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Authors
Wang, Zhihao
Pasternack, Gregory Brian
Jin, Yufang
et al.

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Bridging natural and artificial: Stream reach classification for mixed watersheds

Zhihao Wang[1,2,†], Gregory Brian Pasternack[2], Yufang Jin[2], Costanza Rampini[3], Serena Alexander[4], Nikhil Kumar[2], K. Martin Perales[5], Stephanie Moreno[6], Christopher Lim[7], Rune Storesund[8], and Igor Lacan[9]

[1]*Institute of Space Earth Science, Nanjing University, Suzhou 215163, China*
[2]*Department of Land, Air and Water Resources, University of California, 1 Shields Avenue, Davis, California 95616, USA*
[3]*Department of Environmental Studies, San José State University, One Washington Square, San Jose, California 95192, USA*
[4]*Department of Civil and Environmental Engineering, Northeastern University, Boston, Massachusetts 02115, USA*
[5]*Napa County Resource Conservation District, 1303 Jefferson Street, Suite 500B, Napa, California 94559, USA*
[6]*North Santa Clara Resource Conservation District, 888 N. 1st Street, Suite 204, San Jose, California 95112, USA*
[7]*Contra Costa Resource Conservation District, 2001 Clayton Road, Suite 200, Concord, California 94520, USA*
[8]*SafeR3, 154 Lawson Road, Kensington, California 94707, USA*
[9]*University of California Cooperative Extension, San Mateo/San Francisco Counties, 1500 Purissima Creek Road, Half Moon Bay, California 94019, USA*

ABSTRACT

Heavily managed urban streams, agricultural drainages, and least modified natural streams are rarely analyzed within a single framework, even though modern landscapes include a mix of them. Urbanization, agriculture, deforestation, mining, and other intensive land uses have dramatically altered fluvial systems. Most existing stream classification frameworks were developed for natural streams and rely only on natural geomorphic attributes. The few that address artificial streams focus exclusively on engineered (artificial) characteristics and usually address only a single land-use setting. As a result, these frameworks do not capture the full diversity of stream conditions found in mixed land-use watersheds that are influenced by both natural processes and human interventions. Recognizing this problem, our study proposes a joint geomorphic classification framework that collects and analyzes field data that captures both engineering and geomorphic attributes of streams in mixed land-use watersheds. We implemented this joint framework in a prime example of a mixed land-use watershed—the San Francisco Bay Area, California, USA. We collected a dataset for 164 stream sites. By using hierarchical cluster analysis on 92 variables computed from the field data, we identified 12 regional stream types, including six artificial and six natural ones. Our results demonstrate that this joint framework differentiates unique natural and artificial stream types in urban, agricultural, and wilderness settings. It also captures the subtle internal variability within artificial and natural stream types. Field photograph interpretation corroborates statistical findings that the diverse variables effectively represent real-world conditions of both types. Overall, by blending natural characteristics and the degree of human intervention, our classification provides critical insights that enhance our ability to understand river behavior in heavily managed urbanized, agricultural, and wilderness regions. It holds significant promise for informing targeted restoration and conservation strategies, ultimately contributing to more effective river management and sustainable watershed planning.

INTRODUCTION

Stream conditions vary widely within and across watersheds, encompassing a mix of land uses ranging from urban to agricultural to wilderness areas. The variability in stream conditions are primarily a result of the effects of direct or indirect human activities, often reflected in the morphology and composition of streams (Flatley et al., 2018; Castro and Thorne, 2019). Previous studies have broadly categorized streams based on the extent of human intervention into two main types: natural and artificial streams (Wohl and Merritts, 2007). More research has been done on the diversity of natural streams, including the extent to which they are distinct from each other or subtle variations along a gradient. Meanwhile, there are few studies of the types of artificial streams, their diagnostic variables, and how clustered or continuous sites are in n-dimensional variable phase space (e.g., plotting width versus median grain size versus degree of entrenchment versus bed slope versus valley confinement, etc.). Therefore, to advance the understanding of the functional differences within and between artificial and natural streams in mixed land-use watersheds, this study applied a standardized field protocol for natural and artificial conditions to quantify reach-scale characteristics and integrate results into a unified stream classification, providing a novel and comprehensive framework for geomorphic analysis.

What Are Natural and Artificial Streams?

Natural streams are watercourses whose planform, profile, banks, and bed materials are produced and sustained by hydrogeomorphic and biotic processes rather than determined by engineered works (Rosgen, 1994; Montgomery and Buffington, 1997; Brierley and Fryirs, 2013). At the reach scale, they typically exhibit irregular morphologies (e.g., sinuous, meandering, and braiding) and are composed of natural sediments (e.g., sand, cobbles, and boulders). Natural streams may be, and often are, impacted by adjacent and catchment-scale human activities, but they exhibit resilience by adjusting their geomorphic characteristics in a variety of ways to maintain functional integrity (Wohl and Merritts, 2007; Pasternack, 2013).

Zhihao Wang https://orcid.org/0000-0001-6342-5784
[†]zhhwa@ucdavis.edu

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In contrast, artificial streams are channels whose geometry, hydraulics, or stability are substantially set by design or ongoing maintenance, typically for purposes such as flood control, irrigation, or bank protection (Davenport et al., 2004). Compared to natural streams, artificial streams usually are less topographically complex, featuring straightened channels and regularized cross-sectional forms (e.g., trapezoidal or rectangular) that remain consistent along their length (Flatley et al., 2018). They also may have engineered bed and/or bank materials (e.g., concrete, riprap, gabions, or stitch piers). These morphological and material differences result in artificial streams exhibiting distinct hydrogeomorphic processes and ecological functions at the reach scale (Stenfert Kroese et al., 2020). For example, artificially straightening streams with impervious surfaces tend to have a reduction of in-stream habitat and decrease habitat diversity. Some artificial types may be deposition dominated while others are erosion dominated, given the same hydrological and sediment supply regimes.

When working in regions and catchments that have both natural and artificial streams, challenging problems arise in developing a systematic approach to data collection and classification that works for all sites. One key issue arises from the lack of presence of or inability to identify process-based bankfull dimensions in engineered, highly degraded streams (Johnson and Heil, 1996), dryland streams (Chin, 2022), or every 200 m of even ideal temperate streams (Edwards et al., 2019). Thus, a suitable framework is needed to capture representative geomorphic characteristics of diverse streams in a region without relying on all the assumptions embedded in the bankfull-geometry paradigm.

Review of Geomorphic Reach-Scale Stream Classifications

For decades, relying on attributes measured at the reach scale, numerous geomorphic stream reach classification schemes have been proposed to describe and understand the diversity of channel forms across a landscape. To frame the new research herein, we organize this history in terms of three key issues: top-down versus bottom-up approach, a lack of spanning natural and artificial types, and a lack of addressing the diversity of artificial stream types.

Top-Down and Bottom-Up Approaches

One important conceptual distinction in these schemes is between "top-down" and "bottom-up" approaches (Wyrick and Pasternack, 2014; Guillon et al., 2020; Woodworth and Pasternack, 2022). In a top-down (concept-driven) approach, stream types are defined a priori based on theory or expert knowledge. In contrast, a bottom-up (data-driven) approach defines stream types inductively from observed data. Neither approach is inherently more "process-based," as that outcome depends on what the classification designer is cognizant of and what data is collected. Thus, each approach has pros and cons; both merit continued research. A brief synopsis of the recent studies that have adopted geomorphic reach-scale stream classification, highlighting whether they use a top-down or bottom-up approach, whether they require field-based metrics, and their typical applicability to natural and/or artificial streams, is given in Table 1.

The top-down classification process involves stepping through a decision logic to determine which stream type a particular reach belongs to, often considering hydraulic and sedimentary conditions, and sometimes envisioning morphodynamic processes. For example, the River Styles Framework classifies streams into expert-defined types based on natural river characteristics (constrained, meandering, etc.). Experts identify these types in the field by examining the valley context, planform, and geomorphic units (Brierley and Fryirs, 2013). However, top-down approaches inherently reflect the biases or limitations of their predefined stream types, resulting in unusual reaches that do not fit the expected patterns and may be forced into a less-than-ideal stream type.

In contrast, bottom-up approaches utilize statistical techniques (e.g., cluster analysis) to group reaches into stream types based on similarity across multiple variables. For example, Byrne et al. (2020a) applied a cluster analysis in grouping natural rivers in the California coastal region and named each stream type according to the field-based metrics (e.g., bankfull width). However, bottom-up approaches can only classify what is in the data, and in relative abundance in the data, forcing users to gather as much data as possible, which is constrained by time, budget, and effort.

Lack of Spanning Natural and Artificial Types

A second important conceptual distinction is that no classifications span natural and artificial stream types, despite the richness of geomorphic stream reach classification frameworks available (Table 1). Most classification approaches have been developed predominantly for natural streams in relatively undisturbed environments, often neglecting the engineered modifications found in urban or suburban streams (e.g., Byrne et al., 2020b). This results in artificial streams being largely absent from reference datasets used to build classifications. While some studies have been designed to focus exclusively on artificial streams by emphasizing the engineered features in urban environments, such approaches tend to overlook the intrinsic variability and complex geomorphic processes that occur in natural stream systems to bring such insights into the artificial realm (e.g., Davenport et al., 2004). Consequently, there is a failure to accommodate natural sediment flux and habitat functions in class design, ultimately undermining both the performance and ecological integration of artificial streams. In addition, although recent studies have increasingly recognized artificial streams as essential components of stream networks (Castro and Thorne, 2019; Buffington and Montgomery, 2022), artificial streams are still classified in a very simplified manner, often labeled simply as "channelized" and treated as a separate category without further geomorphic differentiation.

As categorically different as natural and artificial streams are, studies have documented how their morphodynamic trajectories can change them to take on features of the other. Urban stream syndrome exemplifies pathways by which natural streams develop attributes similar to artificial ones (Walsh et al., 2005), though usually not with the same design lateral slopes and artificial composition elements. Meanwhile, some artificial streams may regain natural features and processes over decades, yet that legacy needs to be characterized to contextualize site history and future potential. This has been documented by post-project geomorphic adjustments on the Provo River (Provo, Utah, USA; Goetz, 2008) and tidal-process recovery at Dotson Family Marsh (Richmond, California, USA; Bowen, 2012). It is also important to recognize effects at the subreach scale wherein artificial features (i.e., rock weirs, localized bank protection, bed sills, etc.) may significantly degrade natural stream landforms and processes, while natural features (e.g., beaver dams, sediment deposits, proto meandering, etc.) may significantly enhance those of artificial streams. For example, inset floodplain benches in two-stage agricultural ditches, engineered log jams in wood-starved reaches, or beaver-dam analogs in incised corridors have been shown to enhance hydraulic and geomorphic functions and habitat (Davis et al., 2015; Kalcic et al., 2018).

