JOURNAL OF THE AMERICAN WATER RESOURCES ASSOCIATION

Vol. 57, No. 2 AMERICAN WATER RESOURCES ASSOCIATION April 2021

A Landscape Assessment and Associated Dataset of Stream Confluences for the Conterminous U.S.

Donald Ebert, James Wickham, Anne Neale, and Megan Mehaffey

Research Impact Statement: Stream confluences may be biological hotspots. We present a USA stream confluence dataset to stimulate further ecological research. The dataset contains 1,085,629 confluences and 383 attributes.

ABSTRACT: Stream confluences are important components of fluvial networks. Hydraulic forces meeting at stream confluences often produce changes in streambed morphology and sediment distribution. These changes often increase habitat heterogeneity relative to upstream and downstream locations, which have led some to identify them as biological hotspots. Despite their potential ecological importance, there are relatively few empirical studies documenting ecological patterns upstream and downstream of confluences. We have produced a publicly available dataset of stream confluences and associated watershed attributes for the conterminous United States. The dataset includes 1,085,629 stream confluences and 383 attributes for each confluence organized into 15 dataset tables for both tributary and mainstem upstream catchments and watersheds. Themes in the dataset include hydrology (e.g., stream order), land cover, land cover change, geology (e.g., calcium content of underlying lithosphere), physical condition (e.g., precipitation), measures of ecological integrity, and stressors (e.g., impaired streams). Additionally, we used measures of ecological integrity to assess the condition of the stream confluences. Aside from a generally positive east-to-west gradient in ecological condition, we found that approximately one-third of the confluences had markedly contrasting ecological conditions between mainstem and tributary, catchment and watershed, or both. The dataset should support many, multifaceted studies of stream confluence ecology.

(KEYWORDS: EnviroAtlas; headwaters; NLCD; stream networks; StreamCat; watersheds.)

INTRODUCTION

Stream confluences emerged as important elements of lotic ecosystems as their conceptualization advanced from continua to networks (Rice 1998; Rice et al. 2001; Benda, Andras, et al. 2004; Benda, Poff, et al. 2004). Every stream confluence is conditioned by the hydraulic forces of its two or more upstream sources. The hydraulic forces introduced by a tributary can produce changes in the morphology of the streambed (e.g., scours, aggradation) and distribution of sediment at the confluence and further downstream (Rhoads 1987; Best 1988). Common streambed geomorphic changes include the development of avalanche faces at the mouths of the mainstem and tributary, a scour hole, flow separation (water volumes from each confluent do not mix immediately), separation bars (a ridge of

---

Paper No. JAWR-20-0022-P of the *Journal of the American Water Resources Association* (JAWR). Received February 26, 2020; accepted November 9, 2020. Published 2020. **Discussions are open until six months from issue publication**.

Office of Research and Development, Center for Public Health and Environmental Assessment, U.S. Environmental Protection Agency, Research Triangle Park, North Carolina, USA (Correspondence to Wickham: wickham.james@epa.gov).

Citation: Ebert, D., J. Wickham, A. Neale, and M., Mehaffey. 2021. "A Landscape Assessment and Associated Dataset of Stream Confluences for the Conterminous U.S.." *Journal of the American Water Resources Association* 57 (2): 315–327. https://doi.org/10.1111/1752-1688.12899.

sediment in the zone of flow separation), and zones of stagnation (sediment deposition) and mixing of the main stem and tributary water volumes (Best 1988). Confluence angle, tributary water volume, and differences between mainstem and tributary stream bed elevations influence the likelihood of occurrence and magnitude of these geomorphic features (Rhoads 1987; Best 1988; Best and Roy 1991). These changes are temporally dynamic and spatially variable because of ever-changing discharge volumes and potential asynchrony in the timing of mainstem and tributary high-flow events (Rhoads 1987; Rice et al. 2001), place-to-place differences in confluent stream angles (Best 1988), place-to-place differences in sediment supply (Rice et al. 2001) river shape (Rhoads and Johnson 2018), and upstream differences in land cover and other watershed characteristics (Jones and Schmidt 2017).

Often depending on the size of the tributary, Rice (1998), Rice et al. (2001), Benda, Andras, et al. (2004) and Benda, Poff, et al. (2004) recognized that geomorphic changes at stream confluences may also constitute habitat changes. Many benthic macroinvertebrates, for which measures of presence and composition are preferred indicators of water quality (Barbour et al. 2000), are also sensitive to change in a host of biotic and abiotic factors. Statzner and Higler (1986) have suggested that hydraulic forces are an integrating factor for understanding the distribution of stream benthos. Benda, Poff, et al. (2004) referred to stream confluences as biological hotspots because of the likelihood of greater habitat heterogeneity arising from the collision of two hydrologic forces. Many others have adopted their perspective, and there is a growing body of empirical evidence supporting the effect of stream confluences on the spatial patterning of lotic and lotic-associated biota (Table 1).

Our main objective is to present the development of a stream confluence dataset for the conterminous United States (U.S.). To our knowledge, no such a dataset exists. It's development and use would support further research of the ecology of stream confluences. Some examples include effects related to: (1) geographic differences (e.g., Benda, Andras, et al. 2004); (2) urbanization and other land cover changes; (3) differences between mainstem and tributary channel gradients; (4) position in the stream network (e.g., Grenouillet et al. 2004; Thornbrugh and Gido 2010); (5) influence of lithology (Hellman et al. 2015); (6) influences of stressors and disturbance (e.g., Katano et al. 2009; Boddy et al. 2019); (7) influence of soil differences, and; (8) interaction between tributary size (discharge) and differences in mainstem and tributary watershed characteristics (e.g., Jones and Schmidt 2017). Some of the aforementioned topical examples have not been studied to our knowledge (Table 1), such as land cover change, and complementary studies for topics reported

TABLE 1. Studies of ecological patterns in the vicinity of stream confluences.

Author (year)	Location[1]	Result
Rice et al. (2001)	British Columbia, CA	Discontinuities in longitudinal profile of MI abundance and evenness attributable to SC at one of two sampled rivers
Knispel and Castella (2003)	Rhône R, CH	MI richness increased downstream of a small tributary
Franks et al. (2002)	Loughborough, UK	Differential patterns of some macroinvertebrate species by confluence zones
Fernandes et al. (2004)	Amazon R, BR	Tributaries enriched electric fish diversity
Grenouillet et al. (2004)	Saône R, FR	Fish richness influenced by downstream factors for ≥5th order streams
Beckmann et al. (2005)	Rhine R., DE	Mainstem influenced tributary MI richness
Kiffney et al. (2006)	Skagit R., US	Ecological variables were highest near SC
Hitt and Angermeier (2008)	eastern US	Sites nearer stream confluences had greater fish richness
Rice et al. (2008)	Stillaguamish R, US	Scale-dependent pattern of salmon spawning locations attributable to SC
Katano et al. (2009)	Kiso-gawa R, JP	Tributary mitigated dam-induced effects on MI
Thornbrugh and Gido (2010)	Kansas R, US	Fish species richness was higher in tributaries connected to higher order streams
Mac Nally et al. (2011)	Acheron R, AU	MI richness and density were unaffected by SC
Milesi and Melo (2014)	Rio Grande do Sul, BR	SC influence on MI was dependent of size of tributary
Clay et al. (2015)	Tagliomento R, IT	Stream confluence effects on MI was influenced by context
Czeglédi et al. (2016)	Marcal R, HU	Tributary fish abundance and composition decreases upstream from confluence; seasonal effects were significant
Hellman et al. (2015)	Susquehanna R, US.	Geology-mediated changes in MI composition and diversity patterns across confluence zones
White et al. (2018)	Colorado R, US	Riparian habitat complexity was highest at SC; results were scale dependent
Boddy et al. (2019)	Canterbury, NZ	Disturbance-mediated patterns of fish abundance attributable to SC
Milner et al. (2019)	American R, US	Increased MI diversity at tributary on regulated river; no downstream effects

Note: MI, macroinvertebrate; SC, stream confluence.

[1] Two-letter country abbreviation source — https://www.worldstandards.eu/other/tlds/; location identified by river system where practicable.

in the literature would likely help to advance a nascent field (Rice et al. 2008; Jones and Schmidt 2017). For example, conversion of forest to urban would likely lead to increased erosion, which may change confluence dynamics. To demonstrate the utility of the dataset, we classify conterminous U.S. stream confluences using available data on ecological conditions and overlay the classification results with other attributes included in the dataset.

