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Advancing the science of headwater streamflow for global water protection

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The protection of headwater streams faces increasing challenges, exemplified by limited global recognition of headwater contributions to watershed resiliency and a recent US Supreme Court decision limiting federal safeguards. Despite accounting for ~77% of global river networks, the lack of adequate headwaters protections is caused, in part, by limited information on their extent and functions—in particular, their flow regimes, which form the foundation for decision-making regarding their protection. Yet, headwater streamflow is challenging to comprehensively measure and model; it is highly variable and sensitive to changes in land use, management and climate. Modelling headwater streamflow to quantify its cumulative contributions to downstream river networks requires an integrative understanding across local hillslope and channel (that is, watershed) processes. Here we begin to address this challenge by proposing a consistent definition for headwater systems and streams, evaluating how headwater streamflow is characterized and advocating for closing gaps in headwater streamflow data collection, modelling and synthesis.

The protection of valuable yet vulnerable waters is a pressing global concern. This is exemplified by their lack of recognition by the European Water Framework Directive (in headwaters with catchments <10 km^2)[1], a recent US Supreme Court decision limiting federal safeguards for headwater streams and wetlands[2] and general limited protections throughout much of Africa[3].

Headwaters are therefore at risk[4]. Despite intensive studies of individual headwater streams, science and policy practitioners have limited synthetic information to (1) delineate their extent (mapping resolutions often do not capture their small sizes[5], for example, Strahler stream orders 1 and 2) and (2) quantify their individual and cumulative functions across a myriad of ungauged global watersheds. Headwater streams account for approximately 77% (Fig. 1 and ref. 6) of river network extents worldwide. However, inadequate understanding and lack of protection of headwater streams creates the risk of altering headwater flows—and, thereby, watershed resiliency—in the face of environmental changes[7].

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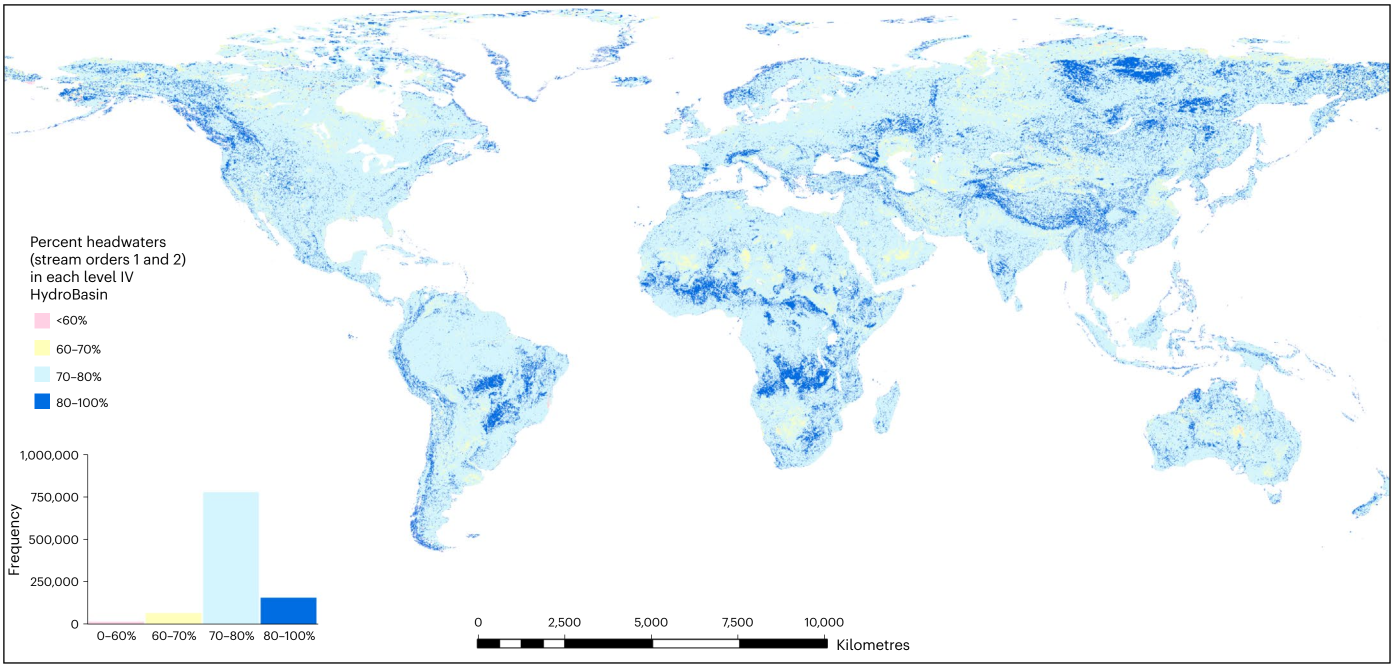

Fig. 1 | Percentage of headwater streams by length in level 4 HydroBASINS across the globe using the MERIT Hydro-based stream network (with a 5 ha drainage threshold) as used in the Hydrography90m global hydrography dataset. Headwater streams are operationally defined here as Strahler stream orders 1 and 2. For level 4 HydroBASINs data and the Hydrography90m global hydrography dataset, see ref. 116 and ref. 103, respectively.

Headwater streams are the most upgradient reaches of river networks with concentrated streamflow occurring at least part of the year. The frequency, magnitude, duration and timing of these flows are primary controls on watershed-scale functions, including biogeochemical processing[8], water quality[9], flood and drought controls[10], biodiversity[11] and ecological functions[12], and on ecosystem services[13]. Furthermore, stream protections are often based on flow regimes[14], and understanding these flows is also important for quantifying water availability and other ecosystem services. Therefore, there is a clear need for accurate headwater flow monitoring and predictions to quantify the impacts of growing headwater vulnerabilities.