Lack of Diversity of Artificial Stream Types

A third important conceptual distinction is that there may be significantly different types of artificial channels depending on the land use. Artificial channels in urban, suburban, cultivated farmland, rangeland, wilderness, and mining settings may be so different that they require mindful differentiation. For example, drawing from the study area in this article, lower Wildcat and San Pablo Creeks, Contra Costa County, Califor-

TABLE 1. EXAMPLES OF CLASSIC AND RECENT GEOMORPHIC REACH-SCALE STREAM CLASSIFICATION FRAMEWORKS IN THE LITERATURE, HIGHLIGHTING WHETHER THEY USE A TOP-DOWN (CONCEPT-DRIVEN) OR BOTTOM-UP (DATA-DRIVEN) APPROACH, WHETHER THEY REQUIRE FIELD-BASED METRICS FOR GEOMORPHIC CLASSIFICATION, AND THEIR TYPICAL APPLICABILITY TO NATURAL AND/OR ARTIFICIAL STREAMS

Reference	Geomorphic classification approach	Requires field-based metrics for geomorphic classification	Applicable to
Davis (1973)	Top-down (continuum from youthful to old age)	Geological interpretation.	Only natural streams; not designed for artificial streams. Underlying theory is generally no longer held per Hack (1960).
Wolman and Leopold (1957); see also reviews by Alabyan and Chalov (1998) and Kleinhans (2010) on planform classifications citing preexisting and subsequent variants.	Top-down (planform types, generally braided, meandering, and straight channels)	Yes; two metrics (bankfull discharge and slope; over time more discriminators have been found).	Only natural streams; not designed for artificial streams.
Kellerhals et al. (1976)	Top-down (multiple types and their features without a simple set of groups)	No quantitative delineations. Six considerations (channel-valley flat relation, channel-valley walls relation, channel pattern, lateral channel activity, islands, and channel bars and major bed forms).	Only natural streams; not designed for artificial streams.
Schumm (1977); see also review of longitudinal zonal classifications by Rowntree et al. (2000), which includes a newer typology in this line.	Top-down (originally three types; Rowntree et al. is up to 10 types)	Originally conceptual with qualitative characteristics; some use slope.	Only natural streams; not designed for artificial streams.
Brice (1982)	Top-down (multiple types and their features)	Yes; 14 metrics.	Only natural streams; not designed for artificial streams.
Frissell et al. (1986)	Top-down (predefine nine types for small mountain streams)	Yes; eight metrics (gross typology, morphogenetic class, morphogenetic process, relative length, mean slope, dominant substrates, developmental trend, and potential persistence).	Only natural streams; not designed for artificial streams.
Kleinhans (2010)	Bottom-up (statistical analysis of changes in each variable)	Yes; six metrics (entrenchment ratio, width to depth ratio, sinuosity, number of channels, slope and sediment particle size).	Only natural streams; not designed for artificial streams.
Montgomery and Buffington (1997); for a variant with 4 alluvial and 5 bedrock types, see Rowntree et al. (2000).	Top-down (predefine seven mountain channel types)	Yes; four metrics (slope, grain size, shear stress, and roughness).	Only natural streams; not designed for artificial streams.
Newson et al. (1998)	Hybrid using both approaches. Bottom-up analysis yielded 13 types	Yes; 22 metrics.	One variable quantifies % of reach that is artificial but then data must also include three variables for bankfull dimensions that do not exist in artificial channels.
Brierley et al. (2002)	Top-down (multiple types and their features without a simple set of groups)	No; a visual assessment of a river style (reach) based on the degree of valley confinement, bed material texture, geomorphic units, and the presence and continuity of the channel.	Only natural streams; not designed for artificial streams.
Davenport et al (2004)	Bottom-up (cluster analysis)	Yes; detailed riverbed and riverbank materials.	Urban streams with engineering modifications; not natural streams.
Schmitt et al. (2007)	Bottom-up (cluster analysis with 17 types)	Yes; 31 metrics.	Only natural streams; not designed for artificial streams.
Piégay et al. (2009)	Bottom-up (cluster analysis of mountainous braided rivers)	Yes; number of metrics used in cluster analysis is not stated.	Only natural braided streams; not designed for artificial streams
Sutfin et al. (2014)	Top-down (predefine five ephemeral channel types)	Yes; eight metrics (stream gradient, width to depth ratio, ratio of valley width to channel width, shear stress, dimensionless shear stress, median grain size, stream power, and unit stream power).	Only natural streams; not designed for artificial streams.
Ghosh (2016)	Top-down (predefine four channel types)	Yes; nine metrics (channel cross-sectional area, volume of channel reach in between two cross sections, bankfull width, thalweg depth, width to depth ratio, the maximum width to depth ratio, sinuosity, entrenchment ratio, and channel slope).	Only natural streams; not designed for artificial streams.
Lane et al. (2017)	Bottom-up (cluster analysis of mountainous rivers in one hydrologic regime context yielding 9 types)	Yes; 17 metrics (wetted width to depth ratio, bankfull depth and width, bankfull width to depth ratio, bankfull depth/D50, entrenchment ratio, shear stress, shields stress, slope, sinuosity, D50, D84, Dmax, wetted depth and width variance, and bankfull depth and width variance).	Only natural streams; not designed for artificial streams.
Flatley et al. (2018)	Top-down (predefine six artificial channel types)	No.	Only for artificial streams that relate channels to new pathways.
Meehan and O'Brien (2019)	Top-down (predefine five ephemeral channel types)	Yes; seven metrics (entrenchment ratio, width to depth ratio, sinuosity, channel slope, median grain size, bank height ratio, and meander-width ratio).	Prairie streams.
Byrne et al. (2020b)	Bottom-up (cluster analysis of mountain and valley streams with 10 types)	Yes; nine metrics (water surface slope, bankfull depth, bankfull width, bankfull width to depth ratio, coefficient of variation of bankfull depth, coefficient of variation of bankfull width, median grain size, 84th percentile grain size, and channel roughness) and three GIS-derived metrics (hydrologic contributing area, sinuosity, valley confinement distance).	Only natural streams; not designed for artificial streams.
Lane et al. (2022)	Bottom-up (cluster analysis aggregating 62 regional types into 10 statewide types)	Yes; nine metrics (reach slope, bankfull depth, width, width to depth ratio, coefficient of variation of bankfull depth and width, median and 84th percentile grain size, and channel roughness).	Only natural streams; not designed for artificial streams.
Li et al. (2024)	Top-down (predefine channel types)	Yes; four metrics (entrenchment ratio, width to depth ratio, slope, and grain size).	Only natural streams; not designed for artificial streams.

nia, illustrate hardened, entrenched designs and subsequent levee-rehab and setback efforts for urban flood-control corridors (Denninger, 2015). In significant contrast to those, the streams east of Vacaville, California, consist of small, trapezoidal agricultural drainage ditches experiencing erosion that feed into large trapezoidal (sometimes bank-hardened) suburban drainage canals experiencing deposition.

Study Purpose

The world's river networks include a mix of natural and artificial rivers, yet this dichotomy has not been defined and quantified. As such, there is a compelling need for a unified, reach-scale framework that simultaneously collects and integrates the geomorphic and engineered features of streams in order to classify the full diversity of stream conditions in mixed land-use watersheds (Flatley et al., 2018). In this article, we propose a joint natural/artificial, data-driven geomorphic stream reach classification framework by conceptualizing and using a set of artificial-stream attributes related to the composition and shape of riverbed and riverbank, as these influence hydraulic processes, sediment transport, and channel stability (Miller and Craig Kochel, 2013; Rinaldi et al., 2016). We also propose a modification of traditional natural-stream attributes, by removing the requirement to measure "bankfull" dimensions that often are not present at human-impacted reaches and outright do not exist in artificial reaches, thereby making a measurement system that is useable regardless of the presence of bankfull conditions.

By integrating geomorphic and engineering perspectives, we advance the science of river classification to include coupled natural–human systems, recognizing the interdependence between natural processes and human activities in shaping streams. The results obtained by the joint classification framework can capture the diversity of natural to artificial stream types, providing new insights into how human interventions alter river form and process as well as just how extensive such modifications have been globally. In practice, it can improve regional stream inventories, yielding the well-cited benefits of stream classification for regional river management when taking a systemic approach (e.g., Everard and Powell, 2002). For example, guiding restoration and nature-based solutions requires moving beyond identifying natural reference conditions to also setting realistic targets for artificial channels. To do that, it is first critical to know what these artificial types are and what the unique geomorphological processes and ecological functions are for each type. Rather than ending the debate on stream classification, we hope this study opens the way for an expansion for basic scientific inquiry across natural and artificial streams, which is sorely lacking.

MATERIALS AND METHODS

Study Area

Ranging from densely urbanized centers and suburban developments to agricultural fields and wilderness areas, the nine-county San Francisco Bay Area, California, represents a quintessential example of modern, mixed land-use watersheds. It has a 2023 population of over 7.7 million people and average human densities exceeding 1500 people per km^2 in core urban counties (2023 U.S. Census; Metropolitan and Micropolitan Statistical Areas Population Totals: 2020–2023: https://www.census.gov/data/tables/time-series/demo/popest/2020s-total-metro-and-micro-statistical-areas.html). According to the 2019 National Land Cover Database, 42% of the region's surface area is mapped as developed, 13% as agriculture, and the remainder as forest, shrubland, or open water. The developed share was ~36% in the early 2000s (Multi-Resolution Land Characteristics Consortium, https://www.mrlc.gov/data [accessed July 2025]).

Located in the Mediterranean climate zone, the San Francisco Bay Area experiences cool wet winters and warm dry summers (Krugler et al., 2025). Mean annual precipitation ranges from roughly 250 mm in the rain-shadowed east bay to over 2500 mm in the high-elevation headwaters, with most rain falling between November and March (Rahimi et al., 2020). The stream network in the San Francisco Bay Area spans a diversity of channel conditions, such as wild and natural in the remote mountains and completely engineered in the dense urban core. Urbanization, rangeland and cultivated farmland agricultural practices, historic mining and logging, wildfire, suburban sprawl, and other cumulative catchment dynamics collectively altered channel morphology and sediment dynamics. Relatively few streams have dams and flow regulation, but some do (e.g., San Pablo Dam, Anderson Dam, and Conn Dam). Many streams run dry in the summer, especially in the southern and eastern subregions.

There is no preexisting, dedicated stream classification for the San Francisco Bay Area that accounts for natural and artificial stream types together. Lane et al. (2022) classified the natural stream network in California into 62 regional stream types and aggregated them into 10 statewide types. But this contraction goes too far for use in the San Francisco Bay Area, and it excludes artificial and anthropogenically altered types. While not making a stream classification per se, San Francisco Estuary Institute-Aquatic Science Center (2021) made a bed and bank composition typology from 287 field sites in Sonoma and Santa Clara counties.

To fill this gap in stream classification frameworks, we conducted the experimental implementation of a new site-selection and stream classification framework in the San Francisco Bay Area. It was built on the National Hydrography Data set Plus High Resolution (NHDPlusHR; 2022 National Geospatial Program Standards and Specifications, https://www.usgs.gov/ngp-standards-and-specifications/hydrography-standards-and-specifications [accessed May 2024]), which was made using the High Resolution (1:24,000-scale or better) National Hydrography Data set, the nationally complete Watershed Boundary Data set, and the 10 m 3D Elevation Program data (Moore et al., 2019). Following Byrne et al. (2020b), we divided the stream network into 200 m intervals from network tips and moving downstream. Finally, after removing short residual intervals at tributary junctions, 42,144 two-hundred-meter intervals within a 13,344.91 km^2 catchment area were extracted.