METHODS

Datasets

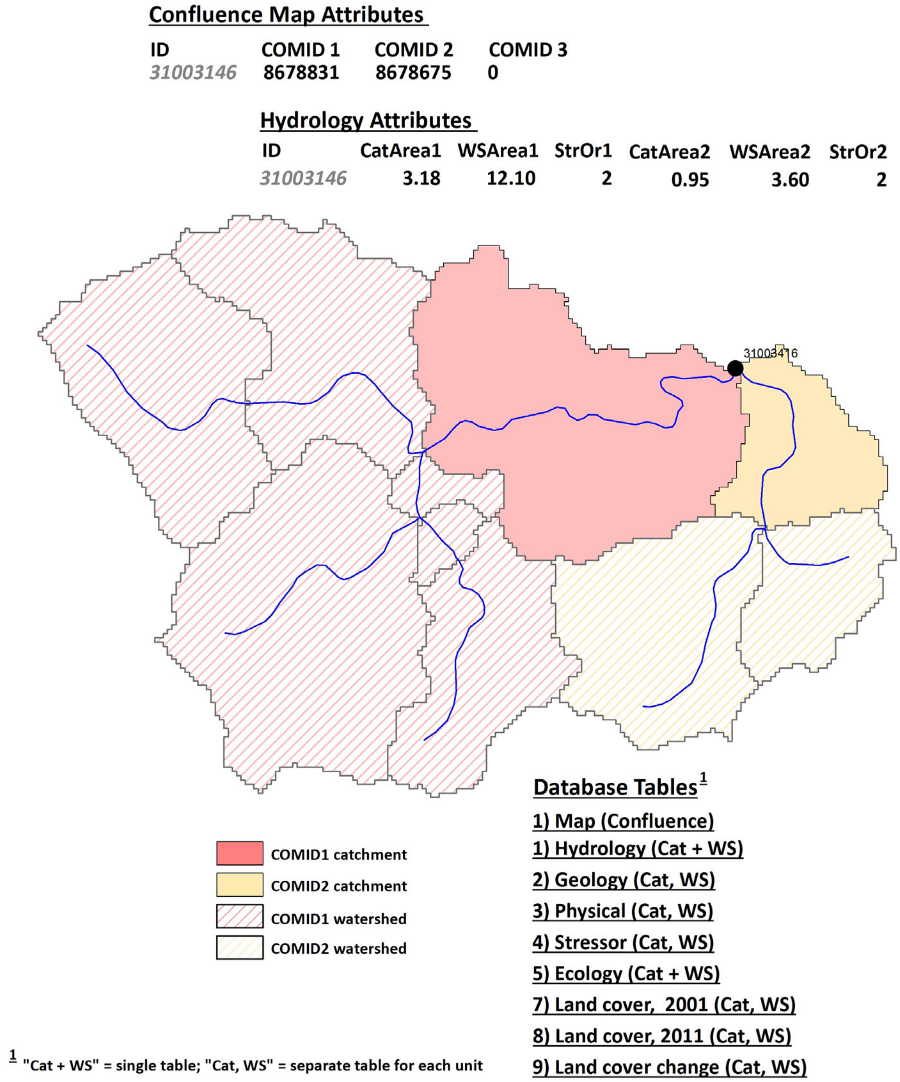
Two datasets were used to identify stream confluences and associated landscape attributes: (1) hydrographic data from the National Hydrography Dataset Plus Version 2 (NHDPlus V2) (http://www.horizon-systems.com/nhdplus/nhdplusv2_home.php) and (2) landscape attributes from StreamCat (Hill et al. 2016; https://www.epa.gov/national-aquatic-resource-surveys/streamcat). The NHDPlus V2 flowlines (i.e., streams) were used to identify the confluences, and NHDPLUS V2 catchments were used to summarize landscape attributes. Elevation-based catchments are defined for each NHD stream reach, where a stream reach is the length of stream between upstream and downstream confluences (Johnston et al. 2009). StreamCat (Hill et al. 2016) is a conterminous U.S. national database of watershed attributes including climate, geology, soils, and land cover.

We used NHD as our hydrography data because it includes stream network topology and it was the hydrography data used to develop StreamCat (Hill et al. 2016). Consistent with NHD terminology (Johnston et al. 2009), we use the term catchment to refer to the drainage basin that drains a stream reach, excluding upstream inputs, and watershed to refer to the target catchment and all upstream catchments (Figure 1). There are many more catchments than confluences because catchments are defined by hydrographic feature type (Johnston et al. 2009) such that there would be two catchments for a stream if it changed, for example, from intermittent to perennial or perennial to canal (see Figure 1). StreamCat includes landscape attributes for both NHD catchments and watersheds.

Identification of Confluences

NHD does not include confluences per se. All NHD stream reaches that had flow direction, regardless of class, were used to identify confluences. We identified confluences by converting the most downstream node of each NHD stream reach to a point. The node-to-point conversion produced two or more points for each confluence where one or more streams joined another (one for each stream reach). Pivot table analysis (i.e., rows to columns) was used to reduce the number of points to the actual number of confluences. The data table resulting from the pivot table analysis had 1 row and 2 fields (columns) for a confluence with one inflowing stream. The stream reach IDs were used as the link to the matching catchment ID (an NHD stream reach unique ID is equivalent to the NHD catchment unique ID in which it occurs). The NHDPlus V2 attribute linking the stream reach (i.e., stream reach ID) and the catchment (i.e., catchment ID) is COMID (Figure 1). Node-to-point conversion and pivot table analysis resulted in the identification of 1,085,629 confluences for the conterminous U.S. The number of streams coming together at a confluence ranged from one to three and the corresponding frequencies were 138,430 (1 incoming stream), 942,226 (2 incoming streams), and 4,973 (3 incoming streams). Nodes with only one incoming stream identified streams flowing into water bodies.

Our confluence dataset includes 383 landscape attributes that were primarily from StreamCat (Hill et al. 2016) organized into 15 different data tables representing 8 different themes: map, hydrology, land cover, land cover change, physical, geology, stressors, and ecology (Figure 1; Table S1). The map attribute table includes the stream and catchment unique IDs (i.e., COMID), the 2-, 8-, and 12-digit hydrologic unit codes (HUC) from the NHDPlus V2 Watershed Boundary Dataset (WBD), which is available at the aforementioned NHD website (USGS and USDA-NRCS 2013), and classification results from the disjoint cluster and decision tree analyses (discussed below). We present separate catchment and watershed attribute tables each for the physical, geology, and stressors themes. The same division into catchment and watershed was used for land cover, producing a total of six tables, two each for 2001, 2011, and 2001–2011 change. Catchment and watershed land cover percentages in StreamCat (Hill et al. 2016) were derived from NLCD 2011 (Homer et al. 2015). We used the land cover proportions available from StreamCat (Hill et al. 2016); we did not derive them from the NLCD 2011 (Homer et al. 2015). Land cover change (not available from StreamCat) was estimated as 2011 land cover percentages minus 2001 values. NLCD 2016 (Yang et al. 2018; Homer et al. 2020) was not included in our stream confluence dataset because these data were not available when this project was initiated. Catchment and watershed attributes were combined into a single table for the



Confluence Map Attributes

ID	COMID 1	COMID 2	COMID 3
31003146	8678831	8678675	0

Hydrology Attributes

ID	CatArea1	WSArea1	StrOr1	CatArea2	WSArea2	StrOr2
31003146	3.18	12.10	2	0.95	3.60	2

Database Tables[1]

1) Map (Confluence)
1) Hydrology (Cat + WS)
2) Geology (Cat, WS)
3) Physical (Cat, WS)
4) Stressor (Cat, WS)
5) Ecology (Cat + WS)
7) Land cover, 2001 (Cat, WS)
8) Land cover, 2011 (Cat, WS)
9) Land cover change (Cat, WS)

[1] "Cat + WS" = single table; "Cat, WS" = separate table for each unit

FIGURE 1. Catchment-watershed organization and database structure. A watershed is comprised of all catchments (i.e., solid + hatched) draining to an outlet. Table S1 provides a description of each data table and its indicators. [Color figure can be viewed at wileyonlinelibrary.com]

hydrology and ecology themes. Attributes in the hydrology data table were derived from the NHD Value Added Attributes (VAA). We added an additional variable, not in the NHD VAA tables, to identify the confluence mainstem and tributaries (mainstem = 1 and tributary = 2). The incoming stream with the largest watershed (not catchment) area was assumed to be the mainstem (Rhoads 1987). The value of mainstem-tributary identifier was determined by the rank order of watershed areas when there were three incoming streams. We also added stream channel slope (%) as an attribute (physical data table) based on elevations of the most upstream and downstream nodes and the catchment stream length; stream channel slope is only available for the catchment.

Demonstration of Dataset Utility

To demonstrate the potential utility of the dataset, we classified the confluences using measures of catchment and watershed ecological integrity (Thornbrugh et al. 2018) included in the StreamCat database (Hill et al. 2016). This was done for all confluences joining two incoming streams that had ecological integrity measures ($n = 941{,}469$). The main objective of the demonstration was to provide a national assessment of the ecological condition of stream confluences. Given the emerging ecological importance of stream confluences (Table 1), the classification of stream confluences based on ecological integrity should be a useful resource for the numerous watershed assessments conducted throughout the country (e.g., Shilling et al.

