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ORIGINAL ARTICLE

# Identifying Headwater Streams across the Conterminous United States

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## Abstract

Headwater streams play critical roles in hydrologic and biogeochemical processes and functions, yet their spatial distribution and land cover context remain poorly understood at continental scales, and no dedicated geospatial dataset exists. Building from a high-resolution conterminous United States (CONUS) hydrography network dataset, we quantified the spatial extent, density, and upstream catchment characteristics of headwater stream segments across the CONUS. We identified approximately 8.4 million kilometers of headwater streams, finding that 77% of the total stream network consists of headwaters, nearly double the total length represented in prior estimates. Stream density varied fivefold across regions, from $< 1$ km·km$^{-2}$ in arid basins to $> 5$ km·km$^{-2}$ in humid, forested areas. Over 73% of the CONUS landmass drains from headwater streams. The majority of

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headwater stream length occurred in forested and cultivated catchments across the CONUS, while substantial regional differences were evident for headwater stream distribution in other land cover classes (for example, wetlands, urban areas, shrublands, and herbaceous-dominated catchments). The dedicated and novel geospatial dataset, HELiOS (HEadwater streams and Low-Order Systems) is introduced for management and research use. The HELiOS dataset provides the first continental-scale, high-resolution characterization of headwater streams, offering new insights and opportunities for hydrologic modeling, ecological assessments, and environmental policy.

**Key words:** Headwater streams; Headwater catchments; HELiOS; Land cover; Land use.

## Highlights

- New headwater streams and systems dataset for the conterminous United States (CONUS)
- Headwater streams comprise ~ 77% of CONUS stream length and drain > 73% of the landmass
- Headwater systems have predominately forested, shrub, and cultivated land covers

## Introduction

Headwater streams are found in mountainous, piedmont, and low-lying areas worldwide (Allen and others 2018). They represent the most upstream loci of concentrated flow and sediment transport (Wang and others 2018), typically within well-defined banks, emerging from visible and defined channels as concentrated surface water flow from hillslope processes and groundwater contributing areas (Montgomery and Dietrich 1988, 1989). Though coarse in their mapped resolution, current global estimates of headwater stream extents suggest they comprise nearly 77–89% of river networks (Allen and others 2018; Messager and others 2021) and perform functions that substantially contribute to watershed scale processes and resilience (for example, hydrological flow maintenance, biogeochemical cycling, and nutrient processing; Alexander and others 2007; Hill and others 2014, Fritz and others 2018; Gómez-Gener and others 2021; Lane and others 2023; Price and others 2024). For instance, recent modeling analyses suggest that ephemeral headwater streams that flow only in direct response to precipitation contribute approximately 55% of the streamflow to large downstream rivers across the conterminous United States (CONUS; Brinkerhoff and others 2024). However, headwater streams are regionally and globally imperiled due to the lack of specific protections as well as the paucity of mapped extent (Wohl 2017; Sullivan and others 2020); as such, they have been termed ''vulnerable waters'' (Creed and others 2017).

Despite the growing attention on these streams, analyses and syntheses remain stymied by the lack of readily available spatial data delineating headwater streams and headwater systems with known accuracy and provenance. Headwater systems, following Golden and others (2025), are discrete and spatially bounded drainage areas contributing surface and groundwater, material, and energy to a headwater stream. Headwater streams are thus contained within these headwater systems.

To overcome existing limitations of geospatially explicit mapped headwater stream extent (Fritz and others 2013), researchers are incorporating novel approaches toward more finely identifying headwater reaches and their concomitant ephemeral, intermittent (that is, seasonally connected to groundwater systems yet with annual drying cycles), or perennial stream flows (Messager and others 2021). These include the use of satellite constellations (Wang and Vivoni 2022), machine-learning approaches (Villines and others 2015; Greenhill and others 2024), fractal and power-law analyses (Allen and others 2018; Barefoot and others 2019), and contributing area estimations (Fesenmyer and others 2021; Amatulli and others 2022), as well as intensive field expeditions (refer to an in-depth review by Christensen and others 2022). Yet headwater streams are typically small. For example, an analysis of over 4000 headwater stream width measurements across seven intensely analyzed catchments in North America and New Zealand determined that headwater stream width was typically 32 ± 7 cm (Allen and others 2018). Their size, therefore, makes them challenging to consistently identify across broad spatial extents (for example, large watersheds, regions, and continents). Further work is needed in the United States and on the global stage to uniformly and consistently map headwater stream longitudinal extent and headwater system contributing areas. Such maps provide the opportunity to quantify headwater stream functional contributions to downstream waters in a repeatable and transparent manner (for example, through modeling approaches, Golden and others 2025).

Conventional headwater stream definitions are based on a geomorphological perspective. That is, they are defined as concentrated flow within visible and defined channels originating at a channel head. A channel head is defined as ''the upslope limit of erosion and concentration of flow within steepened banks'' (Montgomery and Dietrich 1989, p. 1909), where a definable bank ''must be recognizable as a morphological feature independent of the flow'' (Dietrich and Dunne 1993, p. 178). Such a definition allows us to describe how these streams appear in the field.

However, there is a lack of consistent and readily available headwater stream and catchment geospatial data that uniformly identifies headwater streams and systems for mapping, modeling, and management across broad spatial extents. The solution for this requires application of an ''operational definition'' of headwater streams, defined by Golden and others (2025, p. 18), as Strahler (Strahler 1957) stream orders 1 and 2 in a ''1:24,000 or similar scale stream network map.'' This operational approach enables headwater stream identification across readily available global datasets through analysis of a typical stream network component attribution (that is, stream order). Recently, Golden and others (2025, their supplemental Table S1) provided additional context for identifying headwater streams as Strahler stream orders 1 and 2, including an annotated bibliography wherein headwater stream definitions across the literature are introduced. We ultimately agree with their conclusions: invoking the operational definition of Strahler stream orders 1 and 2 on 1:24,000 maps establishes a benchmark with mapped headwater streams in this rubric discharging into the larger-order stream network. This operational approach provides a clear spatial limit to the headwater stream extent—though not a limit to the downstream functional contributions of headwater streams (for example, Alexander and others 2007; Hill and others 2014; Fritz and others 2018; Ali and English 2019; Brinkerhoff and others 2024).