Site Selection

Site selection is essential for bottom-up river classification to capture geomorphic diversity spanning known types in a region as well as stream types that are present but not recognized yet (Lane et al., 2017). For this study, we employed the novel site-selection framework of Wang et al. (2025) developed as part of this project. In brief, the framework involved three steps: (1) initial field site selection via machine learning from prior datasets about stream conditions, (2) selected field site accessibility evaluation and observation, and (3) additional field site decision and selection via an iterative learning process. This approach allows users to efficiently allocate limited resources by focusing on the essential samples needed for classification. We prioritized identifying and sampling previously unknown or underrepresented stream types by iteratively updating our list of potential field sites.

The field team surveyed 164 stream sites from April to December of 2023 (Fig. 1). Because much of the San Francisco Bay Area is privately owned, some targeted sites were ultimately inaccessible for lack of permission to access them. Nevertheless, substantial effort was made to track down and sample the diversity of stream conditions present within the sampling domain.

Field Observation Protocol

A novel field protocol was used that can be applied consistently across natural to artificial

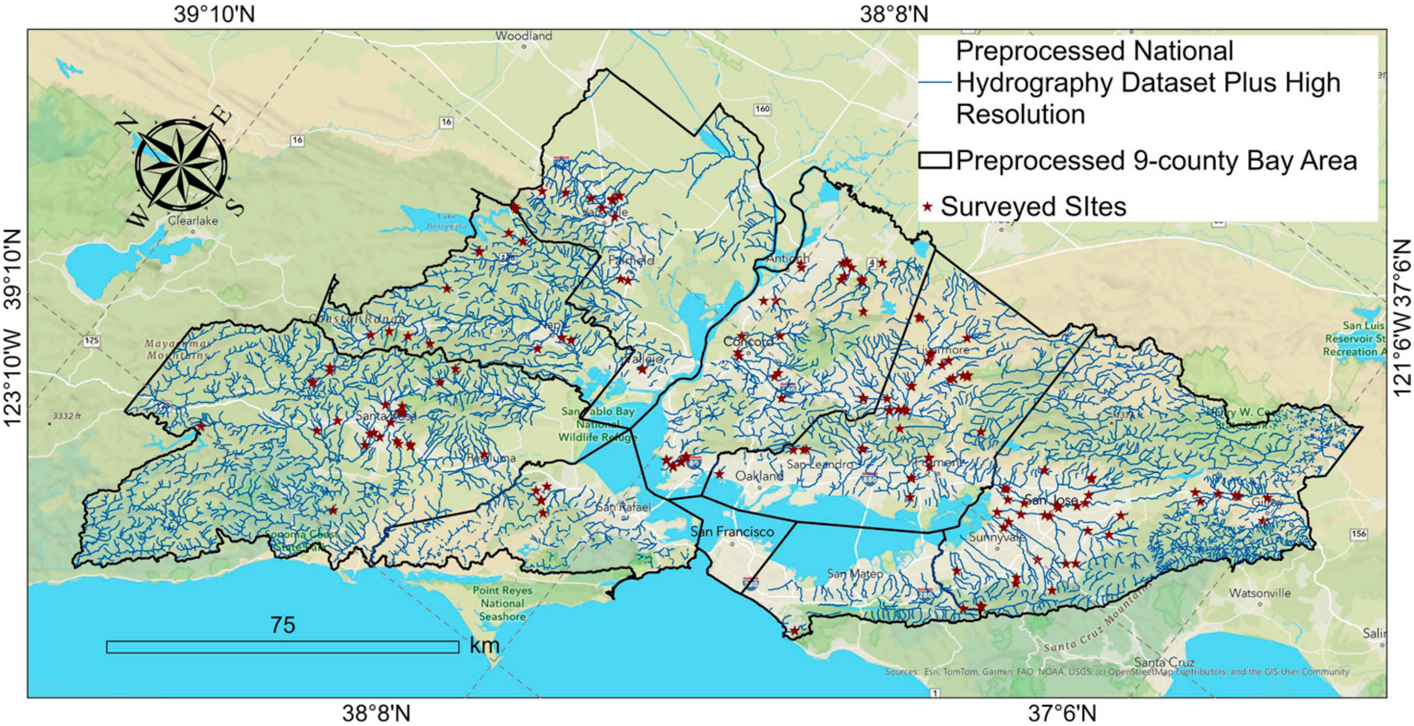


Figure 1. Locations of 164 surveyed sites in the San Francisco Bay Area. Area is divided into counties with thicker black lines. Large white areas are water bodies, estuarine marshes, or unchanneled agricultural and range lands.

streams, which can be summarized in five steps (Table 2 and Fig. 2). The detail of each protocol step is provided in Supplemental Material Text S1,[1] including a supplementary video, a detailed PDF presentation, and a set of digital field datasheets. Our field protocol generated a comprehensive dataset comprising both qualitative and quantitative variables, which can be further processed to derive an expanded set of classification variables. For qualitative variables, such as left and right riverbed toe, the field crew discusses them together to come to an expert-based group consensus. Subsequently, a quality assurance procedure is undertaken in which the senior geomorphologist and lead field scientist use the numerous photos taken at each site and aerial imagery to review every decision; they can also discuss individual difficult sites with field crew members to understand any context missed in the photos and aerial images. Instead of obtaining traditional cross-section variables based on stream-gaging historical origins, such as a single channel width or depth (e.g., active or bankfull dimensions), this protocol obtains every width and depth for every present lateral slope break at each transect. It also enables subsequent calculation of lateral slopes for every landform at each transect on each side of the stream relative to the riverbed toe on the same side and calculation of longitudinal slope at each persistent landform lateral slope break.

Based on previous studies (Davenport et al., 2001, 2004; Gurnell et al., 2007; Hohensinner et al., 2018), we propose a new set of criteria for identifying artificial streams (Table 3). Both composition (com) and shape are assessed visually during the field survey. These are assessed for both riverbanks and riverbeds, independently. After all cases are reviewed in the quality control procedure, edge cases are reviewed to establish rules to guide decision-making.

Since bankfull dimensions cannot be collected across all stream types, we replaced the commonly used entrenchment variable of Rosgen (1994) with an absolute entrenchment height measure. Absolute entrenchment is sensible within a region, but height thresholds may need to be adjusted between regions. For the San Francisco Bay Area, we found two reasonable thresholds. At each site, we visually assess the vertical distance from the thalweg to the valley-floor break in slope considering human height and assign one of three classes: slightly entrenched (<1.82 m, <6 U.S. ft), moderately entrenched (1.82–3.64 m, 6–12 U.S. ft), or highly entrenched (>3.64 m, >12 U.S. ft). The protocol also collects quantitative entrenchment values as the height between the thalweg and the valley floor edge, for sites where that is present (Section 2.4). Moreover, we distinguish this from a measure of the relation between a channel and its valley walls (i.e., confinement), recognizing entrenchment as a geomorphic adjustment process (e.g., Macklin et al. 2013) and confinement as a valley-form constraint (Fryirs et al., 2016).

Not all protocol features are present at every transect or site. Thus, some variables will not be useable for classification, though they can still be used for the characterization of individual stream types. For example, if the field crew consistently identifies bankfull dimensions in a stream type, then those variables can be used to help understand the type they are found in. Overall, this new protocol yields a comprehensive topographic dataset for river characteriza-

[1]Supplemental Material. Additional figures and tables that support and expand upon the methods, results, and interpretations presented in the main text, including a detailed field protocol (Text S1), Pearson correlation analyses for the full set of surveyed variables considered (Fig. S1), the distribution of 12 stream types for 164 field sites (Fig. S2), the distribution of variables used in classification (Fig. S3), decision rules for identifying artificial stream types and natural stream types by using a number of geomorphic attributes that have clear field meaning, the process of identifying the optimal number of clusters or stream types based on silhouette method and expert-based heuristic refinement (Table S1), and the median values of each variable used for classification and interpretation in each stream type (Table S2). Please visit https://doi.org/10.1130/GSAB.S.31329154 to access the supplemental material; contact editing@geosociety.org with any questions.

TABLE 2. ESSENTIAL STEPS AND DATA COLLECTED IN THE NOVEL FIELD SURVEY PROTOCOL USED IN THIS STUDY

Protocol step	Descriptions
1. Conduct site assessment	Absolute degree of entrenchment, split channel presence/absence, bed and width undulation presence/absence, artificial channel presence/absence and artificial bed/bank attributes (Table 3), inset deposit presence/absence, bankfull indicators presence/absence, channel width and length, establishment of decision tree, and surveying technology decision (i.e., auto level, real-time kinematic GPS, or total station).
2. Locate transects	Locate evenly spaced transects with abundance dependent on general site assessment. If present, locate pool trough and riffle crest transects, widest and narrowest transects, and deepest and shallowest transects.
3. Survey transects (Fig. 2)	Minimum data requirement at each cross section is to measure coordinates of thalweg as well as left and right pairs on either side of thalweg at riverbed toes and the river corridor-to-valley floor edge (VFE) slope break. When present, add left and right pairs for all other lateral slope breaks up to the VFE, potentially including inset baseflow channel toes and tops, active or bankfull channel tops, and all terrace toes and tops.
4. Measure riverbed sediment	Pebble count procedure with gravelometer at every equal-interval transect to measure 80 grains total, including visual estimate at each transect of fraction <2 mm, fraction of bedrock/cement, and fraction of boulders >1 m diameter.
5. Collect photo documentation	A pair of photos at each equal-interval transect with upstream and downstream views. When and where possible, take photos from higher vantage points. Photos used in quality control review procedure to evaluate decisions made for the qualitative, expert-based variables (i.e., bank material, bank shape, bed material, and entrenchment levels) in the general site assessment.

tion and classification spanning artificial and natural settings.

Stream Reach Variables

Whereas most reach classification frameworks measure the classification variables directly in the field, in our protocol we collect many topo-bathymetric measurements in the field and then subsequently produce variables useful for classification and characterization, without a priori decision as to which ones will be best for what purpose. Although previous research has identified key variables for natural streams (e.g., Schmitt et al., 2007), this new protocol introduces variables that can also characterize artificial streams. We extracted 92 variables measured from field surveys and added one reach-scale valley-width variable. These variables are grouped into five categories: (1) channel morphometry variables, (2) grain-size variables, (3) valley-floor variables, (4) engineering variables documenting human modifications using shape and composition observations, and (5) split-channel conditions.

Channel morphometry variables, including the width and depth of each topographic location along a cross section (e.g., riverbed toes, thalweg, and valley floor edge), are determined by calculating the mean of all survey transect measurements for each topographic location at each stream site. The coefficients of variation of width (CWV) and depth (CDV) of each topographic location are calculated as the ratio of standard deviation to mean variable values across all surveyed transects. The lateral slopes for all the available topographic locations relative to the riverbed on either side of the river are calculated as the mean value of all survey transects on either side of the river. Additionally, the longitudinal slopes of thalweg and riverbed toes are calculated based on their elevations across all survey transects. Site-scale slopes can be up rather than down given complex subreach-scale landforms and in-channel structures, and this difference from other protocols may enable greater differentiation of stream types.

