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Assessing placement bias of the global river gauge network

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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 disproportionally 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 society[3]. Collecting and archiving long-term hydrologic data is required for analysis of hydroclimatic trends[4] and quantification of the effects of flow regime alteration on the ecology[5], capacity to transport pollutants[6] and biogeochemistry (for example, carbon fluxes[7]) 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 needs[8]. 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 estimates[9], 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 goals[12], challenge the estimation of hydrologic impacts of human activities[13] and undermine best practices for determining environmental and cultural flow standards[14]. 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) dataset[15],

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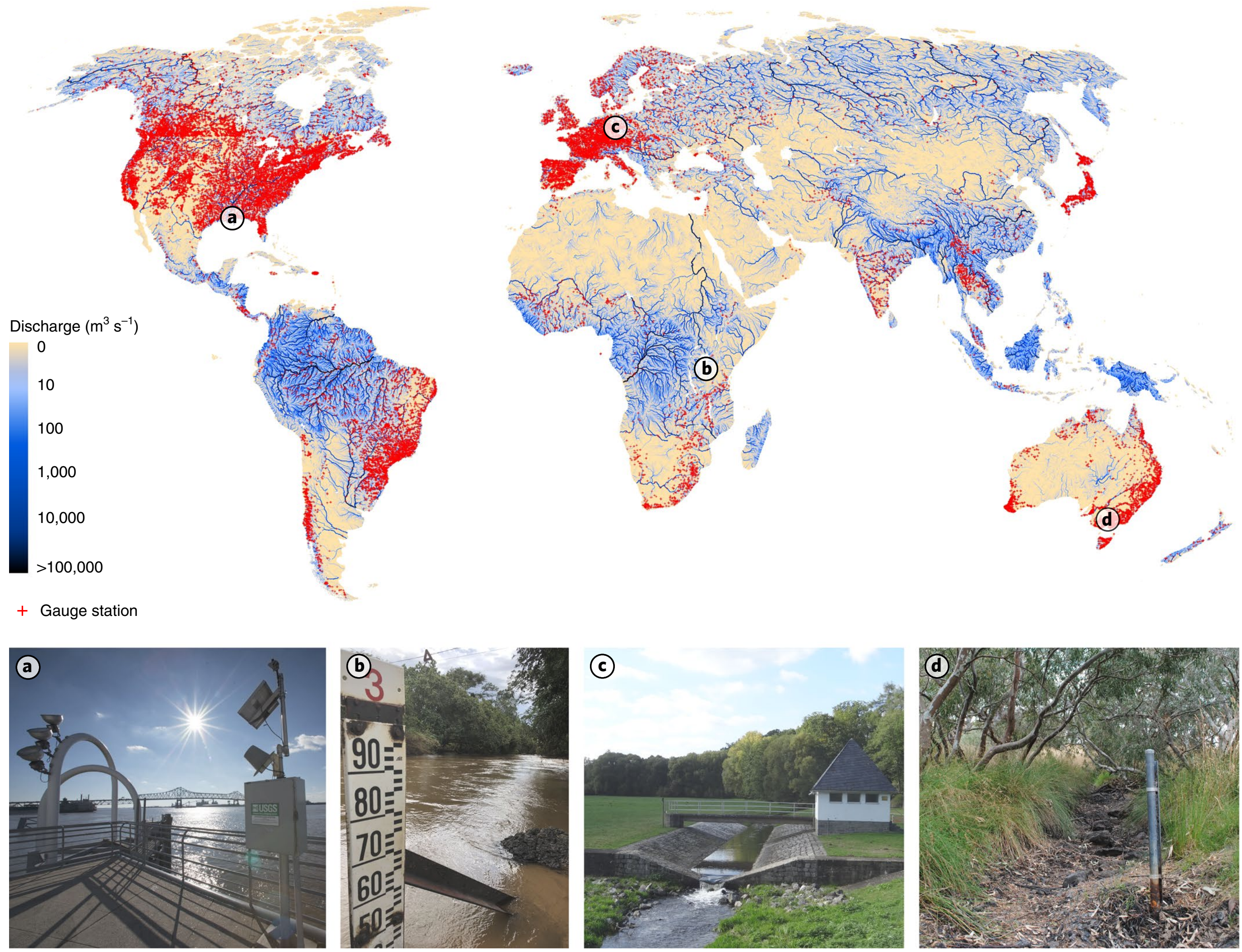

