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Channel reach morphology and landscape properties are linked across a large heterogeneous region

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Abstract
Given the complex array of processes influencing river networks, conceptual frameworks of rivers are critical to our understanding of channel processes and response potential as well as restoration efforts. Yet despite their wide usage, many classifications are based on limited observations over homogenous landscapes, raising questions about their general applicability and quantitative thresholds. Leveraging a large, transect-based morphological field dataset across California, USA, we use data-driven methods to evaluate multivariate patterns in channel morphology and linkages with landscape properties considering a diversity of physio-climatic settings. Emergent patterns highlight the variability in channel form observed across an extensive dataset over heterogeneous but spatially linked watersheds. In general, identified dominant channel attributes and landscape properties align with established channel types defined through expert judgement, but key differences also emerge. Similar to past studies, bed sediment composition and sub-reach depth variability were discriminating channel attributes. The dominance of landscape properties associated with sediment supply or transport capacity suggests that morphological diversity largely reflects these differences as posited by prior classifications. Results also show some channel forms to be largely independent of valley confinement, with several channel bedforms and dominant grain sizes occurring across valley settings. This data analysis study demonstrates the utility of considering channel reaches and landscapes as multidimensional features to elucidate and test established geomorphic understanding over large field datasets.

Key Words: Channel morphology, classification, data-driven, California, clustering, sediment supply

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Introduction

Broadly, variable channel reach morphology along a river network results from complex interactions between climate, tectonics, and lithology driving large-scale variations in water and sediment supply (Castelltort et al., 2012; Gabet, 2019). The diverse processes by which sediment is locally supplied to, and then transported through the river network make it difficult to distinguish the relative influences of those processes on channel reach form and disturbance response potential. Here, a channel reach refers to a river interval with relatively uniform characteristics over lengths of 10-20 channel widths and is a useful scale over which to relate channel morphology to watershed and channel processes, response potential, and habitat characteristics (Frissell et al., 1986; Montgomery and Buffington, 1997; Byrne et al., 2020).

In general, the degree of hillslope-channel coupling changes along the river network, resulting in changes in both the characteristics (composition, volume, frequency) and delivery mechanisms (e.g., bank failure, debris flow, hillslope erosion) of sediment supplied to a channel (e.g., Rice, 1994; Montgomery and Buffington, 1997; Church, 2002; Rice, 1994). Because the amount and size of sediment that a river can transport, or its transport capacity, is controlled by channel shape, roughness, and discharge (Lane, 1955; Bagnold, 1966), several studies have proposed the occurrence of distinct channel reach forms falling along a continuum of sediment supply to transport capacity limited (e.g., Schumm, 1985; Montgomery and Buffington, 1997; Church, 2006; Buffington, 2012).

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Because both sediment supply and transport capacity are field-measurable variables, it should in theory be possible to predict channel form based on the relationship between the two metrics. In practice, however, observed reach-scale channel form may differ appreciably for several reasons. First, neither supply of sediment nor transport capacity are fixed over time, and characteristics of a channel reach adjust dynamically to variations in water and sediment supply through mutual interactions between channel geometry, sediment composition, and flow dynamics that govern sediment mobility and thus transport capacity (Hack, 1957; Dunne and Jerolmack, 2020; Lane, 1955; Church, 2006; Pfeiffer et al., 2017; Mueller and Pitlick, 2013). Second, in imposed-form channels, local flow obstructions by rock outcroppings, coarse or resistant alluvium, or large wood can also force channel reach morphology that differs from that expected in alluvial channels of similar sediment supply and transport capacity (Wohl et al., 2004). As a result of these complex interactions, field measurements of sediment supply and transport rates can be logistically challenging and the time-scales of field-derived estimates may be poorly correlated with the processes directly influencing channel morphology (Kirchner et al., 2001; von Blanckenburg, 2005; Pfeiffer et al., 2017).

To better understand this geomorphic complexity, several established mountain river classifications provide simplified frameworks for interpreting channel reach morphology across a stream network (e.g., Lane, 1955; Schumm, 1977; Grant et al., 1990; Rosgen, 1994; Montgomery and Buffington, 1997; Kondolf et al., 2003; Brierly and Friers, 2013; Beechie and Imaki, 2014). Building on Lane's (1955) balance between sediment supply and transport capacity, Schumm's (1977) delineation of erosion, transport, and deposition reaches provides a general framework for

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examining channel form and landscape setting in mountain drainage basins. Montgomery and Buffington (1997) expanded on this work through development of a conceptual framework within which to classify channel reach form and predict response potential on the basis of sediment supply relative to transport capacity. They describe a spatial distribution of alluvial channel types from sediment-limited steep headwater channels with high hillslope-channel coupling to transport-limited channels further downstream where hillslope coupling is buffered by wider valleys. Many channel classifications have followed (e.g., Rosgen, 1994; Brierley and Fryirs, 2005), as described and compared in Kasprak et al. (2016).

In the absence of exhaustive geomorphic data, classifications remain fundamental to our understanding of fluvial geomorphic processes and channel response potential, and provide critical tools for the communication and simplification of inherently complex systems which can aid in public understanding and watershed management (Kasprak et al., 2016). Yet, despite their wide usage, many of these classifications suffer from one or both of two shortcomings: (1) their heavy reliance on expert opinion, and (2) their basis in field data spanning relatively small areas (10^1 - 10^3 km^2) and homogenous landscape properties due to data and resource limitations (e.g., Montgomery and Buffington, 1993; Brierley and Fryirs, 2005; Sear et al., 2009; Rinaldi et al., 2015). In the case of the former limitation, the outputs of any channel classification framework are simplifications of reality binned into discrete groups, the number and characteristics of which may be defined *a priori* by the developer(s). As a result, it is possible that multiple individuals tasked with classification of a similar region will produce schemes with appreciably different reach types and defining characteristics; see, for example, the classification developed by O'Brien et al.

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(2017) versus that of Montgomery and Buffington (1997) for a geomorphically similar region. In the case of the latter limitation, limited data coverage constrains the range of geology, topography, and climate conditions influencing the resulting morphological diversity in any one study area. For instance, while Kasprak et al. (2016) found high agreement between channel classifications within a single geomorphically diverse watershed, it is unknown how transferable the range of channel types and process linkages are outside the landscape properties exhibited by that watershed. This raises questions regarding the general applicability of these frameworks across landscape properties and regions, and quantitative thresholds for transitioning between distinct morphologies. Given how widely cited and used some classifications are for addressing distant, different places, one wonders how transferable and universal local to regional channel reach classifications really are?

Recent advances in remote-sensing and computational power offer the potential for comprehensive, data-driven assessment of relationships between landscape properties and channel morphology across large areas and datasets. Remote-sensing derived landscape information (e.g., Stout and Belmont, 2014; Legleiter, 2021) has spurred development of geomorphic feature mapping and terrain analysis over larger extents (Bizzi et al., 2015; Wheaton et al., 2017; Piégay et al., 2020). Numerous studies have linked various remotely-sensed or derivative landscape properties to hillslope erosion rates and sediment supply, including measures of lithology, catchment slope, topographic roughness, and valley confinement (e.g., Summerfield and Hulton, 1994; Pazzaglia and Brandon, 2001; Ahnert, 1994; Montgomery and Brandon, 2002; Attal and Lavé, 2006; Norton et al., 2011; O'Connor et al., 2014; Menting et al., 2015; Mueller et al., 2016; Braun et al., 2014).

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Valley slope has also been used as a measure of relative transport capacity (Gartner, 2016; Jain et al., 2006).

To help address the lack of large-scale quantitative relationships among sediment supply, transport capacity and channel reach morphology, the current study evaluates regional multivariate patterns in channel reach morphology and landscape controls over a large, heterogeneous landscape considering a diversity of geomorphic settings and landscape properties. This study leverages a unique dataset of channel reach morphological attributes measured in-situ at 1,013 locations distributed across a wide range of physio-climatic settings in California, USA. Following the reductionist approach of previous river classifications (e.g., Montgomery and Buffington, 1993), we reduce complexity by statistically grouping field sites into distinct channel reach types based on their morphological attributes, thus reducing the reliance on expert opinion. We then statistically assess the linkages between these channel types and remotely-sensed landscape properties previously associated with channel sediment supply and/or transport capacity. Dominant channel attributes and landscape linkages identified over the study area are then compared with those found in prevailing conceptual frameworks for mountain rivers. These comparisons aim to highlight how the geomorphic variability exhibited across California supports or diverges from expectations, and not to promote a specific classification methodology over another.

Methods

The following subsections describe the methodology to derive a data-driven statewide geomorphic classification and statistically analyze relationships between

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the resulting groups of channel reaches, or channel types, and a suite of geospatial variables representing a range of possible topography, climate, land use and cover controls (Figure 1).

