



Assessing placement bias of the global river gauge network

Corey A. Krabbenhoft¹✉, George H. Allen², Peirong Lin³, Sarah E. Godsey⁴, Daniel C. Allen⁵, Ryan M. Burrows⁶, Amanda G. DelVecchia⁷, Ken M. Fritz⁸, Margaret Shanafield⁹, Amy J. Burgin¹⁰, Margaret A. Zimmer¹¹, Thibault Datry¹², Walter K. Dodds¹³, C. Nathan Jones¹⁴, Meryl C. Mims¹⁵, Catherin Franklin¹⁶, John C. Hammond¹⁶, Sam Zipper¹⁷, Adam S. Ward¹⁸, Katie H. Costigan¹⁴, Hylke E. Beck¹⁹ and Julian D. Olden^{20,21}

Knowing where and when rivers flow is paramount to managing freshwater ecosystems. Yet stream gauging stations are distributed sparsely across rivers globally and may not capture the diversity of fluvial network properties and anthropogenic influences. Here we evaluate the placement bias of a global stream gauge dataset on its representation of socioecological, hydrologic, climatic and physiographic diversity of rivers. We find that gauges are located disproportionately in large, perennial rivers draining more human-occupied watersheds. Gauges are sparsely distributed in protected areas and rivers characterized by non-perennial flow regimes, both of which are critical to freshwater conservation and water security concerns. Disparities between the geography of the global gauging network and the broad diversity of streams and rivers weakens our ability to understand critical hydrologic processes and make informed water-management and policy decisions. Our findings underscore the need to address current gauge placement biases by investing in and prioritizing the installation of new gauging stations, embracing alternative water-monitoring strategies, advancing innovation in hydrologic modelling, and increasing accessibility of local and regional gauging data to support human responses to water challenges, both today and in the future.

Stream gauging stations that measure water level surface elevation and estimate volumetric discharge (collectively referred to here as ‘flow’) are fundamental to water information systems^{1,2}. Networks of stream gauging stations (or ‘stream gauges’) inform water-allocation decisions to support human and ecosystem water needs and help forecast flood and drought risk to society³. Collecting and archiving long-term hydrologic data is required for analysis of hydroclimatic trends⁴ and quantification of the effects of flow regime alteration on the ecology⁵, capacity to transport pollutants⁶ and biogeochemistry (for example, carbon fluxes⁷) of freshwater ecosystems. Thus, information from gauge networks underpins our understanding of global water and elemental cycles and provides critical knowledge for managing water resources.

The location of gauging stations is influenced by many factors, most notably the need for information for managing water for human water needs⁸. However, gauge installation dictated by local and national planning may have yielded inadvertent biases in data when describing rivers and streams across regional or global scales.

Hydrometric networks should be representative of regional socioecological factors, climate conditions and landscape heterogeneity. For example, skewed spatial representation in the rain gauge network is a source of bias in precipitation estimates⁹, and similar landscape bias exists in the locations of US Geological Survey (USGS) stream gauges^{10,11}. Similar placement bias in the global stream gauge network may limit our understanding of human water-supply systems, compromise efforts to achieve global biodiversity goals¹², challenge the estimation of hydrologic impacts of human activities¹³ and undermine best practices for determining environmental and cultural flow standards¹⁴. Yet our ability to assess the global representativeness of gauges has, until recently, been limited by a lack of global-scale stream gauge and environmental data.

Here we leverage recent global hydrologic datasets to report an investigation of potential biases in the spatial distribution of the global stream gauge network. We represented the global river network using the Global Reach-level A priori Discharge Estimates for Surface Water and Ocean Topography (GRADES) dataset¹⁵,

¹Department of Biological Sciences and Research and Education in Energy, Environment and Water (RENEW) Institute, University at Buffalo, Buffalo, NY, USA. ²Department of Geography, Texas A&M University, College Station, TX, USA. ³Institute of Remote Sensing and GIS, School of Earth and Space Sciences, Peking University, Beijing, China. ⁴Department of Geosciences, Idaho State University, Pocatello, ID, USA. ⁵Department of Ecosystem Science and Management, The Pennsylvania State University, University Park, PA, USA. ⁶School of Ecosystem and Forest Sciences, The University of Melbourne, Burnley, Victoria, Australia. ⁷Department of Biology, Duke University, Durham, NC, USA. ⁸Office of Research and Development, US Environmental Protection Agency, Cincinnati, OH, USA. ⁹National Centre for Groundwater Research and Training, College of Science and Engineering, Flinders University, Bedford Park, South Australia, Australia. ¹⁰Kansas Biological Survey—Center for Ecological Research, Environmental Studies Program, and Department of Ecology & Evolutionary Biology, University of Kansas, Lawrence, KS, USA. ¹¹Department of Earth and Planetary Sciences, University of California, Santa Cruz, CA, USA. ¹²INRAE, UR Riverly, Centre Lyon-Grenoble Auvergne-Rhône-Alpes, Villeurbanne, France. ¹³Division of Biology, Kansas State University, Manhattan, KS, USA. ¹⁴Biological Sciences, University of Alabama, Tuscaloosa, AL, USA. ¹⁵Department of Biological Sciences, Virginia Tech, Blacksburg, VA, USA. ¹⁶US Geological Survey MD-DE-DC Water Science Center, Catonsville, MD, USA. ¹⁷Kansas Geological Survey, University of Kansas, Lawrence, KS, USA. ¹⁸O’Neill School of Public and Environmental Affairs, Indiana University, Bloomington, IN, USA. ¹⁹Joint Research Centre of the European Commission, Ispra, Italy. ²⁰School of Aquatic and Fishery Sciences, University of Washington, Seattle, WA, USA. ²¹Department of Wildlife, Fish & Environmental Studies, Swedish University of Agricultural Sciences, Umeå, Sweden. ✉e-mail: cakrabbe@gmail.com