Grain-size variables that characterize sediment composition at each site are generated based on recorded sediment counts within each particle-size range defined by a gravelometer and using the standard Wolman count method (Wolman, 1954). They include raw counts of each particle-size range and the percentages of fine sediment (DPfines, $\leq$2 mm), coarse sediment (DPcoarse, >2 mm and $\leq$1000 mm), boulder (DPboulder, >1000 mm), and bedrock/cement (DPbedrock) of each surveyed site (Bunte, 2001; Lane et al., 2022). Grain-size distributions of coarse sediments are further summarized by the 16th (D16), 50th (D50), and 84th (D84) percentiles at each stream site by using the empirical cumulative distribution. Additionally, we recorded sediment counts within each particle-size range defined by a gravelometer, considering that raw counts might be useful as classifying or characterizing variables directly, without processing into distribution metrics.

Valley-floor variables consist of qualitative, absolute degree of entrenchment and reach-scale valley width (VW). Entrenchment is directly observed in the field and reviewed in the quality-control procedure. Valley width of each stream site is computed from a 10-m resolution digital elevation model, first using the valley polygon extraction algorithm of Koehl et al. (2024) and then inputting that to the valley width calculation algorithm of Byrne et al. (2020b).

Engineering variables include the composition and shape of the riverbank (Ba_com and Ba_shape) and riverbed (Be_com and Be_shape), with each variable coded as 0 for natural and 1 for artificial. These are visually determined by the field crew on-site, photographed, and double checked in photographs by senior experts later.

If the surveyed site has two or more channels (i.e., "split") within the survey length, the depth of each topographic feature is calculated as the mean depth of each split channel at a given transect, while the width of each topographic feature is determined as the sum of the widths of all split channels. A binary split condition variable (Split) indicates whether a surveyed site contains channel splits within the surveyed length.

Classification Variable Subset

While all variables can be useful for stream type characterization, only a subset of 14 were appropriate for classification (Table 4). First, variables that were not measured among all sites were removed. Previous studies have pointed out that, when variables are available only for a subset of sites, the resulting analysis may fail to represent the full variability of the stream network (Pasternack et al., 2018; Buffington and Montgomery, 2022). Next, since using highly correlated variables can lead to redundancy and ignore the contribution of the other key variables (Dormann et al., 2013), we calculated Pearson correlations of all variables and used 0.6 as a threshold to select low-correlation variables (Figs. 3 and S1).

Classification and Validation

An unsupervised classification was performed using Ward's hierarchical clustering (Ward, 1963; Murtagh and Legendre, 2014), with subsequent heuristic refinement. The "hclust" function from the "cluster" R package, utilizing the "Ward.D2" method, was applied to perform Ward's hierarchical clustering (Maechler et al., 2024). Following Kasprak et al. (2016), Gower's distance was adopted as a distance metric due to its effectiveness for geomorphic datasets. The silhouette method was used to determine the initial optimal number of clusters (potential stream types) by identifying the number of clusters that maximize the average silhouette width (Shahapure and Nicholas, 2020). Expert-based heuristic refinement, which emphasizes balancing granularity and interpretability, was then applied to ensure that the final number of stream types reflects real-world differences

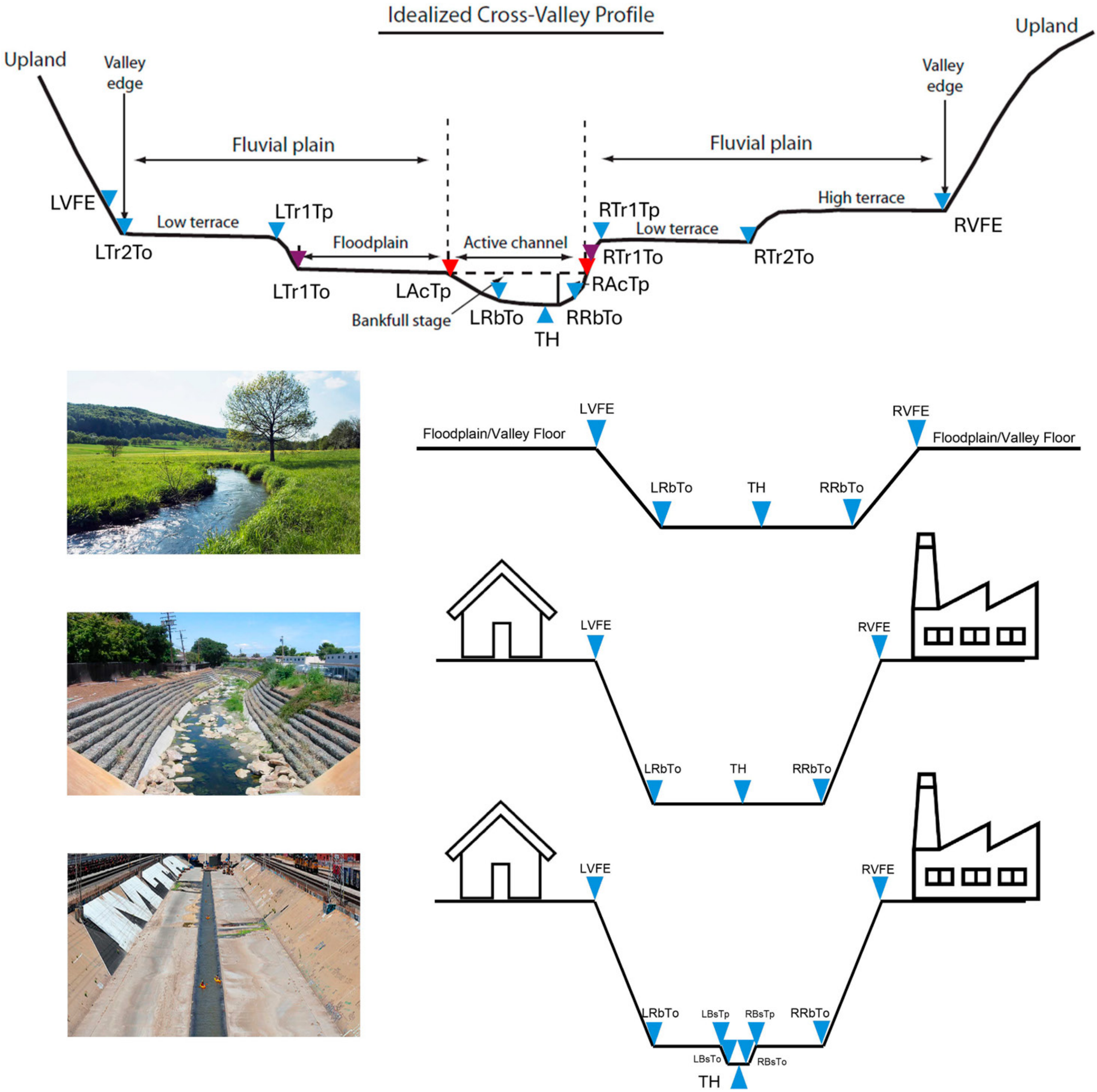


Figure 2. Topographic surveying locations (e.g., active location, terrace, and outer valley floor edge) for each transect with some examples. The labels indicate the abbreviation for each location used during the field survey, including the deepest point of the surveyed sites (TH) and various terrace positions (e.g., LTr1To, RTr1To). More details are provided in the Supplementary Material (see text footnote 1).

while remaining consistent with the statistical classification.

Although the clustering approach provides natural groupings of the attributes into distinct clusters, the interpretation of those identified clusters as meaningful stream types needs further analysis. Accordingly, the classification result from the clustering approach was evaluated, interpreted, and validated quantitatively and qualitatively. First, the classification and regression tree (CART) algorithm was applied as a tool to check the reasonableness of classification results and interpret each stream type based on multiple variables, which is achieved by using the "rpart" package (De'ath and Fabricius, 2000; Therneau et al., 2025). For example, the artificial stream type should have at least one engineering variable equal to 1 (i.e., "engineered"). Second, cross-validation accuracy is a qualitative measure of the model to generalize to unseen data (Wong and Yeh, 2020). The cross-validation

TABLE 3. THE DEFINITION OF ARTIFICIAL SHAPE AND COMPOSITION FOR RIVERBANKS AND RIVERBEDS

	Riverbank	Riverbed	Note
Artificial shape	Human-carved shape, such as a trapezoid, rectangle, or triangle.	Human-carved shape, smooth with no longitudinal bed undulations.	• If an artificial channel becomes incised over many years, such that there is a new inset naturalized channel within it, it is still an artificial channel. • If ≥50% of the stream length (or observed cross sections) is determined to be artificial in shape and/or composition, then the site is classified as artificial shape/composition OR if one whole side of the channel is artificial in shape and/or composition, then it is considered artificial shape/composition.
Artificial composition	Human-brought materials, including concrete, shotcrete gabion structures, riprap, streambank revetments, wood piers, fencing, and so on.	Human-brought materials, such as shotcrete. If there is an artificial bed, such as shotcrete and then sediment covers it, then the decision comes down to thickness and mobility. • If the deposition is so thick that the underlying artificial material is now inconsequential and cannot be seen or cannot impact channel dynamics, then it is a natural composition. • If there is a thin veneer of sediment over artificial substrate and that veneer can be expected to wash away during the next high flow, then it is artificial composition.	

TABLE 4. FOURTEEN VARIABLES USED FOR REGIONAL STREAM CLASSIFICATION, INCLUDING STATISTICS FOR EACH AMONG 164 STREAM SITES

Variable		Description	Min	Max	Median
Channel morphometry variables	Be_width	Cross-sectional width of riverbed toes	0.43	93.24	3.74
	Be_depth	Vertical distance from the riverbed toes to the thalweg (the deepest part of the channel)	0.02	4.07	0.23
	Be_CWV	Coefficient of variation of cross-sectional riverbed toe width	0.02	0.65	0.24
	Be_CDV	Coefficient of variation of cross-sectional riverbed toe depth	0.04	2.28	0.58
	Slope_thalweg	The longitudinal slope of the thalweg (the deepest part of the channel) along the surveyed site	−0.02	0.21	0
Grain-size variables	DPcoarse	The percentage of coarse sediment in the surveyed site	0	100	71.25
	DPboulder	The percentage of boulder in the surveyed site	0	46.25	0
	S16	The total count of individual sediment particles with dimensions >300 mm and ≤1000 mm observed at a surveyed site	0	20	0
Valley-floor variables	Entrenched	Entrenchment: high (3; >3.64 m), medium (2; 1.82–3.64 m), and low (1; <1.82 m)	1	3	2
	VW	The valley width of each 200-m interval	7.8	10,000	4501.7
Engineering variables	Ba_shape	The shape of riverbank—artificial (1) and natural (0)	0	1	0
	Ba_com	The composition of riverbank—artificial (1) and natural (0)	0	1	0
	Be_com	The composition of riverbed—artificial (1) and natural (0)	0	1	0
Split		The presence (1) or absence (0) of a split condition (e.g., channel bifurcation or division) within a surveyed site.	0	1	0

Note: Dimensional variables have units of meters.

accuracy above 75% is generally taken as evidence of reliable model generalization (Lane et al., 2017; Byrne et al., 2020a). Third, variable importance scores, computed by tallying how frequently each variable is used to split nodes and weighting these counts by the corresponding improvements in classification accuracy, ranked the contributors. Moreover, the pairwise permutational multivariate analysis of variance (pairwise PERMANOVA) is also applied within the artificial and natural stream-type groups to test whether each stream type within its own differs significantly from the rest. It is a nonparametric, multivariate analysis of variance that evaluates differences between stream types based on a chosen distance metric (e.g., Euclidean) and derives p-values by randomly permuting stream types (Sutfin et al., 2014; Pyne et al., 2017). In our study, we adopted a 95% confidence level ($p = 0.05$) to determine whether each stream type within the artificial and natural stream-type groups differs significantly (Byrne et al., 2020b).