2005). The stream confluence dataset could be a framework for incorporating stream confluences into such assessments. Also, a national ecological assessment of stream confluences is lacking. The demonstration fills that void and may motivate further research on the ecological roles of stream confluences.

We used disjoint clustering to classify the stream confluences and decision tree analysis (SAS Institute Inc 2015) to validate the cluster result. The indices of ecological integrity for catchments (ICI) and watersheds (IWI), developed by Thornbrugh et al. (2018) and provided in the StreamCat database (Hill et al. 2016), were used as the input variables for the cluster analysis. The ecological integrity indices are multimetric estimates of a stream's water chemistry, sediment load, hydrologic connectivity, habitat provision, and its capacity to regulate stream temperature (Thornbrugh et al. 2018; Supporting Information). Because of the high correlation ($r \geq 0.8$) among the mainstem and tributary ICI and IWI (Table S2), only ICI and IWI for the mainstem along with four contrast variables were used as cluster analysis input. The four contrast variables were as follows: (1) ICI minus IWI for the mainstem; (2) ICI minus IWI for the tributary; (3) mainstem ICI minus tributary ICI, and; (4) mainstem IWI minus tributary IWI. In total, six variables were used as input for the cluster analysis. We refer to the four measurements based on differences between ICI and IWI as contrast variables because they emphasize differences in ecological integrity between watersheds and catchments and mainstems and tributaries. They have intuitive appeal because the ICIs and IWIs of the two incoming streams, which may be very different, should be influential in determining the ecological condition of the confluence. The contrast measures were not correlated with each other or the mainstem ICI and IWI (Table S2). Use of the contrast measures also created the potential for clustering to identify groups based on catchment-watershed and mainstem-tributary differences.

The difference between the observation and the cluster median rather than the cluster mean (i.e., *k*-means) was used as the clustering criterion to minimize sensitivity to outliers (SAS Institute Inc 2015). The input variables were not transformed prior to disjoint clustering because ICI and IWI are scaled between 0 and 1, and therefore the contrast (difference) measures are scaled between -1 and 1 (Table S3). The appropriate number of clusters was evaluated using a measure of cluster separation (see Van Craenendonck and Blockeel 2015) for outputs ranging from 10 to 30 clusters in increments of two (10, 12, …, 30). The 16-class result maximized cluster separation and was validated using decision tree analysis (Supporting Information). The cluster and decision tree results are included in the map data table (see Table S1). Inclusion of the cluster and decision tree assignments and their associated attributes provides additional measures of cluster assignment uncertainty.

We labeled the 16 clusters as poor, moderate, good, or contrast based on the cluster mean values of ICI and IWI for the mainstem and the four contrast variables to simplify the reporting of the cluster analysis results. Clusters were labeled as contrast if one or more of the cluster's mean values for the four contrast variables were $\geq|0.1|$ regardless of the mainstem cluster mean values for ICI and IWI. Clusters with a mean ICI or IWI < 0.35 were labeled as poor, and clusters with mean values of ICI and IWI ≥ 0.60 were labeled as good. Clusters with mean ICI and IWI values ≥ 0.35 and < 0.60 were labeled as moderate. Overall, clusters labeled as contrast had mean mainstem ICI and IWI values that were distinctly different unless the mean contrasts $\geq|0.1|$ were between the mainstem and the tributary.

Results from the statistical analyses were summarized using the HUC units in the WBD (USGS and USDA-NRCS 2013). The WBD dataset is a nested set of hydrologic (polygonal) units identified by digital codes whose length (number of digits) decreases as the size of the unit increases. The number of HUC 2 (e.g., 02), HUC 8 (e.g., 02020303), and HUC 12 (e.g., 020203030404) units are 18, ~2,000, and ~87,000, respectively. Catchments (defined above) are much smaller than the HUC 12 units and generally nest within the WBD units but do not use the same integer coding (McKay et al. 2018). There are about 2,500,000 catchments in the conterminous U.S.

Following the cluster analysis, we attributed the classified stream confluences with the ratio of tributary watershed area to mainstem watershed area. The tributary-mainstem ratio derives from studies of the geomorphological effects of tributary discharge into mainstems (Rhoads 1987). It is an index of the potential significance of the incoming tributary on the geomorphic characteristics of the stream confluence. Empirical studies of relative sizes of tributary and mainstem watershed areas on confluence geomorphology indicate geomorphic changes at confluences tend to be become common as the tributary watershed area approaches and exceeds 60% of the mainstem watershed area (Rhoads 1987; Benda, Andras, et al. 2004). For the demonstration, we chose 0.6 as a threshold for confluences where tributary effects might be significant, recognizing that several factors likely influence threshold effects (Rice 1998; Rice et al. 2001). The objective of the overlay was to further classify confluence ecological conditions by the likelihood of the confluence being a biological hotspot (sensu Benda, Poff, et al. 2004). For simplicity, we hereafter refer to the tributary-mainstem watershed areas ratio as the symmetry ratio (sensu Rhoads 1987) and confluences with symmetry ratios ≥0.6 as hydraulically significant. The symmetry ratio was based on the watershed areas of the mainstem and tributary, not the catchment areas. It is included hydrology dataset table.

RESULTS

Catchment-watershed and mainstem-tributary contrasts were useful for identifying groups of confluences. Eleven of 16 groups (clusters), comprising about 35% of all confluences, had large absolute average values (>|0.1|) for one or more of the four contrast measures (Table 2). The remaining five groups had either average catchment-watershed or mainstem-tributary contrasts that were <|0.1|. About 27% of the confluences were in Cluster 4, which had average mainstem ICI and IWI values of 0.85 and very small (<|0.01|) average catchment-watershed and mainstem-tributary contrasts. Nearly the same percentage of the confluences had average mainstem ICI and IWI values <0.55 (Clusters 6, 7, and 13) with generally small (<|0.02|) average catchment-watershed and mainstem-tributary contrasts.

The main geographic pattern was an east-west contrast in the preponderance of confluences in good ecological condition and concentration of the confluences in the poorest condition in the agriculturally dominated midwest and Mississippi River valley (Figure 2). In general, watersheds in the western U.S. had relatively uniform distributions of confluences in good condition and therefore relatively few confluences with contrasting conditions (Figure 2a, 2d), whereas watersheds east of the Colorado Front Range had more heterogeneous confluence conditions and were in poorer condition overall. The main exception to this pattern occurred in the northwestern Great Lakes and northern New England, where watersheds tended to have confluences in good condition.

The inherent nestedness of the dataset can be used to examine the spatial pattern of confluence conditions across a range of spatial scales, from the spatial pattern for HUC 8 units across the country (Figure 2) to HUC 12 units nested in HUC 8 units (Figure 3b) to individual confluences within HUC 12 units (Figure 3a). There was often considerable spatial variability in confluences conditions within the HUC 12 units that comprise a HUC 8 (e.g., Figures 2a vs. 3b) and there was often considerable spatial variability in confluence conditions within the HUC 12 units themselves (e.g., Figure 3a vs. 3b). The scale of individual confluences is often the scale at which restoration occurs because of cost factors (Wickham, Riitters, et al. 2017) and an interesting example of how the data could be used to support local ecological restoration efforts is represented by the confluence encircled in black in Figure 3a. The property description for the land surrounding the confluence includes the term "conservation easement" (https://appomattoxgis.timmons.com/#/mwl?zoom=15&location=-78.933669_37.434599) but much of the property is not forested,

TABLE 2. Means of input variables by cluster. Contrast values ≥ |0.1| are underlined to aid interpretation.

Cluster	# Obs	ICIm	IWIm	ICWIm	ICWIt	ICId	IWId	Label
1	38,355	0.486	0.317	0.176	0.000	0.141	−0.015	Contrast
2	27,081	0.813	0.380	0.397	0.000	0.390	−0.005	Contrast
3	24,923	0.352	0.568	−0.207	0.000	−0.013	0.205	Contrast
4	256,318	0.851	0.856	0.000	0.000	0.000	0.000	Good
5	35,417	0.401	0.402	0.000	0.000	−0.228	−0.221	Contrast
6	52,689	0.544	0.536	0.000	0.000	−0.007	−0.009	Moderate
7	99,352	0.332	0.333	0.000	0.000	0.019	0.015	Poor
8	26,280	0.781	0.446	0.340	0.000	0.015	−0.290	Contrast
9	29,037	0.407	0.684	−0.265	0.000	−0.311	−0.013	Contrast
10	24,911	0.848	0.456	0.364	0.370	0.000	0.000	Contrast
11	61,005	0.832	0.709	0.131	0.000	0.045	−0.071	Contrast
12	41,710	0.695	0.676	0.000	0.000	0.200	0.160	Contrast
13	119,369	0.196	0.192	0.000	0.000	−0.009	−0.001	Poor
14	17,708	0.382	0.336	0.033	0.444	−0.402	0.006	Contrast
15	13,270	0.389	0.671	−0.263	−0.325	0.047	0.000	Contrast
16	74,044	0.698	0.743	−0.030	0.000	−0.082	−0.034	Good

Notes: The column, Label, provides a simple, nominal classification to aid interpretation of Figure 2. Clusters were labeled "contrast" if one or more of the contrast variables was ≥|0.1| (e.g., Clusters 1 and 3). ICIm and IWIm values of ≥0.35 and 0.60 were used as threshold for the "moderate" and "good" labels.

m, mainstem; t, tributary; ICWI, catchment — watershed; d, mainstem — tributary.