Headwater streamflow is more variable than that of larger downstream systems, in part because in-stream processes and diverse watershed transit times disperse peak flows as they propagate downstream. Headwater reaches are therefore frequently flashy—quickly wetting and drying in response to rainfall or snowmelt—and often present as intermittent or ephemeral surface waters (Fig. 2a). The rapidly changing 'wetness' state of headwaters renders them sinks for solutes and suspended particulates during dry periods and then sources of these same constituents, once resuspended or transformed, via transport downstream[15–17]. Headwater streamflow variability also makes it challenging to predict associated flow behaviour in small watersheds compared with larger systems (Fig. 2b). Moreover, these same rapid flow variations increase the vulnerability of headwater streams to climate change, with half of the US non-perennial flow gauges already showing changes in their intermittency regimes[18].

Despite their functional contributions to watershed processes[7], their ecological importance[11,12,16,19,20], their societal and economic benefits[4] and the need for timely observed and modelled data on headwater reaches and their associated flow regimes (particularly across large areas such as river basins), headwater reaches are becoming increasingly imperilled worldwide. A profound opportunity in headwater stream research, echoing that of hydrology more widely, is to transcend individual studies of headwater streamflow and build a broader integrative understanding of headwater systems and their flow regimes across space and time[21].

To address this global opportunity, here we use United States-based examples to (1) propose uniform definitions for headwater systems and headwater streams for applications across sites and regions, (2) summarize the regulatory and data-based status of headwater streams, (3) synthesize current data and modelling approaches used to characterize headwater streamflow across space and time and (4) provide guidance for advancing the understanding of headwater hydrology for improved mapping, modelling and data syntheses to support better management. We submit this Perspective at a critical downward turning point in headwater stream protections, when research on headwaters and their downstream effects on watershed resiliency (via delivery of water quality, flood and drought, and biological benefits) is imperative.

Defining headwaters for an integrative understanding

Headwater streams and headwater systems are inconsistently defined. Currently, headwater-related definitions fluctuate with varying focal points: stream width[6,22,23], watershed size[24,25], geomorphology[26,27] and/or biotic communities[27] (see Supplementary Table 1 for examples). Definitions also differ by research or management objective and by the spatial and temporal extent being considered. A unified description of both is necessary to integrate the science and understanding of headwaters across multiple spatial scales and regions for improved management. Therefore, although we recognize that headwaters structurally and dynamically vary site to site, our goal is to provide definitions for comparisons across broad spatial extents (for example, nationally and continentally). In our definitions, headwaters encompass non-perennial flow regimes, specifically low-order ephemeral streams (which flow in direct response to precipitation) and intermittent streams (which dry up annually but are connected seasonally to groundwater systems), as well as perennially flowing low-order systems.

We propose a definition of headwater systems, as well as conceptual and operational definitions of headwater streams. Furthermore, we henceforth refer to a combined headwater system and its associated streams as headwaters. Specifically, we define headwater systems

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(in which headwater streams reside) as the surface-water catchment areas and groundwater zones contributing water, material and energy to a headwater stream. Headwater systems occur in areas with substantial topographic relief as well as low-gradient regions. Headwater flow regimes can be described by the magnitude, frequency, duration, timing and rate of change, as well as the lateral, vertical and longitudinal expansion and contraction, of headwater streamflow[28].

We suggest a conceptual definition of headwater streams following Wohl[29] and Montgomery and Dietrich[30,31] as visible and distinct channels, originating at a channel head, itself described as the "upstream-most point of concentrated water flow and sediment transport between definable banks"[29]. This concentrated flow occurs for at least part of the year. Headwater streams emanate from headwater systems where distinct channels emerge from diffusive hillslope processes[29]. The presence of surface water in headwater streams is often spatially and temporally dynamic. Due to their dynamic nature, the downstream extent of headwaters is an imprecise transition zone or continuum that may shift spatially and temporally, depending upon the focus of interest. Conceptually, the downstream extent represents the transition zone where local water, material or energy contributions are less substantial than upstream flow contributions (for example, due to volumetric mixing[32]). This definition allows us to describe, in theory, how headwater streams are visualized and studied in the field. However, implementing the conceptual definition across broad spatial extents (for example, nationally and continentally) is challenging, particularly because definitions (Supplementary Table 1) are either unable to be operationalized for modelling (in part because downstream extents are often difficult to define) or interpreted differently across diverse watersheds.

We therefore also propose an operational definition of headwater streams for modelling and analyses across broad spatial expanses. We require that the operational definition enables us to identify the lower boundary of headwaters for all mapped rivers and streams across national to continental extents. Our operational definition therefore defines headwaters as the most distal extents—encompassing stream orders 1 and 2—of a 1:24,000 or similar scale stream network map. This approach (1) uses readily available attributes (that is, stream orders) associated with any mapped stream network globally and (2) provides a lower headwater stream boundary, below which a headwater stream discharges into the wider river network and above which all other potentially small stream reaches currently unmapped by large stream network datasets exist. In the United States, the National Hydrography Dataset Plus High Resolution (NHDPlus HR)[33] is a primary example, providing finer-resolution data than previously mapped in the United States[34]. Globally, other mapped stream networks at the finest resolution can be a starting point, including but not exclusive to examples from Canada[35], the United Kingdom[36] and the European Union[37], all at 1:50,000 scales. This operational definition is designed to be applied over large spatial extents and sample sizes without requiring detailed data, such as channel heads, stream origins or the transition zone to downstream waters, that are not easily accessible from most mapped stream networks. Products such as NHDPlus HR also provide information attributing headwater streams to ephemeral and intermittent flow permanence classifications; however, they may need further validation[16].