RESULTS

Stream Types

We obtained 12 stream types in the San Francisco Bay Area through hierarchical cluster analysis (Fig. 4; Table S1). The spatial distribution of 12 stream types for the 164 surveyed sites is shown in Figure S2. Based on the median value of each variable (Table S2), we synthesized concise textual descriptions, complemented by representative field photographs (Fig. 5). In addition, we provided concise, plain-language decision rules that distinguish between the 12 types (Fig. S4). We also produced a set of "ID cards" describing and illustrating each stream type as a supplementary material (i.e., S_IDCard.pdf) to help professionals and the public gain familiarity.

The resulting CART tree structure indicated that the variables displayed at each node represented the best local split for that subset of data (Fig. 4B). The primary variable, riverbank shape, split the stream types into six natural stream types (N1–N6) and six artificial stream types (A1–A6). Among artificial stream types, the composition of riverbank and riverbed, the percentage of coarse sediments, the count of particles that are >300 mm and ≤1000 mm, and entrenchment level were important variables for distinguishing artificial stream types. For natural stream types, entrenchment level, valley width, the percentage of coarse sediments and boulder, and the longitudinal slope of the thalweg reflect the differences among natural stream types. Moreover, 10-fold cross-validation achieved an overall accuracy of 82.9%, corroborating the robustness of the classification. Variable importance scores showed that valley width, entrenchment, and percentage of coarse sediments were the top three contributors (Fig. 4C). Channel morphometry variables, i.e., the coefficient of variation of cross-sectional riverbed toe width, and the longitudinal slope of the thalweg were closely followed in importance.

Regardless of whether considered locally (CART) or globally (variable importance), all of the variables used in the classification process contributed meaningfully to the final model outcomes. For example, although riverbank shape did not rank among the highest in the variable importance metrics, its role as the primary splitting variable at the root node is key to organizing and partitioning the data. It divides the surveyed sites into two primary groups, natural and artificial stream types, and sets the stage for all subsequent decisions in the model. Box plots illustrating the distribution of each variable used for classification in reach-scale artificial stream types and natural stream types are shown in Figure S3.

Differences Among Artificial Stream Types

The pairwise PERMANOVA results demonstrated that artificial stream types showed statistically significant differences among their respective subgroups at the $p < 0.05$ threshold, indicating clear geomorphic or compositional distinctions within each stream type. The pairwise p-values for all stream-type comparisons

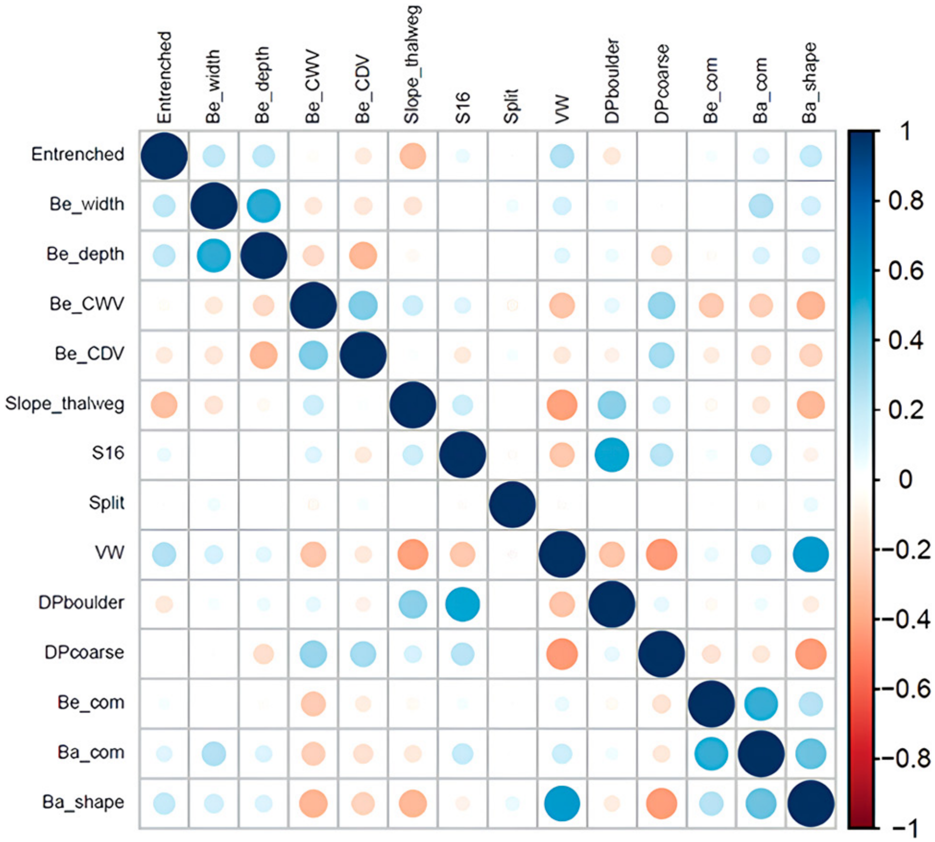


Figure 3. Pearson correlation metrics of the final 14 variables selected for classification, with all Pearson correlation values below 0.6. In the upper-right portion of the plot, correlations are represented visually. Narrow and darker colors represented more highly correlated. Positive correlations are blue, while negative correlations are red.

were <0.02, except for the comparisons involving A1 versus A2with p-values of 0.03, which are highly statistically significant. For A1 versus A2, the riverbed and riverbank compositions were the primary variables to divide them into different groups (Fig. 4A). The relatively higher p-value (0.03) for comparisons involving A1 versus A2 might reflect the intrinsic similarity in these physical characteristics among the groups.

Engineering variables, grain-size variables, valley-floor variables, and channel morphometry variables exhibited significant differences among artificial stream types at the $p < 0.05$ threshold generated by the analysis of variance (Fig. 6). The composition of the riverbed and riverbank served as the primary distinguishing factor (Fig. 6A). Most artificial streams displayed middle (entrenched = 2) to high (entrenched = 3) levels of entrenchment and with large valley width values. Coarse sediment metrics were the primary grain-size variables in distinguishing artificial stream types. Channel morphometry variables showed less significant differences than other variables' groups. For example, A5 and A4 had similar distributions in the coefficients of variation of riverbed toe depth (Fig. 6B). However, no individual artificial stream type showed distinct distributions across all variables, and a combination of different variable groups was necessary to effectively differentiate them. For example, A3 and A6 had the same compositions of the riverbed and riverbank, but they showed different distributions in coarse sediments and entrenchment levels.

Differences Among Natural Stream Types

All natural stream types showed the same statistically significant differences among their respective subgroups at the $p < 0.05$ threshold based on pairwise PERMANOVA results. This uniform significance across all pairwise comparisons indicated that natural stream types showed clear and robust differences in their geomorphic characteristics.

We identified valley-floor variables, channel morphometry variables, and grain-size variables as representative influential variables that differentiate the stream types (Fig. 7). Among them, entrenchment level was the primary distinguishing factor, followed by valley width (Fig. 7A). The distributions of entrenchment and valley width were broadly dispersed, which likely reflected the heterogeneous land-use patterns across the watershed. The longitudinal slope of the thalweg was the primary channel morphometry variable in distinguishing natural stream types, such as N1 might represent the steep streams in remote areas. The coarse and boulder sediment fractions were the primary grains in distinguishing natural streams. Moreover, the distribution of valley width revealed a clear separation within natural stream types; that is, one group comprising N1, N3, and N4, and another consisting of N2, N5, and N6. In particular, channel morphometry variables and grain-size variables displayed different distributions between these two groups, which appear related to landscape position (with N1, N3, and N4 being in steeper, smaller catchment positions) and the degree of human impacts associated with that positioning. For example, streams with lower valley widths, low depth to bedrock, and coarse sediment should be less impacted by human activities. As a result, they showed more uniform characteristics, such as N3 and N4, which had similar distributions in channel morphometry variables (e.g., riverbed toe width) and grain-size variables (e.g., coarse sediments).

Stream Type Characterizations

Based on our expert understanding of the stream types thus far, we have conceptualized illustrative morphodynamic processes for each stream type at event-to-interdecadal time scales (Table 5), which helps to understand the threshold differentiation between types rather than considering the types as along a continuous gradient of subtle differences. Some stream types were observed to be dominated by erosional morphodynamics (e.g., A3, N4, N6), while others depositional morphodynamics (e.g., A4, A5, N2). Meandering appears diagnostic of A2 and N5, while knickpoint migration appears diagnostic of N1. While several stream types likely experience flow convergence routing (e.g., A2, N1, N3, N4, and N5), comparable results from Nogueira et al. (2024) showed marked differences in how this processes manifests among five natural, ephemeral southern California stream types.

If in fact the conjectured process regimes are different among stream types, then there should be significant differences in their observable conditions, and that is what this study found. All computed variables were used for the interpretation of each stream type. Box plots and statistical analyses showed that numerical values of key variables differed by stream type (Figs. 6