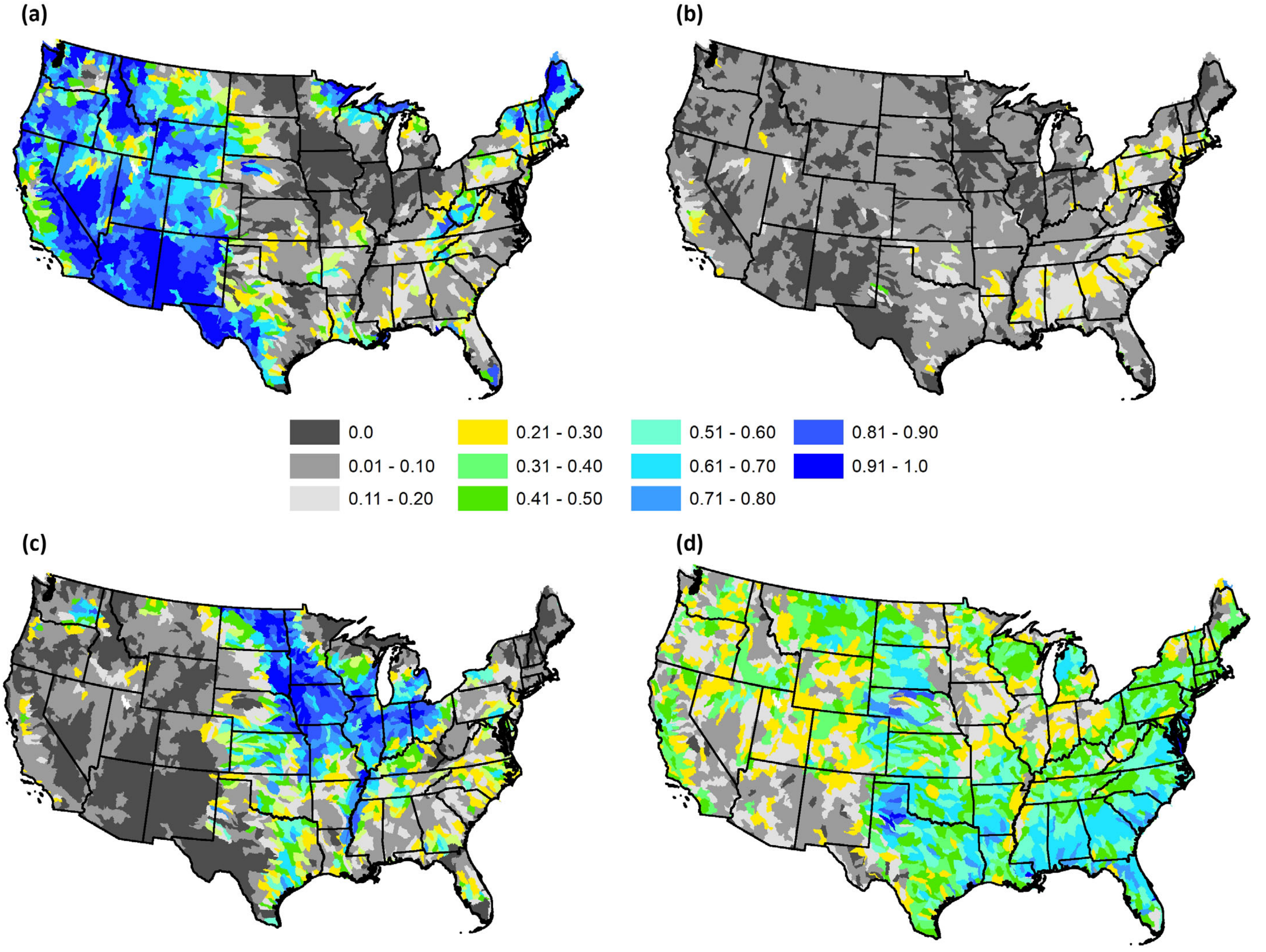


FIGURE 2. Proportion of confluences within 8-digit hydrologic units (HUC 8) in (a) good, (b) moderate, (c) poor, and (d) contrasting ecological conditions (see Table 1). The HUC 8 highlighted in red in panel a is depicted in Figure 3. [Color figure can be viewed at wileyonlinelibrary.com]

which is the potential natural vegetation in this region of the U.S. (Daubenmire 1978). Our confluence dataset can be used alone and in combination with other GIS data to support ecological conservation and restoration efforts.

Across the conterminous U.S., about 20% ($n = 196{,}818$) of the confluences were hydraulically significant, and their distribution across the clusters was uneven (Figure 4). The percentage of hydraulically significant (symmetry ratio ≥ 0.6) confluences by cluster ranged from about 2% (Cluster 8) to nearly 50% (Cluster 10). About 3% of the hydraulically significant confluences had incoming streams where both stream orders were >1 ($n = 5{,}933$), of which 25% were in Cluster 10. Cluster 10 confluences have mainstem and tributary catchments in good ecological condition and mainstem and tributary watersheds in moderate ecological condition (Table 2). The geographic pattern of hydraulically significant confluences was consistent with geographic pattern for all confluences.

DISCUSSION

Confluences are an understudied component of lotic systems that readily facilitate and fit into stream network conceptual models. We classified confluences by characteristics attributable to the catchments and watersheds of the incoming streams and found that about 35% of the confluences in the conterminous U.S. had distinctly different conditions between the mainstem and tributary, the catchment and watershed, or both, suggesting that the condition