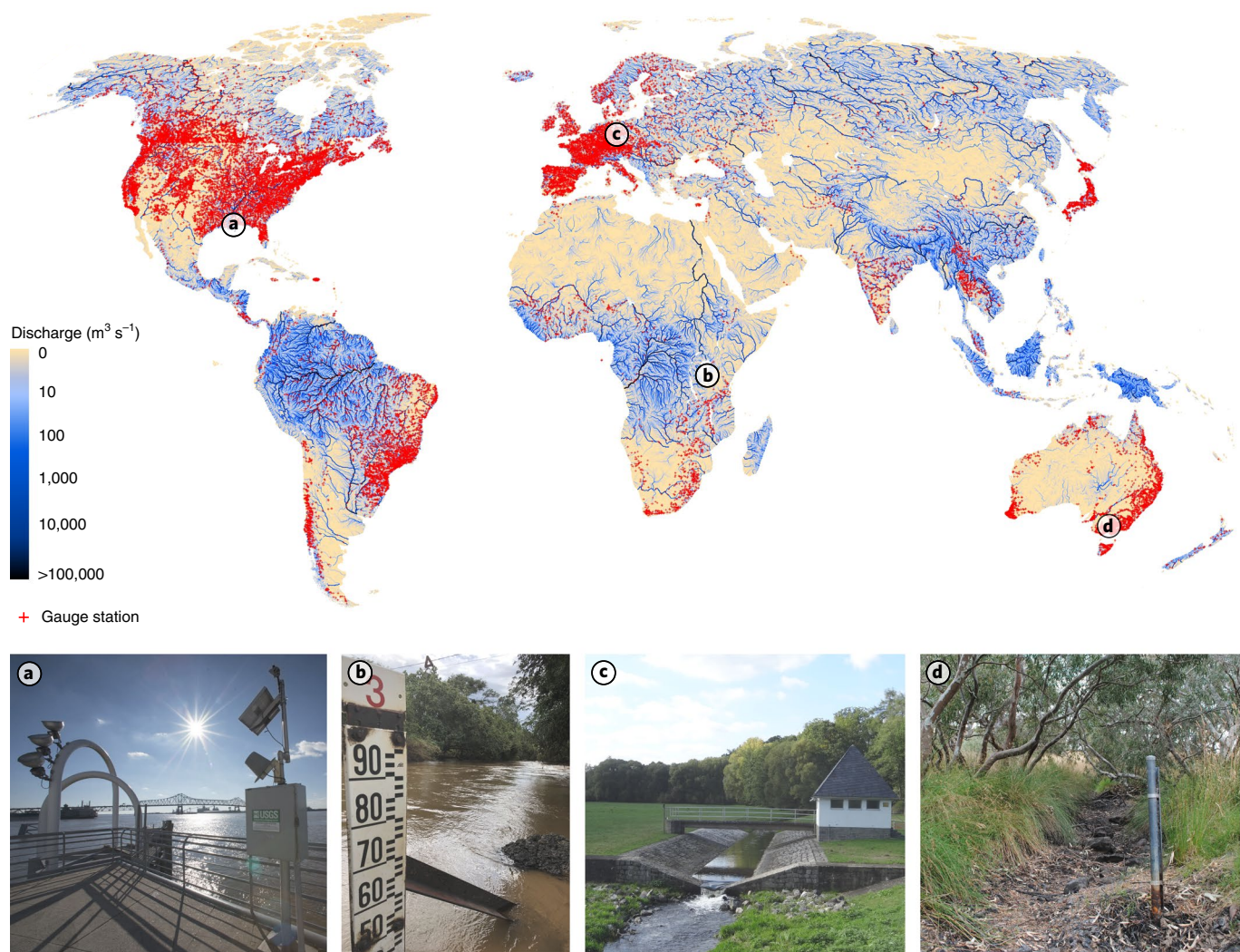


Fig. 1 | Global distribution of stream gauges with four examples. Global distribution of stream gauges (red crosses; $N=32,091$) along the river network (blue) identified by GRADES¹⁵ with four example gauges shown. **a–d**, Examples of river gauges. **a**, Mississippi River, Louisiana, United States (station: USGS 07374000). **b**, Little Ruaha River, Tanzania (station: 1KA2A). **c**, Weida, Thuringia, Germany (station: 57729). **d**, Kororoit Creek, Victoria, Australia. Credits: **a**, USGS; **b**, J.D.O.; **c**, R. Dupas; **d**, T. Fletcher.

which derived nearly 3 million river segments based on the 90 m MERIT Hydro digital elevation model¹⁶ (Supplementary Methods). GRADES also contains daily discharge estimates from 1979–2013 at these ~3 million river segments with drainage areas >25 km² (Fig. 1). We used a global database of 32,091 stream gauges^{17,18} to map gauge placement along the GRADES river network. We combined this with a suite of socioecological, climatic and physiographic characteristics of rivers from HydroATLAS¹⁹ to assess spatial and landscape biases in gauge placement. Leveraging these global databases, we (1) determined whether the current network of stream gauges accurately reflects the distribution of socioecological and environmental conditions among global rivers, (2) quantified the representativeness of the existing gauge network within major freshwater habitat types that shape global patterns in biodiversity and (3) identified priority geographic areas where new gauge installation would reduce global biases in gauge placement.

Biases of the global gauge network

We compared currently gauged river segments to a global river dataset (GRADES) according to 13 geospatial attributes that represent important aspects of hydrology, climate, physiography

and socioecological conditions (Fig. 2; details in Supplementary Table 2). We used Wasserstein distance^{20,21} to contrast the statistical distribution of each attribute of gauged versus all river segments to identify the types of river that are over- or under-represented by the current gauge network (Fig. 2 and Supplementary Fig. 4). Gauge placement favoured large (high Strahler stream order), perennial and highly dam-regulated rivers (Fig. 2a,b,d). Watersheds with high population density and large human footprints (a composite metric for anthropogenic influences) were over-represented, whereas rivers with high proportions of upstream protected areas (lands conserved by governmental or other organizations) and small human footprints were under-represented (Fig. 2a,c). The gauge network also disproportionately favoured mid-latitude (Supplementary Fig. 1) and mesic climates, whereas gauge coverage in extremely hot or cold regions was relatively sparse (Fig. 2e).

The overall patterns of bias in stream gauge placement suggested under-representation of areas previously identified as critical to freshwater conservation efforts²², including catchments with protected areas²³ and headwater streams²⁴. A lack of monitoring in areas with minimal human impact or those with unique ecological features limits the potential to develop and implement science-based