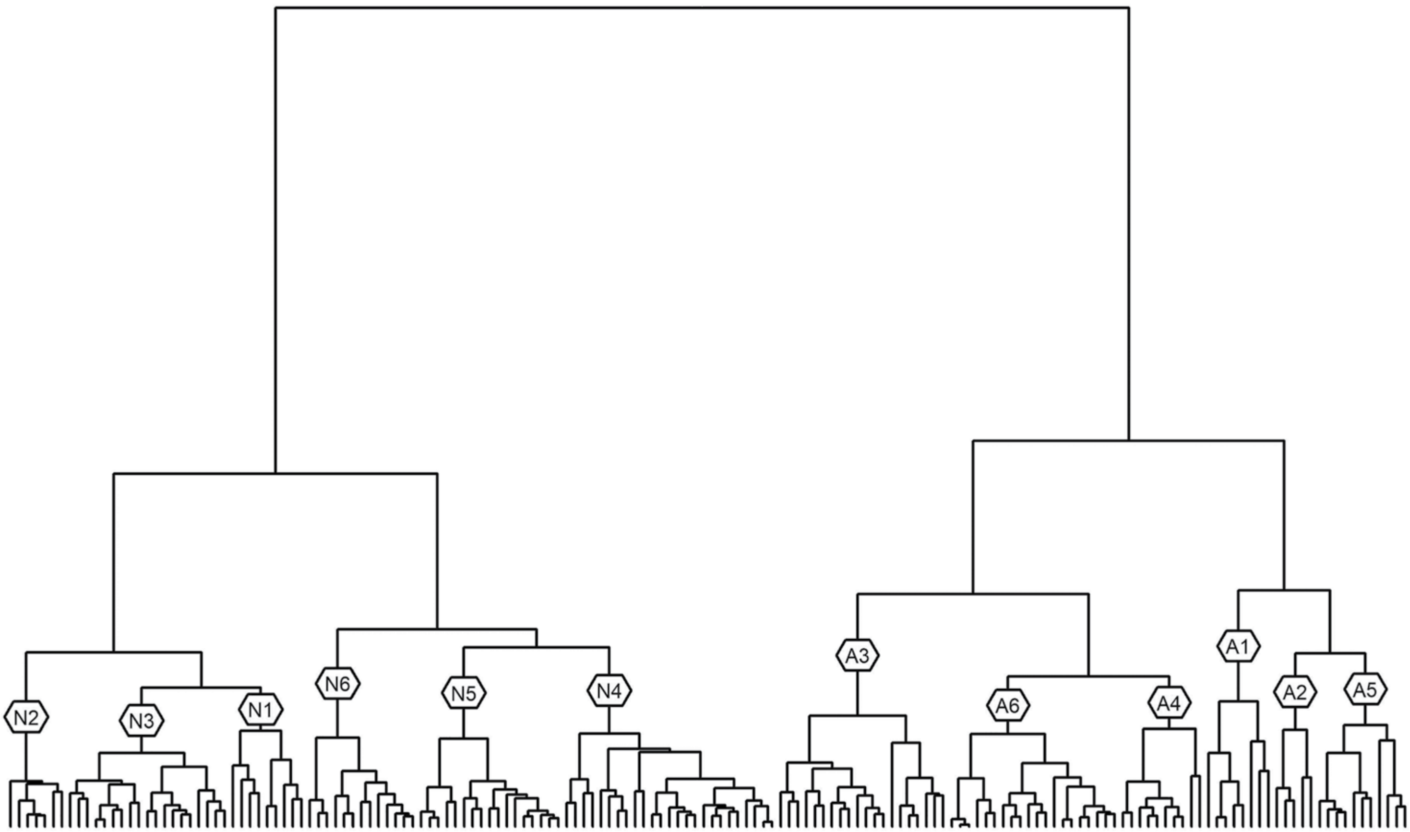


Figure 4. (A) Hierarchical clustering by Ward's algorithm analyses. (B) A classification tree constructed using the CART (classification and regression tree) algorithm, where each node indicates the splitting variable and threshold; leaf nodes are labeled with final group identifiers. (C) Variable importance ranking from the same model, showing that higher values indicate greater contribution to the classification.

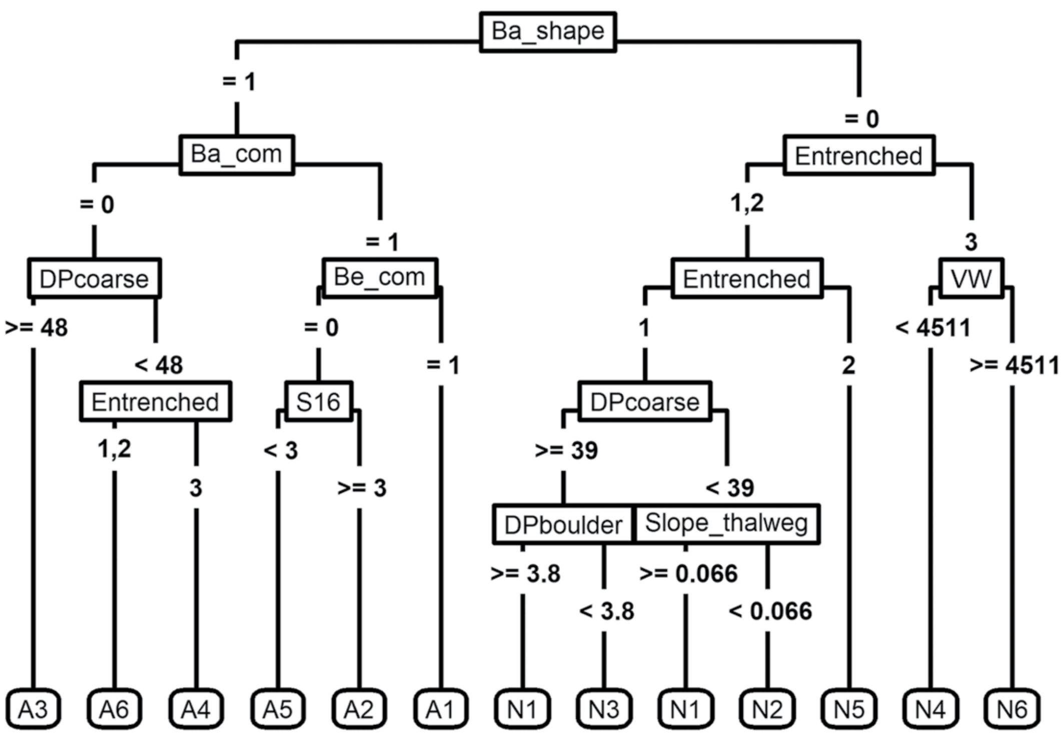


Figure 4. (*Continued*)

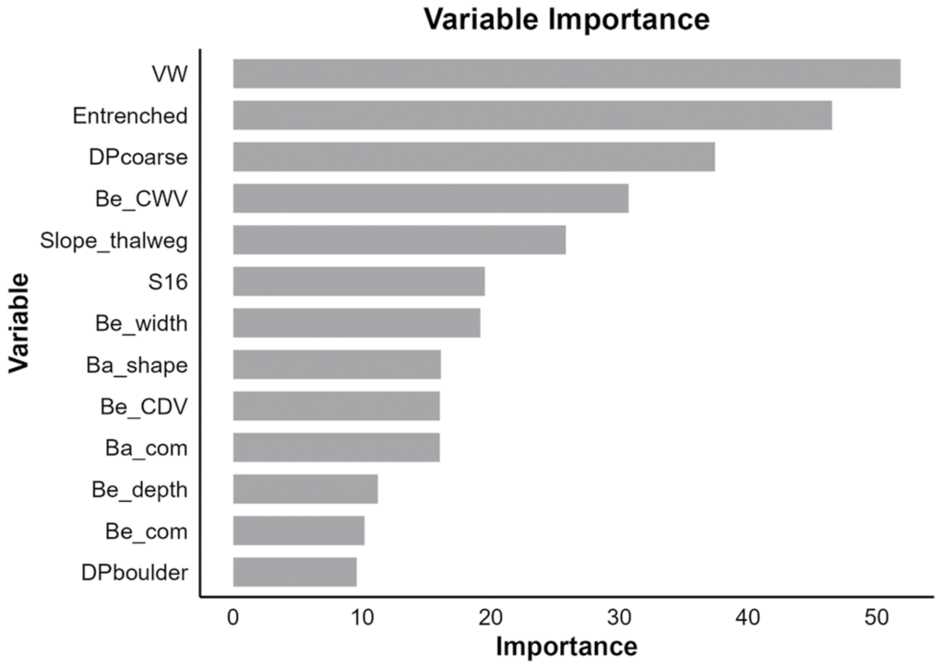


Figure 4. (***Continued***)

and 7). Beyond that, many other variables also show significant differences (Table S2), even if there is insufficient space herein to address all of them in detail. As one example, a non-typical variable quantified in this study was lateral bank slope measured from the edge of a landform to the riverbed toe. For streams that had observable active or bankfull channel height indicators, the lateral slopes of the active or bankfull streambanks were computed in radians for both sides of the channel. Even artificial streams can have active channel dimensions, making comparison possible. Aggregating among artificial types yielded a mean bank slope of 0.445 and for natural types 0.784. This result makes sense on a process basis, because artificial streambanks are constructed to modest slopes for stability. In contrast, natural streams have steeper lateral slopes because of confinement and/or incision, depending on the setting.

Besides quantitatively distinguishing stream types, each stream type can be identified in observable terms, such as bank shape, sediment, and entrenched levels from the qualitative perspective (Fig. S4). For artificial streams, the decision rule first distinguished bank form, then bank composition and riverbed material, followed by entrenchment and planform or bed configuration (Fig. S4A). For example, A5 is present when banks are artificial, but the bed is natural with fine sediment. A2 is present when banks are artificial and the bed is natural with coarse sediment. For natural streams, the decision rule first evaluates whether the valley is highly confined with a steep channel containing boulders and bed undulations (Fig. S4B). For example, unconfined low-slope channels with fine sediment map to N2, while confined ones with coarse sediment map to N3. A decision tree that trained users can implement quickly using only visual observation is an important product of this study, and in the San Francisco Bay Area, it has subsequently identified stream types for 315 sites thus far.

DISCUSSION

Site Selection, Field Observation, and Remote Sensing

Historically, site selection was not a major methodological feature of river classification, but with the increasing use of bottom-up classification (Table 1), robust site selection is essential. In this study, we employed the novel site selection framework developed by Wang et al. (2025) that enabled us to observe 164 sites out of individual 200 m stream intervals in the study area. This sampling strategy was highly effective at capturing diverse stream conditions (both known and unknown), such that all classes show a major break sufficient to define an additional level of subtypes, if desired, although with less statistical robustness. Our robust classification with 12 different stream types spanning natural and artificial settings further confirmed that the integration of machine learning with human expertise in empirical, sampling-based environmental studies has the potential to greatly improve our ability to infer complex patterns and relationships with limited resources.

As a heuristic evaluation of the sampling strategy, the senior geomorphologist conducted an extensive review of Google Earth imagery to identify any potential stream types that may have been overlooked during sampling. Not counting deep, wide, tidal rivers that were intentionally excluded, the only potential uncharacterized stream type in the region was the mainstem Russian River (Sonoma and Mendocino counties, California), which is a large, wide, dynamic river that was not sampled because of logistical challenges. However, two sites on Arroyo Mocho (Santa Clara County, California), the next largest river of similar geomorphology, were sampled, and the Russian River could be classified into the resulting framework despite not being directly observed. Using the qualitative decision tree (Fig. S4), it classifies as N5, which is reasonable.

A field survey is crucial in observing artificial modifications for a comprehensive understanding of river processes and controls (Gurnell and Hill, 2022). Previous studies have pointed out that GIS and remote sensing datasets often fail to capture the detailed engineering attributes that define many modern streams (Gurnell et al., 2016; Pyne et al., 2017; Williams et al., 2022). In particular, artificial modifications may be subtle or partially obscured in urban or agricultural landscapes. For example, a trapezoidal stream with partially naturalized banks might appear "semi-natural" in aerial imagery but is, in fact, constrained by hidden concrete slabs or embedded riprap.

Artificial and Natural Streams Classification

The proposed joint classification framework, which integrates both engineering-driven and geomorphic variables, has demonstrated a robust capacity to capture the diversity of natural and artificial streams with a single field observation protocol, while revealing their underlying geomorphic complexity (Figs. 4 and 5). This dual emphasis on engineered attributes (e.g., riverbank and riverbed compositions) and geomorphic metrics (e.g., slope, riverbed toe depth, sediment size) allows for a comprehensive portrayal of mixed land-use stream networks that recent frameworks often overlook (Lane et al., 2017; Pyne et al., 2017; McManamay et al., 2018; Buffington and Montgomery, 2022).