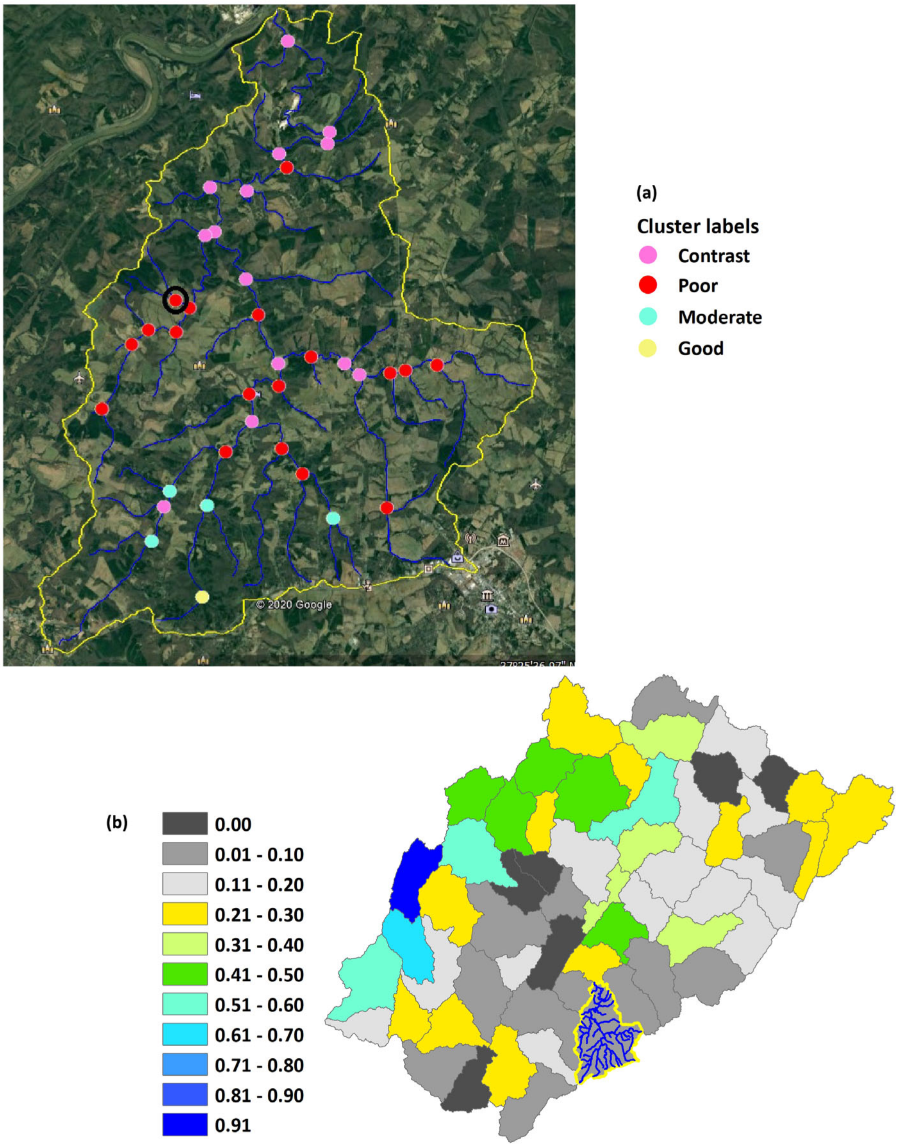
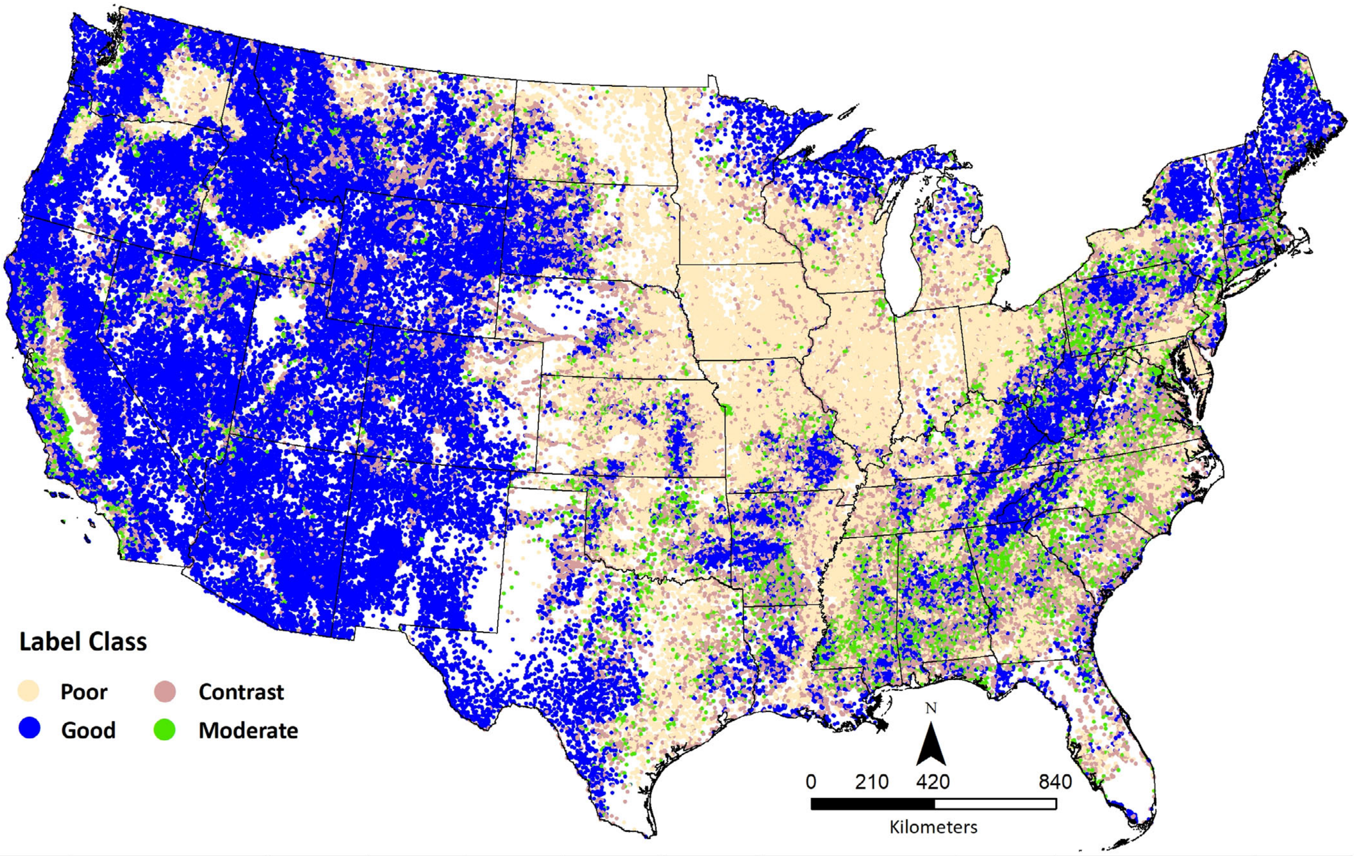


FIGURE 3. Spatial distribution of (a) confluence conditions for a HUC 12 and (b) the proportion of confluences in good ecological condition for the HUC 12 units nested within a HUC 8. The HUC 12 highlighted in (b) is depicted in (a). The confluence encircled in black in (a) is discussed in the Results. The HUC 8 in (b) is highlighted in Figure 2. The Google Earth™ image date is February 2, 2019. [Color figure can be viewed at wileyonlinelibrary.com]

of about one-third of the stream confluences in the conterminous U.S. is defined by inflowing streams with distinctly different ecological characteristics. It would be difficult to ascertain information on contrasting catchment-watershed and mainstem-tributary conditions from a similarly broad-scale assessment that was based on watersheds (e.g., Jones et al. 1997; Wickham et al. 1999).

When compared to the number of field studies we found on the ecologic characteristics of confluences, the number of confluences in the conterminous U.S. tends to support the view that knowledge of the ecological roles of stream confluences is still in an emergent stage (Grant et al. 2007; Rice et al. 2008; Jones and Schmidt 2017), and the list of worthwhile research topics appears to be long (see Grant et al. 2007). The dataset developed for this project should support many of these topics. For example, the influence of climate, geology, and topography on riverine characteristics (Poff et al. 1997) suggests that there should be geographic differences in the hydraulic significance of confluences and the occurrence of biological hotspots. Benda, Andras, et al. (2004) and Benda, Poff, et al. (2004) found differences in geomorphic characteristics of confluences in the western U.S. when the data were split into humid and arid locations. Similarly, rivers in coastal plain settings, may have low-sediment transport capacity (Slattery and



	Frequency			Proportion				Frequency			Proportion		
Cluster	Count	Ws ratio ≥ 0.6	Stream Order > 1	Ws ratio ≥ 0.6	Stream Order > 1	Label	Cluster	Count	Ws ratio ≥ 0.6	Stream Order > 1	Ws ratio ≥ 0.6	Stream Order > 1	Label
1	38,355	3927	192	0.102	0.0050	Contrast	9	29,037	4333	345	0.149	0.0119	Contrast
2	27,081	3804	344	0.140	0.0127	Contrast	10	24,911	12443	1493	0.499	0.0599	Contrast
3	24,923	1430	22	0.057	0.0009	Contrast	11	61,005	8480	628	0.139	0.0103	Contrast
4	256,318	64121	775	0.250	0.0030	Good	12	41,710	8811	113	0.211	0.0027	Contrast
5	35,417	5501	13	0.155	0.0004	Contrast	13	119,369	25355	394	0.212	0.0033	Poor
6	52,689	13624	248	0.259	0.0047	Moderate	14	17,708	4678	334	0.264	0.0189	Contrast
7	99,352	20293	283	0.204	0.0028	Poor	15	13,270	4983	470	0.376	0.0354	Contrast
8	26,280	672	5	0.026	0.0002	Contrast	16	74,044	14363	274	0.194	0.0037	Good

FIGURE 4. Confluence condition where symmetry (Ws) ratio ≥0.6 and inflowing stream orders >1. [Color figure can be viewed at wileyonlinelibrary.com]

Phillips 2011), suggesting that geomorphic and concomitant ecological effects may be different for confluent, low-sediment streams compared to those with more typical sediment volumes.

Threshold tributary effects on stream confluences have been developed based on the symmetry ratio and other factors (Rhoads 1987; Rice 1998; Rice et al. 2001; Benda, Andras, et al. 2004). Based on the symmetry ratio alone, threshold effects occur between 0.6 and 0.7 (Rhoads 1987; Benda, Andras, et al. 2004). Notwithstanding potential hydraulic effects on stream biota (Statzner and Higler 1986), possible effects attributable to other factors (e.g., Hellman et al. 2015; Boddy et al. 2019) have not been tested empirically to our knowledge. The Jones and Schmidt (2017) conceptual model can be viewed as an acknowledgment of the potential importance of factors other than hydraulic forces. In their conceptual model, dissimilarity in the landscape characteristics of the inflowing streams reduces the symmetry ratio at which threshold effects may be realized. Differences in the amount of impervious cover between the watersheds of confluent streams would seem to be one example in which landscape characteristics would affect the symmetry ratio at which threshold effects might occur. The results reported by Boddy et al.