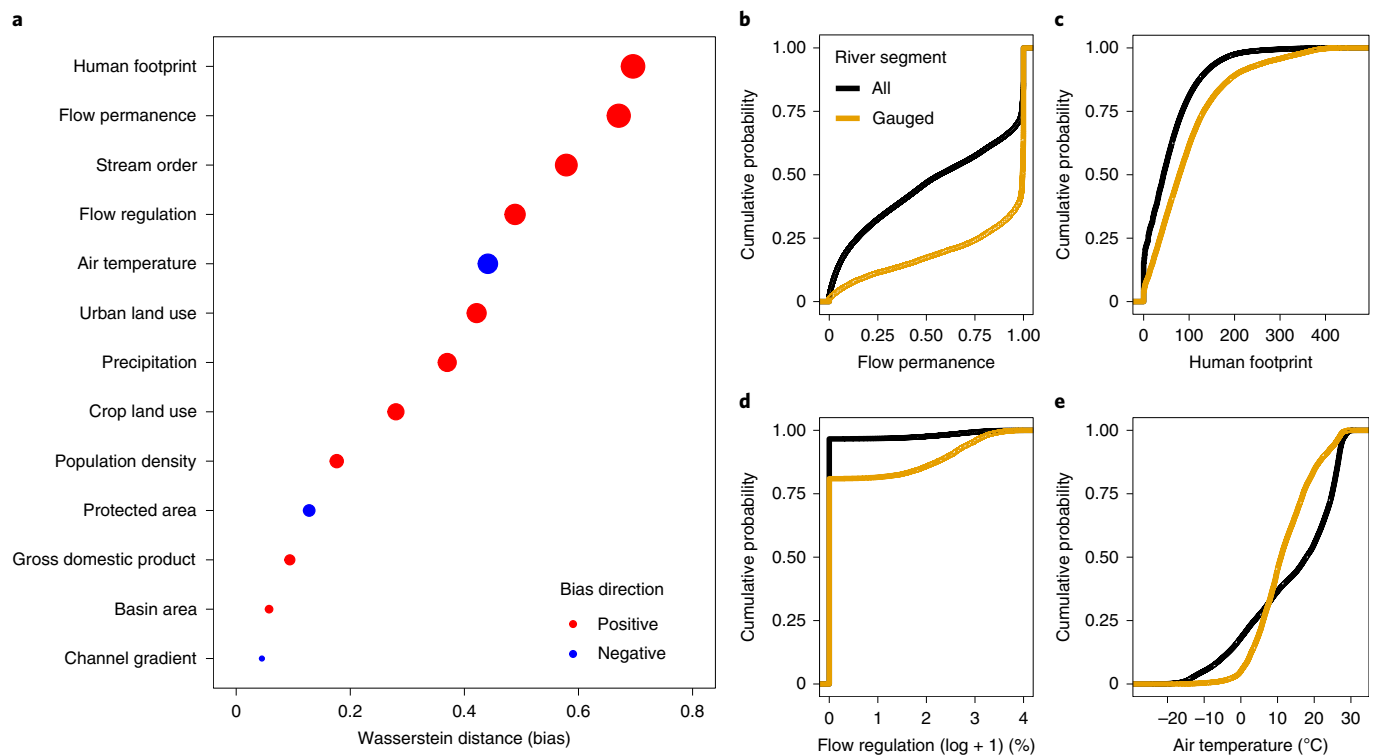


Fig. 2 | Comparison of currently gauged river segments to the GRADES dataset according to geospatial attributes. a, Bias in the global gauge network according to variables describing hydrology, climate, physiography and socioecological conditions. Symbol size is scaled according to the magnitude of bias (Wasserstein distance) and colour indicates direction of bias; red indicates over-representation (positive standardized bias), and blue indicates under-representation (negative standardized bias). **b–e**, Examples of gauged river segments (yellow) versus all global river segments (black) for values of flow permanence (**b**), human footprint (**c**), degree of flow regulation (**d**) and mean annual air temperature (**e**). Where gauged segments show lower cumulative probability than all segments, it indicates under-representation of those values (along the x axes) in the gauge network and vice versa.

water policy. For example, free-flowing watersheds (Fig. 2, ‘Flow regulation’) and those containing protected areas (Fig. 2, ‘Protected area’) provide freshwater habitat critical to preserving biodiversity¹² but are under-represented in the existing gauge network (bias values of 0.49 and 0.13, respectively; Fig. 2a). Furthermore, monitoring rivers in protected areas is crucial for evaluating threats such as encroaching urban and rural development^{23,25} and for developing reference sites and realistic conservation, restoration and management goals²⁶. Similar data are needed for non-perennial streams and free-flowing rivers, many of which are changing in abundance in response to climate change^{13,27}. Inadequate monitoring of habitats relative to their prevalence (or their conservation importance) also hinders our ability to inform policy decisions regarding their protection²⁸. Thus, the intersection of conservation priorities and gauge location emphasizes the need to adequately capture watershed heterogeneity in hydrometric networks.

Biases in terms of major habitat types

The global stream gauge network is biased towards specific river and landscape attributes, and patterns in gauge placement bias may not be uniform across all habitat types. We assigned a major freshwater habitat²⁹ to each gauge and conducted bias analyses within each habitat type to identify patterns in gauge placement bias specific to particular habitats (Fig. 3). Similarities in bias patterns among habitat types were found, particularly with respect to climate. Rivers in tropical and temperate habitats each clustered based on patterns of bias, with patterns in precipitation and air temperature especially pronounced. Biases in polar fresh waters varied from some overall trends, including an under-representation of areas with high human footprints. The greatest instances of bias largely

occurred in polar and xeric freshwaters, while temperate habitats had the lowest degree of bias overall. Representation (or lack thereof) was consistent across all habitat types for some variables, including under-representation of catchments containing protected areas and a high bias towards increased flow permanence (the proportion of days with active flow; Methods). The tendency for gauge placement to favour heavily regulated rivers was also greatest in xeric regions, presumably due to the greater need to monitor water in water-scarce environments³⁰. Small rivers (that is, low Strahler stream order) were under-represented across all habitat types, a pattern most pronounced in large river deltas and tropical and subtropical rivers, ecosystems facing tremendous freshwater biodiversity challenges³¹. Note that patterns for both flow permanence and stream order are probably much more exaggerated than what we show here given the 25 km² watershed size limitation present in our river network.

The tendency for extreme climates to be under-represented in the global gauge network highlights a present-day challenge for water resource professionals. If the global hydrometric network does not adequately capture variability in environmental characteristics among rivers, hydrologic patterns of many watersheds become difficult to understand and forecast³². For example, it is challenging to investigate patterns in intermittent and ephemeral streams due to biases against gauge placement in non-perennial rivers^{33,34}. Interest in non-perennial rivers has increased over the past several decades³⁵, and the potential source of error from skewed discharge estimates could present a challenge for identifying changes over time³⁶. Investing in monitoring environmental ‘extremes’ now will improve future modelling efforts as these characteristics (for example, intermittency) become more common³⁷. Similarly,

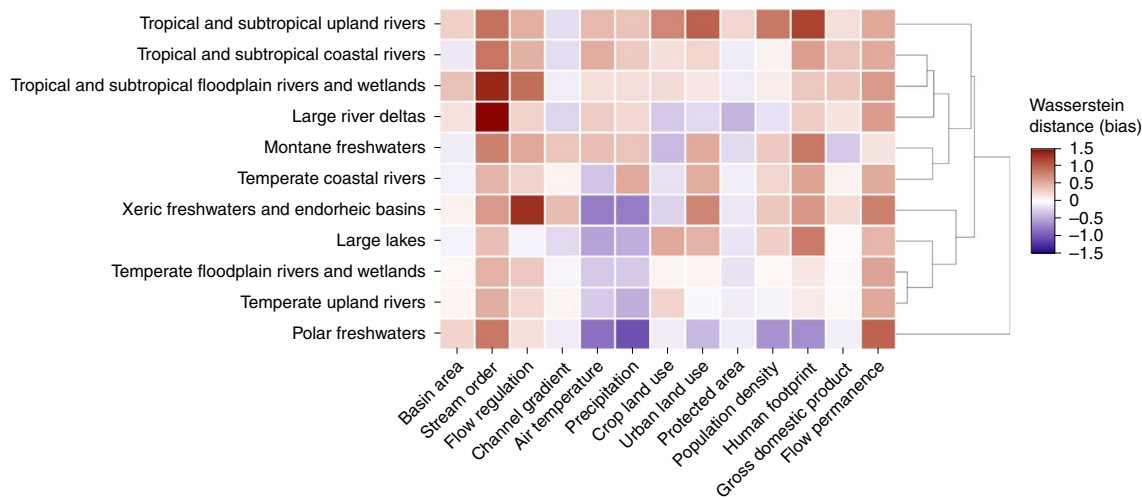


Fig. 3 | Bias in the gauge network. Bias in the gauge network for 11 freshwater ecoregions of the world²⁹ according to variables describing hydrology, climate, physiography and socioecological conditions. Bias values range from positive (red, over-represented) to negative (blue, under-represented) according to magnitude (Wasserstein distance) and direction (standardized bias). Ecoregions are hierarchically clustered based on bias values.

systematic under-representation of small rivers across habitats limits our understanding of watershed structure and function, including regional probability of drying³⁸, upstream contributions to watershed carbon budgets³⁹ and the importance of headwater streams in supporting biodiversity and ecological integrity throughout their corresponding watersheds²⁴. Building gauge infrastructure to adequately reflect hydrologic diversity within a watershed is thus fundamental to building effective water and ecosystem management approaches in the future.