The need for an authoritative dataset that identifies headwater streams and their drainage areas (that is, headwater systems) across broad spatial extents is paramount. Recent events in the United States regarding the local, state, and federal management of surface waters, including headwater streams, have underscored the importance of available, approachable, and uniform headwater stream extent data for analyses (Greenhill and others 2024). Stream protections and/or management options at the local, state, tribal, or federal levels may well hinge on the prevalence of perennial versus non-perennial flows within headwater streams and on down gradient network connections (Brinkerhoff 2024). As a result, substantial advances in modeling and analyzing stream network locations and characteristics to estimate flow prevalence and material contributions are necessary (Jaeger and others 2019; Mahoney and others 2023; Lane and others 2025). Failing to provide these data for resource managers limits options for managing headwater streams and their functions (Creed and others 2017). In short, the current lack of an existing and readily accessible CONUS-wide operationally defined headwater stream geospatial dataset is affecting local, regional, and national-level analyses, syntheses, and management of headwater streams and our understanding of their contributions to downstream flows, water quality, and ecological processes (Fritz and others 2013; Hill and others 2014; Creed and others 2017; Fesenmyer and others 2021; Erickson and others 2023; Lane and others 2023; Du and others 2024; Golden and others 2025).

Here, we identify the headwater streams and headwater system extents across the CONUS with the goal of providing a novel CONUS-based headwater stream and headwater system geospatial dataset of known provenance, which we term HELiOS (HEadwater streams and Low-Order Systems). We use the best publicly available and downloadable data for research and management questions (that is, NHDPlus-HR; Moore and others 2019), modified to create CONUS-wide headwater stream topology and appropriate density distributions across the CONUS, and apply a uniform operational headwater stream definition recently promulgated by Golden and others (2025). We demonstrate an application of these data to provide insights on current land cover distributions in headwater systems across the CONUS (Homer and others 2020). The availability of the HELiOS geospatial data will facilitate emerging headwater stream and system research in the CONUS and beyond, research which will improve headwater management options and the timely and important need for estimating in-stream and drainage-based headwater contributions to downstream aquatic systems and communities (Hughes and others 2023).

## Materials and Methods

In our analyses, we used the foundational National Hydrography Dataset (NHD; USGS Geological Survey 2022), which was developed by the United

States Geological Survey (USGS) and is ''…considered to have the best available stream/river data for the CONUS…'' (Christensen and others 2022, p.3). An NHD coproduct, the NHDPlus-HR (for ''High Resolution'', Moore and others 2019) was built by the US Environmental Protection Agency (US EPA) and the USGS on the 1:24,000 (or more detailed) NHD and contains ''value-added attributes'' with substantive hydrography data—including identification of initiating stream nodes, attribution of contributing areas to stream nodes, and a modified Strahler (1957) stream order (SO) calculation for networks throughout the CONUS (Johnston and others 2009). This Strahler stream order determination can be used by definition and convention as a proxy to identify headwater streams within the dataset, as we further describe below. Note that the term ''modified Strahler'' SO calculation relates to the approach used in the derivation of the base data used herein (NHDPlus-HR, described further below). As described by Moore and others (2019), the NHDPlus-HR stream order algorithm incorporates flow splits, whereas the original Strahler stream order (1957) does not.

## Derivation of Stream Orders and Headwater Networks

### *CONUS Stream Orders*

To delineate the lotic network components required for our analyses and the derivation of the HELiOS geospatial dataset, we acquired the full, CONUS-wide NHDPlus-HR from USGS data repositories (https://www.usgs.gov/national-hydrography/nhdplus-high-resolution, accessed August 2023). USGS provides attributes within the NHDPlus-HR useful for geospatial analyses, including characterizing the first segment of a flowing water network (Moore and others 2019). However, we were interested in both the lotic network (rather than only the first headwater segment) and in applying the conventional and operational headwater definitions (that is, SO1 and SO2 network components on mapped stream networks with 1:24,000 mapped resolution or better (Golden and others 2025)). We therefore focused on the ''StreamOrder'' attribute within NHDPlus-HR, modified as noted below and applied CONUS-wide to attribute the spatial data with updated Strahler stream order values (Figure 1). We thereby used these stream order values to define headwater streams and contributing headwater systems. The geospatial processing to create the stand-alone HELiOS geospatial data can be conceptualized as follows: within the NHDPlus-HR, segments with Strahler stream order 1 values are the mapped origins of streams (Meyer and others 2003; Wohl 2018; Wohl and others 2019). When two SO1 network components are connected at a node (that is, a stream convergence), the node initiates a stream order 2 network (refer to, for example, Figure 1). The areas cumulatively draining the SO1 and SO2 network components are the headwater systems.

However, as others have noted (Christensen and others 2022; Brinkerhoff and others 2024), a preliminary analysis of the NHDPlus-HR CONUS-scale data indicated stream density variability due to inconsistent mapping decisions by cartographers creating the network lines (Christensen and others 2022). That is, certain CONUS areas have stream networks appearing ''over-densified'', meaning they have unusually high stream density when contrasted with other similarly situated watersheds within ecoregions or across state boundaries (Figure 2). While we do not assess the accuracy nor granularity of NHD updates entered over time by state and local data stewards (Arnold 2014), as stream orders are derived as an additive metric and are dependent on the granularity of the mapped system (that is, the mapped resolution; Baker and others 2007), consistency is important to characterize the CONUS-scale headwaters. Thus, regional inconsistencies due to cartographic decisions by data stewards (Moore and others 2019) create differences affecting network analyses; and hence, NHDPlus-HR stream order calculations include over-densified areas relative to surrounding watersheds (for example, Lane and others 2017, Christensen and others 2022, Brinkerhoff and others 2024). This necessitated a revision of the data in certain regions for consistency in stream density within ecoregions and across the CONUS.

We identified over-densified watersheds through assessment of USGS Hydrologic Unit Code (HUC) – twelve-digit basin-identifier stream network densities. Following Lane and others (2017) and Brinkerhoff and others (2024), we visually identified marked and abrupt differences in mapped drainage densities that do not correspond to physiographic boundaries (for example, Figure 2). We noted over-densified areas throughout the state of Indiana, including the following Level III ecoregions (Omernik 1987): Interior Plateau, Interior River Valley, Central Corn Belt, Eastern Corn Belt, Drift Plains, and Huron–Erie Lake Plains. Though not as starkly evident as Indiana, an area located in western North Carolina and South Carolina, including the Blue Ridge and Piedmont ecoregions (refer to Figure 2), was also visually identified as