(2019) in which disturbance in the tributary watershed affected ecological changes attributable to stream confluences appear to be empirical evidence supporting Jones and Schmidt's (2017) conceptual model.

Rice et al. (2008) discussed several fascinating examples of stream confluence effects on aquatic ecology that are not necessarily dependent on high symmetry ratios, including use of tributaries for predator avoidance, differential use of mainstem and tributary based on life stage, thermal refugia, and preferential use of stream confluences as feeding grounds. Our motivation for producing a stream confluence dataset and classifying the confluences was to support and invigorate the study of the ecology of stream confluences. One example is the use of our classification results to develop ecological reference sites for stream confluences. Ecological reference sites (sites free or nearly free of anthropogenic influence) are often determined by expert judgment, and the subjectivity inherent in such judgment may lead to misclassification — sites incorrectly labeled as representing (or not) reference conditions (Whittier et al. 2007). Our classification is based on consistently quantified metrics of ecological condition (Thornbrugh et al. 2018) that are further supported by several measures of classification uncertainty. In addition, dataset elements such as stream order (Whittier et al. 2007) and geology (Hellman et al. 2015) can be used to bring context to reference site identification.

DATE AVAILABILITY AND DATA LIMITATIONS

Data Availability. The data are freely available https://doi.pangea.de/10.1594/PANGEA.909230 (Wickham 2019). The data are provided as ArcMap shapefiles and associated dbase files. ArcMap shapefiles for streams (line) and catchments (polygon) are also included. The data will also be made available by the U.S. Environmental Protection Agency at their EnviroAtlas geospatial portal (Pickard et al. 2015; https://www.epa.gov/enviroatlas). The Methods and Supporting Information serve as metadata for the dataset posted at PANGEA, and its subsequent posting on EPA's EnviroAtlas website will include information from the Methods and Supporting Information sections, and additional documentation.

Data Limitations. Like so many other geographic research efforts, the work described herein embodies the concept that maps are models (sensu Board 1967; see also King 1982). As such, the work was subject to the constraints of generality, realism, and precision (Levins 1966; see also Weisberg 2006) that all modeling efforts must address. As is the case with many broad-scale (i.e., large geographic extent) studies, our effort emphasized generality at the expense of precision. Depending on the objectives, our emphasis on generality may or may not impact the use of these data at local scales (e.g., Figure 3a). The hierarchical stream habitat classification system developed by Frissel et al. (1986) is perhaps a useful guide on the limitation of the use of the stream confluence dataset. The authors identify five levels of classification broadly defined by length scales ranging from 10^{-1} m to 10^3 m in units of 10^1. The stream confluence dataset would seem to be most useful at the Frissel et al. (1986) 10^3 and 10^2 classification levels and begin to breakdown at the 10^1 classification level.

The potential impact on our results of the broad-scale geographic perspective and emphasis on generality extend to the primary input data (NHD, StreamCat, and NLCD) we used. The source materials and data capture methods used to develop NHD have resulted in inconsistent drainage densities, omission of many headwater streams, and omission of all ephemeral streams (Lang et al. 2012; Fritz et al. 2013; Benda et al. 2016). Others have noted that streams removed (i.e., buried), most often as a result of urbanization, also are missing from NHD (Elmore and Kaushal 2008; Roy et al. 2009). The reported shortcomings of NHD were based on studies that were local in scale and emphasized precision (Elmore and Kaushal 2008; Roy et al. 2009; Lang et al. 2012; Fritz et al. 2013; Benda et al. 2016). Missing streams in NHD indicate missing stream confluences in our dataset. The tendency for missing streams to be small, headwater streams also suggests that the associated missing stream confluences likely would be hydrologically significant since the merging streams would likely have similar discharge volumes. Our results for hydrologic significance for stream orders greater than one (i.e., Figure 4) could also be affected if the inclusion of headwaters changed the spatial pattern of stream orders. NHD Plus High Resolution (NHD Plus HR) data (1:24,000-scale) (https://www.usgs.gov/core-science-systems/ngp/national-hydrography/nhdplus-high-resolution#WhatIsIt) include more streams than the NHDPlus V2 data (1:100,000-scale) we used and likely would have resulted in identification of more stream confluences. However, Fritz et al. (2013) found closer, but far from perfect, agreement in stream class type (ephemeral, intermittent, or perennial) between field-determined streams (Fritz et al. 2008) and NHD Plus HR than between field-determined streams and NHDPlus V2. NHD Plus HR is still in beta version and not complete for the entire conterminous U.S. Similarly, the models developed by Thornbrugh et al. (2019) to estimate ICI and IWI emphasize generality rather than precision because they were based on input data that were available across the conterminous U.S. A similar effort on a local scale emphasizing precision (i.e., higher quality data) might derive different estimates for ICI and IWI. Like NHD, NLCD is a broad-scale, widely used database. NLCD 2011 (Homer et al. 2015) user's accuracies (complement of commission error) and producers accuracies (complement of omission error) range from 80% to 95% for its urban, forest, shrubland, grassland, and agriculture classes for both the 2001 and 2011 components of the database, and accuracy of change results (e.g., forest loss), while lower, compare favorably with other land cover change products (Wickham, Stehman, et al. 2017). Translating recent quantitative estimates of the spatial pattern of land cover change accuracy (Wickham, Stehman, et al. 2018) to the expression of land cover change in our stream confluence dataset indicates that accuracy should increase as the difference between 2001 and 2011 proportions increases. Availability of higher resolution land cover is becoming more widespread (Popkin 2018; www.chesapeakeconservancy.org; www.epa.gov/enviroatlas), and comparison of NLCD with such data indicates higher resolution data would yield different area estimates and different spatial patterns but these high-resolution datasets are not without error (Wickham, Herold, et al. 2018; Wickham et al. 2020; Wickham and Riitters 2019).

SUPPORTING INFORMATION

Additional supporting information may be found online under the Supporting Information tab for this article: Supporting information on database indicators and classification methods.

ACKNOWLEDGMENTS

The research described in this paper has been funded by the U.S. Environmental Protection Agency. We thank the anonymous reviewers and Scott Leibowitz (USEPA) for their valuable comments on earlier versions of the paper. The paper has been subjected to Agency review and has been approved for publication. The views expressed in this journal article are those of the authors and do not necessarily reflect the views or policies of the U.S. Environmental Protection Agency. Mention of trade names or commercial products does not constitute endorsement or recommendation for use.

AUTHORS' CONTRIBUTIONS

Donald Ebert: Formal analysis; validation; writing-original draft; writing-review & editing. **James Wickham:** Conceptualization; formal analysis; investigation; methodology; project administration; validation; visualization; writing-original draft; writing-review & editing. **Annie Neale:** Data curation; project administration; writing-review & editing. **Megan Mehaffey:** Data curation; project administration; supervision.

LITERATURE CITED

Barbour, M.T., W.F. Swietlik, S.K. Jackson, D.L. Courtemanch, S.P. Davies, and C.O. Yoder. 2000. "Measuring Attainment of Biological Integrity in the USA: A Critical Element of Ecological Integrity." *Hydrobiologia* 422/423: 453–464.

Beckmann, M.C., F. Schöll, and C.D. Matthaei. 2005. "Effects of Increased Flow in the Main Stem of the River Rhine on the Invertebrate Communities of its Tributaries." *Freshwater Biology* 50: 10–26. https://doi.org/10.1111/j.1365-2427.2004.01289x.

Benda, L., K. Andras, D. Miller, and P. Bigelow. 2004. "Confluence Effects in Rivers: Interactions of Basin Scale, Network Geometry, and Disturbance." *Water Resources Research* 40: W05402. https://doi.org/10.1029/2003WR002583.

Benda, L., D. Miller, J. Barquin, R. McCleary, T. Cai, and Y. Ji. 2016. "Building Virtual Watersheds: A Global Opportunity to Strengthen Resource Management and Conservation." *Environmental Management* 57: 722–729. https://doi.org/10.1007/s00267-015-0634-6.

Benda, L., N.L. Poff, D. Miller, T. Dunne, G. Reeves, G. Pess, and M. Pollock. 2004. "The Network Dynamics Hypothesis: How Channel Networks Structure Riverine Habitats." *BioScience* 54: 413–427.

Best, J.L. 1988. "Sediment Transport and Bed Morphology at River Channel Confluences." *Sedimentology* 35: 481–498.

Best, J.L., and A.G. Roy. 1991. "Mixing-Layer Distortion at the Confluence of Channels of Different Depths." *Nature* 350: 411–413.