Study area

The state of California, USA, spans 423,967 km^2 and is characterized by highly heterogeneous hydro-climatic regimes, geologic history, and topography (Dettinger et al., 2011). California contains 13 Level III ecoregions, including both the highest (4,418 m) and lowest (-86 m) points in the conterminous United States and annual average precipitation from 0 to 4,300 mm. California's geologic settings include the volcanic dominated Modoc Plateau, the sedimentary Coast Ranges, the granitic Sierra Nevada and the lowland alluvial Central Valley (Griffith et al., 2016). A diverse range of disturbance regimes also exists, including floods, wildfires, droughts, earthquakes, mass wasting, and tsunamis.

Feld surveys of 1,013 channel reaches previously collected across eight water management regions in California (SWRCB, 2019) provide the data for this study: Klamath, North Coast, North Central Coast, South Central Coast, South Coast, Sacramento, San Joaquin Tulare, and Southeastern California (Figure 2). Field sites in this dataset span drainage areas from 1 to 10,177 km^2 and were generally limited to wadeable, minimally impaired mountain and foothill rivers because reaches near and below reservoirs or other major flow or channel regulation were excluded. The following section describes the study and sampling designs used to acquire this field dataset.

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Data collection and study design

We sought to design the study as objectively as possible to ensure representation of a wide diversity of channel morphology and landscape properties (Lane et al., 2017). The study was also designed around the goal of predicting channel reach types across the entire state of California as a management support tool (Guillon et al., 2020). Throughout the study area, all stream networks were dissected into 200-m intervals based on the United States Geological Survey 10-m National Elevation Dataset (Gesch et al., 2002) and streamlines defined by the National Hydrography Dataset (NHDPlusV2, McKay et al., 2012). We then applied a two-tiered equal-effort, stratified-random sampling scheme to choose field sites among all available 200-m intervals in order to avoid over-sampling abundant settings or under-sampling rare settings. Specifically, for each management region, 200-m stream intervals were successively stratified by desktop-based measures of the following two pairs of variables: valley confinement (O'Brien et al., 2019) and sediment supply [estimated using the Revised Universal Soil Loss Equation (RUSLE, Renard et al., 1994), then local valley slope (Neeson et al., 2008), and contributing area. This study design, detailed in Byrne et al. (2020), yielded 30 sampling bins (i.e., five valley slope - area groups within six valley confinement - RUSLE groups) in each management region (Figure 2). At least 60 individual stream intervals were then randomly selected among 30 bins per region to ensure that a large range of channel settings was represented. Ultimately, the number of field sites was dictated by available resources and site access.

A transect-based sample design was applied to capture reach-averaged conditions as well as measures of subreach-scale longitudinal channel bed and width variability understood to act as hydraulic controls at the morphological unit scale (Lane et al.,

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2017; Byrne et al., 2020). Field surveys were completed by multiple field teams from several universities in summers 2015 through 2018. Field teams trained together to minimize data collection bias across regions. While site selection was made using 200-m stream intervals, actual stream survey lengths were fifteen times mean bankfull width, conforming to the consensus approach for channel reach measurement. Ten equally spaced cross-sections were surveyed per site beginning at the upstream riffle crest using rod and level techniques following Lane and Byrne (2021). This approach was selected given limited prior knowledge of the presence and spacing of geomorphic features at any given site and to align with existing regional sampling protocols (Ode et al., 2016). Bankfull stage was estimated using geomorphic and vegetative indices as defined by Ode et al. (2016) including lateral slope breaks, changes in vegetation and sediment size. A 100-sample Wolman pebble count was conducted along each cross-section (Wolman, 1954). Finally, a longitudinal elevation profile was surveyed, including the thalweg at each surveyed cross-section and additional significant slope breaks. Complete sampling protocols are available in Lane and Byrne (2021).

Field survey data was processed to generate a suite of nine channel reach geomorphic attributes: reach slope, bankfull depth, width, width-to-depth ratio, coefficient of variation of bankfull depth and width, median (D50) and 84th percentile (D84) grain size, and channel roughness. Water surface slope was estimated from the best-fit regression line of surveyed low flow water surface elevations at each transect. The coefficients of variation of bankfull depth and width were calculated as the ratios of standard deviation to reach-average depth and width values, respectively, across ten site transects (Lane et al., 2017).

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Statistical classification approach

Field sites were grouped into distinct channel types to identify emergent patterns from the data. These patterns were then used to reduce the noise associated with our large field dataset, evaluate correlation between distinct channel forms and landscape properties, and facilitate direct comparison with existing channel typologies. We applied the multivariate statistical classification approach detailed in Byrne et al. (2020) to distinguish groupings of field sites with limited *a priori* hypotheses or beliefs, thus reducing (but not eliminating) the need for expert opinion in channel classification. Such an approach is particularly useful in large regions with spatially heterogeneous climate, geology and topography like California, where classification systems developed in particular physio-climatic settings and with particular questions in mind may be inappropriate over part or all of the study area. The classification used the nine channel reach geomorphic attributes described above as well as desktop-based valley confinement (O'Brien et al., 2019) and contributing area, both known to influence channel morphology and found to significantly improve the statewide clustering outcome (Byrne et al., 2020).

Four major classification steps were performed: (1) cluster field sites based on the 11 geomorphic attributes and landscape properties described above; (2) train a classification tree model to identify dominant attributes; (3) assess the clustering solution; and (4) interpret resulting channel types. As the geomorphic attributes were measured along different scales, they were all rescaled between 0 and 1 to avoid skewing the outcome to attributes with large values and give similar weight to each attribute (Byrne et al., 2020). The field sites were clustered based on the eleven attributes using Ward's hierarchical clustering (Murtagh, 1983) and post hoc heuristic refinement following Byrne et al. (2020). Ward's clustering minimizes within-cluster

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variance and maximizes between-cluster variance based on Euclidean distances. The graphical Hubert and Arabie (1985) index was used to assess the suggested number of hierarchical clusters. An iterative heuristic refinement process included examining site photographs and interpreting geomorphic context of sites and their defining channel types to determine whether statistical branches were representative of differences in channel reach form.

Classification results consisted of the identified channel types, their geomorphic attribute ranges, and key splitting attributes in the classification tree model. The R programming language was used for all statistical analysis (R Core Team, 2017) and every effort was taken to make the classification process objective, transparent and repeatable. Dynamic notebooks as well as an R package were produced to facilitate transparency and reclassification given additional field data. Since the focus of this paper is linkages between channel geomorphic attributes and landscape properties rather than the classification methodology, detailed documentation of the classification effort can be found in Byrne et al. (2020), technical reports (Byrne et al. 2019, 2020; Guillon et al., 2019) and *Supplemental Information* (Figures S1-S10).

Geospatial variables

To represent a diverse array of possible topographic, climate, and land use/cover controls on channel morphology, we considered 255 desktop-based continuous and categorical geospatial variables previously derived for the study area by Guillon et al. (2020) along with several additional variables (See Table S6). All variables were either publicly available statewide raster and vector GIS datasets or derivative GIS products, and most were derived from the 10-m National Elevation Dataset, the NHDPlusV2 stream network, and the Stream-Catchment dataset (StreamCat, Hill et al., 2016). The variables described below were either expected to be and/or

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ultimately deemed important in the statistical analyses. Valley width and confinement level were delineated from the 10-m National Elevation Dataset using a GIS-based methodology similar to previous literature (Gilbert et al., 2016; O'Brien et al., 2019). For the purposes of this study, 25% slope was chosen as a threshold between valley bottom and valley wall capturing a medial value between clay and sand dominated hill footslopes (Carson, 1972). For each <25% valley slope polygon, four cross-sections per 200-m of stream length were averaged to calculate a single valley confinement distance. One of three valley confinement settings (confined, partly confined, unconfined) was then assigned to each field site. Sites in valleys <100 m wide were characterized as confined, sites in valleys between 100 m and 1000 m wide were considered partly confined, and sites in valleys >1000 m were considered unconfined. While this approach may introduce some discrepancies between estimated and on-the-ground confinement, it represents a rapid and repeatable method based on expert opinion of the significance of these thresholds for channel-hillside interaction (Byrne et al., 2020). The same valley width variable was used in the clustering analysis as described above.

Numerous variables thought to be associated with sediment supply were considered. Land use/ land cover variables available from StreamCat included the percent catchment area in different lithology types, land cover/use types, and soil composition (clay, sand), and RUSLE. These variables were calculated over two scales, the entire upstream catchment for each field site as well as the 100-m riparian buffer of the local NHD sub-catchment. The USGS lithology setting (Jennings et al., 1977) is a categorical dataset describing the dominant underlying

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geology at each field site. Mean annual precipitation based on PRISM (Daly et al., 1994) provided a measure of relative climate across the field sites.