Spatial distribution of under-represented rivers

Our analyses identified areas where additional gauge installation would improve the hydrologic, climatic, physiographic and socioecological representation by the global gauge network. Priority areas were determined by adding a hypothetical gauge to a river segment currently lacking a gauge then calculating the resulting change in overall average bias of the resulting global network and repeating for all segments currently without gauges (Methods). Positive or negative values indicate whether adding a gauge to a river segment would increase or decrease global overall bias, respectively. Regions with the lowest contribution to bias reduction were in North America, Europe and Asia, largely due to existing gauge coverage (Fig. 4 and Supplementary Fig. 1). Addition of gauges to arid regions was consistently important for bias reduction, including across large swaths of western North America, northern Africa, central and northern Australia and the Eurasian steppe. As large rivers were over-represented in the current gauge network, adding more gauges on larger rivers contributed little to global bias reduction, regardless of the surrounding segment attributes, as seen in the Nile River in Egypt and Sudan (Fig. 4). Although there is correlation between areas of high priority (Fig. 4) and currently under-gauged geographic regions (Fig. 1), variation in priority was better explained by geospatial attributes. For example, non-perennial rivers are globally common yet under-gauged, so rivers in xeric regions remain a high priority for new gauges regardless of existing gauge density (for example, southwestern North America). On the other hand, high-gradient mountainous regions have generally high global gauge coverage (Fig. 3) and are thus low priority (for example, the Himalayas) regardless of current gauge presence. It is thus important to note that contribution to global bias reduction does not necessarily correspond to conservation priority or importance for human water needs (for example, the Himalayas⁴⁰).

Addressing patterns of gauge placement bias on a global scale requires greater integration of gauging infrastructure and data platforms from local to international levels³. Stream gauges serve a variety of water resource and management needs^{41,42}; thus, strategies to develop a more representative gauge network that balances local water-management information needs with larger-scale priorities to reduce global bias in which regions and biomes are represented would increase societal value of the overall gauging network. Improvements to gauge infrastructure must also balance equity and data access for communities requiring more informed water-management practices⁴³. Multiple alternatives to adding gauges may help bring this goal within reach. For example, advances in remote sensing technology⁴⁴ have enabled global water resource estimates. While remote sensing cannot fully replace in situ discharge monitoring, the addition of these methods for large rivers may enable a shift of in-stream gauging resources to smaller rivers. The addition of remote sensing and subsequent reallocation of in-stream monitoring can improve overall watershed coverage and enable detailed, large-scale assessments of river networks⁴⁵. Furthermore, community science efforts can provide data for systems lacking stream gauges⁴⁶, and greater river network coverage can improve modelling approaches where costs of new gauge infrastructure are prohibitive³⁸. Our analysis provides an important first step to identify representation disparities in global water information systems; this information, coupled with continued communication between water infrastructure decisionmakers and data users, will help ensure stream gauge networks adequately support human and ecosystem water information needs.

Discussion

By demonstrating the biases in the current global gauge network, we underscore the need for additional (or relocation of) gauging to improve representation of certain river attributes in the global network. Unbiased representation will improve our ability to understand ways to support human and ecosystem water needs into the future, particularly as valuable long-term data are generated³. Gauge placement decisions are made to satisfy a variety of local factors, but the use of gauge data to draw conclusions about watershed hydrology, ecology and human water needs comes with the necessity that the gauge network is representative of the attributes of all rivers¹¹. Better accounting for socioecological and environmental heterogeneity in gauge networks will improve hydrologic models⁴⁷

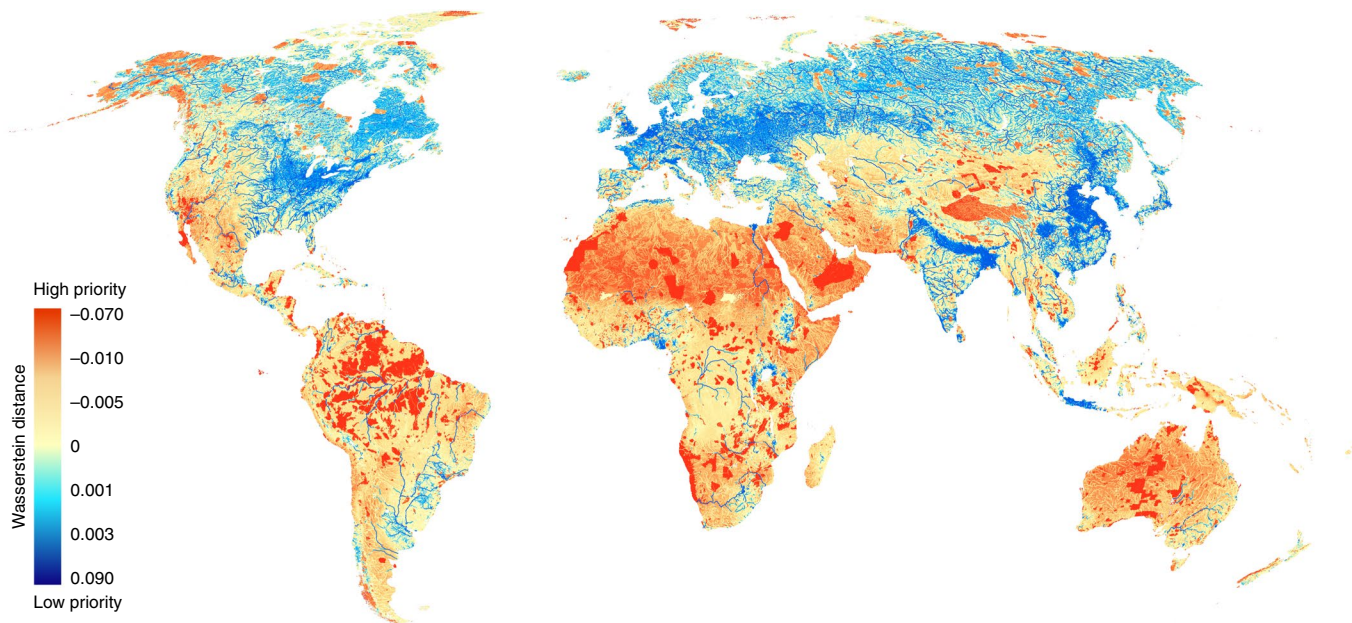


Fig. 4 | Estimated global mean bias change from gauge installation. Estimated amount of global mean bias change (Wasserstein distance) resulting from a gauge being installed on each river segment. Red indicates priority areas for potential new gauges (which would result in greater reduction in global bias). Specific river segment colouration does not denote actual representation by gauges, but the general importance of that 'type' of river in the bias reduction of the global hydrometric network.

and their utility in informing water security challenges and strategies for addressing the freshwater biodiversity crisis¹². Further, given the paucity of water information in some of the world's river basins, additional gauges and advances in alternative data sources can substantially improve the information base upon which water resource-management decisions are made. Although local and regional assessments need to work within the bounds of community data needs, a global perspective illustrates that the locally driven process of building hydrometric networks has led to a biased system which falls short of equitably meeting social and ecosystem water information needs. However, local and global data needs are not at odds so long as representation (or lack thereof) of river heterogeneity is considered when investigating gauge data across large spatial scales.