In the future, improved spatial resolutions and automated processing of remote sensing data may allow our current operational definition—reliant on underlying mapping scales—to be replaced by one that is physically based and that ensures consistency across regions. This would also catalyse a stronger link between our field-based conceptual and model-based operational definitions of headwater streams. Promising candidates include a definition based on relationships between channel width and stream order[23]. Currently, such information is not available across national to continental extents other than by estimates based on hydraulic relationships[20].

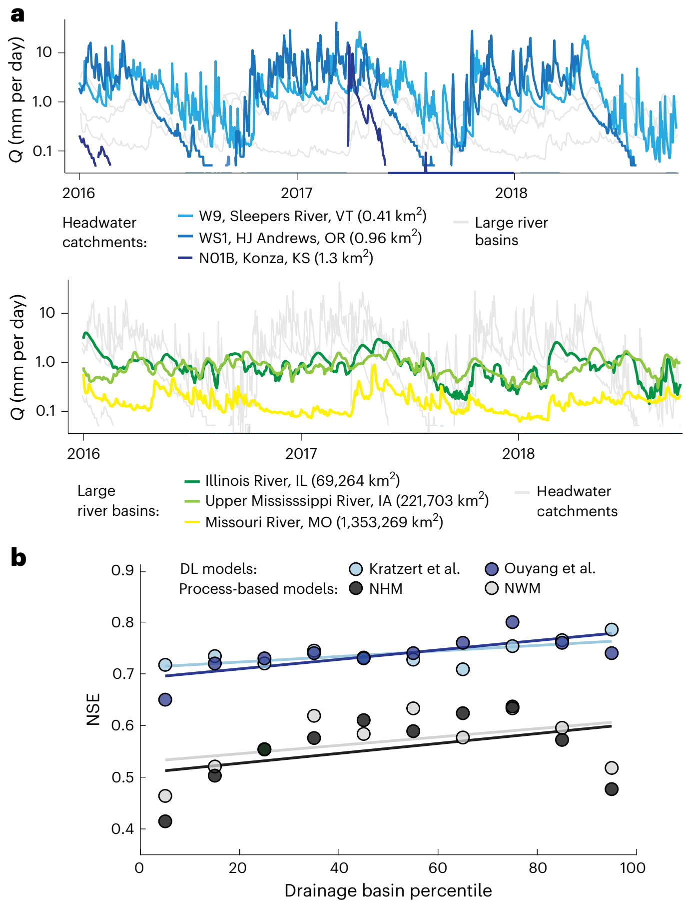

Fig. 2 | Comparing observed and predicted headwater flows with those of larger rivers, with flows normalized by area. a, The observed streamflow (Q) from exemplar headwater streams and large rivers demonstrates greater headwater streamflow variability and flashiness compared with the less variable flows of large rivers. **b**, The daily model performance (Nash–Sutcliffe efficiency, NSE) across drainage basin percentiles for data-driven DL long short-term memory (LSTM) neural networks predicting streamflow (Kratzert et al.[117] using CAMELS data; Ouyang et al.[118] using US Geological Survey Geospatial Attributes of Gages for Evaluating Streamflow (GAGES-II data[119])) and US-based national-scale process-based models (NWM[92] and the NHM[93]). Lines of best fit are shown for each of the four models, and drainage basin percentiles demonstrate a comparable generalized summary of model results. Model performance (NSE) in both the LSTM models and process-based models improves with increasing drainage area (here, drainage basin percentiles). One exception is the largest 20% of basins, where heavily managed flows are not well reproduced because of the complexity of coordinated water storage, release, transfer and diversion. For detailed results, see Supplementary Figs. 2–4.

We do, however, acknowledge the limitations in the mapped headwater extents underlying the proposed operational definition[38]. Stream networks mapped across large spatial extents can still miss small localized headwater streams[39] and are conservative estimates of headwater extents[16]. Yet, the selection of this approach is driven by several major factors. First, we compared three different common approaches for delineating stream networks using publicly available spatial datasets (NHDPlus HR stream orders and two flow accumulation threshold-based methods) to assess how these approaches may affect our operational headwater stream definition. The approaches varied minimally (<4% average difference) in the estimated proportion of the watershed stream network considered headwater streams (Supplementary Text, Supplementary Fig. 1 and Supplementary Table 2). Second, our operational definition of headwater streams defines the downstream boundary of the headwater system based on widely available data and is easily integrated with detailed local data that can help define the stream network above that point. Such an approach that combines standardized widely available data for large sample comparisons, trend detection and model development with the best available local data is valuable for today's increasing number of global hydrology applications. Third, because it accounts for differences in drainage density, a base data layer such as NHDPlus HR incorporates differences among physiographic regions that are not captured by threshold-based approaches (Fig. 3).

Given these key points, global analyses of headwater streams (stream orders 1 and 2) could be conducted using maps of similar resolution, albeit with known limitations (for example, Mapping Elevation Requirements for Inland Topography (MERIT) Hydro; Fig. 1). Post-processing using machine learning (ML) techniques demonstrates potential to improve global analyses based on the information in high-quality datasets such as the NHDPlus HR[40]. Importantly, using our operational definition, currently available data can provide actionable information about the character of headwaters (for example, where their densities are high (Fig. 3)) and allow comparisons of headwaters across regions.