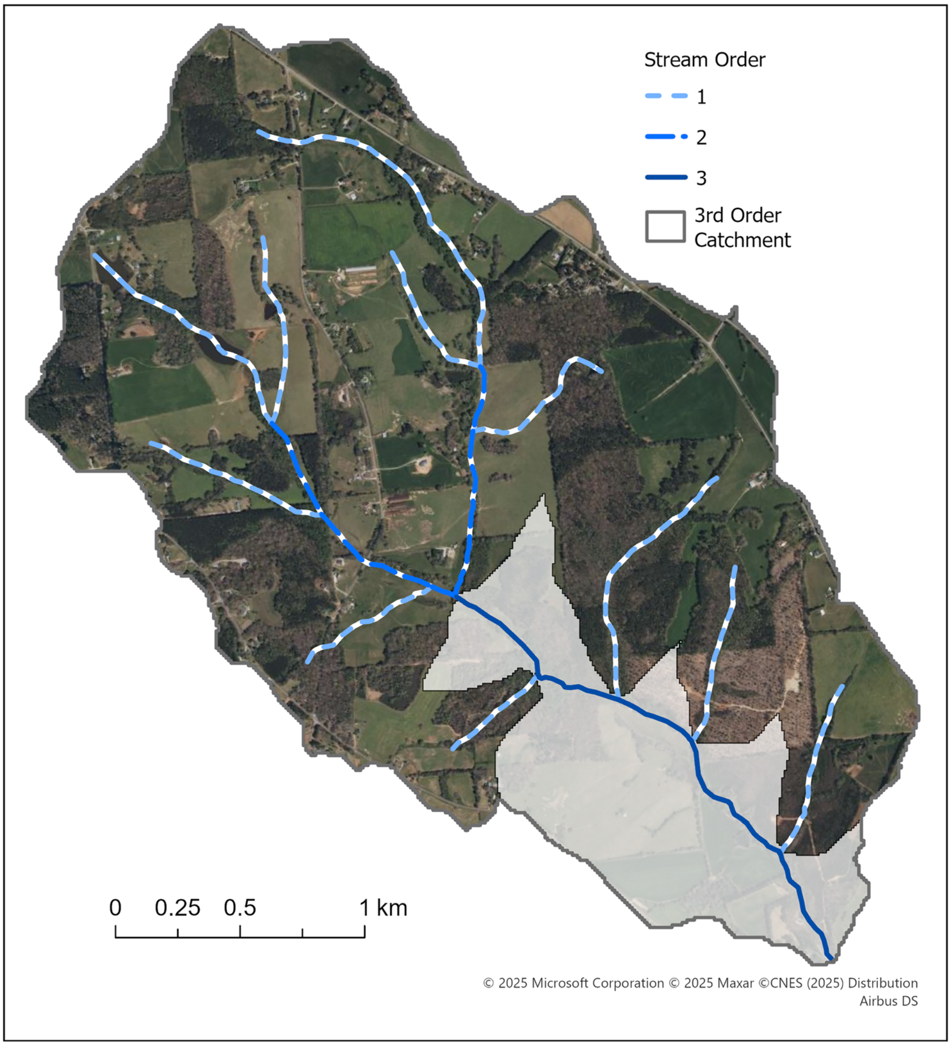


**Figure 1.** Headwater stream networks are operationally defined as Strahler (Strahler 1957) first and second stream order (SO) streams, here identifying SO1 and SO2 streams flowing into Yellowdirt Creek (SO3), Georgia (12-digit HUC 031300020405). Note that SO1 streams converge to form SO2 streams in the Strahler convention; however, lower-order streams can also flow directly to larger-ordered systems, as demonstrated with the four SO1 streams mapped as tributaries to the SO3 (with its contributing systems grayed out) in the bottom portion of the panel

over-densified and required modification of stream order attribution. As detailed in the Supplemental Material (Table S1), we corrected for over-densified areas by examining mapped stream densities and calculating the mean contributing area for each stream order by ecoregion. We contrasted the mean density values within and across state boundaries (for example, contrasting Interior Plateau watersheds entirely in Indiana to Interior Plateau watersheds entirely in Illinois) and adjusted the stream network origins via stream order to be consistent throughout the ecoregions. This inevitably resulted in a decrease in the mapped network density and extent in certain putatively over-densified areas, yet was deemed necessary for the creation of a consistent geospatial data set for mapping headwater streams across CONUS (that is, the HELiOS).

Following the network adjustments in over-densified areas, (refer to, for example, Brinkerhoff and others 2024), we derived revised Strahler stream orders using the Assign River Order (ARO; available in ArcHydro) tool within ArcGIS Pro 3.3 (ESRI, Redlands, CA). Input data for the ARO tool are vector lines, from-to nodes, and a table derived from the NHDPlus-HR data maintaining the typological relationships between upstream–downstream segments. By removing the over-densified areas and using a systematic approach based on median drainage densities for SO1 and SO2 within