Fig. 1 | Global distribution of stream gauges with four examples. Global distribution of stream gauges (red crosses; $N = 32{,}091$) along the river network (blue) identified by GRADES[15] with four example gauges shown. **a**–**d**, Examples of river gauges. **a**, Mississippi River, Louisiana, United 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 model[16] (Supplementary Methods). GRADES also contains daily discharge estimates from 1979–2013 at these ~3 million river segments with drainage areas >25 km^2 (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 HydroATLAS[19] 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 efforts[2,22], including catchments with protected areas[23] and headwater streams[24]. 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

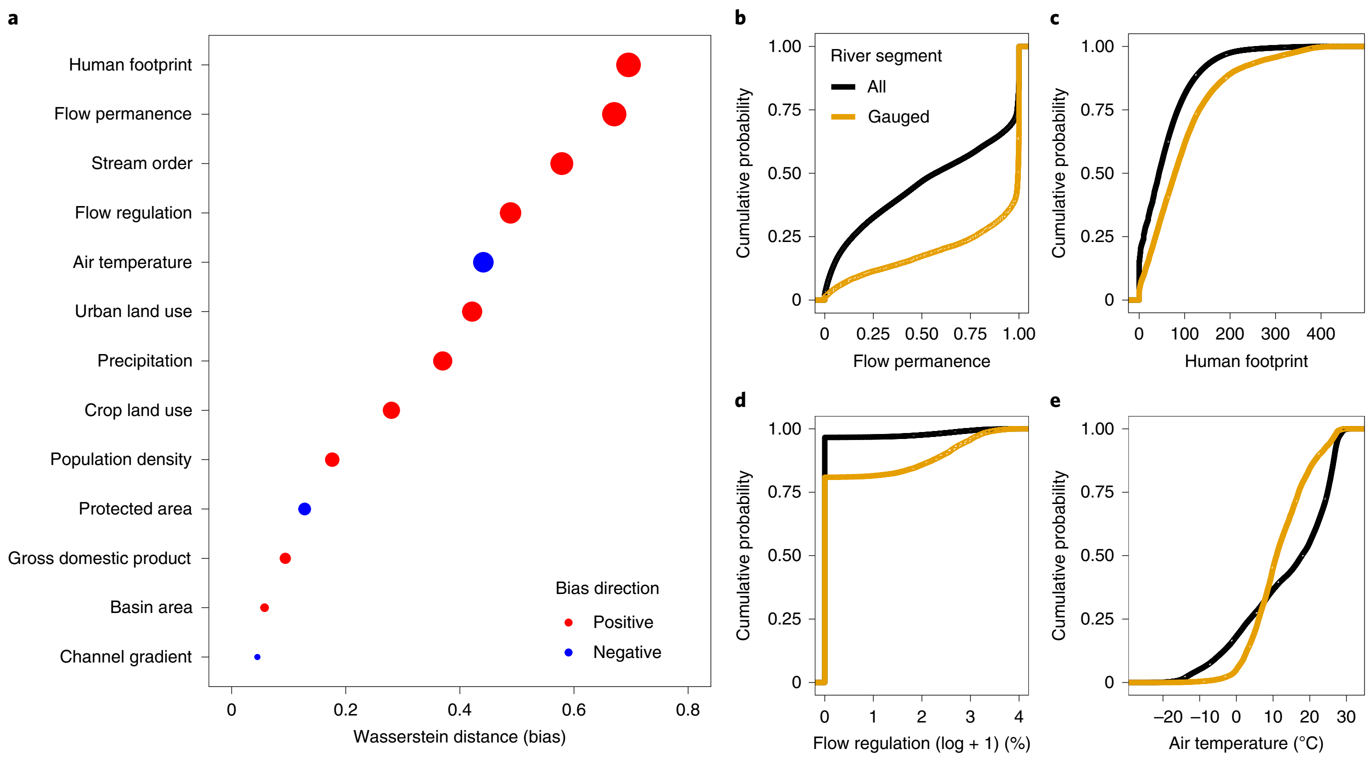

Fig. 2 | Comparison of currently gauged river segments to the GRADES dataset according to geospatial attributes. a, Bias in the global gauge network according to variables describing hydrology, climate, physiography and socioecological conditions. Symbol size is scaled according to the magnitude of bias (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 biodiversity[12] 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 goals[26]. 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 protection[28]. 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 habitat[29] 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 environments[30]. 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 challenges[31]. Note that patterns for both flow permanence and stream order are probably much more exaggerated than what we show here given the 25 km^2 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 forecast[32]. 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 decades[35], and the potential source of error from skewed discharge estimates could present a challenge for identifying changes over time[36]. Investing in monitoring environmental 'extremes' now will improve future modelling efforts as these characteristics (for example, intermittency) become more common[37]. Similarly,