Status of headwater protections and flow data

Scientists and water managers across the globe require concise and readily available information on headwater flow regimes to improve decision-making regarding their protection. However, limited datasets currently capture headwater stream extents and heterogeneity[38], and standardized regional and national streamflow data programmes provide limited information in headwater systems. For example, only 8% of active stream gauges across the conterminous United States are in headwater streams (Fig. 4), even though headwater streams account for approximately 77% of stream and river extents across the conterminous United States (Fig. 3). While some areas across the globe are expanding headwater monitoring networks (for example, France's L'observatoire national des étiages (ONDE)[41]), this general lack of information leads to headwaters being poorly understood across a wide variety of headwater systems, being undervalued as contributors to watershed resiliency and having varying protections due to the ever-changing landscape of regulations across the United States and around the globe.

In the United States, the Clean Water Act (CWA) is the main tool for the federal protection of headwater streams. Identifying which headwater streams to protect is largely based on definitions related to the permanence of their flow regimes. In May 2023, a US Supreme Court decision[2] narrowed where the CWA applies for many headwater streams by eliminating the protection of non-relatively permanent tributary waters (a subset of non-perennial streams), regardless of size. The subsequent rule, the 'Revised Definition of "Waters of the United States; Conforming"'[42], thereby limited CWA protections for tributaries to only 'relatively permanent' streams and rivers. In light of this loss of protections, a future synthesis of shared knowledge about headwater hydrological processes, their emergent flow regimes and their cumulative watershed-scale importance would advance future scientific and management approaches.

We can, however, learn from the past. Over several decades, multiple studies have advanced the science of headwater streams and headwater systems, focusing on the physical, chemical and biological functions of individual stream reaches or systems (for example, see ref. 43). In fact, small catchment studies have been at the forefront of developing our knowledge of headwater flow regimes[44]. Throughout the past 90 years, others have explored the downstream effects of headwater flows on these same functions[19,43,45] and have synthesized headwaters via maps[34] or their watershed-scale functions[46,47]. Improving our broad, integrative understanding of headwaters and their hydrological regimes is the first step in advancing their protection[48,49]. To do so, we must explore how we use data and models to integrate across regions and further characterize headwater extent and functions.

Characterizing headwater flows

Water managers and research scientists require data to characterize headwater flow regimes and thereby advance and support headwater protection. Headwater flow measurements are made in situ (on the ground) or via remotely sensed (satellite) imagery across a variety of temporal and spatial scales. Observed data can be used independently, form the basis for empirical models or be integrated into more complex models to characterize headwater streamflow. These data help to support the development of perceptual models (that is, a figure-based summary of our current understanding[50]) of headwater systems, enabling hypothesis testing via models and providing a solid foundation for projecting hydrological regimes beyond the temporal and spatial scale of measured data. Debates continue over the competing and complementary roles of field studies and other data collection methods compared with modelling-based approaches in hydrology[51,52]. However, combined, both observational and model-based efforts represent powerful approaches towards characterizing headwater streams across scales.

Observational approaches

Hydrologists began characterizing headwater flow regimes in the early 1900s (that is, ref. 45). Seminal works from United States-based experimental headwater systems, such as the Coweeta Hydrologic Lab (for example, the Variable Source Area Concept[43]) and Hubbard Brook Experimental Forests (for example, the discovery of acid rain[53]), still influence our perceptual understanding of key headwater hydrological processes. Furthermore, hydrological observations (for example, rainfall and streamflow) in small agricultural watersheds led to the widespread use of empirical relationships such as the curve number method.

Traditionally, streamflow is measured at watershed outlets, although within-watershed measurements of hydrological fluxes among system components (for example, surface runoff[54], throughfall (the shedding of water by leaves)[55], hyporheic exchange (stream channel water moving between the surface and subsurface)[56] and plant–atmosphere interactions[57]) are also possible. Yet, despite over 100 years of data collection in diverse headwater systems, we still (1) lack unifying theories for broad-scale generalizations about dominant and systems-specific emergent hydrological processes and (2) struggle to accurately predict flow in ungauged locations, which are often headwater streams[58].

Recent advances in data collection focus on understanding the spatial and temporal dynamics of flowing water in headwater streams. For example, modifications to stream temperature or light intensity sensors and electrical conductivity sensors[59–61]—along with field camera traps[62,63]—afford surface-water presence and absence measurements at subdaily intervals across headwater networks. Although such modified sensors cannot estimate flow magnitudes (but see ref. 64), they can measure the frequency, duration and timing of surface-water presence, measurements needed for informing headwater management. Spatially dispersed modified sensor deployments estimate headwater stream network expansion and contraction (for example, ref. 61), flow durations (for example, ref. 65) and variations in stream inundation and flow states[66] and can augment traditional field sampling campaigns.

Several technological methods to characterize headwater flow regimes show future promise. Although remote sensing methods are still rarely used in headwaters (for example, ref. 67), increasingly fine-grain imagery gathered from satellite missions has great potential, albeit with some challenges (for example, limited by tree cover in forested headwater systems[68]). However, progress is being made, for example, via ML methods that can train remotely sensed imagery with local surveys to produce discharge–stream network relationships at headwater system outlets[69].