Board, C. 1967. "Maps as Models." In *Models in Geography*, edited by R. Chorley, and P. Haggett, 671–725. London: Methuen.

Boddy, N.C., D.J. Booker, and A.R. McIntosh. 2019. "Confluence Configuration of River Networks Controls Spatial Patterns in Fish Communities." *Landscape Ecology* 34: 187–201. https://doi.org/10.1007/s10980-018-0763-4.

Clay, P.A., J.D. Muehlbauer, and M.W. Doyle. 2015. "Effect of Tributary and Braided Confluences on Aquatic Macroinvertebrate Communities and Geomorphology in an Alpine River Watershed." *Freshwater Science* 34: 845–856. https://doi.org/10.1086/682329.

Czeglédi, I., P. Sály, P. Takács, A. Dolezsai, S.A. Nagy, and T. Erős. 2016. "The Scales of Variability of Stream Fish Assemblages at Tributary Confluences." *Aquatic Sciences* 78: 641–654, https://doi.org/10.1007/s00027-015-0454-z.

Daubenmire, R. 1978. *Plant Geography: With Special Reference to North America*. New York: Academic Press. ISBN 0-12-204150-X.

Elmore, A.J., and S.S. Kaushal. 2008. "Disappearing Headwaters: Patterns of Stream Burial Due to Urbanization." *Frontiers in Ecology and the Environment* 6: 308–312. https://doi.org/10.1890/070101.

Fernandes, C.C., J. Podos, and J.G. Lundberg. 2004. "Amazonian Ecology: Tributaries Enhance the Diversity of Electric Fishes." *Science* 305: 1960–1962. https://doi.org/10.1126/science.1101240.

Franks, C.A., S.P. Rice, and P.J. Wood. 2002. "Hydraulic Habitat in Confluences: An Ecological Perspective on Confluence Hydraulics." In. *The Structure, Function, and Management Implications of Fluvial Sediment Systems*, edited by F.J. Dyer, M.C. Thoms, and J.M. Olley, 61–69. IAHS Publication 276, Centre for Ecology and Hydrology. Oxfordshire, UK: IAHS Press.

Frissell, C.A., W.J. Liss, C.E. Warren, and M.D. Hurley. 1986. "A hierarchical framework for stream habitat classification: Viewing Streams in a Watershed Context." *Environmental Management* 10: 199–214.

Fritz, K.M., E. Hagenbuch, E. D'Amico, M. Reif, P.J. Wigington, Jr., S.G. Liebowitz, R.L. Comeleo, J.L. Ebersole, and T.-L. Nadeau. 2013. "Comparing the Extent and Permanence of Headwater Streams from Two Field Surveys to Values from Hydrologic Databases and Maps." *Journal of the American Water Resources Association* 49: 867–882. https://doi.org/10.1111/jawr.12040.

Fritz, K.M., B.R. Johnson, and D.M. Walters. 2008. "Physical Indicators of Hydrologic Permanence in Forested Headwater Streams." *Journal of the North American Benthological Society* 27: 690–704.

Grant, E.H.C., W.H. Lowe, and W.F. Fagan. 2007. "Living in the Branches: Population Dynamics and Ecological Processes in Dendritic Networks." *Ecology Letters* 10: 165–175. https://doi.org/10.1111/j.1461-02480.6006.01007.x.

Grenouillet, G., D. Pont, and C. Hérissé. 2004. "Within-Basin Fish Assemblage Structure: The Relative Influence of Habitat versus Stream Spatial Position on Local Species Richness." *Canadian Journal of Fisheries and Aquatic Sciences* 61: 93–102. https://doi.org/10.1139/f03-145.

Hellman, J.K., J.S. Erikson, and S.A. Queenborough. 2015. "Evaluating Macroinvertebrate Community Shifts in the Confluence of Freestone and Limestone Streams." *Journal of Limnology* 74: 64–74. https://doi.org/10.4081/jlimnol.2014.935.

Hill, R.A., M.H. Weber, S.G. Leibowitz, A.R. Olsen, and D.J. Thornbrugh. 2016. "The Stream-Catchment (StreamCat) Dataset: A Database of Watershed Metrics for the Conterminous United States." *Journal of the American Water Resources Association* 52: 120–128. https://doi.org/10.1111/1752-1688.12372.

Hitt, N.P., and P.L. Angermeier. 2008. "Evidence for Fish Dispersal from Spatial Analysis of Stream Network Topology." *Journal of the North American Benthological Society* 27: 304–320. https://doi.org/10.1899/07.096.1.

Homer, C., J. Dewitz, L. S. Jin, G. Xian, C. Costello, P. Danielson, L. Gass et al. 2020. "Conterminous United States Land Cover Change Patterns 2001–2016 from the 2016 National Land Cover Database." *ISPRS Journal of Photogrammetry and Remote Sensing* 162: 184–199. https://doi.org/10.1016/j.isprsjprs.2020.02.019.

Homer, C., J. Dewitz, L. Yang, S. Jin, P. Danielson, G. Xian, J. Coulston, N. Herold, J. Wickham, and K. Megown. 2015. "Completion of the 2011 National Land Cover Database for the Conterminous United States — Representing a Decade of Land Cover Change Information." *Photogrammetric Engineering & Remote Sensing* 81: 345–354.

Johnston, C.M., T.G. Dewald, T.R. Bondelid, B.R. Worstell, L.D. McKay, A. Rea, R.B. Moore, and J.L. Goodall. 2009. "Evaluation of Catchment Delineation Methods for the Medium-Resolution National Hydrography Dataset." U.S. Geological Survey Scientific Investigations Report 2009–5233. https://pubs.usgs.gov/sir/2009/5233/pdf/sir2009-5233.pdf.

Jones, K.B., K.H. Riitters, J. Wickham, R.D. Tankersley, R.V. O'Neill, D.J. Chaloud, E.R. Smith, and A.C. Neale. 1997. *An Ecological Assessment of the United States Mid-Atlantic Region: A Landscape Atlas*. Washington, DC: United States Environmental Protection Agency, Office of Research and Development. https://www.srs.fs.usda.gov/pubs/misc/epa_600_r-97_130.pdf.

Jones, N.E., and B.J. Schmidt. 2017. "Tributary Effects in Rivers: Interactions of Spatial Scale, Network Structure, and Landscape Characteristics." *Canadian Journal of Fisheries and Aquatic Sciences* 74: 503–510. https://doi.org/10.1139/cjfas-2015-0493.

Katano, I., J.N. Negishi, T. Minagawa, H. Doi, Y. Kawaguchi, and Y. Kayaba 2009. "Longitudinal Macroinvertebrate Organization over Contrasting Discontinuities: Effects of a Dam and a Tributary." *Journal of the North American Benthological Society* 28: 331–351. https://doi.org/10.1899/08-010.1.

Kiffney, P.M., C.M. Green, J.E. Hall, and J.R. Davies. 2006. "Tributary Streams Create Spatial Discontinuities in Habitat, Biological Productivity, and Diversity in Mainstem Rivers." *Canadian Journal of Fisheries and Aquatic Sciences* 63: 2518–2530. https://doi.org/10.1139/F06-138.

King, R. 1982. "On Geography, Cartography and the 'Fourth Language'." *Geographical Research Forum* 5: 42–56.

Knispel, S., and E. Castella. 2003. "Disruption of a Longitudinal Pattern of Environmental Factors and Benthic Fauna by a Glacial Tributary." *Freshwater Biology* 48: 604–618. https://doi.org/10.1046/j.1365-2427.2003.01030.x.

Lang, M., O. McDonough, G. McCarty, R. Oesterling, and B. Wilen. 2012. "Enhanced Detection of Wetland-Stream Connectivity Using LIDAR." *Wetlands* 32: 461–473. https://doi.org/10.1007/s13157-012-0279-7.

Levins, R. 1966. "The Strategy of Model Building in Population Biology." *American Scientist* 54: 421–431.

Mac Nally, R., E. Wallis, and P.S. Lake. 2011. "Geometry of Biodiversity Patterning: Assemblages of Benthic Macroinvertebrates at Tributary Confluences." *Aquatic Ecology* 45: 43–54. https://doi.org/10.1007/s10452-010-9332-z.

McKay, L., T. Bondelid, T. Dewald, J. Johnston, R. Moore, and A. Rea. 2018. "NHDPlus Version2: User Guide (Data Model Version 2.1)." https://nhdplus.com/NHDPlus/NHDPlusV2_documentation.php#NHDPlusV2%20User%20Guide.

Milesi, S.V., and A.S. Melo. 2014. "Conditional Effects of Aquatic Insects of Small Tributaries on Mainstream Assemblages: Position within Drainage Network Matters." *Canadian Journal of Fisheries and Aquatic Sciences* 71: 1–9. https://doi.org/10.1139/cjfas-2013-0092.