We recommend future gauge placement decisions consider under-represented geospatial attributes when adding to existing gauge networks. Specifically, we recommend prioritizing additional gauge placement in areas of environmental vulnerability in addition to locations in need of socially relevant hydrologic data. We show that gauge infrastructure is lagging in areas critical to freshwater conservation, particularly areas with low human impact and intermittent flow conditions. We do not support the removal of gauges to compensate for bias, as loss of any gauge data could pose negative consequences for local data needs; however, our framework could be used to characterize compound losses associated with discontinuation of gauges. Fluctuations in the operation and availability of stream gauge data pose a substantial challenge for water information systems⁴⁸. Previous studies² have offered a series of solutions to water information challenges that highlight the need for greater cooperation among practitioners in making data widely and openly available. Such cooperation from local to international entities will be necessary to modify or grow existing hydrometric networks to reduce bias on continental or greater scales. Many areas that are under-represented occur in countries that face major economic challenges (for example, parts of Africa, Southeast Asia and Central and South America). These areas may need financial assistance to improve the gauge network that forms a vital part of their

water infrastructure. Cooperative solutions to irregular coverage in water information systems (for example, the World Bank 'National Hydrology Project for India') either through greater data accessibility or alternative gauging solutions could provide the best opportunity to address global water challenges of the future.

Methods

We used an international assemblage of stream gauge datasets and a compilation of 13 geospatial attributes that span a range of hydrologic, climatic, physiographic and socioecological conditions to assess the spatial representativeness of the current gauge network (Fig. 1). Our global gauge network contains 32,091 stream gauging stations compiled from two global stream gauge datasets: the Global Streamflow Indices and Metadata Archive (GSIM¹⁸) with additional gauges from a recent publication¹⁷ that provides daily discharge data for a subset of gauges. Hydrologic data were obtained from the GRADES hydrographic dataset¹⁵ and include the river network, river morphometry and modelled daily discharge from 1979–2013 at 2,896,897 river segments with drainage areas larger than 25 km². Here we defined 'segments' as contiguous sections of river between two tributaries or else the mouth or origin of the river. Climatic, physiographic and socioecological attributes were obtained from the HydroATLAS v1.0 database¹⁹, which describes landscape characteristics relevant to individual river segments (or reach¹⁵). Climatic factors included estimates of air temperature and precipitation; physiographic variables described river morphometry (stream order, gradient, catchment area); and socioecological attributes correspond to various landscape features relevant to human impact on rivers (regulation, catchment land cover and a cumulative metric of human landscape impact called 'footprint') and social well-being (gross domestic product). Finally, major freshwater habitat types were quantified according to the Freshwater Ecoregions of the World map^{19,29} to allow for habitat-specific analyses. Freshwater Ecoregions of the World delineates the globe into 426 units that are 311,605 km² on average. Units belong to 12 potential habitat types based on common attributes of freshwater 'biomes'. Each biome is characterized by the biotic, chemical and physical characteristics of ecoregions as they apply to ecosystem dynamics and biodiversity in freshwater systems²⁹.

We combined GRADES and HydroATLAS datasets through geospatial analysis performed using the Python GeoPandas library⁴⁹. Specifically, the middle point of each of the 2.9 million GRADES river segments was linked with HydroATLAS by finding the nearest HydroATLAS river segments by a radius search of 5 km (details in Supplementary Information 'Geospatial Attributes'). HydroATLAS attribute data were then assigned to GRADES river segments and combined with GRADES-estimated flow permanence (Supplementary Fig. 2) to provide a full accounting of relevant hydrologic (Strahler stream order; flow permanence), climatic (air temperature and precipitation, localized to the segment), physiographic (upstream catchment area; segment channel gradient) and

socioecological (degree of regulation at the segment pour point; cropland and urban land use in the upstream catchment; the extent of protected area contained within the segment catchment; human population density and human footprint in the upstream catchment; sum of the gross domestic product of the upstream catchment) conditions for all river segments (Supplementary Table 2). Gauge locations were snapped to GRADES river segments by first performing an automatic nearest search and then human corrections to identify the segments with existing gauge infrastructure (Fig. 1). All global river segments were then assigned to one of 11 major freshwater habitat types²⁹ via spatial overlay (polar freshwaters, $n = 410,501$; large river deltas, $n = 21,089$; tropical and subtropical floodplain rivers and wetlands, $n = 364,853$; montane freshwaters, $n = 76,118$; temperate coastal rivers, $n = 282,660$; temperate upland rivers, $n = 169,271$; temperate floodplain rivers and wetlands, $n = 319,541$; tropical and subtropical coastal rivers, $n = 241,372$; tropical and subtropical upland rivers, $n = 205,441$; large lakes, $n = 80,244$; xeric freshwaters and endorheic basins, $n = 715,829$).

In addition to the variables provided by HydroATLAS, we investigated patterns of flow intermittency, as it is an increasingly common but under-studied aspect of global rivers^{34,50}. As a measure of discharge, we estimated flow permanence (that is, proportion of gauge record with non-zero flow³⁵) using GRADES simulated discharge¹⁵ and daily discharge observations from one of the gauge station databases that was used in this study¹⁷. Note that the GSIM gauge database¹⁸ does not contain daily discharge values that are necessary for this analysis, so flow permanence was estimated for all segments based on discharge data from 17,406 gauges. We also note that GRADES is a modelled daily discharge product, so it requires adaptation and acknowledgement of its limitations before it can be used to estimate flow permanence: first, GRADES is not free of biases and uncertainties according to its evaluation against >14,000 gauges in Lin et al.¹⁵; second, GRADES was not specifically developed to estimate no-flow occurrence. As a result, GRADES rarely estimates a discharge of zero but rather reports a very small discharge (for example, $10^{-2} \text{ m}^3 \text{ s}^{-1}$), which indicates very low flow, possibly zero discharge. Therefore, we needed to establish a low discharge threshold for GRADES that can be used to categorize whether a river segment is flowing, which also addresses the small discharge bias. As there was no pre-established threshold, we examined the simulated GRADES discharge when stream gauges reported zero flow⁴². We used the gauge dataset¹⁷ to accomplish this task and validated our results with measurements from two independent datasets of streamflow observations. Of the 17,406 gauges in the flow permanence dataset¹⁷, 3,925 gauges contained zero-flow observations, yielding a total of 4,680,335 zero-flow observations from 1979–2013. When gauges reported zero flow, the GRADES simulated discharge had a median value of $0.16 \text{ m}^3 \text{ s}^{-1}$ with a first quartile value of $0.028 \text{ m}^3 \text{ s}^{-1}$ and a third quartile value of $0.83 \text{ m}^3 \text{ s}^{-1}$ (Supplementary Fig. 3). We used the median value to threshold the GRADES discharge, meaning if GRADES simulated a discharge below $0.16 \text{ m}^3 \text{ s}^{-1}$, we deemed that this discharge was at zero flow, similar to the methods used elsewhere⁵¹. We also applied the same technique using the first and third quartile discharge values. We then estimated flow permanence by calculating the proportion of days from 1979–2013 that a river segment in GRADES was estimated to be actively flowing (Supplementary Fig. 2).