Other key challenges concerning observational headwater streamflow measurements are (1) the limited number of sites with headwater

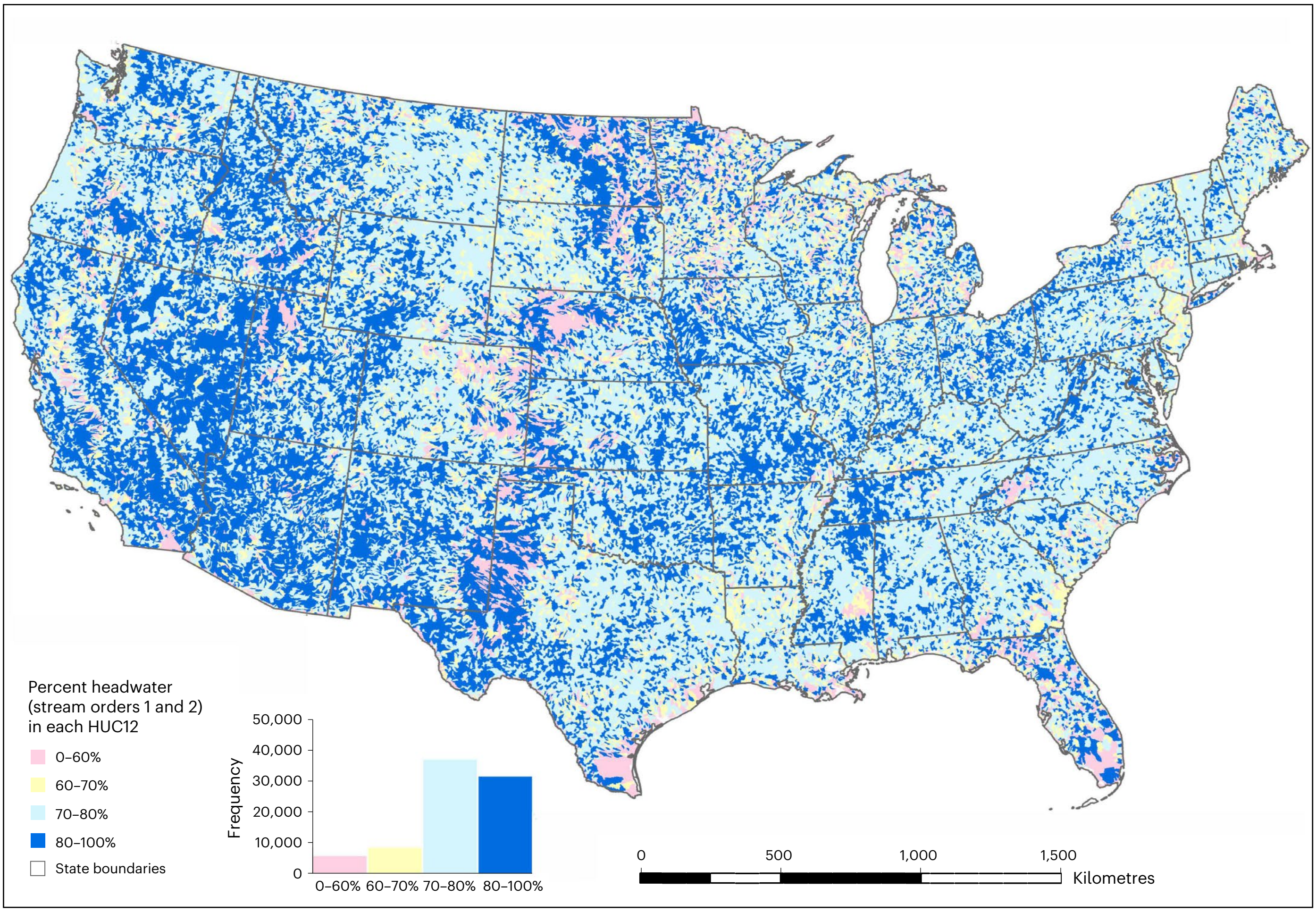

Fig. 3 | Percentage of headwater streams by length in US Geological Survey Hydrologic Unit Code (HUC)12 watersheds across the conterminous United States. Headwater streams are operationally defined and mapped here as Strahler stream orders 1 and 2, based on the NHDPlus High Resolution V2[33]. State boundaries were derived from the US Census Bureau[120]. Despite using different base layers, Figs. 1 and 3 similarly demonstrate that headwaters generally account for >70% of watershed stream networks. However, while similar in most regions, comparisons between Fig. 1 and Fig. 3 also illustrate physiographic differences in the landscape, information that may not be fully captured when using a flow accumulation threshold approach to the stream network as in Fig. 1.

streamflow data (Fig. 4; and even more so for developing countries, for example, ref. 70) and (2) the need for more comprehensive regional-, continental- and global-scale streamflow databases developed by the hydrological science community. However, emerging efforts are beginning to address these gaps. For example, across the conterminous United States, the US Geological Survey's National Water Information System houses streamflow data for select headwater streams, often with streamflow records spanning more than 20 years[71]. This dataset has been used in recent studies to quantify drying patterns in non-perennial streams, many of which occur in headwaters[18,72,73]. Similarly, large-scale international community science efforts are quantifying spatial and temporal patterns of drying in headwaters[74–76]. Combined, and as standalone efforts, observational data provide key insights into headwater flow regime variability and support the development and application of headwater flow models.

Modelling approaches

Modelling hydrological behaviours within and across headwater systems (for example, refs. 77–79) is essential for filling gaps where observed data are not available across space and time. Modelling approaches range from conceptual (for example, spatially lumped rainfall–runoff models) and empirical (for example, data driven at different spatial characterizations[77,80]) models to distributed modelling applications. Models also reside along a spectrum of reduced complexity approaches to fully distributed, physically based modelling frameworks[78,79,81,82].

Streamflow data at national and regional gauged sites, as well as data from highly instrumented headwater sites, represent hydrological observations both within the watershed and at the watershed outlet that have advanced how we predict the timing and magnitude of headwater hydrological fluxes and storages. These data support a growing literature addressing key modelling challenges, including parameter and model transferability across spatial scales and locations (for example, refs. 58,83,84), parameterization of physical processes (for example, ref. 85), coupling of processes at varying spatial and temporal scales[24,86] and assessment of model error[87,88]. However, headwater streamflow representations in empirical and physically based models at national scales are based only on streams that are mapped—not small, unmapped headwater streams, which are abundant across the globe[4].

