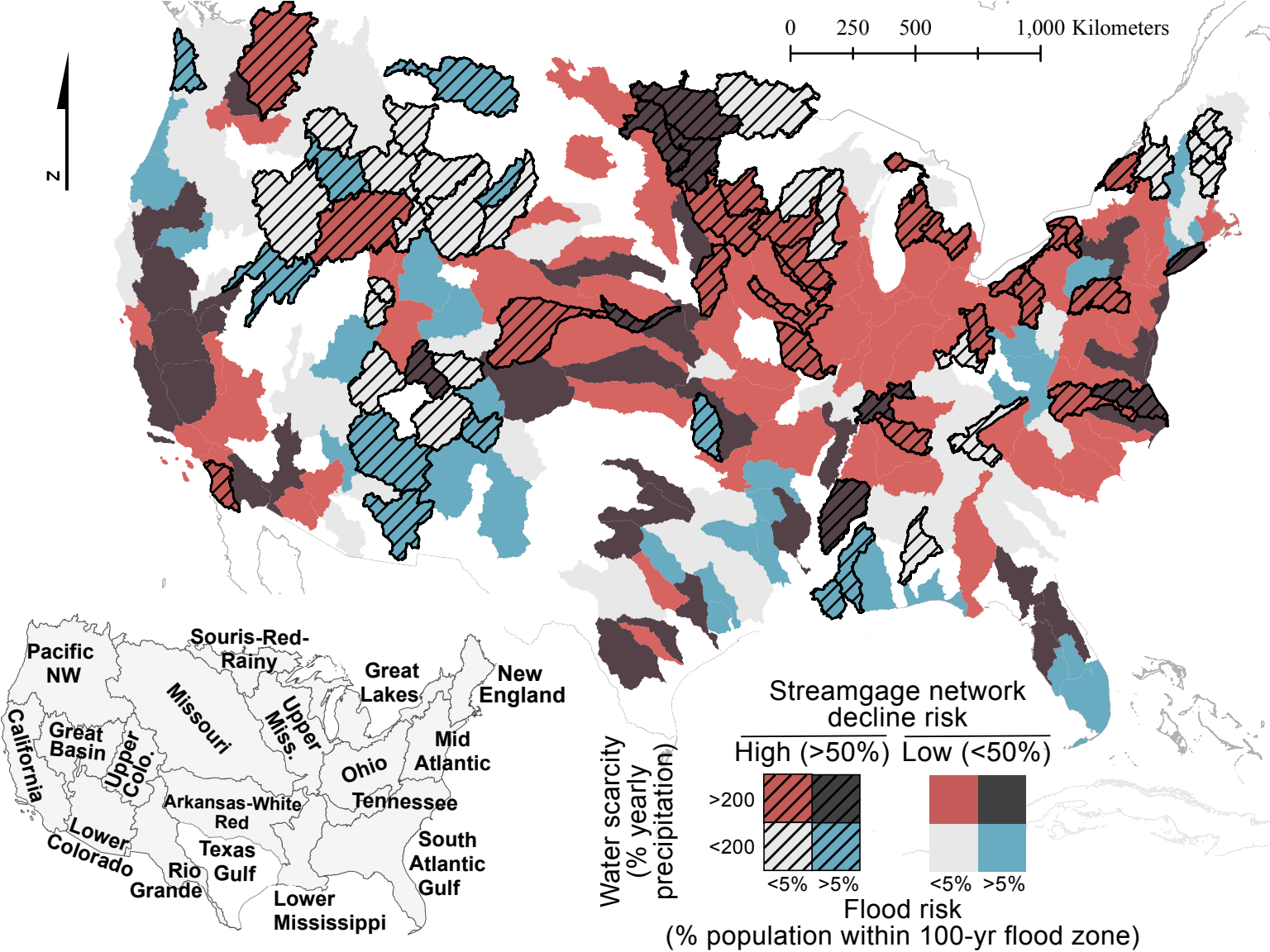
Fig. 4. Spatial distribution of streamgaging decline risk in the United States (see interactive map here: shiny.sesync.org/apps/gages). We represent the U.S. conterminous river basins (Hydrological Unit Code 6) under streamgage decline risk ('imperiled' basins), inferred via time-series analysis of USGS 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
8000
7000
6000
5000
4000
3000
2000
1000
0
All
> 15 yrs
> 30 yrs
> 50 yrs
> 100 yrs
1800
1820
1840
1860
1880
1900
1920
1940
1960
1980
2000
2010
Year


Number of active gages in USGS hydrometric network
8000
7000
6000
5000
4000
3000
2000
1000
0
All
> 15 yrs
> 30 yrs
> 50 yrs
> 100 yrs
1860
1880
1900
1920
1940
1960
1980
2000
2016
Year


Water scarcity
Normalized Deficit Cumulated (NDC)
40
30
20
10
0
High streamgaging decline risk (> 50%)
Water scarce (NDC > 2)
Not water scarce (NDC < 2)
Insufficient gage data
Flood risk
% population living within flood zone
0.4
0.3
0.2
0.1
0.0
High streamgaging decline risk (> 50%)
High flood risk (> 5% population)
Low flood risk (< 5% population)
Insufficient gage data
No flood risk data
Fish diversity
Endemism weighted richness/units (EWU)
3
2
1
0
High streamgaging decline risk (> 50%)
High fish diversity (> median EWU)
Low fish diversity (< median EWU)
Insufficient gage data
Number of active gages in 2016
10
50
100
174
0
25
50
75
100
Streamgage network decline risk (%)


0 250 500 1,000 Kilometers
N
Pacific NW
Souris-Red-Rainy
Great Lakes
New England
Missouri
Upper Miss.
California
Great Basin
Upper Colo.
Mid Atlantic
Ohio
Arkansas-White Red
Tennessee
Lower Colorado
Texas Gulf
Rio Grande
South Atlantic Gulf
Lower Mississippi
Streamgage network decline risk
High (>50%)
Low (<50%)
Water scarcity (% yearly precipitation)
>200
<200
<5%
>5%
<5%
>5%
Flood risk
(% population within 100-yr flood zone)