Continuous topographic variables related to landscape elevation, slope, and roughness were calculated by Guillon et al. (2020) over two spatial scales for each field site to capture: segment hillslope and near-channel. *Segment hillslope* scale refers to a 500 x 500-m tile centered on the midpoint of a stream interval. *Near-channel* scale refers to a 100-m-wide near-channel buffer along the surveyed channel, matching the definition of the 100-m riparian corridor from StreamCat. At both scales, raster datasets were summarized using spatial statistics (i.e., mean, median, max, min, standard deviation, skewness) and attributed to individual field sites. There are limitations to using fixed buffer sizes, but scaling the calculation area by catchment or reach size would be computationally limiting for the 685,926 200-m stream segment in the study area. As a result, these scale distinctions are likely most meaningful for confined valley settings, as defined above, where the 100-m buffer approximately spans the river valley and the 500-m grid captures the surrounding hillslopes.

Landscape roughness variables describe general variability in the topographic relief surrounding a field site (Wilson et al., 2007; Hijmans et al., 2020) that has been linked to differences in erosion rates and sediment supply (Montgomery and Brandon, 2002; Braun et al., 2014). For example, *Roughness* is the difference between the maximum and minimum elevations of a 10-m cell and its surrounding cells, while *Topographic Roughness Index (TRI)* is a measure of the local variation in topography about a central pixel (Hijmans et al., 2020). Considering landscape

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roughness at two scales is important for distinguishing sediment supply characteristics. For instance, if near-channel *Roughness* is better correlated with channel morphology than *Roughness* of the hillslopes surrounding the segment, it may indicate that local episodic sediment contributions like debris flows and bank erosion play a larger role in channel formation and maintenance than hillslope erosion from rilling, sheet wash and soil creep.

Statistical linkages between channel morphology and geospatial variables

Scatterplots

To explore the multivariate dataset across all field sites categorized by our statewide clustering analysis, we initially produced scatterplots mirroring those developed by Montgomery and Buffington (1997) and then using modern algorithms for nonlinear dimensionality reduction. We subsequently quantitatively assessed relationships between channel reach morphology and landscape properties in three ways: mutual information, pairwise statistical analysis, and categorical predictor importance test with bootstrapping uncertainty analysis (Figure 1); each of these methods is detailed below. The code and long-form documentation corresponding to the following analyses are available in a linked open source R package.

Mutual information

A mutual information analysis derived from information theory (Guyon and Elisseeff, 2003) was performed to identify geospatial variables providing the highest statistical correlation with the distribution of channel reach attributes. Mutual information is a generalized measure of dependence between any two variables that can be used to quantify non-linear as well as linear dependencies. Mutual information is an

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attractive alternative to correlation because it more generally evaluates correspondence in states rather than only monotonic relationships (see details in Supplemental Information). Mutual information is well suited for geomorphic problems because variable dependencies in geomorphology are seldom linear or monotonic in nature but, while increasingly applied in hydrologic sciences (e.g., Harrold et al., 2001; Loritz et al., 2018), it has not been applied to explore geomorphic controls. Method details are provided in Supplemental Information. Results were averaged over 500 sub-sampling iterations with an 80% split ratio. Dot plots were generated to visualize the relative amount of information contained in top-ranked geospatial variables.

Pairwise analysis

Pairwise analysis based on the non-parametric Kruskal–Wallis and Dunn tests was performed to investigate the dominance of selected continuous geospatial variables on channel type. Variables were evaluated with respect to the number of significant pairwise comparisons, considering all possible combinations of channel type pairs. There is no direct correspondence between mutual information and the pairwise comparison, although both assess statistical differences in channel types with respect to geospatial variables. The occurrence of numerous significant pairs for a given variable would indicate that the variable can consistently distinguish between field sites in those channel types. For a variable to be considered a significant control, we propose that at least 50% of channel type pairs must show significant differences at the 90% confidence level. Dot plots were generated to visualize the proportion of channel type pairs distinguished by top-ranked variables. Results for key variables were also visualized as matrices using heat maps to display the significance of each channel type pair.

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Categorical variable importance tests

Finally, we sought to evaluate the role of categorical variables like lithology in driving channel type outputs. We first quantified the observed distribution of channel types across categories. Next, we evaluated the likelihood that observed distributions could result from equal-probability random occurrence using statistical bootstrapping, where random occurrence is the null hypothesis. Variable categories were randomly assigned to each field site and the distribution of channel types across categorical settings was compared to the observed data. We generated 1,000 random distributions of channel type among categorical settings to obtain robust statistical expectations of the uniqueness between category and channel type. A low p-value indicates that the null hypothesis is unlikely and occurrence of a given category in a given channel type is statistically significant.

This procedure was used to produce two specific tests. First, for each channel type, the percent of sites occurring in each category was compared between observed and bootstrapped datasets. If the number of sites in a category (observed) is indistinguishable from random (bootstrapped), there is no indication of dominance. For a specific category to be considered a dominant control on channel type, we propose that at least 50% of channel types in that category would deviate from random at the 90% confidence level. Second, we compared the number of categories exhibited by each channel type based on bootstrapped results. Results are deemed significant if the bootstrapped probability of the observed number of categories in a channel type is less than 5% (Byrne et al., 2020). Pairwise test results were again visualized as matrices using a heat map to display the significance of channel type pairs.

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Results

Channel reach morphological diversity

The clustering analysis resulted in ten channel type groups (Figure 3, Figure S1, Figure S8, Table S2) with 44 (4%) to 178 (18%) field sites per group and 81.6% cross-validation performance (Figure S7). Thus, equal effort sampling design based on desktop geospatial variables, while important, could not yield an equal distribution of sites among the final types. D84 and the coefficients of variance of channel depth (CVd) and width (CVw) were the dominant field-based splitting attributes driving the clustering outcome (Figure 3, Figure S7). D84 distinguished steep boulder-dominated channel reaches (CA-1) from all others (>4200 mm), cobble-boulder dominated sites (>1500 mm) (CA-5), and gravel-cobble dominated sites (>440 mm) (CA-6 and CA-10) (Figure 3). Valley confinement was also a dominant splitting attribute.

Below, the statewide channel types are briefly described in order from most to least confined valley settings, given the role of valley confinement as a class splitting variable. Representative images of each channel type are provided in S1. Field sites exhibited the greatest diversity in confined valleys (n=6), spanning most channel bed forms (e.g., plane-bed, pool-riffle) and dominant grain sizes, while field sites in partly-confined valleys exhibited the lowest diversity. *Gravel-cobble cascade/step-pools* (CA-6) were the steepest, narrowest, and most confined headwater reaches. *Cobble-boulder step-pools* (CA-5) were also relatively steep, but were considerably wider and contained larger sediment clasts than CA-6. Moderate sloped *Cobble-boulder uniform* (CA-10) were the most prevalent channel type, distinguished by low sub-reach depth and width variability. *Confined cobble-boulder steep deposit-pools* (CA-1) were similar to CA-10 but had larger grain sizes, leading to rhythmic bed

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patterns comparable to pool-riffle streams (Figure S1). The name derives from the observation that the topographic crests of these bed undulations generally contained boulder deposits and steep faces. *Confined gravel-cobble bed undulating* (CA-4) sites, with lower slopes and smaller grain sizes, were distinguished from *confined gravel-cobble pool-riffles* (CA-9) by higher sub-reach variability. Channel reaches in partly and unconfined valley settings were primarily distinguished by differences in sub-reach variability (Figure 3a-c). *Partly-confined gravel-cobble, pool-riffles* (CA-7) had the largest channel dimensions (i.e., depth and width), while *gravel-cobble uniform* (CA-8) channels were more uniform and considerably smaller. *Unconfined gravel, uniform* (CA-2) and *gravel pool-riffle* (CA-3) channels had similar morphological attributes, but CA-2 channels were more uniform.

There was a relatively balanced distribution of channel types across statewide management regions (Figures S9 and S10, Tables S3-S5). This indicates that, when considering all field sites in California, most regions exhibit a large range of geomorphic forms regardless of physio-climatic setting, and also that the stratified sampling design used to select study sites successfully generated a diverse site distribution across each management region. Most channel types had at least several observations in each region. CA-7 was an exception, with over 80% of sites occurring in the NC region and no sites in SECA (Figure 2). Some regions exhibited dominant channel types, such as SJT (43% CA-1) and NCC (46% CA-4). These regional differences in morphological diversity support the need to assess landscape linkages beyond management region delineations using large field datasets.