Despite these advancements, unique challenges limit our ability to accurately simulate spatially continuous, diel (over 24 h) and subdiel headwater streamflow, necessary actions for advancing the state of headwater science and management. Furthermore, statistical extrapolations to estimate headwater streamflow typically perform poorly[89]. One of the biggest challenges is that headwaters are physically small, yet the drivers of hydrological models—precipitation and

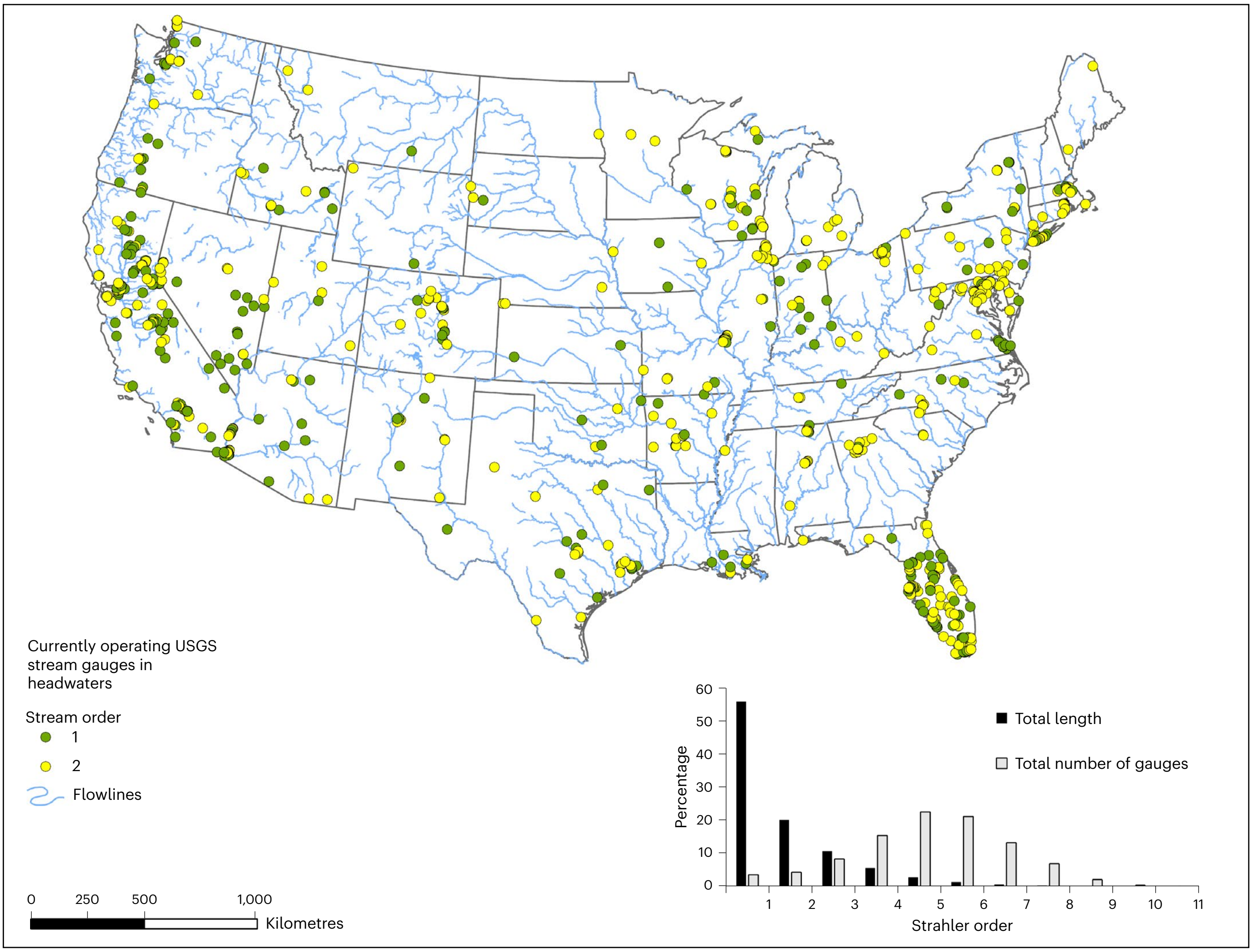

Fig. 4 | Percentage of US Geological Survey (USGS) stream gauges across the conterminous United States with at least 5 years of recent data (2018–2023) that are considered headwaters, as operationally defined by Strahler stream orders 1 and 2, based on the NHDPlus High Resolution (V2) dataset. The stream gauge locations were derived from the National Water Information System[121]. The flowlines in the figure are from NHDPlus High Resolution data and are from stream orders ≥7 for graphical purposes. The state boundaries were derived from the US Census Bureau[120]. The NHDPlus High Resolution (V2) dataset can be found at ref. 33. The currently operating USGS stream gauges in this figure all have an end date after 2019 with at least 5 years of data.

temperature—are typically measured, estimated or approximated at coarser spatial resolutions (for example, 4 km (Parameter-elevation Regressions on Independent Slopes Model (PRISM) data[90]) than advisable for the typical small headwater system. National-scale gridded input data, for example, are too coarse to represent convective rainfall in small headwater systems[91].