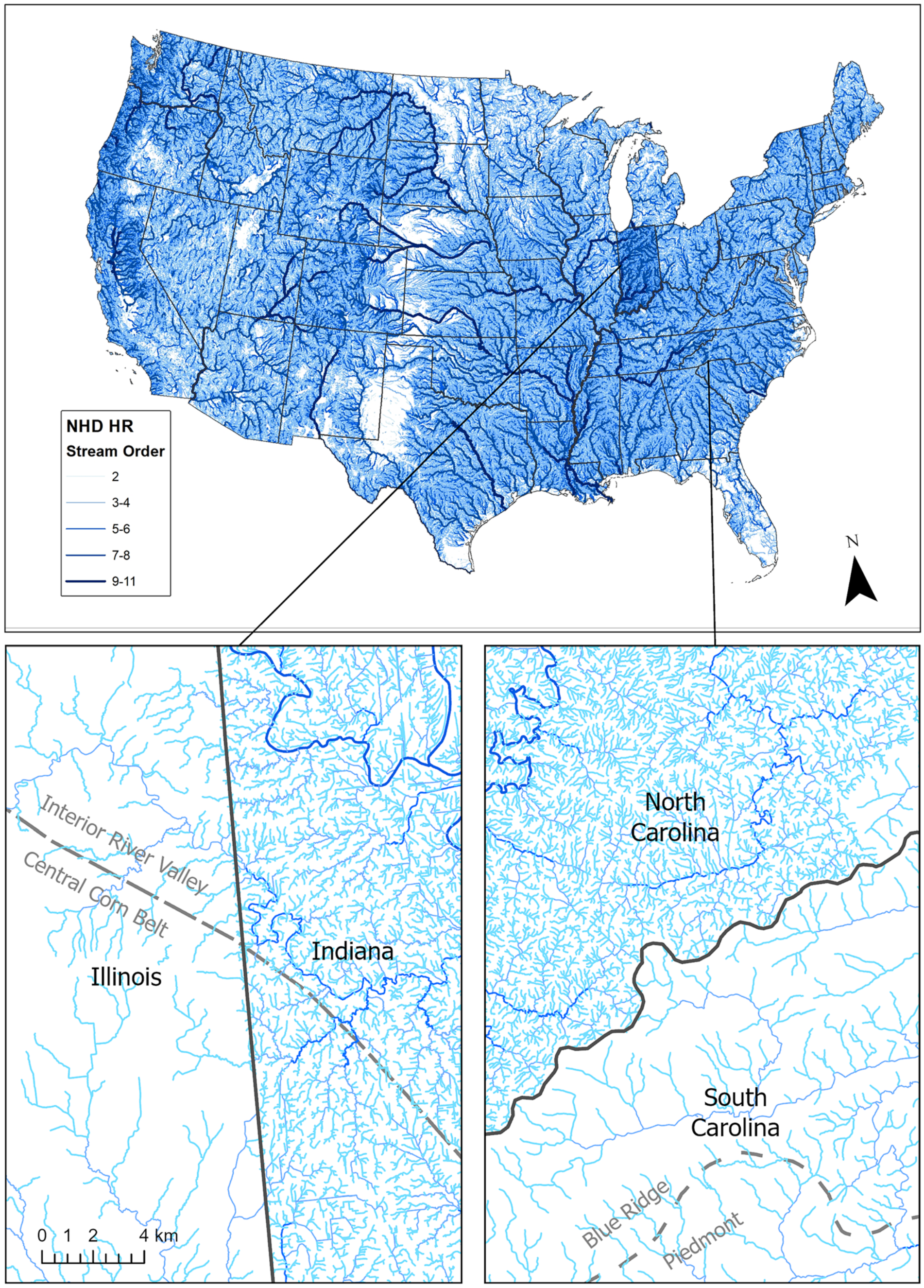


**Figure 2.** Cartographic decisions resulted in portions western North Carolina and South Carolina, as well as all of Indiana, being potentially over-densified (evident in top panel), or having a greater abundance of identified streamlines when contrasted with other watersheds in the same ecoregions (Omernik 1987; refer to also, for example, the stark differentiation between streams mapped on either side of the state lines, bottom panels). In the top panel, from Christensen and others (2022, used by permission), first-order streamlines identified from the NHDPlus-HR ''stream order'' attributions are removed to facilitate visualizing the over-densification issue across the CONUS; the first-order streams are shown in the bottom panels

the over-densified ecoregions, we were able to generate a new CONUS network typology that updated stream orders to ensure consistency across the CONUS.

Strahler stream order 1 (SO1) components typically represent the uppermost portions of the flowing water network (refer to Figure 1). These areas include headwater stream networks that drain the landscapes and merge with other SO1 networks to become components of SO2 headwater streams. However, some SO1 network components do not merge with other SO1 systems and instead drain directly to high-order reaches (for example, such as a third or fourth-order river system) or contribute directly to other waters. These SO1 headwater network components that drain to higher-order systems or other waters are maintained in the geodatabase and are also defined as headwater streams. SO2 networks include SO1 networks that drain and merge with another SO1 network to become an SO2 network.

*Transboundary and Coastal Watersheds*

We analyzed headwater stream distribution through the CONUS using twelve-digit HUC watersheds (n = 83,539, covering 8,253,834 km$^2$) to spatially bound the network, noting that twelve-digit HUCs are the smallest watershed boundaries (that is, the most granular) applicable across the CONUS. However, the NHDPlus-HR may not have complete coverage in transboundary areas—watersheds extending into either Canada or Mexico typically lack complete stream characterization of the watershed (Figure S1). Further, watershed delineation into coastal areas similarly creates situations where watershed areas extend into estuarine and marine systems, potentially underestimating the portion of the HUC basin included in headwaters or adding additional artificial lines through the marine systems to maintain network connectivity (for example, Figure S1). For the purposes of reporting these data herein we exclude transboundary and coastal watersheds from our analyses and report hereafter on interior watersheds that do not cross boundaries with Canada or Mexico and exclude watersheds in the coastal zone. We identified the international boundaries, coastlines, and waterbodies associated with the coastline (for example, bays and inlets) using TIGER/Line files (US Census Bureau 2010); these data are included in the publicly available dataset. To avoid erroneously including potentially problematic transboundary or coastal headwater watersheds, we buffered the international (transboundary) border with a 1.0-km buffer and the coastline with a 0.1-km buffer, identifying and flagging twelve-digit HUC watersheds intersecting those buffers as border or coastal watersheds, respectively. These border-flagged (n = 1123, 1.8% of the CONUS area) and coastal-flagged twelve-digit HUCs (n = 2148, 6.7% of the CONUS area) were not included in these analyses. However, noting that others may wish to include transboundary and coastal twelve-digit HUC watersheds in their analyses, we provide this dataset for completeness, including the flagged NHDPlus-HR watersheds extending into Canada and Mexico and coastal watersheds, for end users to acquire (refer to the Data Availability statement).

*Final CONUS Headwater Stream Network Product*

Our final geospatial end-product of these analyses, the mapped stream network comprising the CONUS-wide extent of headwater streams (that is, SO1 and SO2 on a 1:24,000 or finer map), incorporated the data described above into a novel CONUS headwater stream geodatabase, the HELiOS. These geospatial data are available at the twelve-digit HUC watershed scale (refer to Data Availability statement). We further report headwater stream density stream density (streamlength (km) / watershed area(km$^2$)) per two-digit HUC as a potential measure of headwater stream contributions to surface runoff processes affecting biogeochemical functions, precipitation-based flood-response in stream networks, and sediment load dynamics in headwater stream systems (Godsey and Kirchner 2014). We chose two-digit HUCs as an application of the data at the CONUS scale that could be reasonably described and discussed herein.

## Headwater Systems

As noted, headwater systems are discrete, spatially bounded drainage areas contributing surface and groundwater, material, and energy to a headwater stream (Golden and others 2025). Headwater streams are contained within these headwater systems. Following the derivation of the CONUS-wide headwater stream network, we analyzed the NHDPlus-HR to identify the watersheds (that is, the land areas) associated with, and draining to and through, our derived headwater stream network. We developed novel Python code and R scripts to delineate upstream, contributing watersheds across the CONUS for the headwater stream network (that is, the headwater networks defined above). Utilizing the NHDPlus-HR watershed boundary polygons, an upstream drainage area was created for each of the headwater network components across the CONUS. Headwater watershed polygons were converted to 10-m raster data using ArcGIS Pro (version 3.3) to remove any potential area overlap of watershed topology and to aid in the land cover analyses. The novel headwater watersheds are included as part of the CONUS headwater stream geodatabase (that is, the HELiOS) and, similar to the headwater streams described above, are available by twelve-digit HUC (refer to the Data Availability statement).

## HELiOS Dataset Application

Once we identified the linear headwater stream extent and the corresponding headwater system areal extent, we analyzed land cover within these systems (Odum 2002) to demonstrate an application of the HELiOS geospatial data. We assessed the extent and composition of land cover data within the HELiOS using the 2021 National Land Cover Database with 30-m spatial resolution (Dewitz 2023). The total area of each of the NLCD categories (explicit definitions given in Table S2) within twelve-digit HUC watersheds were calculated using Tabulate Area Analysis for the CONUS in ArcGIS Pro (version 3.3). These data are available by twelve-digit HUC (refer to the Data Availability statement).