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The scatter plots in Figure 4 illustrate the underlying field sites categorized according to our and Montgomery and Buffington's (1997) classifications in multi-dimensional space. Channel type color hue maps to valley confinement so that cyan (red) corresponds to the most unconfined (confined) channel type, and lightness maps to median field-derived reach slope so that channel types with low (high) slope are in lighter (darker) colors. Figures 4a and 4b use the same axes as plots in Montgomery and Buffington (1997) to facilitate direct comparison in familiar variable space: (a) drainage area - channel slope and (b) channel slope - relative roughness. Figure 4b illustrates the much larger variable space range represented in our dataset. The scatterplot in Figure 4c results from a Uniform Manifold Approximation and Projection (UMAP), a state-of-the-art algorithm for nonlinear dimensionality reduction, which projects the field sites from multivariate to two-dimensional space for visualization purposes (McInnes et al., 2018). Compared to the more common Principal Component Analysis and Non-Metric Dimensional Scaling, UMAP preserves local distances between observations rather than the global distance structure of the entire dataset. It is also highly scalable and non-linear, but does so at the cost of interpretability as the solution is non-unique and the projection axes have limited meaning. Comparing the categorized observations in the simple two-dimensional slope-area and relative roughness-slope spaces (Figures 4a and 4b) with the UMAP multi-dimensional dataset projection (Figure 4c) underlines the better class separation achieved when considering channel morphology as a high-dimensional process. While UMAP retains some variance, the overlap between channel types is reduced and there is an apparent structure in the progression from one cluster to another. These plots can be explored dynamically in the linked R package.

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Statistical linkages with landscape properties

Across the study area, desktop-based *valley confinement* shared the most mutual information with the channel types (MI=0.38) (Figure 5a). Other top-ranking geospatial variables included continuous measures of segment-scale (500-m grid) topographic roughness (e.g., *Elev-std*, *Roughness*, *TRI*) and slope (mean, median, minimum) as well as *valley slope*. However, these variables all had substantially lower MI (0.14 - 0.22), indicating poor explanatory power. Although *contributing area* was also an input to the classification, it exhibited low MI as an explanatory variable. No near-channel topographic variables or contextual variables ranked in the top 15, including those related to basin lithology or land cover.

Similarly, the pairwise analysis primarily identified continuous topographic roughness and topographic slope variables as distinguishing the most channel type pairs (Figure 5b). Figure 6 shows the resulting channel type pair significance matrices for variables related to topographic relief, topographic slope, and valley slope. The maximum number of significant pairs, 76% or 34 out of 45 possible pairs, was achieved by *Slope-min-seg*, followed closely by *Elev-std-nr*, *TRI-min-seg* and *Roughness-min-seg.* In contrast with mutual information, several top-ranked topographic variables were near-channel scale (100-m buffer), including median, mean, and minimum near-channel slope and roughness (e.g., *Elev-std, TRI, Roughness)*. *Valley slope* and *contributing area* both ranked in the top 15 (Figure 5b). *Valley slope* could distinguish between but not within field sites falling in three major channel slope groups [i.e., steep (CA-6,-5), moderate (CA-1,-10,-9,-4,-8), and low (CA-2,-3,-7)] (Figure 6b). While *Slope-mean-nr* and *valley confinement* did not perform as well as *valley slope* overall (Figure 5b), unlike *valley slope* they could distinguish CA-7 sites from CA-2 and -3 and between CA-10 and -8. No variables

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could explain the higher sub-reach topographic variability of CA-3 than CA-2, or of CA-4 than CA-9.

With respect to USGS lithology categories, only alluvium and granite significantly influenced channel morphology based on our proposed significance threshold (50% of sites), although sedimentary and limestone were significant with respect to some channel types (Figure 7a). Alluvium had six channel types with significant returns and granite, limestone, and sedimentary had five, four, and four, respectively. When combined with the site occurrence frequency, this indicates that unconfined low slope sites in CA-2 (n=70) and CA-3 (n=76) disproportionately occur in alluvium (73% and 57% of sites, respectively) (Figure 7b). Alternatively, confined sites were also significant in terms of alluvium, but their low occurrence (<5%) indicates that they are significantly unlikely to occur there. Field sites in CA-1, -5, and -6 occurred disproportionately in granite (>25% sites each), CA-6 and -7 in sedimentary (>30% sites), and CA-4 and -8 in limestone (>35% sites). The second categorical variable test indicated that sites in CA-2, -4, -7 and -8 occur in fewer settings than expected. This is true for CA-2 because a significant proportion of sites fall in alluvium (51 of 70), resulting in only five settings being represented instead of the eight expected under random occurrence (Figure 7b). Similarly, a significant portion of CA-7 sites occur in sedimentary settings (18 of 44). CA-1,-5,-6 and -10 were significant in the first but not the second test, highlighting the importance of using multiple lines of evidence to interpret these multidimensional relationships.

Discussion

This study leveraged a 1,013-site, transect-based field dataset of channel reach morphology attributes over a large range of geology, climate and topography to

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elucidate patterns in river morphological diversity and statistical linkages with landscape properties. Below, we discuss the dominant geomorphic attributes and landscape linkages identified in the context of prevailing channel classifications and conceptual frameworks for mountain rivers. These comparisons highlight how the geomorphic variability exhibited across California both reflects and diverges from expectations, and the utility of data-driven analysis.

Field observations in the context of past studies and future research

Study findings demonstrate that the dominant field-based geomorphic attributes identified across California using data-driven techniques largely align with key attributes of established conceptual frameworks for mountain rivers but also show some important unique outcomes. Our field sites spanned a much larger range of morphological attributes (e.g., reach slope, relative roughness) and landscape properties than past studies (Figure 4) and were selected through a more rigorous equal-effort, stratified-random sampling design. Even so, some primary splitting attributes in the multivariate clustering analysis - D84 and sub-reach topographic variability (Figure 3) - align with Montgomery and Buffington's (1997) diagnostic features of alluvial channel types, which include dominant grain size, bedform pattern and dominant roughness elements. Bedform pattern, which refers to the oscillation structure of the channel bed, broadly maps to the more quantitative coefficient of variation of channel depth we used. Cross-sectional geometry and channel reach slope also vary by channel type in both classifications.

On the other hand, a key finding from our study is that valley confinement is distinct from landscape position. Past field studies have found that unconfined valleys primarily contain plane-bed and pool-riffle channels, while confined valleys frequently

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exhibit step-pool and plane bed morphologies (e.g., Montgomery and Buffington, 1997; Nagel et al., 2014; Buffington, 2012), although exceptions arise where local forcing elements, such as rock outcroppings and hillslope sediment inputs drive discrete confinement variability. However, in hydroclimatic and geologically diverse landscapes, this patterning of valley and channel type as a function of landscape position breaks down, even at longer reach scales. Because this patterning is not assumed in our classification approach, the outcome is that we are able to distinguish channel types with a similar form, but which are present within valleys of quite different confinement. For example, plane-bed and riffle-pool channels were observed in unconfined, partly confined, and confined valleys (Figure 3 and S1, Table S2). O'Brien et al. (2019) recently highlighted the distinct role of valley confinement from landscape position using detailed downstream relationships between reach-scale valley confinement and more conventional controls on river channel morphology (e.g., contributing area, slope, stream power). Kasprak et al. (2016) also found that divergence in agreement between different channel classifications was primarily observed at reaches where channel planform was decoupled from valley setting.

As just one example, consider a generic riffle-pool channel type which is classified within a framework that does not consider valley setting. At baseflow, valley confinement may be relatively unimportant while, at higher discharges, morphodynamic evolution of the channel may be starkly different between valley settings as a function of valley roughness elements and overbank accommodation space. While Fryirs and Brierly (2012) pushed for acknowledging valley confinement as a major control within a hierarchically nested classification approach, their focus on understanding catchment-specific patterns differs from our goal of evaluating

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morphological diversity and landscape linkages over *many* heterogeneous catchments. It is beyond the scope of this study, but our California dataset is large enough to further investigate the distribution (i.e., positioning, total length, segment length) of each channel reach type across valley settings. While classification and analysis methods increasingly consider valley structure (Nagel et al., 2014; O'Brien et al., 2019), there are surprisingly few valley-type classifications, let alone quantitative ones, so this is an important topic for further research.