Models developed for large watersheds or regions more readily leverage coarse spatial data (for example, 90–250 m grids). These coarse-scale data (for example, topography, vegetation, geology and river network extent) are ill-suited for headwater models. As a result, (1) most headwater modelling efforts are concentrated in a small subset of watersheds where high-resolution information exists and (2) coarse-scale data and model discretization in large-scale models leads to simulated headwater flows that are not well matched to observed data. The latter is demonstrated using large national-scale United States-based models (for example, the National Water Model (NWM[92]) and the National Hydrologic Model (NHM[93])) where coarse-scale data and discretization result in poor model performance for headwater and small watersheds streamflow compared with larger watersheds (Fig. 2b).

Headwater systems have highly variable forms (for example, critical zone properties) and functions (for example, flow regimes), leading to divergence in which hydrological processes are represented in models at different sites. Misrepresentation or inability to resolve fine-scale runoff generation processes in national-scale models can lead to an overly smooth simulated flow time series in flashy headwater systems[94]. As a purely conceptual exercise based on our knowledge of studies in each system type, we theorize that headwater streamflow models have low data availability (Fig. 4) compared with those focused on other spatial scales (from plots to basins), particularly when balanced against the high level of process heterogeneity that needs to be considered to accurately model headwater flows (Fig. 5).

The variability in form and function of headwater systems has led to site uniqueness for many headwater flow models. This, in turn, has stymied the modelling community from discerning emergent headwater hydrological processes and expanding headwater system-specific models to other headwater sites. Numerous efforts have begun to address hydrological model transferability by classifying watersheds[95], developing simple 'bucket' hydrological models that conceptualize watersheds as bulk buckets that receive, store and move

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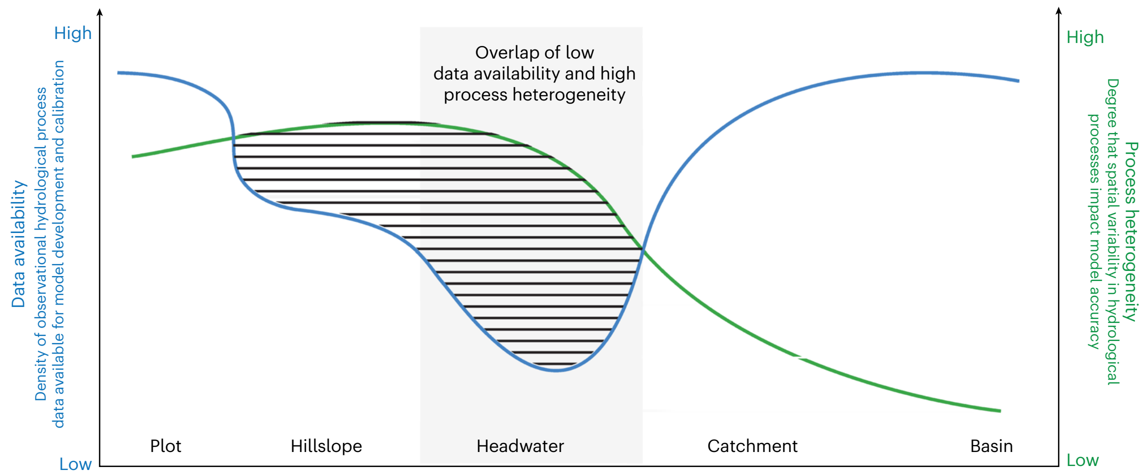

Fig. 5 | Simple conceptualization of data availability balanced against hydrological process heterogeneity at different scales of flow regime modelling. We are required to capture a relatively dense level of process heterogeneity (compared with catchment- and basin-scale models) to get an accurate headwater flow regime model, yet the spatial density of data required to do this is limited—except for a handful of highly instrumented headwaters, nationally and around the globe. For our purposes, plots are small, highly instrumented parts of the landscape unrelated to drainage areas; hillslopes are sloped areas of the land draining to streams; headwaters are defined herein; catchments are small-to-medium drainage areas or watersheds (~1–1,000 km^2); and basins are large drainage areas >1,000 km^2).

water that are transferable across sites (for example, the Hydrologiska Byråns Vattenbalansavdelning (HBV) model[96]) and applying ML[97]. Nonetheless, the hydrological community still lacks a cohesive way to address this model uniqueness issue in headwater systems. Thus, despite progress, the longstanding goal of classifying and conducting similarity analyses of experimental watershed hydrology[21] remains elusive.

Hydrological data available in the still relatively small number of experimental headwater systems across the globe are valuable for testing and improving runoff generation models, that is, the modelling–measuring cycle. Among many achievements, model experiments in headwater systems have identified the dominant controls on streamflow variability in conceptual models (for example, Mahurangi watershed, New Zealand[98]), have demonstrated how to combine measurements of multiple hydrological variables to build a process-based model structure (Maimai watershed, New Zealand[99]; Luxembourg watersheds[100]) and have tested new developments in established models such as TOPMODEL (for example, in Panola watershed, United States[101]). Providing easy access to quality-controlled data from experimental watersheds is critical in enabling headwater discovery science and model development.

Synthesizing data and advancing headwater flow science

Headwater systems and their associated hydrological regimes mediate multiple watershed-scale functions, ultimately imparting watershed resilience to flooding, drought, water quality degradation and biological impairment[7]. Advances in the science of headwater systems and their streamflow have rapidly evolved in the past decades, including data collection and modelling advancements. Important papers on unique challenges and advances needed in linking headwater hydrology to biogeochemistry (for example, ref. 8) and hydrologically mediated biological dynamics in these systems (for example, ref. 102) have also been recently published. Yet, to enable sustainable management and protection of these vulnerable systems[4], new approaches to understanding headwater hydrology into the next decades are required. Here, we frame key topics for improving the science of headwater hydrology via three integrated directions: measurements and mapping, modelling for process-based understanding, and synthesizing available data towards novel and insightful analyses.