**Table 1.** Headwater Stream Data across the CONUS, Reported Here at the Two-digit HUC Level (n = 18)

| Two-digit hydrologic unit code Basin | Total number of HUC12s analyzed | Summed HUC12 basin area ($km^2$) | Total flowline length (km) | Headwater stream length (km) summed | Headwater stream length as a percent of total flowline length (%) | Headwater stream density (within HUC12, $km \cdot km^{-2}$) |
|---|---|---|---|---|---|---|
| 01—New England | 1562 | 137,001 | 161,181 | 120,406 | 75 | 0.9 |
| 02—Mid-Atlantic | 2756 | 233,937 | 311,512 | 233,204 | 75 | 1.0 |
| 03—South Atlantic-Gulf | 7207 | 664,886 | 883,691 | 656,262 | 74 | 1.0 |
| 04—Great Lakes | 3378 | 276,402 | 282,474 | 208,748 | 74 | 0.8 |
| 05—Ohio | 5278 | 421,966 | 591,373 | 451,882 | 76 | 1.1 |
| 06—Tennessee | 1075 | 105,949 | 187,971 | 145,869 | 78 | 1.4 |
| 07—Upper Mississippi | 5727 | 491,440 | 542,364 | 409,336 | 76 | 0.8 |
| 08—Lower Mississippi | 2538 | 252,522 | 447,768 | 337,653 | 75 | 1.4 |
| 09—Souris-Red-Rainy | 1425 | 144,114 | 85,977 | 61,859 | 72 | 0.5 |
| 10—Missouri | 13,386 | 1,314,966 | 1,928,771 | 1,459,785 | 76 | 1.1 |
| 11—Arkansas-White-Red | 6493 | 642,213 | 897,156 | 688,515 | 77 | 1.1 |
| 12—Texas-Gulf | 4104 | 440,950 | 538,829 | 408,151 | 76 | 1.0 |
| 13—Rio Grande | 3044 | 324,454 | 395,265 | 314,237 | 80 | 1.0 |
| 14—Upper Colorado | 3179 | 293,569 | 500,429 | 390,554 | 78 | 1.4 |
| 15—Lower Colorado | 3746 | 356,093 | 592,532 | 478,619 | 81 | 1.4 |
| 16—Great Basin | 3200 | 367,049 | 578,260 | 462,667 | 80 | 1.3 |
| 17—Pacific Northwest | 7978 | 692,312 | 1,225,519 | 949,016 | 77 | 1.4 |
| 18—California | 4192 | 396,789 | 741,947 | 584,587 | 79 | 1.6 |

*Flowlines as given in the table include the summed length of connectors (NHDPlus-HR attributed as feature code [FCODE] 334), canals/ditches (FCODE 336), underground conduits (FCODE 420), pipelines (FCODE 428), streams and rivers (FCODE 460), artificial paths (FCODE 558), and coastlines (FCODE 566)*

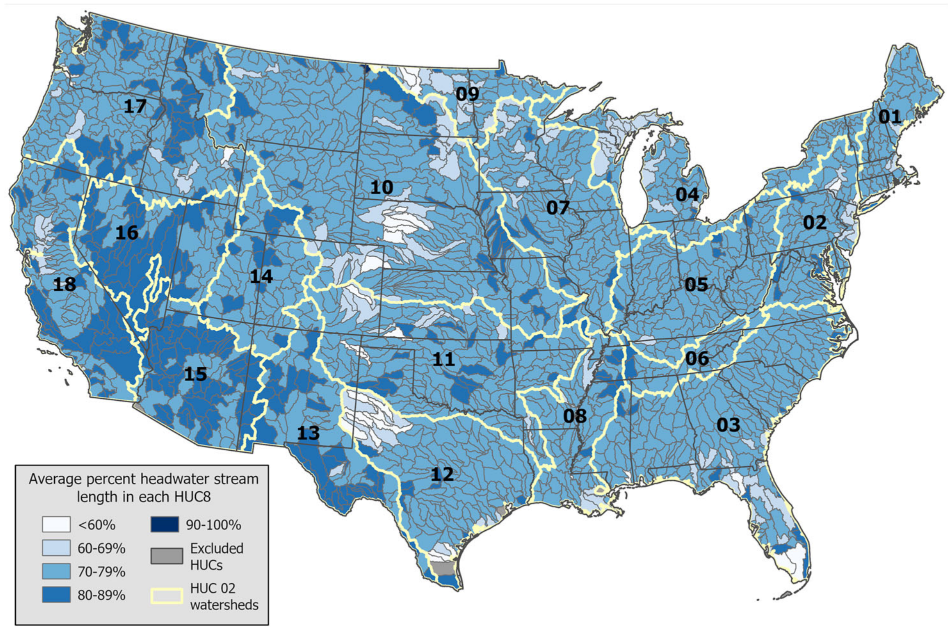


**Figure 3.** Proportional extent of headwater stream length as compared to total stream length across CONUS at 8-digit HUC scale (n = 2086). The CONUS-wide average within the interior 8-digit HUCs is 77%. The names of the 2-digit HUCs are provided in Table 1. (Modified from Lane and others 2023)

**Table 2.** Headwater Stream Systems Drained Over 5.5 Million km$^2$, or > 73% of the Landmass, across the CONUS

| Two-digit hydrologic unit code Basin | Headwater stream system area (km$^2$) | Headwater stream systems (% of HUC12s) |
|---|---|---|
| 01—New England | 99,674 | 73 |
| 02—Mid-Atlantic | 168,950 | 72 |
| 03—South Atlantic-Gulf | 489,740 | 74 |
| 04—Great Lakes | 208,420 | 75 |
| 05—Ohio | 325,456 | 77 |
| 06—Tennessee | 81,281 | 77 |
| 07—Upper Mississippi | 353,010 | 72 |
| 08—Lower Mississippi | 192,842 | 76 |
| 09—Souris-Red-Rainy | 104,654 | 73 |
| 10—Missouri | 899,517 | 68 |
| 11—Arkansas-White-Red | 488,116 | 76 |
| 12—Texas-Gulf | 327,265 | 74 |
| 13—Rio Grande | 240,719 | 74 |
| 14—Upper Colorado | 219,452 | 75 |
| 15—Lower Colorado | 276,789 | 78 |
| 16—Great Basin | 264,387 | 72 |
| 17—Pacific Northwest | 508,871 | 74 |
| 18—California | 290,874 | 73 |
| Total | 5,540,016 | 73 |