As another key difference, the clustering analysis highlights major differences in sub-reach scale topographic variability across field sites and the need for additional assessment of these attributes and their landscape linkages. Field sites distinguished primarily by sub-reach depth and width variability (<20 bankfull channel widths) fell largely in unconfined valley settings (Figure 3). This is consistent with the notion that channels in wide alluvial valleys with low channel-hillslope coupling are buffered from direct hillslope impacts by floodplains, making these reaches more dependent on fluvial processes (Montgomery & Buffington, 1997). As a result, alluvial channels lower in the watershed may be expected to adjust through changes in hydraulic geometry and longitudinal variability more than slope or sediment composition- although local forcing by outcroppings, valley walls, or wood can also have a significant yet localized effect (Rice, 1994). As valleys become less confined, this gives rise to channel change patterns driven by aggradation and transition to more complex sub-reach topography such as undulating bed forms and braiding (e.g., Schumm, 1977). We note, however, that relative field-measured slope ranges are similar across confined and unconfined channels, and streams in unconfined valleys may exhibit similar relative slope adjustments in response to water or sediment regimes but these adjustments are masked by the narrow slope range

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relative to that exhibited over the entire study area (Figure 3c). In spite of these established linkages, the type and nature of sub-reach morphological features have traditionally been considered part of an assemblage characteristic of a channel type rather than distinct, measurable attributes that may provide unique insight into landscape connectivity and channel processes (Lane et al., 2017). The field data collected for this study could be used to explore alternative sub-reach topographic variability attributes and their linkages to landscape properties and channel response potential. These attributes could range from standard deviation of channel depth and width to more complex measures of longitudinal variance and covariance (e.g., Pasternack et al., 2018) or continuous multi-scale wavelet analysis (Duffin et al., 2021). However, assessment of sub-reach scale variability is constrained in our dataset to evenly spaced transects, and higher resolution channel topography would be needed to more fully consider the importance of variability.

The variability exhibited by the field sites and their landscape linkages emphasizes both the importance and the difficulty of organizing and reducing data-driven results into a meaningful conceptual framework. The morphological assemblages that make up each channel type are the result of non-linear feedbacks between multidimensional, multi-scale processes. Given the inherently fuzzy nature of channel types and the fact that field sites exhibit varying degrees of variability about their singular geomorphic archetype, the scatterplot of all the field sites projected in nondimensional multivariate space in Figure 4c provides the most complete representation of the dataset. Despite its clarity, the figure has little explanatory power, limiting our ability to interpret observed patterns relative to past studies. We therefore attempted to map our data-driven channel types onto a well-known figure by Montgomery and Buffington (1997, see their Figure 6) that describes a smooth

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downstream transition from cascade to pool-riffle along a sediment supply- to transport-limited continuum (Figure 8a). While some channel types fit readily into this framework, channel types describing plane bed, bed undulating, and pool-riffle channel geometries in confined valley settings do not fit neatly along this continuum due to the low correlation between landscape position and valley confinement. We speculate that this is because these three channel types can exist at many points along the continuum of supply-to-transport limited channels.

An alternative diagram instead organizes the statewide channel types in terms of valley confinement and channel bedform (Figure 8b). Representative field site photos for each channel type are provided, with those channel types that broadly map onto the Figure 8a conceptual model outlined in red in Figure 8b. Notably, even in Figure 8b, channel types CA-4 and -10 are both shown as pool-riffle bedforms while in reality CA-4 sites are ‘bed undulating’, meaning they have similar channel bed variability to pool-riffle channels but more uniform widths. This highlights that the four bedforms commonly used to describe river channel morphology only consider channel bed variability but ignore the variance and covariance of channel width (Pasternack et al., 2018). The channel types that do not fit the Montgomery and Buffington (1997) classification occur in confined settings which were primarily found in mountainous areas, despite the fact that this prior approach was developed specifically in such environments.

Channel morphology can be distinguished based on landscape properties

Observed morphological diversity across the field sites could be distinguished to varying extents by landscape properties previously linked to sediment supply and

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transport capacity, suggesting that these differences may reflect differences in sediment supply relative to transport. The five dominant landscape properties broadly describe: valley confinement, valley slope, average slope of the surrounding landscape (e.g., *Slope-mean-seg*), relief of the near-channel environment (e.g., *Elev-std-nr*), and underlying lithology (e.g., *USGS lithology*) (Figures 5-7). While relationships between channel morphology and landscape properties should not be taken for causation given the high correlation among variables, they provide additional empirical support for the findings of past studies over a larger range of geology, climate and topography. For instance, landscapes in different dominant lithologies (Pizzuto, 1995; Attal and Lavé, 2006; Norton et al., 2011; O'Connor et al., 2014; Menting et al., 2015; Mueller et al., 2016), topographic roughness (Braun et al., 2014) and topographic slope (Montgomery and Brandon, 2002) have been associated with different sediment supply rates and composition, while valley slope has been used to compare sediment transport rates (Gartner, 2016; Jain et al., 2006).

The categorical variable importance tests indicated that lithology could explain some of the morphological differences between field sites. While the StreamCat variables describing percent catchment area in different lithology settings were not significant in the mutual information or pairwise analyses, the hardest (granite) and softest (sedimentary, limestone) lithologies were correlated with certain channel types (Figure 7). Specifically, the fact that channels underlain by granite were disproportionately likely to be steep and boulder-dominated (CA-1, -5, and -6) is consistent with studies indicating that lower sediment supply drives coarser grain sizes (e.g., Dietrich et al., 1989; Eaton and Church, 2009). The greater diversity of dominant grain sizes observed in channels underlain by harder rocks (Figure 7) is

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also consistent with observations that low sediment supply channels may adjust primarily through changes in sediment composition without substantial adjustments to downstream geometry (Dietrich et al., 1989; Madej et al., 2009; Eaton and Church, 2009; Pfeiffer et al., 2017). Furthermore, field sites in highly erosive sedimentary settings typical of the northern California coastal range - such as fractured mudstone and sandstone (McLaughlin et al., 1994)- exhibited the widest channels (*large gravel-cobble pool-riffle*), supporting the idea that streams draining erosive lithology can be wider as a result of long-term high sediment inputs (Roering et al., 2005; May et al., 2013; Beeson et al., 2018). It should be noted, however, that these statistical outcomes do not account for potential correlation among geospatial variables. Evaluating variables more directly linked with sediment supply or transport capacity within the same statistical analysis framework would increase the explanatory power and reduce misattribution of landscape linkages. This is possible using the current field dataset, but would require limiting analysis to the subset of field sites for which selected landscape information is available.

In summary, the data-driven analyses described here provide insights into the landscape properties and scales influencing channel reach morphology over a large, diverse region that may be useful to the field-, remote sensing-, and physics-based fluvial geomorphology communities as well as the river management community. For the field-based fluvial geomorphology community, which is the target audience for this paper, our data analysis framework and results provide a less biased verification of previous channel classifications and a way to organize and begin to make sense of the complexity of channel morphology over large spatial scales. The data used here could additionally inform fluvial geomorphic studies well outside of channel classification, including grain size prediction, testing for the presence of threshold

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channels, and habitat suitability modeling for a variety of aquatic species. For the remote-sensing community, the distillation of hundreds of available spatial metrics for describing reach-scale properties may streamline workflows for describing and classifying channels over broad, geomorphically diverse regions (Kasprak et al., 2016; O'Brien et al., 2019). For the physics-based fluvial geomorphology community (e.g., Phillips and Jerolmack, 2016; Phillips et al., 2021), it would be useful to know which landscape properties are significant based on field observations and which may be ignored in order to prioritize key aspects of mechanistic theory to focus on. For the river management community, climate or land use changes resulting in major shifts in sediment supply may significantly affect the occurrence and distribution of channel reach settings across a region, with major implications for channel morphodynamics and aquatic habitat. The channel type organization and landscape linkages described in this study could help river restoration practitioners or management agencies predict how the characteristics of a given channel reach may change in response to short-term alterations of streamflow or sediment supply that occur over time-scales relevant to humans and aquatic populations.

Caveats and Future Questions

While the consistency of relationships between channel reach morphology and multi-scale landscape properties across the state of California supports their widespread applicability, extending our statistical analysis framework over more and larger ranges of landscape properties would help identify conditions in which these relationships break down. For instance, similar to how valley confinement played a distinct role in our study relative to past studies of mountain rivers, the observed lithology controls may be limited to certain spatial scales. Aalto et al. (2006) and Andrews and Antweiler (2012) found that lithology drives sediment supply in basins

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<10^3 km^2 in area while Syvitski and Milliman (2007) found that lithology played a small role in sediment yield fluctuations at larger scales (>10^5 km^2). Since our field sites all had contributing areas <10^3 km^2, extrapolation to larger catchments should be performed with caution. In very low order channels, lithology controls may diminish as well. Mueller et al. (2016) found that sediment supply from the hillslope was independent of lithology over short distances (~3 kilometers) in confined settings. In this case, valley confinement may provide more direct linkages to hillslope-channel coupling and sediment supply characteristics that do not suffer from the same scale limitations. Additionally, more nuanced measurements of valley confinement may provide better insight into the role of hillslopes in affecting channel form and process. The confinement of channels which are anomalously wide or narrow within a given valley may not be characterized accurately through measurement of valley width alone. For example, Brierley and Fryirs (2005) propose the delineation of confinement classes be completed based on the proportion of reach length that abuts a valley margin, as opposed to the more basic valley width measurement, and such an approach may improve the extendibility of our classification framework to other regions.