Measurements and mapping

Characterizing the spatial and temporal extent of headwaters at regional and national levels is needed for advancing headwater hydrology[38]. To manage headwaters, we need to know where they are and how they vary in space and through time. We propose headwater definitions herein, but we also recognize that criteria defining a headwater may sometimes vary on the basis of the research or management question. Therefore, developing national and global headwater maps using these different definitions would benefit future headwaters research, identify which headwater streams change status (for example, from ephemeral to intermittent) on the basis of their definition and help guide the management of headwaters. A good start would be the recently developed Hydrography90m global streams and rivers dataset[103] from which headwaters could be derived and mapped. Expanding remote sensing methods to further capture headwater streamflow dynamics in areas without dense forest canopy is also essential, building on efforts in larger downstream systems[67].

Leveraging publicly available streamflow data from existing monitoring networks at regional or national scales will be necessary to further our understanding of hydrological connectivity between headwaters and downstream systems. Quantifying these connections is essential for (1) inferring headwater flow regimes from gauged downstream sites and (2) understanding what controls the propagation of headwater flows down the stream network. Furthermore, while leveraging existing data is key, limited streamflow measurements in headwaters demands a systematic expansion and organization of headwater streamflow monitoring across diverse physiographic regions, nationally and globally—using existing and developing frameworks, such as the National Ecological Observatory Network[104], as guides.

Modelling

When long-term data are absent, robust models are needed to simulate and classify the protected status of headwater flows. This need should translate to robust research advancements in representing and predicting headwater flows in models—a limiting factor in many modelling frameworks, particularly in those covering large spatial extents (for example, regions, nations and the globe). Analyses illuminating where and why headwater flow regimes are poorly predicted at national to global scales would additionally advance the science.

Models are essential to extrapolate process knowledge from well-studied sites across diverse physiographic and climatic conditions. Approaches may derive from models rooted in physical insights, from new and novel methods for classifying headwater flow regimes or from ML or deep learning (DL)—a subset of ML—techniques. ML and DL show promise for extracting new information from hydrological observations and transferring this information between sites[97]. In fact, ML[105] and DL[106] applications for accurately predicting streamflow regimes are on a rapid upswing, but their poorer performance in smaller watersheds (Fig. 2b) shows that these approaches may be limited by data availability in headwater systems. Such work may be augmented by other DL approaches such as process-guided DL[107], eXplainable DL[108] and differentiable modelling[109] to uncover patterns, drivers and explanations behind hydrological predictions.

To facilitate the next generation of modelling efforts within headwater systems, we recommend improving the linkages between our conceptual understanding of watershed processes and our approaches to simulating headwater system behaviour at ungauged sites, from regional to global scales. We also recommend linking traditionally separate headwater modelling approaches: those using hillslopes and watersheds as the modelled system boundaries and those focused solely on headwater stream networks and their associated riparian systems. To determine where and when these linkages are needed, model intercomparisons at different sites will help. They will also assist in resolving where greater model complexity is required versus locations where model parsimony is preferred. Such advancements are necessary to operationalize the simulation of headwater behaviour at broad spatial scales.

Organizing and synthesizing headwater streamflow data

Prioritizing which headwaters to manage and protect—and those in which more research is needed—will result from systematic syntheses of long-term streamflow records. Such syntheses will allow us to quantify how sensitive headwater systems are to key drivers, such as climate change, relative to larger systems. However, conducting such analyses across large sets of long-term streamflow data requires easily accessible information. We therefore need improved frameworks and central locations housing regional, national (and even global) streamflow data with the capacity, via an attribute system, to identify data located in headwater streams[110]. The United States-based Consortium of Universities for the Advancement of Hydrologic Science, Inc. (CUAHSI) HydroShare[111], an online platform for sharing and publishing hydrological data and models, provides one foundational example of how these frameworks may develop. Streamflow data organization and consolidation should also move beyond gauged data to include observational data (for example, sensors) and community science data for more comprehensive and system-representative models and syntheses[112].

To better understand the hydrological processes, complexities and patterns unique to headwaters, a headwater hydrology benchmark dataset is needed, nationally and globally. Datasets consolidating watershed data, such as Catchment Attributes and Meteorology for Large-sample Studies (CAMELS[113,114]) and the Comprehensive Hydrologic Observatory Sensor Network (CHOSEN[44]), are examples well formatted for rapid download and analyses. However, many of these datasets include few to no headwater systems (for example, the average CAMELS watershed is 477 ± 473 km^2; the median is 310 km^2). New headwater hydrology benchmark datasets could support advances in understanding how and why headwater flow regimes vary across space and time.

As we expand and organize headwater and associated streamflow data, we require a clear understanding of the extent and distribution of headwaters across different physiographic, climatic and hydrological regimes. Identifying the physical attributes, processes and hydrological signatures across those regimes will enable managers and policymakers to better assess the headwaters and the impacts of their policies[13,115]. Therefore, we echo earlier calls for headwater classification systems[21,95] so that headwater data can be more readily interrogated, analysed and synthesized on the basis of similar headwater system traits. We hope that these classification systems will lead us to unifying hydrological theories for headwater science.

Conclusion

Lack of protections across the globe, recent decision-making and developing climate change challenges render headwaters and their emergent streamflow regimes threatened, now more than at any other time in recent history. Given that the protection of headwaters is often based on their flow regimes, improved mapping, modelling and syntheses of current data and knowledge about headwater flow regimes (and charting a path forward for future research and mapping of headwaters) will help move the needle towards increased protection of these vulnerable systems.

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Competing interests
The authors declare no competing interests.

Additional information
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