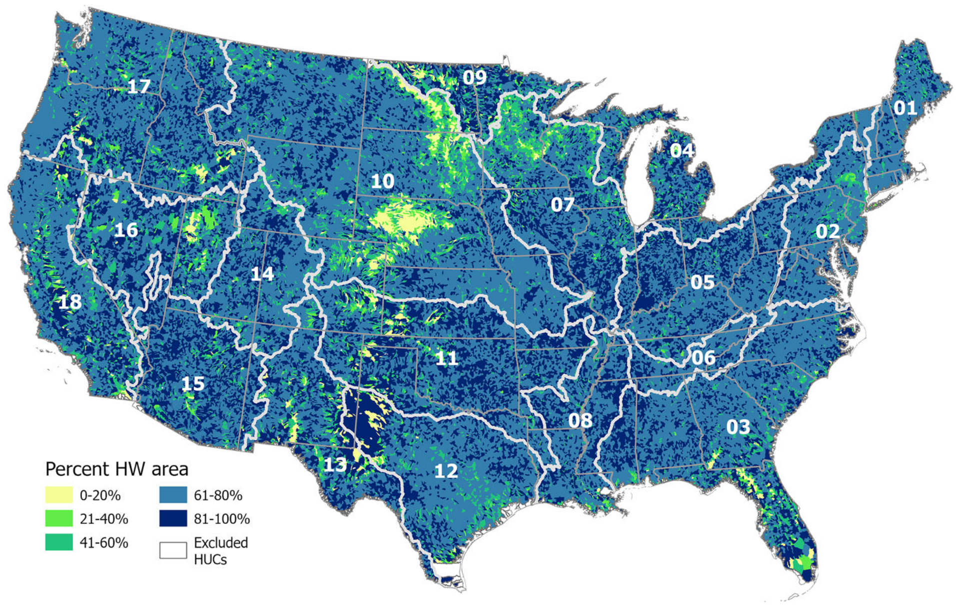


**Figure 4.** Proportion of each12-digit HUC draining from headwater (HW) systems varied across the CONUS and averaged approximately 73%. The 2-digit HUCs are given as numbered basins (refer to Table 1)

# Results

## Headwater Stream Network

Our analysis and the creation of the HELiOS, derived through value-added analyses of the NHDPlus-HR, identified 8,361,345 km of headwater streams across the CONUS (Table 1). Analyzing results within the 18 two-digit HUCs spanning the CONUS, the total headwater stream length ranged from 61,859 km (09—Souris-Red-Rainy) to 1,459,785 km (10—Missouri). Headwater streams comprised a substantial proportion of all stream extents across the CONUS, averaging 77% of the total stream length across the two-digit HUCs and ranging from 72 to 81% (refer to Table 1). The CONUS distribution at the eight-digit HUC scale is presented in Figure 3. Headwater stream density varied from 0.5–1.6 km·km$^{-2}$; the average twelve-digit HUC headwater stream density across CONUS was 1.1 headwater stream km per km$^2$ (refer to Table 1, Figure S2).

## Headwater Stream System

Headwater systems within the HELiOS encompassed 5,540,016 km$^2$ across CONUS (Table 2), meaning that 73% of the non-transboundary and non-coastal CONUS landmass drains from headwaters. The actual area of the two-digit HUCs covered by headwater systems ranged from 81,281 km$^2$ (06 – Tennessee) to 899,517 km$^2$ (10 – Missouri). Despite differences in total area within individual two-digit HUCs, the range in percentage of area that drains headwaters was relatively narrow (refer to Table 2), from a low of 68% (10 – Missouri) to a high of 78% (15 – Lower Colorado). The proportional area of each twelve-digit HUC draining the headwater systems of the CONUS is given in Figure 4.

## Headwater Stream System Land Cover Analysis

The proportional distribution of land cover across CONUS headwater systems indicates that forested, shrubland, and planted/cultivated classes dominate (Figure 5; Table 3). Across the 18 two-digit HUCs comprising the CONUS, the presence of water, barren, and wetland classes was low (typically $< 5\%$ of the headwater stream land cover and defined in Table S2), though certain two-digit HUCs had greater amounts of those land cover classes in their headwater systems (Table 4). For instance, the South Atlantic-Gulf (03), Great Lakes (04), Lower Mississippi (08) and Souris-Red-Rainy (09) two-digit HUCs all had $> 17\%$ of their headwater systems classified as wetlands whereas two-digit HUCs spanning most of the western CONUS were all $\leq 1\%$ wetland land cover (refer to, for example, Table 4). The proportional area of each eight-digit HUC (n = 2085) draining from headwater systems of the CONUS (excluding border and coastal twelve-digit HUCs removed as noted Materials and Methods, above) is given in Figure 5.

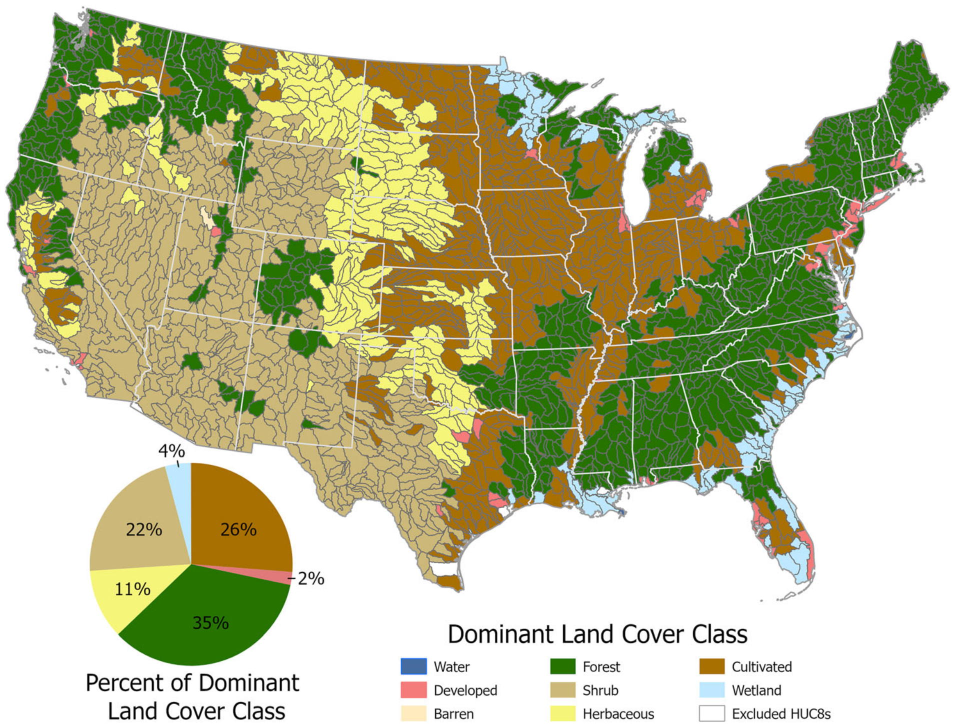


**Figure 5.** Forested and cultivated lands dominated the land cover within headwater systems (NLCD Level 1, refer to Table 4) within each 8-digit HUC (n=2,085, excluding border and coastal HUC12s) across the CONUS. The 8-digit HUC distribution is given in the pie chart to the bottom left, with the same classes as the CONUS legend