We validated the no-flow threshold by examining the timing of no-flow events from two other independent observational datasets. The first dataset from Kennard et al.⁵² contains streamflow observations from 830 Australian gauge stations. The second dataset, from the US Environmental Protection Agency (USEPA) National Aquatic Resource Surveys, contains no-flow observations from 289 sites across the contiguous United States⁵³. We removed all observations that (1) were duplicated with those in the gauge database¹⁷; (2) had drainage areas <25 km², which is the minimum drainage area of the GRADES database and (3) did not fall within the time period 1979–2013. We then snapped these no-flow observations to the nearest GRADES river network segment using a maximum distance threshold of 500 m. Applying these data filters yielded 89,187 no-flow observations from Kennard et al.⁵² and 292 no-flow observations from the USEPA database (Supplementary Fig. 3). Using the timing of no-flow events from these two observational datasets and applying the non-parametric Mann–Whitney *U* test, we found that the distribution of the means of GRADES simulated discharges at zero flow from Kennard et al.⁵² and the USEPA was not statistically different from that of the gauge dataset¹⁷ at a 95% confidence level and concluded that our approach is valid with an acceptable amount of uncertainty. However, we acknowledge that there is uncertainty associated with using gauge data to calculate the GRADES-based zero-flow estimates because of the sparsity of gauges relative to the total river network length and the demonstrated location bias of the global gauge network.

We quantified the representativeness of the global stream gauge network by applying a semi-parametric, permutation-based statistical analysis on the compiled global geospatial datasets²¹. The representativeness of the global gauge network refers to the degree to which the statistical distribution of the environmental and socioecological attributes captured in the gauge network is similar to the statistical distribution of values for all rivers of the world. Representativeness was quantified by the 2-Wasserstein distance, which identifies disparities between the two distributions^{50,21}. Wasserstein distances are absolute values so the directionality of divergence in distributions (whether the disparity was caused by over- or under-representation in the sample distribution) was identified using standardized bias according to variable means⁵⁴. Positive values indicated that variables were

over-represented for river segments containing gauges versus all river segments, whereas negative values indicated under-representation. We performed this analysis for the globe (less Antarctica and Greenland, which do not host stream gauges in this dataset) and for each major freshwater habitat type²⁹.

We conducted simulations to calculate the overall change in global bias in gauge placement (averaged across all variables) if a new gauge were installed to identify high value locations for potential stream gauge additions. This was accomplished by adding a single ‘new’ gauge to each river segment in turn and calculating the resulting change in overall average bias across all geospatial attributes. This process was then repeated for each river segment currently lacking a gauge. This approach results in a ‘bias change’ value for each river segment that reflects its individual contribution to global bias if a single gauge were added to the network. Negative change in bias indicated that the addition of a gauge on that segment would decrease global bias in the gauge network. A positive change in bias indicated that global gauge network bias would increase as a result of gauge placement on that segment. We mapped the global river network to illustrate the contribution of each river segment to improving the representativeness of the global river network and identified spatial patterns in contribution to bias reduction (Fig. 4).

Reporting Summary. Further information on research design is available in the Nature Research Reporting Summary linked to this article.

Data availability

All data from this study are available at <https://doi.org/10.17605/OSF.IO/NYA8R>.

Code availability

R scripts used in this study are available from the Dry Rivers GitHub page at <https://github.com/dry-rivers-rcn/G4>.

Received: 17 August 2021; Accepted: 7 March 2022;

Published online: 25 April 2022

References

- Vörösmarty, C. J. et al. Global threats to human water security and river biodiversity. *Nature* **467**, 555–561 (2010).
- Ruhi, A., Messager, M. L. & Olden, J. D. Tracking the pulse of the Earth's fresh waters. *Nat. Sustain.* **1**, 198–203 (2018).
- Pearson, C. Short- and medium-term climate information for water management. *World Meteorol. Organ. Bull.* **57**, 173–177 (2008).
- Tetzlaff, D., Carey, S. K., McNamara, J. P., Laudon, H. & Soulsby, C. The essential value of long-term experimental data for hydrology and water management. *Water Resour. Res.* **53**, 2598–2604 (2017).
- Carlisle, D. M., Wolock, D. M. & Meador, M. R. Alteration of streamflow magnitudes and potential ecological consequences: a multiregional assessment. *Front. Ecol. Environ.* **9**, 264–270 (2011).
- Shrestha, S., Kazama, F. & Newham, L. T. H. A framework for estimating pollutant export coefficients from long-term in-stream water quality monitoring data. *Environ. Model. Softw.* **23**, 182–194 (2008).
- Lepistö, A., Futter, M. N. & Kortelainen, P. Almost 50 years of monitoring shows that climate, not forestry, controls long-term organic carbon fluxes in a large boreal watershed. *Glob. Change Biol.* **20**, 1225–1237 (2014).
- Hester, G., Ford, D., Carsell, K., Vertucci, C. & Stallings, E. A. *Flood Management Benefits of USGS Streamgaging Program* (National Hydrologic Warning Council, 2006).
- Xu, H., Xu, C.-Y., Chen, H., Zhang, Z. & Li, L. Assessing the influence of rain gauge density and distribution on hydrological model performance in a humid region of China. *J. Hydrol.* **505**, 1–12 (2013).
- Kiang, J. E., Stewart, D. W., Archfield, S. A., Osborne, E. B. & Eng, K. *A National Streamflow Network Gap Analysis* (USGS, 2013).
- Deweber, J. T. et al. Importance of understanding landscape biases in USGS gage locations: implications and solutions for managers. *Fisheries* **39**, 155–163 (2014).
- Tickner, D. et al. Bending the curve of global freshwater biodiversity loss: an emergency recovery plan. *BioScience* **70**, 330–342 (2020).
- Grill, G. et al. Mapping the world's free-flowing rivers. *Nature* **569**, 215–221 (2019).
- Olden, J. D. et al. Hydrologic classification of Tanzanian rivers to support national water resource policy. *Ecohydrology*. <https://doi.org/10.1002/eco.2282> (2021).
- Lin, P. et al. Global reconstruction of naturalized river flows at 2.94 million reaches. *Water Resour. Res.* **55**, 6499–6516 (2019).
- Yamazaki, D. et al. MERIT Hydro: a high-resolution global hydrography map based on latest topography dataset. *Water Resour. Res.* **55**, 5053–5073 (2019).
- Beck, H. E. et al. Bias correction of global high-resolution precipitation climatologies using streamflow observations from 9,372 catchments. *J. Clim.* **33**, 1299–1315 (2020).