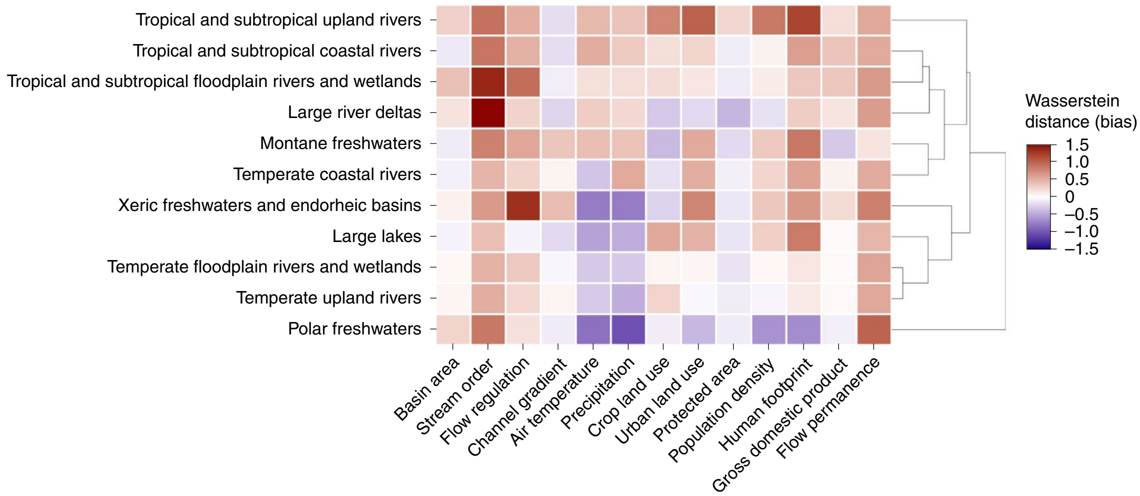

Fig. 3 | Bias in the gauge network. Bias in the gauge network for 11 freshwater ecoregions of the world[29] according to variables describing hydrology, climate, physiography and socioecological conditions. Bias values range from positive (red, over-represented) to negative (blue, under-represented) 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 drying[38], upstream contributions to watershed carbon budgets[39] and the importance of headwater streams in supporting biodiversity and ecological integrity throughout their corresponding watersheds[24]. 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 Himalayas[40]).

Addressing patterns of gauge placement bias on a global scale requires greater integration of gauging infrastructure and data platforms from local to international levels[2]. 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 practices[43]. Multiple alternatives to adding gauges may help bring this goal within reach. For example, advances in remote sensing technology[44] 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 networks[45]. Furthermore, community science efforts can provide data for systems lacking stream gauges[46], and greater river network coverage can improve modelling approaches where costs of new gauge infrastructure are prohibitive[38]. 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 generated[2]. 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 rivers[11]. Better accounting for socioecological and environmental heterogeneity in gauge networks will improve hydrologic models[47]