Our study is limited in applicability as a “general framework” due to its restriction to wadeable streams, and the focus on gravel-cobble-boulder streams, with few bedrock or sand-bedded rivers represented in the dataset despite our stratified random sampling. Every effort was taken to make this process objective, data-driven and repeatable, but several assumptions were critical to the interpretation of results. First, given limited field data, multivariate statistical classifications still require some amount of expert-based heuristic refinement to interpret channel types.

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Second, field datasets were collected by multiple regional field crews to facilitate such a large field campaign. As such, comparability of regional field datasets, and specifically the most subjective attributes associated with bankfull conditions assumes that no substantial biases were incurred in the combination of these datasets into a bottom-up classification. Even so, some biases may exist based on a manual review of the field data, although it is difficult to isolate sampling biases from natural differences in channel attributes between the regions. For instance, some under-prediction of bankfull depth in the North Central Coast likely contributed to the high width-to-depth ratios in that region. We also assumed that field-measured channel morphology represents a steady condition through time (i.e., field observations reflect those measured from remote sensing and GIS datasets at the segment scale, despite potential temporal differences in dataset collection or generation). This is a simplification and may contribute to noise or error in our relationships.

Particularly in light of the above limitations, the statistical relationships observed in this study do not establish causation. Dominant landscape properties may be correlated to other variables that better reflect process controls. For instance, short-term or small-scale but substantial sediment inputs may not be represented by the variables considered here, thus underestimating sediment supply to some channel reaches. A dataset of ^{10}Be derived erosion rates across all field sites similar to Pfeiffer et al. (2017) would better represent coarse sediment supply than geologic setting or RUSLE, but is not available over the entire study area. We also assumed that segment-scale measures of topographic roughness and slope are proxies for sediment supply to the channel, and the discussion above rests on this assumption

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and its consistency across channel types, which may be imprecise at times. In reality, connectivity of surveyed streams to their upstream sediment sources may vary by channel type or site independent of catchment topography. Landscape evolution models would inevitably improve our understanding of physical process controls on channel reach form and morphodynamics if they could include all the processes hinted at by this study.

Conclusions

Given the complex array of processes influencing channel morphology, conceptual frameworks or classifications of river channels are critical to our understanding of channel processes and response potential as well as river restoration efforts. Yet despite their wide usage, many classifications are based on limited observations over homogenous landscapes, raising questions about their general applicability and quantitative thresholds. Leveraging a large transect-based field dataset for California, we used a data-driven approach to elucidate dominant channel attributes and their linkages to landscape properties associated with a diverse array of possible controls on channel morphology. This approach builds on, but diverges from, established frameworks by evaluating emergent patterns from the data rather than imposing classification outputs *a priori* based on limited observations, and by evaluating patterns across a highly heterogeneous study area. The data analysis framework could be applied worldwide to explore underlying linkages between channel morphology and landscape properties over large datasets. The statistical analyses - including multivariate clustering, classification, mutual information, pairwise analysis and categorical variable testing - demonstrate the utility of

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considering channel reaches and landscapes as multidimensional features to elucidate and test established linkages.

In general, dominant channel attributes and landscape properties identified over the study area aligned with established conceptual models for mountain rivers, but there were also key differences. Similar to Montgomery & Buffington (1997), sediment composition and sub-reach depth variability (i.e. bedform pattern) were found to be discriminating channel attributes. Additionally, most significant landscape properties or similar variables have been previously associated with channel sediment supply (e.g., lithology, segment-scale topographic slope and roughness, valley confinement) and transport capacity (e.g., valley slope), suggesting that morphological diversity across the study area largely reflects differences in sediment supply relative to transport capacity as posited by prior channel classifications. Our study also shows that presumed linkages between valley confinement and channel type based on landscape position break down when considering a diverse region beyond glacially-influenced mountain settings. Rather, most channel bedforms (ranging from cascade to uniform) and dominant grain sizes occurred across confined, partially confined, and unconfined valley settings. Finally, the inability of any geospatial variables to distinguish field sites separated on the basis of depth and width variability highlights a need for additional research to characterize sub-reach variability patterns and landscape linkages.

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Data Availability Statement

Code, long form documentation and data are available through the open source R package *RegionalDrivers* at https://doi.org/10.5281/zenodo.4526525.

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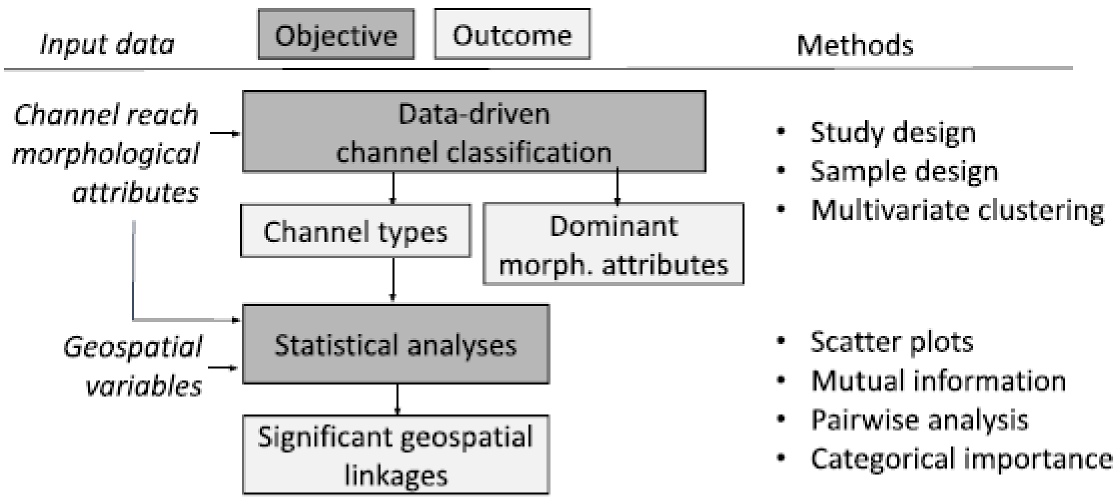

Figure 1. Overview of methods and data used to achieve research aims.

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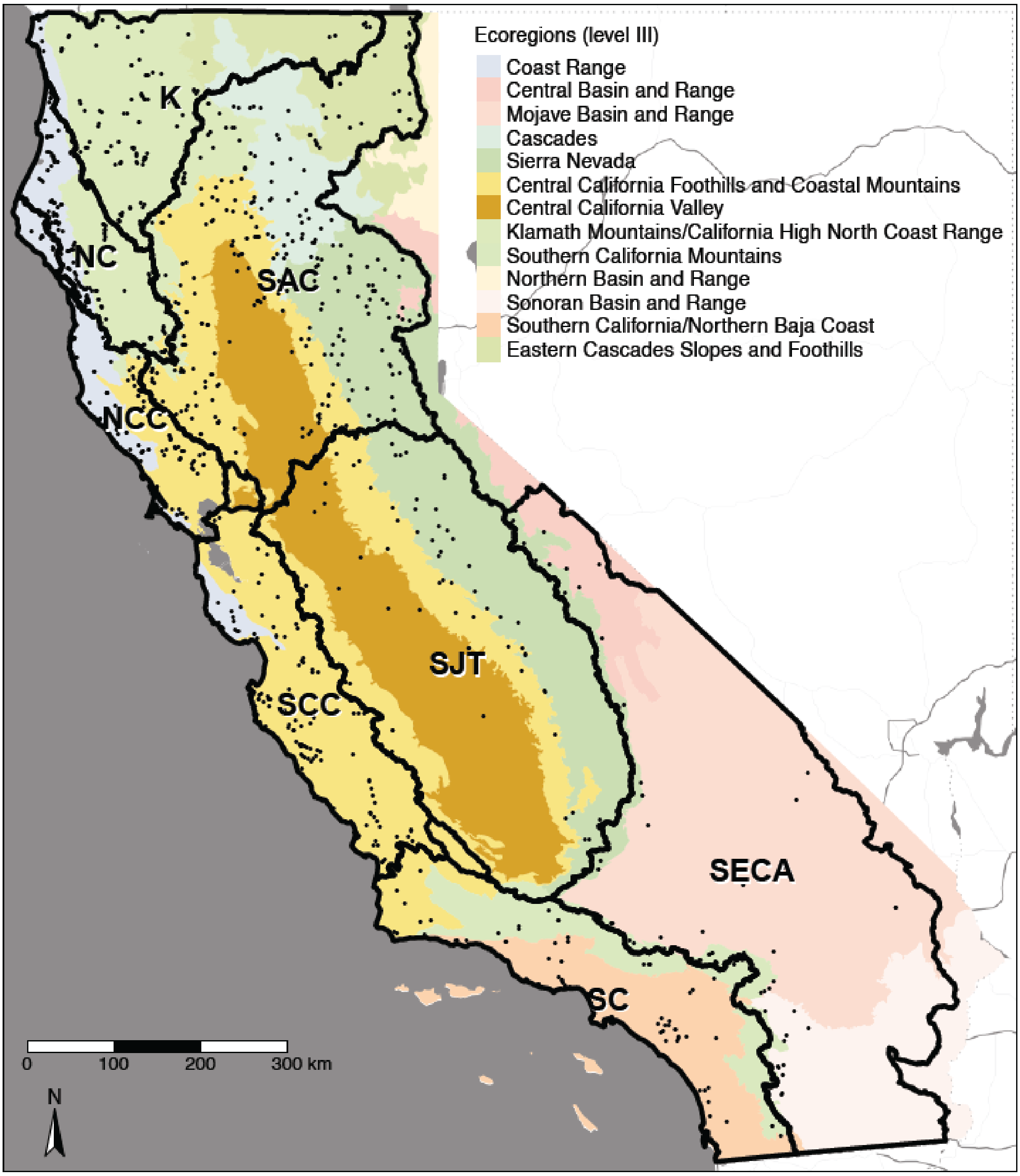