18. Do, H. X., Gudmundsson, L., Leonard, M. & Westra, S. The Global Streamflow Indices and Metadata Archive (GSIM)—part 1: the production of a daily streamflow archive and metadata. *Earth Syst. Sci. Data* **10**, 765–785 (2018).
19. Linke, S. et al. Global hydro-environmental sub-basin and river reach characteristics at high spatial resolution. *Sci. Data* **6**, 283 (2019).
20. Dobrushin, R. L. Prescribing a system of random variables by conditional distributions. *Theory Probab. Appl.* **15**, 458–486 (1970).
21. Schefzik, R., Flesch, J. & Goncalves, A. Fast identification of differential distributions in single-cell RNA-sequencing data with waddR. *Bioinformatics* **37**, 3204–3211 (2021).
22. Reid, A. J. et al. Emerging threats and persistent conservation challenges for freshwater biodiversity. *Biol. Rev.* **94**, 849–873 (2019).
23. Wittemyer, G., Elsen, P., Bean, W. T., Burton, A. C. O. & Brashares, J. S. Accelerated human population growth at protected area edges. *Science* **321**, 123–126 (2008).
24. Colvin, S. A. R. et al. Headwater streams and wetlands are critical for sustaining fish, fisheries, and ecosystem Services. *Fisheries* **44**, 73–91 (2019).
25. Chen, K. & Olden, J. D. Threshold responses of riverine fish communities to land use conversion across regions of the world. *Glob. Change Biol.* **26**, 4952–4965 (2020).
26. Pardo, I. et al. The European reference condition concept: a scientific and technical approach to identify minimally-impacted river ecosystems. *Sci. Total Environ.* **420**, 33–42 (2012).
27. Sauquet, E. et al. Classification and trends in intermittent river flow regimes in Australia, northwestern Europe and USA: a global perspective. *J. Hydrol.* **597**, 126170 (2021).
28. Creed, I. F. et al. Enhancing protection for vulnerable waters. *Nat. Geosci.* **10**, 809–815 (2017).
29. Abell, R. et al. Freshwater ecoregions of the world: a new map of biogeographic units for freshwater biodiversity conservation. *BioScience* **58**, 403–414 (2008).
30. Wilhite, D. A. in *Coping with Drought Risk in Agriculture and Water Supply Systems: Drought Management and Policy Development in the Mediterranean*, Vol. 26 (eds. Iglesias, A. et al.) 3–19 (Springer Science and Business Media, 2009).
31. Winemiller, K. O. et al. Balancing hydropower and biodiversity in the Amazon, Congo, and Mekong. *Science* **351**, 128–129 (2016).
32. Seyfried, M. S. & Wilcox, B. P. Scale and the nature of spatial variability: field examples having implications for hydrologic modeling. *Water Resour. Res.* **31**, 173–184 (1995).
33. Hammond, J. C. et al. Spatial patterns and drivers of nonperennial flow regimes in the contiguous United States. *Geophys. Res. Lett.* **48**, e2020GL090794 (2021).
34. Messenger, M. L. et al. Global prevalence of non-perennial rivers and streams. *Nature* **594**, 391–397 (2021).
35. Busch, M. H. et al. What's in a name? Patterns, trends, and suggestions for defining non-perennial rivers and streams. *Water* **12**, 1980 (2020).
36. Zipper, S. C. et al. Pervasive changes in stream intermittency across the United States. *Environ. Res. Lett.* **16**, 084033 (2021).
37. Jaeger, K. L., Olden, J. D. & Pelland, N. A. Climate change poised to threaten hydrologic connectivity and endemic fishes in dryland streams. *Proc. Natl Acad. Sci. USA* **111**, 13894–13899 (2014).
38. Beaufort, A., Lamouroux, N., Pella, H., Datry, T. & Sauquet, E. Extrapolating regional probability of drying of headwater streams using discrete observations and gauging networks. *Hydrol. Earth Syst. Sci.* **22**, 3033–3051 (2018).
39. Argerich, A. et al. Comprehensive multiyear carbon budget of a temperate headwater stream: carbon budget of a headwater stream. *J. Geophys. Res. Biogeosci.* **121**, 1306–1315 (2016).
40. Molden, D. J., Shrestha, A. B., Nepal, S. & Immerzeel, W. W. in *Water Security, Climate Change and Sustainable Development* (eds. Biswas, A. K. & Tortajada, C.) 65–82 (Springer, 2016).
41. Kaletová, T. et al. Relevance of intermittent rivers and streams in agricultural landscape and their impact on provided ecosystem services—a Mediterranean case study. *Int. J. Environ. Res. Public Health* **16**, 2693 (2019).
42. Zimmer, M. A. et al. Zero or not? Causes and consequences of zero-flow stream gage readings. *WIREs Water* **7**, e1436 (2020).
43. Wine, M. L. Toward strong science to support equitable water sharing in securitized transboundary watersheds. *Biologia* **9**, 907–915 (2020).
44. Alsdorf, D. E. GEOPHYSICS: tracking fresh water from space. *Science* **301**, 1491–1494 (2003).
45. Benstead, J. P. & Leigh, D. S. An expanded role for river networks. *Nat. Geosci.* **5**, 678–679 (2012).
46. Allen, D. C. et al. Citizen scientists document long-term streamflow declines in intermittent rivers of the desert southwest, USA. *Freshw. Sci.* <https://doi.org/10.1086/701483> (2019).
47. Joo, H. et al. Optimal stream gauge network design using entropy theory and importance of stream gauge stations. *Entropy* **21**, 991 (2019).
48. Vörösmarty, C. et al. Global water data: a newly endangered species. *Eos* **82**, 54–58 (2001).
49. Jordahl, K. et al. Geopandas/geopandas. *Zenodo* <https://doi.org/10.5281/zenodo.3946761> (2020).
50. Lin, P., Pan, M., Wood, E. F., Yamazaki, D. & Allen, G. H. A new vector-based global river network dataset accounting for variable drainage density. *Sci. Data* **8**, 28 (2021).
51. Yu, S. et al. Evaluating a landscape-scale daily water balance model to support spatially continuous representation of flow intermittency throughout stream networks. *Hydrol. Earth Syst. Sci.* **24**, 5279–5295 (2020).
52. Kennard, M. J. et al. Classification of natural flow regimes in Australia to support environmental flow management. *Freshw. Biol.* **55**, 171–193 (2010).
53. *Flow/No Flow Observations with Discharge Data from Probabilistic Stream Surveys* (US EPA Office of Research and Development, 2021).
54. Rosenbaum, P. R. & Rubin, D. B. The bias due to incomplete matching. *Biometrics* **41**, 103–116 (1985).

Acknowledgements

This manuscript is a product of the Dry Rivers Research Coordination Network, which was supported by funding from the US National Science Foundation (DEB-1754389 and 2207232 to D.C.A.). Although this work was reviewed by the USEPA and approved for publication, it does not necessarily reflect official USEPA policy. This work has been peer reviewed and approved for publication consistent with USGS Fundamental Science Practices (<https://pubs.usgs.gov/circ/1367/>). Any use of trade, firm or product names is for descriptive purposes only and does not imply endorsement by the US government.

Author contributions

G.H.A., J.D.O., C.A.K., S.E.G., P.L., R.M.B., A.G.D., D.C.A., K.M.F., M.S., M.A.Z., T.D., W.K.D., C.N.J., J.C.H., M.C.M., S.Z., A.J.B., K.H.C. and A.S.W. conceived the study. P.L., H.E.B., K.M.F. and M.S. contributed data. J.D.O., G.H.A., P.L., C.A.K., C.F. and C.N.J. conducted analyses. G.H.A., J.D.O., C.A.K. and P.L. constructed visualizations. C.A.K., J.D.O., G.H.A. and S.E.G. drafted the manuscript, and all authors reviewed and edited the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

Supplementary information The online version contains supplementary material available at <https://doi.org/10.1038/s41893-022-00873-0>.

Correspondence and requests for materials should be addressed to Corey A. Krabbenhoft.

Peer review information *Nature Sustainability* thanks Jefferson DeWeber, Hong Do and Yin-phan Tsang for their contribution to the peer review of this work.