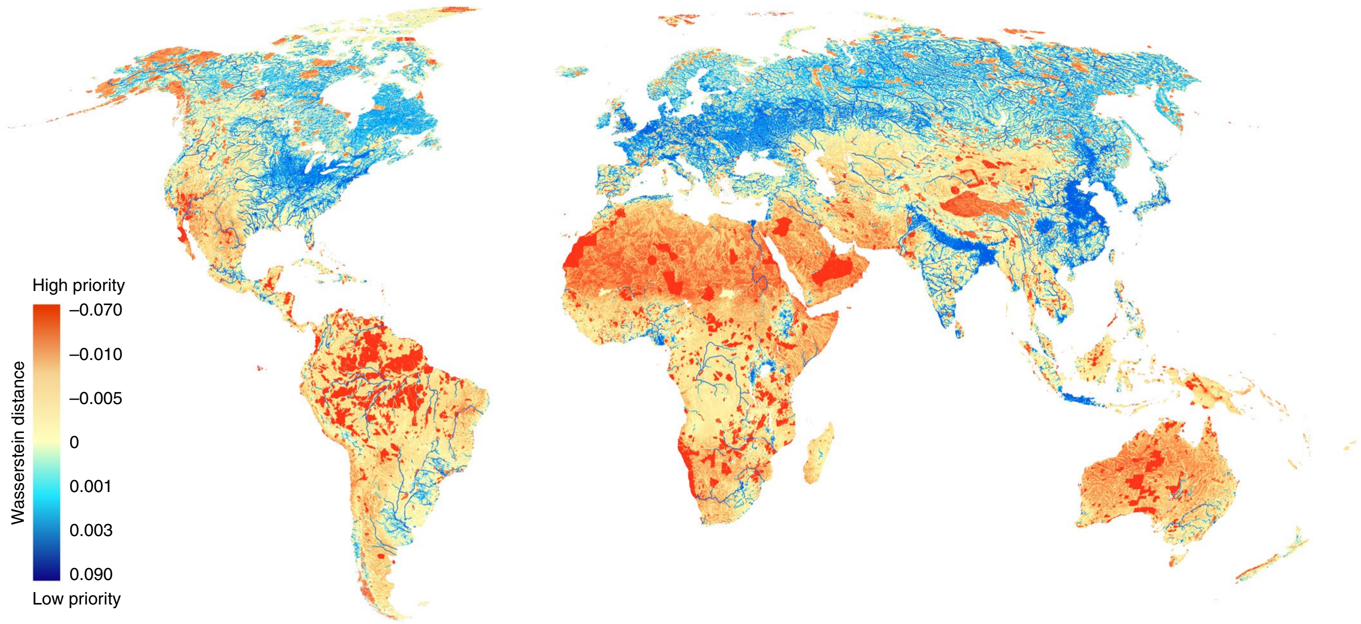

Fig. 4 | Estimated global mean bias change from gauge installation. Estimated amount of global mean bias change (Wasserstein distance) resulting from a gauge being installed on each river segment. Red indicates priority areas for potential new gauges (which would result in greater reduction in global 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 crisis[12]. 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 systems[48]. Previous studies[2] 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 (GSIM[18]) with additional gauges from a recent publication[17] that provides daily discharge data for a subset of gauges. Hydrologic data were obtained from the GRADES hydrographic dataset[15] 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 km^2. 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 database[19], which describes landscape characteristics relevant to individual river segments (or reach[15]). 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 km^2 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 systems[29].

We combined GRADES and HydroATLAS datasets through geospatial analysis performed using the Python GeoPandas library[49]. 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 types[29] 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 flow[35]) using GRADES simulated discharge[15] and daily discharge observations from one of the gauge station databases that was used in this study[17]. Note that the GSIM gauge database[18] 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, $10^{-2}\,m^3\,s^{-1}$), 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 flow[42]. We used the gauge dataset[17] 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 dataset[17], 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 $0.16\,m^3\,s^{-1}$ with a first quartile value of $0.028\,m^3\,s^{-1}$ and a third quartile value of $0.83\,m^3\,s^{-1}$ (Supplementary Fig. 3). We used the median value to threshold the GRADES discharge, meaning if GRADES simulated a discharge below $0.16\,m^3\,s^{-1}$, we deemed that this discharge was at zero flow, similar to the methods used elsewhere[51]. 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 States[53]. We removed all observations that (1) were duplicated with those in the gauge database[17]; (2) had drainage areas $<25\,km^2$, 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 dataset[17] 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 datasets[21]. 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[20,21]. 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 means[54]. 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 type[29].

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.

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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

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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	No software was used in data collection
Data analysis	Geospatial analyses were conducted in ArcGIS (ArcMap 10.5). Statistical analyses were conducted in R (version 4.0.2) using custom scripts.

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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? ☐ Yes ☒ No

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☒	☐ Palaeontology and archaeology
☒	☐ Animals and other organisms
☒	☐ Human research participants
☒	☐ Clinical data
☒	☐ Dual use research of concern

Methods

n/a	Involved in the study
☒	☐ ChIP-seq
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