**Table 3.** Analyses of Land Cover Within Headwater Systems across the CONUS Indicates that Forested, Shrubland, and Planted/Cultivated Classes Dominate. Note that due to rounding the values add to > 100%

| Class | NLCD code | Classification description | CONUS-wide headwater Average |
|---|---|---|---|
| Water | 11 | Open Water | 1% |
| | 12 | Perennial Ice/Snow | 0% |
| Developed | 21 | Developed, Open Space | 3% |
| | 22 | Developed, Low Intensity | 2% |
| | 23 | Developed, Medium Intensity | 1% |
| | 24 | Developed High Intensity | 0% |
| Barren | 31 | Barren Land (Rock/Sand/Clay) | 1% |
| Forest | 41 | Deciduous Forest | 10% |
| | 42 | Evergreen Forest | 13% |
| | 43 | Mixed Forest | 3% |
| Shrubland | 52 | Shrub/Scrub | 25% |
| Herbaceous | 71 | Grassland/Herbaceous | 13% |
| Planted/Cultivated | 81 | Pasture/Hay | 7% |
| | 82 | Cultivated Crops | 17% |
| Wetlands | 90 | Woody Wetlands | 4% |
| | 95 | Emergent Herbaceous Wetlands | 1% |

## Discussion

We derived a novel high-resolution headwater stream and headwater system spatial database for the CONUS, coined herein as the HELiOS (HEadwater streams and Low-Order Systems), based on value-added analyses of NHDPlus-HR. The derivation of these freely available data provides opportunities for end users conducting hydrological, biogeochemical, ecohydrological, and other re-

**Table 4.** Land Cover Within Headwater Systems Presented at the Two-digit HUC Level and Analyzed by NLCD Level 1 Classification system (that is, a Coarser Classification System Combining Similar Land Covers, such as Deciduous [NLCD Code 41 in Table 3], Evergreen [Code 42], and Mixed [Code 43] Forests Summed Here as Forest)

| Two-digit HUC watershed | Headwater Systems by Level 1 NLCD Land Cover Classes (%) | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Water (11,12) | Developed (21–24) | Barren (31) | Forest (41–43) | Shrubland (52) | Herbaceous (71) | Planted/ Cultivated (81,82) | Wetlands (90,95) |
| 01—New England | 3 | 9 | 0 | 69 | 2 | 2 | 4 | 11 |
| 02—Mid-Atlantic | 1 | 15 | 0 | 56 | 1 | 1 | 21 | 5 |
| 03—South Atlantic-Gulf | 1 | 13 | 0 | 38 | 4 | 4 | 21 | 17 |
| 04—Great Lakes | 2 | 10 | 0 | 35 | 1 | 2 | 32 | 19 |
| 05—Ohio | 0 | 11 | 1 | 48 | 0 | 1 | 39 | 1 |
| 06—Tennessee | 1 | 11 | 0 | 60 | 1 | 1 | 24 | 1 |
| 07—Upper Mississippi | 2 | 9 | 0 | 17 | 0 | 0 | 64 | 7 |
| 08—Lower Mississippi | 2 | 8 | 0 | 28 | 3 | 2 | 40 | 18 |
| 09—Souris-Red-Rainy | 3 | 4 | 0 | 9 | 1 | 3 | 60 | 20 |
| 10—Missouri | 1 | 4 | 1 | 9 | 16 | 35 | 34 | 1 |
| 11—Arkansas-White-Red | 1 | 6 | 0 | 21 | 12 | 30 | 30 | 1 |
| 12—Texas-Gulf | 1 | 9 | 0 | 13 | 39 | 9 | 27 | 3 |
| 13—Rio Grande | 0 | 2 | 0 | 13 | 80 | 3 | 1 | 1 |
| 14—Upper Colorado | 0 | 1 | 2 | 26 | 67 | 2 | 2 | 1 |
| 15—Lower Colorado | 0 | 2 | 1 | 16 | 76 | 3 | 1 | 0 |
| 16—Great Basin | 1 | 1 | 5 | 16 | 67 | 8 | 2 | 1 |
| 17—Pacific Northwest | 1 | 3 | 1 | 38 | 30 | 18 | 9 | 1 |
| 18—California | 1 | 5 | 4 | 20 | 44 | 17 | 9 | 1 |
| Conus Total | 1 | 6 | 1 | 25 | 25 | 13 | 24 | 5 |

search to analyze the functions, processes, characteristics, and contributions of headwater streams and systems to down gradient surface waters. Watershed-scale responses to hydrologic and biogeochemical perturbations are dependent, in part, on the proper functioning of headwater streams (Vannote and others 1980; Battin and others 2008; Hotchkiss and others 2015; Price and others 2024). These data can therefore be used to manage watersheds, > 73% of which drain from headwater stream systems on average across the CONUS (refer to Table 2), for continued resilience to anthropogenic disturbances (Lane and others 2023). Our dataset may also support data-driven and model-based watershed scale analyses to discern the hydrological, biogeochemical, and ecological effects of headwater streams and systems on downstream rivers and streams. In particular, the HELiOS data could be used to model the extent to which headwater functions mediate watershed resilience to future land cover and climate disturbances—as well as other hydrological and biogeochemical perturbations (Lane and others 2023; Golden and others 2025).

We present the data herein because there are no recently updated CONUS-extent headwater stream estimates (Christensen and others 2022) and because the spatial resolution of global datasets is coarser than required for CONUS-extent headwater research and management. This paucity of current high-resolution headwater maps leads, in part, to excluding these important ecosystem and watershed components from management and decision making (Fritz and others 2013; Creed and others 2017; Mahoney and others 2023; refer to Figure S3). Nadeau and Rains (2007) provided the first data-based assessment of CONUS-wide headwater extents using the National Hydrography Dataset Medium Resolution data set (1:100,000 scale). They selected headwaters via the data descriptor of ''start reaches'' to identify approximately 53% ($\sim$ 2.9 million km) of NHD-mapped headwater streams across the CONUS. Differences in our input data-layer resolution (1:24,000 versus 1:100,000 in Nadeau and Rains (2007)) as well as differences in operationally defining headwaters (here, for example, as SO1 + SO2 streams versus ''start reaches'') likely drove differences in our findings (for example, $\sim$ 8.4 million headwater stream km in this study, Table 1). Further, while headwater stream identification gaps are being filled at the global scale as well, challenges remain. For example, Amatulli and others (2022) used the MERIT Hydro digital elevation model at 90-m resolution and a 0.05 km$^2$ contributing area to develop a global hydrological data set, a major advancement for global stream and river mapping. However, they report that headwater stream extent is under-estimated by 28% in these new data (Amatulli and others 2022), and estimating the lateral stream location (that is, the precise stream location within a valley bottom) similarly remains a challenge when utilizing coarse-resolution data with a small contributing area. In fact, spatial overlaps between the new global data and the benchmark NHDPlus-HR used in that study occur $<$ 50% of the time using a 100-m buffer, though overlaps increase correspondingly with additional buffer widths. It is evident that higher-resolution topography and more refined derivation of contributing areas will improve our understanding of headwater stream and system extent and functions (Yamazaki and others 2019; Messager and others 2021).