Engineering attributes (e.g., riverbank materials) set the broad types (artificial versus natural), whereas geomorphic variables like slopes or sediment size often refine these types into distinct subtypes (Fig. 4). Notably, bankfull dimensions

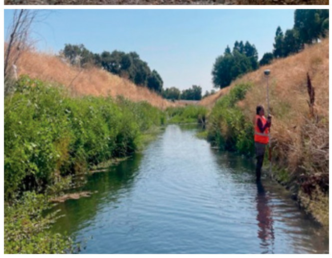
Stream Type	Description	Representative Photo
A1	“Armored channel”. An artificial channel with concrete bed and banks.	
A2	“Bank-hardened river”. A steeper-sloped artificial channel with riprap and/or cement banks as well as a riverbed of natural composition, including coarse sediment, fallen riprap, and some natural boulders.	
A3	“Naturalizing canal”. A wider, deeply entrenched artificial channel dug so that the banks are ambient soil/sediment, and the bed has strong bed-elevation undulations with bed landforms composed of predominantly coarse sediment - both features indicative of coarse bedload transport and morpho dynamics during floods.	
A4	“Large canal”. A wider, deeper, deeply entrenched artificial channel dug so that the bed and banks are ambient fine soil/sediment.	
A5	“Bank-hardened canal”. A gently to very gently sloped artificial channel with riprap and/or cement banks as well as a natural riverbed composed of fine sediment, typically close to base level.	
A6	“Ditch”. A gently sloped artificial channel with low to moderate entrenchment that is dug so that the bed and banks are ambient fine soil/sediment. These include water supply and drainage channels typically in agricultural and suburban settings.	

Figure 5. Overview of identified stream types, highlighting key morphological characteristics and representative field photographs. Names in quote marks attempt to capture essential features, but some sites in a type may not match the name well, given the lack of English words to capture stream-type conditions spanning valley and channel features.

were not needed to obtain well-differentiated natural stream types. This hierarchical classification illustrates the necessity of integrating both engineering and geomorphic attributes in a geomorphic classification framework. That is, the engineering attributes dominate the initial classification boundary due to its strong contrast between human-modified and natural conditions, while geomorphic variables are required to capture the inherent variability within these broader groups. For example, in the CART output, engineering attributes appear in the upper branches, driving the initial splits, whereas geomorphic variables tend to occupy lower branches, further obtaining detailed stream types (Fig. 4B). At the same time, variable importance metrics reveal that although engineering attributes are essential for identifying the overarching classification,

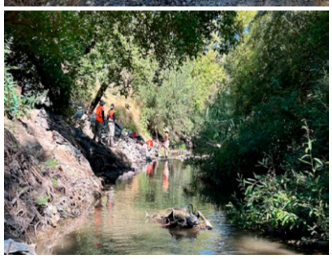
N1	"Headwater steep stream". A very steep gravel to boulder natural channel in a highly confined valley with little entrenchment and strong undulations of bed elevation and width.	
N2	"Lowland/meadow small stream", A low to modest slope, fine-bedded natural channel flowing across an unconfined valley floor with strong channel-floodplain connectivity (if a floodplain is present), fine sediment, and strong undulations of bed elevation and width. May have poorly-defined banks and emergent wetland vegetation. May be flanked by gently rolling hills.	
N3	"Mountain stream". A moderate sloped, gravel-bed natural channel in a confined valley with strong undulations of bed elevation and width.	
N4	"Entrenched riffle-pool stream." A moderate sloped, deeply entrenched, gravel bed natural channel with undulations of bed elevation and width. Typically in a partially confined valleys but also in unconfined ones. May be entrenched to bedrock or have exposed bedrock.	
N5	"Valley floor riffle-pool stream". An all-around average gravel-bed natural channel with moderate entrenchment, and some bed-elevation undulation. Can occur in any confinement but mostly in partially confined and unconfined valleys.	
N6	"Large, entrenched lowland stream". A low-slope, wide, deep, deeply entrenched channel with strong bed elevation undulations and flowing through a large unconfined valley floor. Although this type has a gravel bed, it also has a higher percentage (~27%) of fine sediment associated with its lower slope and larger size compared to N4. This type is the ultimate endmember of urban stream syndrome.	

Figure 5. (***Continued***)

geomorphic variables contribute significantly to the overall model performance by capturing critical variations across all splits (Fig. 4C).

The classification constraints of artificial and natural streams differ. For artificial streams, the constraints might be predominantly influenced by human intervention Although they still show significant differences (i.e., p-value < 0.05), the relatively higher p-value implies that while geomorphic characteristics are similar among these groups, minor discrepancies in engineering modifications can sufficiently differentiate one artificial stream type from another (Fig. 6). In contrast, the classification of natural streams is predominantly governed by inherent geomorphic processes (Fig. 7A). However, our joint classification framework also revealed that human intervention can modify these processes, leading to distinctly different geomorphic characteristics (Figs. 5 and 7B). The contrasting patterns within artificial and natural streams demonstrate the

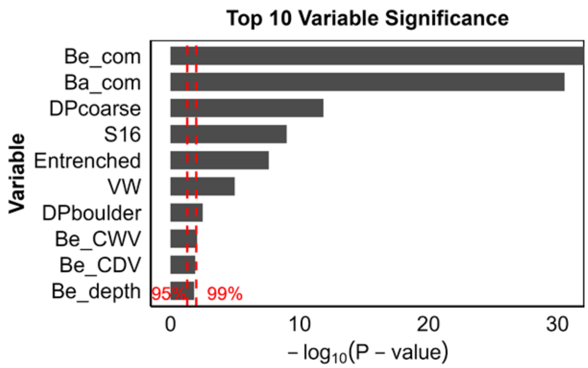


Figure 6. The top 10 geomorphic variables with the most significant differences among artificial stream types (A) and the distributions of the nine significant geomorphic variables (B): bed composition (Be_com); bank composition (Ba_com); the count of particles that are >300 mm and ≤1000 mm (S16); entrenched levels (Entrenched); the percentage of coarse sediments (DPcoarse); valley floor width (Vfe_width); the percentage of boulder (DPboulder); the coefficients of variation of riverbed toe width (Be_CWV); and depth (Be_CDV). The distribution of all used variables can be found in Figure S3 (see text footnote 1).

importance of integrating both engineering and geomorphic variables into a joint classification framework.

The Potential of the Integrated Geomorphic Reach Classification Framework

As environments change quickly under human influence, effective river management requires a comprehensive and flexible geomorphic reach-classification framework and its translation into adaptive management policy (Palmer et al., 2014). Hobbs et al. (2009) demonstrated that hybrid systems retain elements of their historical/original character but now exhibit compositions or functions outside the bounds of past variability, rendering traditional management policies ineffective. In recent years, many streams have departed so far from original conditions that conventional restoration strategies are unrealistic, especially in a mixed land-use watershed (Suding et al., 2015). In the new classification presented herein, some natural classes were found to represent degraded conditions resulting from a variety of anthropogenic impacts (e.g., adjacent land encroachment, changes to water and sediment regimes, and addition of localized artificial structures), but they were still natural streams. Similarly, some artificial streams were found to represent enhanced eco-geomorphic conditions arising from unchecked morphodynamics (e.g., fine sediment deposition forming inset riverine wetlands and proto meandering within coarse-bedded canals). This identification allows researchers and environmental managers to notice possible new ecological functions and informs the design of tailored restoration and ecosystem-service policies, which is in line with Erős et al. (2023).

Management strategies should be tailored to each stream type in order to optimize ecosystem-service delivery, support biodiversity conservation, guide emergency engineering-permit decisions, and meet other objectives (Higgs, 2003; Hobbs et al., 2009). For example, planners need to balance water-quality improvements with restoring habitat connectivity (Erős et al., 2023). In highly engineered urban channels, the initial priority may be flood control, but efforts in helping reintroduce natural processes and boost ecological function should be considered (Trice, 2013). While agricultural

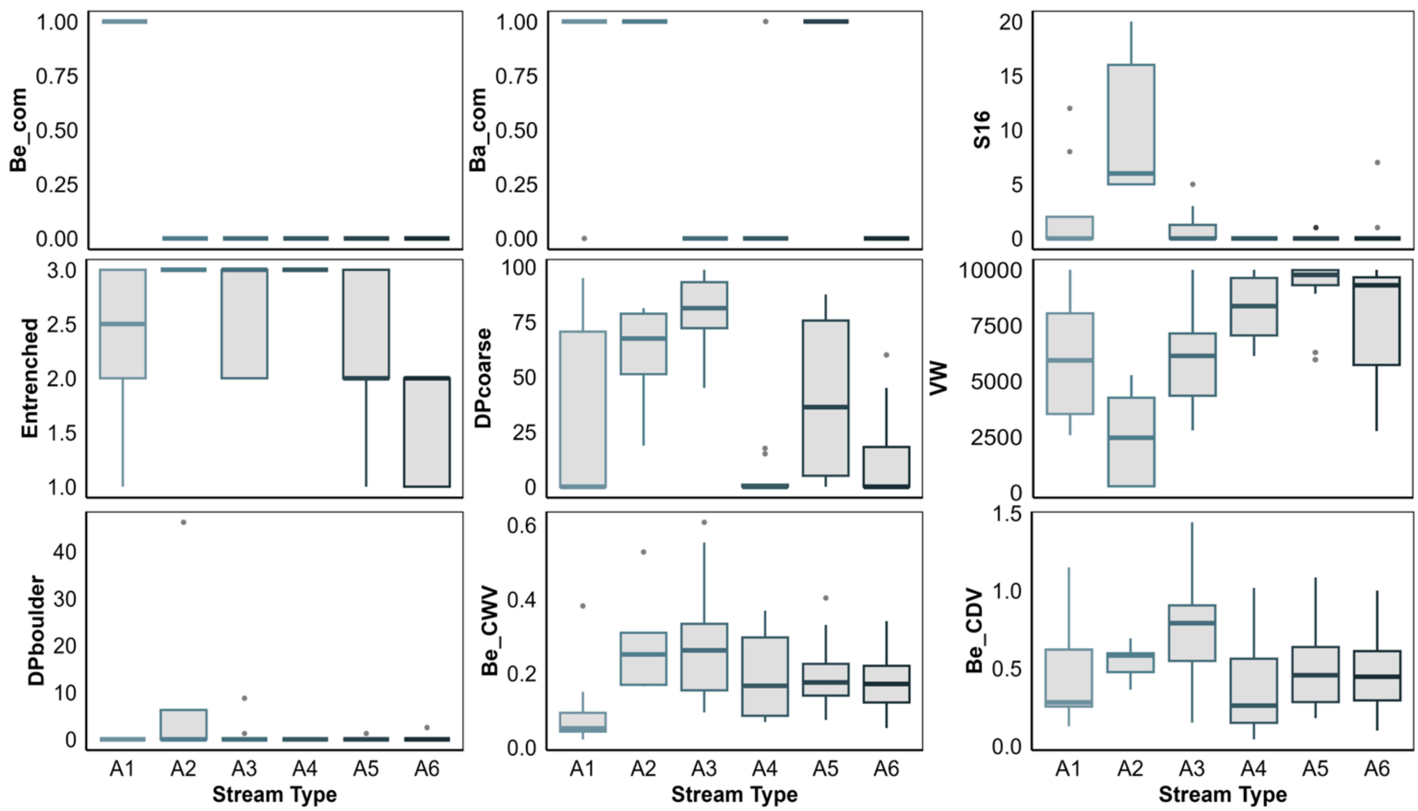


Figure 6. (***Continued***)

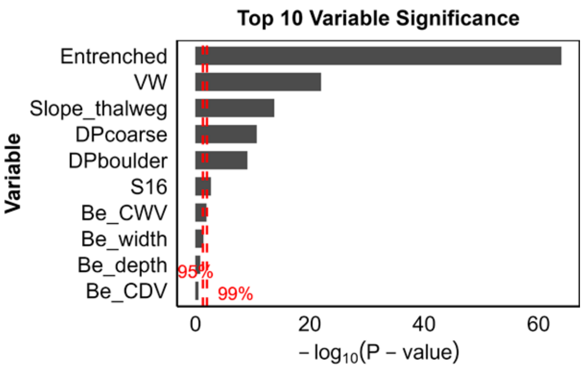


Figure 7. The top 10 geomorphic variables with the most significant differences among natural stream types (A) and the distributions of the right significant geomorphic variables (B): entrenched levels (Entrenched); valley floor width (Vfe_width); the longitudinal slope of the thalweg (Slope_thalweg); the percentage of coarse sediments (DPcoarse); the percentage of boulder (DPboulder); the count of particles that are >300 mm and ≤1000 mm (S16); the coefficients of variation of riverbed toe width (Be_CWV); and riverbed toe width (Be_width). The distribution of all used variables can be found in Figure S3 (see text footnote 1).

canals and ditches are usually maintained for their shape and low sinuosity, they have the significant potential for habitat enhancement that is often neglected (Vought and Lacoursière, 2010; Lenhart et al., 2018).