Figure 2. 1,013 field sites were surveyed across California, USA, spanning eight water management regions and a large range of physio-climatic settings.

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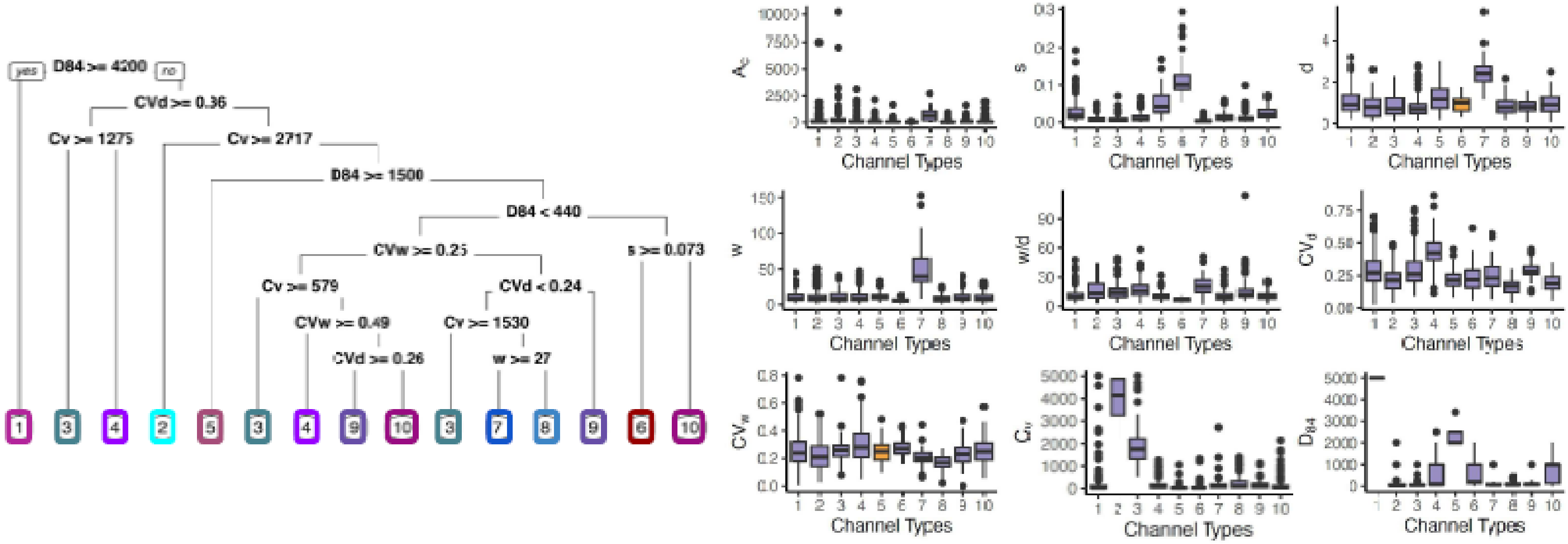

Figure 3. Classification outputs include (left) a regression model indicating dominant attributes and thresholds and (right) box-and-whisker plots of geomorphic attributes across channel types. Purple (orange) boxes represent channel types significantly different (p < 0.05) than multiple (one) other channel types. (*Ac* is contributing area, *s* is surveyed slope, *d* is bankfull depth, *w* is bankfull width, *w/d* is bankfull width-to-depth ratio, *CVd* and *CVw* are coefficient of variation in bankfull depth and width, *Cv* is valley width, and *D84* is the 84th percentile sediment size.)

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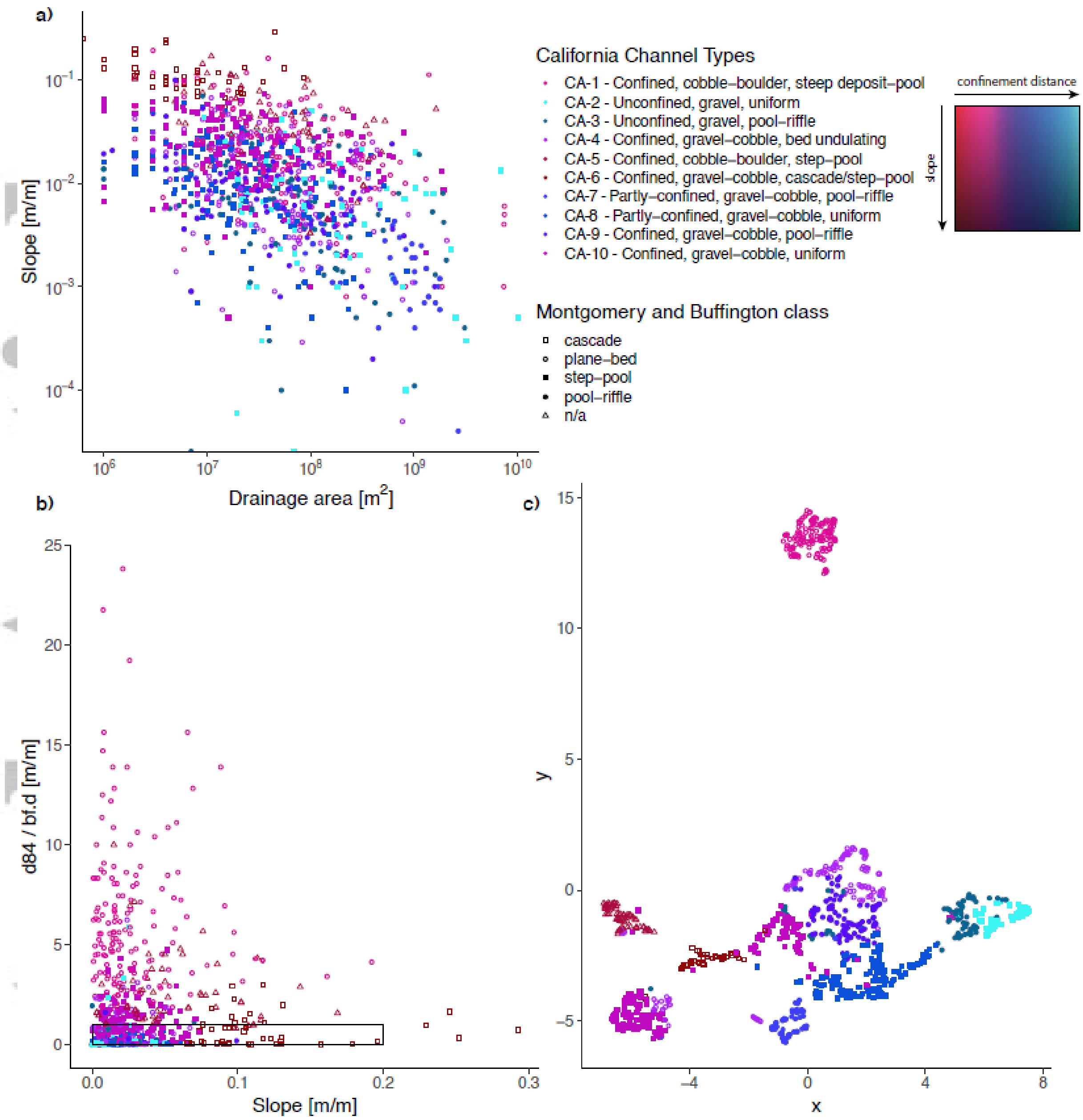

Figure 4. Classified study sites plotted in terms of (a) drainage area and channel slope, (b) slope and relative roughness, and (c) a nondimensional UMAP projection of the multidimensional geomorphic attribute dataset. The box in (b) represents the range of slope and relative roughness considered by Montgomery and Buffington (1997). In all plots, field sites are symbolized based on statewide channel type and closest Montgomery and Buffington (1997) channel type. Statewide channel type color hue maps to confinement so that cyan (red) corresponds to the most unconfined (confined) channel type, and lightness maps to slope so that channel types with low (high) slope are in lighter (darker) colors.