Reprints and permissions information is available at www.nature.com/reprints.

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

© The Author(s), under exclusive licence to Springer Nature Limited 2022

Reporting Summary

Nature Research wishes to improve the reproducibility of the work that we publish. This form provides structure for consistency and transparency in reporting. For further information on Nature Research policies, see our [Editorial Policies](#) and the [Editorial Policy Checklist](#).

Statistics

For all statistical analyses, confirm that the following items are present in the figure legend, table legend, main text, or Methods section.

- | | |
|-----|-----------|
| n/a | Confirmed |
|-----|-----------|
- The exact sample size (n) for each experimental group/condition, given as a discrete number and unit of measurement
 - A statement on whether measurements were taken from distinct samples or whether the same sample was measured repeatedly
 - The statistical test(s) used AND whether they are one- or two-sided
Only common tests should be described solely by name; describe more complex techniques in the Methods section.
 - A description of all covariates tested
 - A description of any assumptions or corrections, such as tests of normality and adjustment for multiple comparisons
 - A full description of the statistical parameters including central tendency (e.g. means) or other basic estimates (e.g. regression coefficient) AND variation (e.g. standard deviation) or associated estimates of uncertainty (e.g. confidence intervals)
 - For null hypothesis testing, the test statistic (e.g. F , t , r) with confidence intervals, effect sizes, degrees of freedom and P value noted
Give P values as exact values whenever suitable.
 - For Bayesian analysis, information on the choice of priors and Markov chain Monte Carlo settings
 - For hierarchical and complex designs, identification of the appropriate level for tests and full reporting of outcomes
 - Estimates of effect sizes (e.g. Cohen's d , Pearson's r), indicating how they were calculated

Our web collection on [statistics for biologists](#) contains articles on many of the points above.

Software and code

Policy information about [availability of computer code](#)

Data collection

Data analysis

For manuscripts utilizing custom algorithms or software that are central to the research but not yet described in published literature, software must be made available to editors and reviewers. We strongly encourage code deposition in a community repository (e.g. GitHub). See the Nature Research [guidelines for submitting code & software](#) for further information.

Data

Policy information about [availability of data](#)

All manuscripts must include a [data availability statement](#). This statement should provide the following information, where applicable:

- Accession codes, unique identifiers, or web links for publicly available datasets
- A list of figures that have associated raw data
- A description of any restrictions on data availability

All data is publicly available and accession codes are noted in our data availability statement. R scripts for analyses are available on GitHub (as noted in the data availability statement).

Field-specific reporting

Please select the one below that is the best fit for your research. If you are not sure, read the appropriate sections before making your selection.

Life sciences Behavioural & social sciences Ecological, evolutionary & environmental sciences

For a reference copy of the document with all sections, see [nature.com/documents/nr-reporting-summary-flat.pdf](https://www.nature.com/documents/nr-reporting-summary-flat.pdf)

Ecological, evolutionary & environmental sciences study design

All studies must disclose on these points even when the disclosure is negative.

Study description	Using 32,091 stream gauges and 13 environmental attributes for 2.9 million stream segments of the global river network, we demonstrate that the locations of global river gauges have led to biases in representation of river heterogeneity and a distorted view of Earth's changing freshwater resources.
Research sample	Our datasets include global stream gauge locations (Do et al. 2018 and Beck et al. 2020; N=32,091), the GRADES hydrographic dataset (Lin et al. 2019; N=2,896,897), the HydroATLAS database of hydro-environmental attributes (Linke et al. 2019), and Major Habitat data from the Freshwater Ecoregions of the World database (Abell et al. 2008).
Sampling strategy	Sample sizes were dictated by availability of global data. The stream gauge locations come from two recently published datasets (Do et al. 2018; Beck et al. 2020). Landscape variables were from the HydroATLAS global river database (Linke et al. 2019). Stream segment locations were from the GRADES database by Lin et al. (2019).
Data collection	GH Allen provided the geospatial GRADES stream network, and used the published discharge estimates (Lin et al. 2019) to calculate flow permanence. GH Allen also collected data from M Shanafield and K Fitz to validate no-flow thresholds in the GRADES discharge data. HE Beck provided stream gauge location information in addition to that available from Do et al. (2018). Gauge locations and landscape variables from HydroATLAS (Linke et al. 2019) were spatially linked to the GRADES database by P Lin and CA Krabbenhoft. Analyses of spatial bias were conducted by JD Olden and mapped by GH Allen.
Timing and spatial scale	The spatial scale was global for all datasets used. The timing of our findings corresponds to a current view of global gauge infrastructure. However, GRADES discharge data was calculated from hydrographic information collected from 1979-2013 (Lin et al. 2019). Stream gauge data includes gauge observations from a previously compiled global database (Do et al. 2018) with additional gauges from Beck et al. (2020). HydroATLAS database is a compilation of resources published between 2000 and 2015 (for the parameters used here), or else calculated separately for the 2019 publication (Linke et al. 2019). Major habitat types were current as of the publication of Abell et al. (2008).
Data exclusions	For spatial analyses, Greenland and Antarctica were excluded because they do not currently host gauges in the databases used. Stream gauge locations were filtered for duplicates among data sources and stream segments that host multiple gauges.
Reproducibility	Flow permanence estimates were validated using independent datasets on flow conditions from an additional 1,119 gauging locations with a total of 89,187 no-flow observations outside of the GRADES database.
Randomization	Grouping factors for our analysis were non-random; major habitat types were according to spatial overlay with Freshwater Ecoregions of the World data (Abell et al. 2008). Additional landscape attributes from HydroATLAS (Linke et al. 2019) were also assigned via spatial overlay with the GRADES stream segments. Gauging stations were snapped to the stream network using a maximum distance of 500m.
Blinding	Blinding was not relevant for this study, because underlying data was concatenated from published sources.
Did the study involve field work?	<input type="checkbox"/> Yes <input checked="" type="checkbox"/> No

Reporting for specific materials, systems and methods

We require information from authors about some types of materials, experimental systems and methods used in many studies. Here, indicate whether each material, system or method listed is relevant to your study. If you are not sure if a list item applies to your research, read the appropriate section before selecting a response.

Materials & experimental systems

- | n/a | Involvement in the study |
|-------------------------------------|--|
| <input checked="" type="checkbox"/> | <input type="checkbox"/> Antibodies |
| <input checked="" type="checkbox"/> | <input type="checkbox"/> Eukaryotic cell lines |
| <input checked="" type="checkbox"/> | <input type="checkbox"/> Palaeontology and archaeology |
| <input checked="" type="checkbox"/> | <input type="checkbox"/> Animals and other organisms |
| <input checked="" type="checkbox"/> | <input type="checkbox"/> Human research participants |
| <input checked="" type="checkbox"/> | <input type="checkbox"/> Clinical data |
| <input checked="" type="checkbox"/> | <input type="checkbox"/> Dual use research of concern |

Methods

- | n/a | Involvement in the study |
|-------------------------------------|---|
| <input checked="" type="checkbox"/> | <input type="checkbox"/> ChIP-seq |
| <input checked="" type="checkbox"/> | <input type="checkbox"/> Flow cytometry |
| <input checked="" type="checkbox"/> | <input type="checkbox"/> MRI-based neuroimaging |