Our classification framework provides a comprehensive list of stream types with their general attributes and the expected eco-geomorphic processes that are likely important to each. This framework is a strong foundation for spatial planning, restoration prioritization, and environmental policy, and can be tuned to different landscape conditions. That said, no classification should be taken as dogma controlling final design and implementation of local site projects at a process-based scale. As part of taking a site project from the planning phase to the final design phase, general classification attributes and expected eco-geomorphic processes should be further investigated and refined through the use of a design hypothesis testing framework (e.g., Wheaton et al., 2004).

To substantiate the utility of the classification for regional environmental planning and stewardship, consider three examples. First, the N4 stream type (i.e., entrenched riffle-pool stream) and its regional pattern of occurrence is immediately recognizable as indicative of a serious societal problem evident and addressable at the planning scale. Deeply entrenched rivers are well-accepted as an extremely difficult problem to solve, especially where structures are built right up to the banks (Darby and Simon, 1999). After identifying this stream type, in 2025 we performed a rapid reconnaissance of 81 N4 sites in the region to gain insights into the scope and severity of the problem. We encountered residential neighborhoods interwoven with N4 streams, with many valuable homes and properties at risk. For example, when we drove up to an accessible stream site that turned out to be an N4 stream, we found that its bank was merely ~1 m away from the fence line for a residential home and property with a Zillow® estimated value of US$2.75 million. The stream was narrow (~5 m wide) and unusually entrenched (~10 m below the valley floor), with a bank section visibly eroding right up to the fence. The homeowner was there and spoke at length about extensive efforts by the opposite hillside landowner at addressing runoff and erosion problems to little

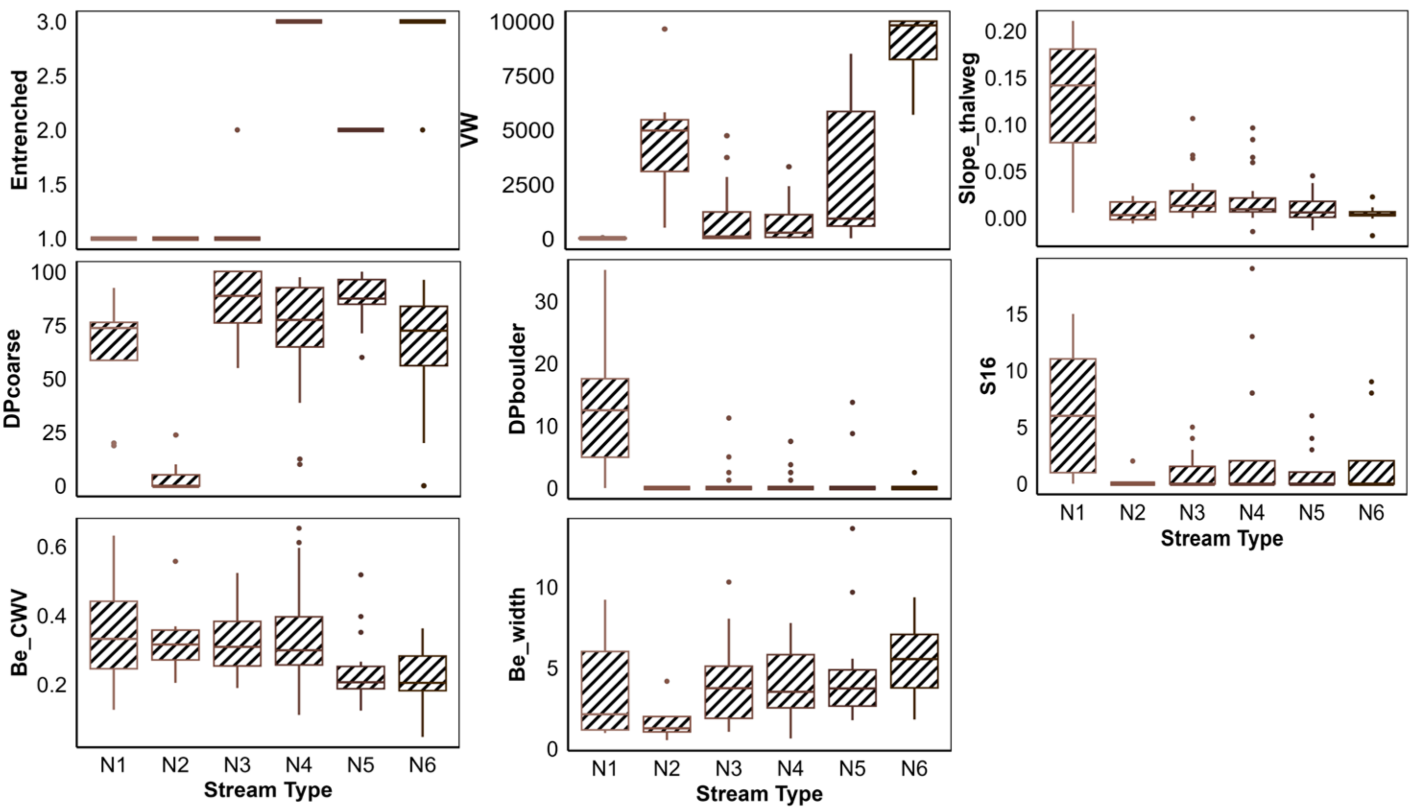


Figure 7. (***Continued***)

TABLE 5. CONJECTURED, ILLUSTRATIVE MORPHODYNAMIC PROCESSES FOR EACH STREAM TYPE AT EVENT-TO-INTERDECADAL TIME SCALES

Stream type	Morphodynamic processes
A1	None
A2	Meandering, flow convergence routing, bed armoring dynamics
A3	Proto-meandering, incision, widening, bed armoring dynamics
A4	Bed aggradation, peat formation
A5	Bed aggradation or incision, depending on sediment supply regime
A6	Bed aggradation or incision, bank erosion
N1	Knickpoint migration, local scour, step-pool formation/rearrangement, flow convergence routing
N2	Peat formation
N3	Flow convergence routing, step-pool formation/rearrangement, processing of steep-hillslope mass-wasting deposits, bed armoring dynamics, local scour and pool formation, large-wood interactions
N4	Incision, widening, knickpoint migration, formation of inset landforms, flow convergence routing
N5	Flow convergence routing, meandering, avulsion, channel-floodplain dynamics
N6	Incision, widening, clogging of coarse bed with fines

avail. With this new classification, there is the potential to obtain a regional map of N4 stream types and then evaluate the seriousness of the societal problem in terms of indicators, such as the relative number of emergency permit filings to address N4 streambank failures.

Second, the N2 stream type (i.e., lowland/meadow small stream) is relatively remarkable, because it includes intact low-energy riverine wetlands, according to the hydrogeomorphic wetlands classification system (Smith et al., 1995), integrated into long segments of poorly defined channels. Where N2 channels are well-defined, the presence of cohesive mud yields steeper lateral slopes than for other natural stream types. Throughout the western United States, extensive efforts are being made at "meadow restoration" with low-tech process-based restoration methods, whereas we found an abundance of such systems in relatively good condition spread throughout the region. As a result, a sensible planning-level management strategy could be implemented to prioritize preservation of these N2 river segments against urban expansion, which is a serious risk they face under pressure from dire housing shortages.

Finally, the A3 stream type (i.e., naturalizing canal) could be prioritized as a win-win among agriculture and environmental community groups if steps were taken to promote habitat enhancements for Pacific salmonids while retaining functioning as agricultural drainage. For example, our crew observed two large dead salmon while performing a subsequent high-resolution topo-bathymetric survey of a naturalizing ditch running through a dense urban neighborhood in Contra Costa County. Perhaps A3 streams could be further encouraged in their proto meandering through mindful placement of large wood or gravel benches.

Providing explicit context for each stream type supports flexible use globally. We provide decision rules that state observable conditions distinguishing among artificial and natural types in Figure S4 and a set of concise identification cards that describe and illustrate each type with representative images and defining attributes in the Supplemental Material. These materials allow users to screen new reaches with field-readable terms such as bank form and material, degree of entrenchment, and bed configuration, and they clarify how combinations of attributes map to type labels. These types can be applied as an initial hypothesis in other watersheds, followed by a lightweight calibration step. For example, the Wang et al. (2025) article on machine learning–guided field site selection demonstrates how calculating uncertainty among existing stream types can improve the understanding of geomorphic characteristics of streams.

CONCLUSION

In summary, our joint classification framework effectively distinguishes the diversity of stream conditions in mixed land-use watersheds by integrating engineering variables (e.g., riverbank and riverbed composition) with geomorphic characteristics (e.g., slope and sediment size). This approach not only reveals significant differences between artificial and natural stream types but also uncovers the subtle internal variability within each category. Statistical analyses, including pairwise PERMANOVA and CART, have confirmed that these integrated variables robustly differentiate the stream types, while field photographs provide qualitative validation by visually confirming expected morphological features. Importantly, we move away from reliance on bankfull-dependent metrics, allowing the framework to accommodate reaches where bankfull is ambiguous or non-diagnostic, especially for fluvial geomorphology in human-altered landscapes.

Our study addresses a critical gap in the basic science of fluvial geomorphic classification, particularly in mixed land-use landscapes that are subject to extensive human intervention. By capturing both engineered modifications and natural geomorphic dynamics, our approach provides a more complete understanding of stream network variability. In the nine-county San Francisco Bay Area, this framework distinguishes stream types from fully artificial concrete channels to entirely natural reaches, enabling restoration practitioners and conservation agencies to prioritize projects and allocate resources based on geomorphic and engineered characteristics of each stream type. Similarly, we surmise that in highly populated regions throughout the world where watersheds span urban, suburban, agricultural, and natural zones (e.g., Melbourne, Australia; Valencia, Spain; Chengdu, China), this framework can be applied to identify each reach's unique geomorphic and engineering attributes. Consequently, this framework represents a robust tool for river management, restoration planning, and conservation strategies, ensuring that interventions are specifically tailored to the unique geomorphic and engineering realities of each stream type.

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