Our new CONUS-wide headwater stream and system HELiOS database is a key step toward developing mapped headwaters across a broad spatial extent for research and management, yet further research and development is needed. First, our data are predicated on the precision of the input NHDPlus-HR to map CONUS flowing waters, the gold-standard for completeness as a CONUS-wide hydrography dataset. However, data limitations affect the outcomes found here. For instance, the NHD does not map all stream systems due to scale limitations (Baker and others 2007; Christensen and others 2022). Fritz and others (2013) characterized 105 forested headwater reaches in the Midwestern US and reported that 43 (or 41%) of the reaches were not delineated on the NHDPlus-HR maps. Hansen (2001) similarly found 1:24,000 maps omitted 25% of the perennial stream length in an analysis of the Chattooga River drainage spanning portions of Georgia, South Carolina, and North Carolina. The NHDPlus-HR is therefore a truncated network. In fact, a full Strahler stream order (or more) may be missing from the mapped extent (Brinkerhoff and others 2024). Conversely, areas such as Indiana and portions of western South Carolina and North Carolina were identified here (and by others, such as Brinkerhoff and others 2024) as presumptively over-densified (refer to, for example, Figure 2). We sought uniformity to conduct our CONUS-wide analyses and removed many of the stream segments in the over-densified areas. However, we recognize that the data stewards who entered these data into the NHDPlus-HR may have been on the leading-edge in mapping low-order stream networks. For the sake of CONUS-scale uniformity, we may have removed extant and mapped headwaters. Ideally, subsequent HELiOS derivations and iterations will raise the base (and map additional headwater streams) rather than raze the top (that is, remove mapped headwater streams) for CONUS-scale uniformity. The coming remapping of US waters through the USGS 3D Hydrography Program (''3DHP'') could substantially improve the identification and delineation of CONUS headwater streams and systems (Anderson and others 2024).

Additional omission errors in headwater stream extents across the country arise from limitations on input data layers that comprise the NHD (for example, issues with identifying stream networks under a tree canopy, Lang and others 2012), methodological decisions in delimiting streams (for example, typically not mapping streams that are $<$ 1.6 km in length, Nadeau and Rains 2007), as well as prevailing and/or antecedent conditions when delimiting stream extents (Hafen and others 2020). For instance, though $\sim$ 59% of CONUS streams may be ephemeral (Brinkerhoff and others 2024), 38 of 50 states do not map ephemeral streams as a defined class in their NHDPlus-HR dataset (Fesenmyer and others 2021). Using novel approaches to expand beyond NHDPlus-HR mapped streams can substantially increase potential mapped headwater stream extents. Fesenmyer and others (2021) applied varying contributing watershed area thresholds and calculated that the NHDPlus-HR under-estimated the stream network by roughly 5.9 million stream kilometers. Non-perennially flowing portions of streams, which are frequently unmapped, also cover greater stream extents than perennial streams in many watersheds (Heine and others 2004; Hamada and others 2016; Fesenmyer and others 2021; Messager and others 2021). Ephemeral reaches may comprise up to 71% of the network length (Hansen 2001; Fritz and others 2013); however, the NHD maps only 8–50% of visible stream extents, depending on the focal area's spatial data resolution and data product. Further, field-based analyses of stream networks indicated that they can vary in their flow lengths annually, up to a factor of five (Prancevic and others 2025). In fact, the non-perennially flowing portion (that which is frequently unmapped) was noted to be many times longer than the perennial system in most watersheds (Prancevic and others 2025). Thus, while our estimate of headwater stream density using the HELiOS dataset appears to follow global density estimates (Lin and others 2021), this may change with increased mapping precision. Future work could potentially leverage evolving remotely sensed data to improve the spatial resolutions of mapped stream networks and create mapped networks that are more physically based (Golden and others 2025).

Continued advancements in deriving geospatially mapped stream networks to the channel head—the "place where rivers are born" (Meyer and others 2003)—are needed. Through advanced approaches and with improved spatial resolution of available data, headwater stream mapping will continue to evolve with greater accuracy. That is, finer-resolution mapping products will become increasingly available (for example, Metes and others 2022; Du and others 2024), and the 1:24,000 based stream maps will become correspondingly coarser in comparison. Therefore, the operational definition of headwater streams (as Strahler stream orders 1 and 2) we use here will move up-gradient and likely decrease in areal extent (while the corresponding higher-orders will increase in number and extent). Put simply, more finely resolved data may identify currently mapped small first-order tributaries as larger-order systems, changing the outcome of the headwater analyses (refer to, for example, Supplemental Figure S3). Subsequent analyses may thus find focusing on the dataset introduced here (that is, the HEadwater streams and Low-Order Systems, HELiOS) provides a construct for analyzing the structure and functional contributions of headwater systems that are identified using scalar products.

## Conclusion

Increased attention to the extent, flow, and functions of headwater stream networks and the systems they drain will improve our understanding of their contributions to watershed scale processes and resilience to disturbance. The application of our headwater stream rubric to the NHDPlus-HR identified > 8.4 million headwater stream km draining 5.5 million km$^2$ of the CONUS landscape. These systems predominantly drain forested and shrub-covered lands, yet a large proportion also drain agricultural and developed landscapes, likely providing useful ecosystem services (for example, Hill and others 2014). This novel finding underscores the importance of expanding highly instrumented and monitored headwater research catchments, traditionally located in forested systems, to arid, agricultural, and urban headwater catchments as well.

The HELiOS data we developed will improve the capacity for researchers and managers to model and estimate headwater system contributions to downstream hydrological, biogeochemical, and ecological functions under future land cover or climate conditions. Further, geospatially benchmarking the existing headwater stream network and system extent will aid in quantifying changes in characteristic flow, function, and benefits of headwater streams and systems over time and through change (for example, Sullivan and others 2020). A worldwide effort to improve the characterization of intermittent rivers and ephemeral streams has substantially improved their incorporation into management decision making (Messager and others 2021). Similarly, calls to advance modeling of headwater streams have begun to proliferate (Golden and others 2025), building on these advances. Identifying the headwater stream networks and headwater systems across spatial scales (that is, the HELiOS) contributing to watershed scale resilience to hydrological and biogeochemical perturbations will continue to illuminate their broad and important functions.

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for descriptive purposes only and does not imply endorsement by the U.S. Government.

## DATA AVAILABILITY

The data used in these analyses are freely and publicly available for download and subsequent analyses at the following DOI hosted by the US EPA https://doi.org/10.23719/1532382 (for metadata) and https://zenodo.org/records/16318572 (for data access). Contact the corresponding author with additional data requests.

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