Milner, V.S., S.M. Yarnell, and R.A. Peek. 2019. "The Ecological Importance of Unregulated Tributaries to Macroinvertebrate Diversity and Community Composition in an Unregulated River." *Hydrobiologia* 829: 291–305. https://doi.org/10.1007/s10750-018-3840-4.

Pickard, B.R., J. Daniel, M. Mehaffey, L.E. Jackson, and A. Neale. 2015. "EnviroAtlas: A new geospatial Tool to Foster Ecosystem Services Science and Resource Management." *Ecosystem Services* 14: 45–55. https://doi.org/10.1016/j.ecoser.2015.04.005.

Poff, N.L., J.D. Allan, M.B. Bain, J.R. Karr, K.L. Prestegaard, B.D. Richter, R.E. Sparks, and J. C. Stromberg. 1997. "The Natural Flow Regime." *BioScience* 47: 769–784. https://doi.org/10.2307/1313099.

Popkin, G. 2018. "US Government Reviews Data Fees." *Science* 556: 417–418.

Rhoads, B.L. 1987. "Changes in Stream Channel Characteristics at Tributary Junctions." *Physical Geography* 8: 346–361. https://doi.org/10.1080/02723646.1987.10642333.

Rhoads, B.L., and K.K. Johnson. 2018. "Three-Dimensional Flow Structure, Morphodynamics, Suspended Sediment, and Thermal Mixing at an Asymmetrical River Confluence of a Straight Tributary and Curving Main Channel." *Geomorphology* 323: 51–69. https://doi.org/10.1016/j.geomorp.2018.09.009.

Rice, S.P. 1998. "Which Tributaries Disrupt Downstream Fining along Gravel-Bed Rivers?" *Geomorphology* 22: 39–56.

Rice, S.P., M.T. Greenwood, and C.B. Joyce. 2001. "Tributaries, Sediment Sources, and the Longitudinal Organisation of Macroinvertebrate Fauna along River Systems." *Canadian Journal of Fisheries and Aquatic Sciences* 58: 824–840. https://doi.org/10.1139/F01-022.

Rice, S.P., P. Kiffney, C. Greene, and G.R. Pess. 2008. "The Ecological Importance of Tributaries and Confluences." In *River Confluences, Tributaries, and the Fluvial Network*, edited by S.P. Rice, A.G. Roy, and B.L. Rhoads, 209–242, John Wiley & Sons, Ltd. ISBN 978-0-470-02672-4.

Roy, A.H., A.L. Dybas, K.M. Fritz, and H.R. Lubbers. 2009. “Urbanization Affects the Extent and Hydrologic Permanence of Headwater Streams in a Midwestern US Metropolitan Area.” *Journal of the North American Benthological Society* 28: 911–928. https://doi.org/10.10899/08-178.1.

SAS Institute Inc. 2015. *SAS/STAT® 15.1 User’s Guide*. Cary, NC: SAS Institute Inc.

Shilling, F., S. Sommarstrom, R. Kattelmann, B. Washburn, J. Florsheim, and R. Henly. 2005. “California Watershed Assessment Guide.” Prepared for the California Resources Agency. http://cwam.ucdavis.edu/cwam_chapters/cwag_web_bw.pdf; https://www.lgc.org/resource/california-watershed-assessment-manual/

Slattery, M.C., and J.D. Phillips. 2011. “Controls of Sediment Delivery in the Coastal Plain.” *Journal of Environmental Management* 92: 284–289. https://doi.org/10.1016/j.jenvman.2009.08.022.

Statzner, B., and B. Higler. 1986. “Stream Hydraulics as a Major Determinant of Benthic Invertebrate Zonation Patterns.” *Freshwater Biology* 16: 127–139. https://doi.org/10.1111/j.1365-2427.1986.tb00954.x.

Thornbrugh, D.J., and K.B. Gido. 2010. “Influence of Spatial Positioning with Stream Networks on Fish Assemblage Structure in the Kansas River Basin, USA.” *Canadian Journal of Fisheries and Aquatic Sciences* 67: 143–156. https://doi.org/10.1139/F09-169.

Thornbrugh, D.J., S.G. Leibowitz, R.A. Hill, M.H. Weber, Z.C. Johnson, A.R. Olsen, J.E. Flotemersch, J.L. Stoddard, and D.V. Peck. 2018. “Mapping Watershed Integrity for the Conterminous United States.” *Ecological Indicators* 85: 1133–1148. https://doi.org/10.1016/j.eoclind.2017.10.070.

USGS, USDA-NRCS (U.S. Geological Survey and U.S. Department of Agriculture, Natural Resources Conservation Service). 2013. *Federal Standards and Procedures for the National Watershed Boundary Dataset (WBD)* (Fourth Edition). U.S. Geological Survey Techniques and Methods 11–A3, 63 pp. https://pubs.usgs.gov/tm/tm11a3/.

Van Craenendonck, T., and H. Blockeel. 2015. “Using Internal Validity Measures to Compare Clustering Algorithms.” In AutoML Workshop at International Conference on Machine Learning (ICML), Lille, France, 7–9 July, 2015, 1–8. https://lirias.kuleuven.be/retrieve/330191.

Weisberg, M. 2006. “Forty Years of ‘The Strategy’: Levins on Model Building and Idealization.” *Biological Philosophy* 21: 623–645. https://doi.org/10.1007/s10539-006-9051-9.

White, M.S., B.G. Tavernia, P.B. Shafroth, T.B. Chapman, and J.S. Sanderson. 2018. “Vegetative and Geomorphic Complexity at Tributary Junctions on the Colorado and Dolores Rivers: A Blueprint for Riparian Restoration.” *Landscape Ecology* 33: 2205–2220. https://doi.org/10.1007/s10980-018-0734-9.

Whittier, J.R., J.L. Stoddard, D.P. Larsen, and A.T. Herlih. 2007. “Selecting Reference Sites for Stream Biological assessments: best Professional Judgement or Objective Criteria.” *Journal of the North American Benthological Society* 26: 349–360.

Wickham, J.2019. “A United States National Database of Stream Confluence Landscape Characteristics.” PANGEA. https://doi.org/10.1594/PANGAEA.909230.

Wickham, J., N. Herold, S.V. Stehman, C.G. Homer, G. Xian, and P. Claggett. 2018. “Accuracy Assessment of NLCD Impervious Cover for the Chesapeake Bay Region.” *International Journal of Photogrammetry and Remote Sensing* 146: 151–160. https://doi.org/10.1016/j.isprsjprs.2018.09.010.

Wickham, J., K.B. Jones, K.H. Riitters, R.V. O’Neill, R.D. Tankersley, E.R. Smith, A.C. Neale, and D.J. Chaloud. 1999. “An Integrated Environmental Assessment of the US Mid-Atlantic Region.” *Environmental Management* 24: 553–560.

Wickham, J., and K.H. Riitters. 2019. “Influence of High Resolution Data on the Assessment of Forest Fragmentation.” *Landscape Ecology* 34: 2169–2182. https://doi.org/10.1007/s10980-019-00820-z.

Wickham, J., K. Riitters, P. Vogt, J. Costanza, and A. Neale. 2017. “An Inventory of Continental U.S. Terrestrial Candidate Ecological Restoration Areas Based on Landscape Context.” *Restoration Ecology* 25: 894–202. https://doi.org/10.1111/rec.12522.

Wickham, J.S.V., C.G. Stehman, and C.G. Homer. 2018. “Spatial Patterns of the United States National Land Cover Dataset (NLCD) Land-Cover Change Thematic Accuracy (2001–2011).” *International Journal of Remote Sensing* 39: 1729–1743. https://doi.org/10.1080/01431161.2017.1410298.

Wickham, J., S.V. Stehman, L. Gass, J.A. Dewitz, D.G. Sorenson, B.J. Granneman, R.V. Poss, and L.A. Baer. 2017. “Thematic Accuracy Assessment of the 2011 National Land Cover Database (NLCD).” *Remote Sensing of Environment* 191: 328–341. https://doi.org/10.1016/j.rse.2016.12.026.

Wickham, J., S.V. Stehman, A.C. Neale, and M. Mehaffey. 2020. “Accuracy Assessment of NLCD 2011 Impervious Cover for Selected USA Metropolitan Areas.” *International Journal of Applied Earth Observation and GeoInformation.* 84: 101955. https://doi.org/10.1016/j.jag.2019.101955.

Yang, L., S. Jin, P. Danielson, C. Homer, L. Gass, S.M. Bender, A. Case et al. 2018. “A New Generation of the United States National Land Cover Database: Requirements, Research Priorities, Design, and Implementation Strategies.” *ISPRS Journal of Photogrammetry and Remote Sensing* 146: 108–123. https://doi.org/10.1016/j.isprsjprs.2018.09.006.