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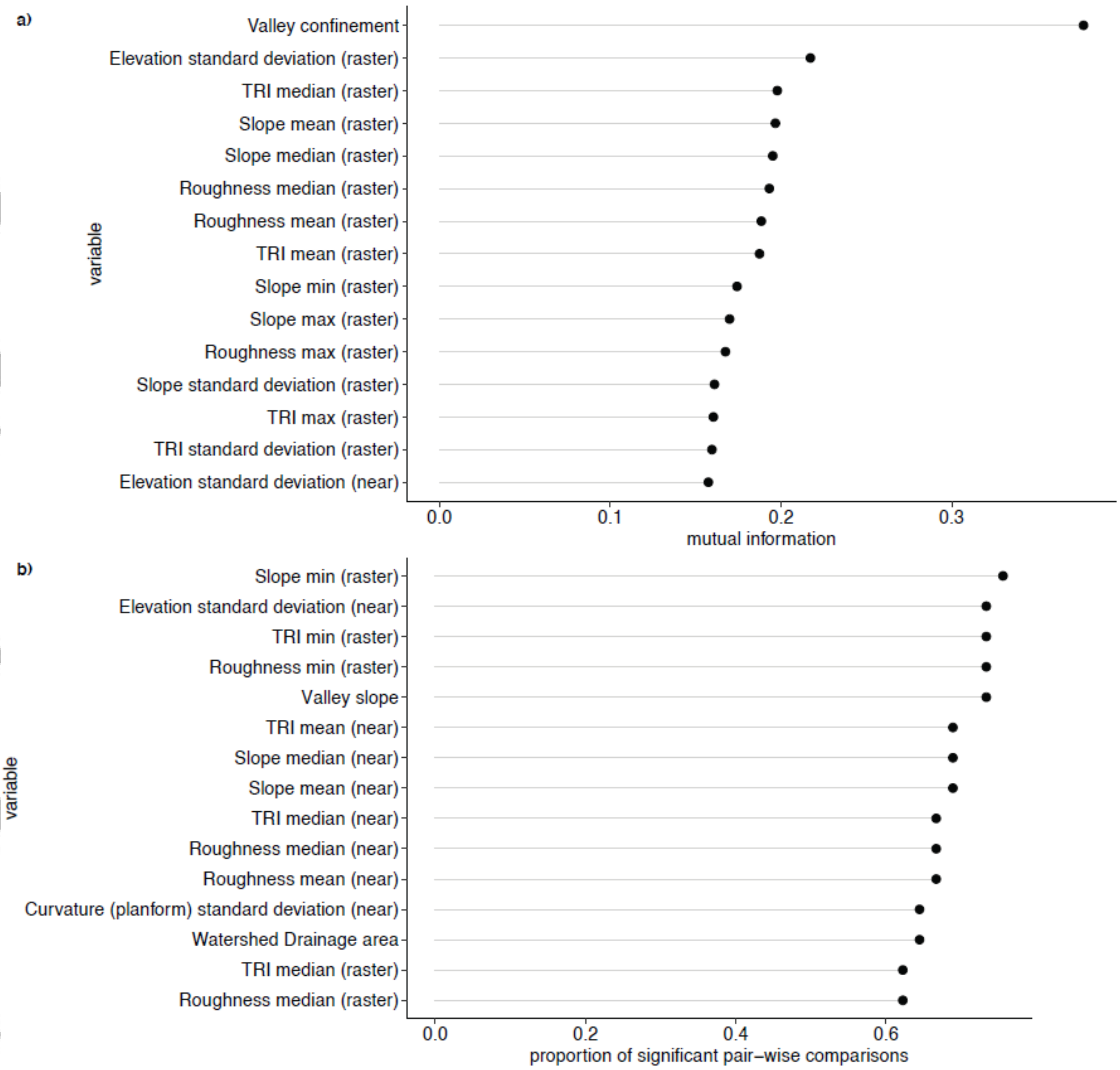

Figure 5. Top 15 geospatial variables ranked according to (a) mutual information and (b) pairwise analysis based on the proportion of significant channel type pairs. Variables indicated as *raster* are calculated at the segment scale (500-m grid), and variables indicated as *near* are calculated at the near-stream scale (100-m buffer).

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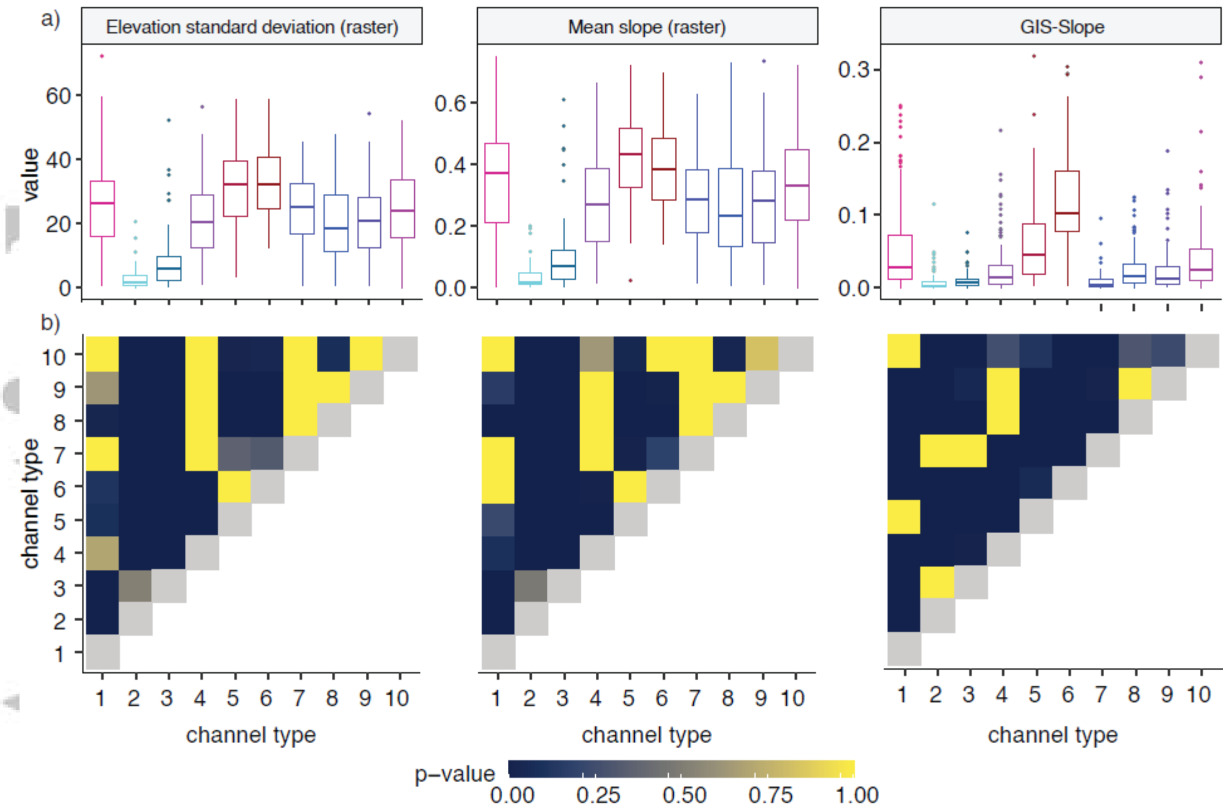

Figure 6. (a) Box plots and (b) pairwise significance results for geospatial variables describing segment-scale topographic roughness, topographic slope, and valley slope across all field sites in each channel type. Darker cells indicate higher significance based on p-value.

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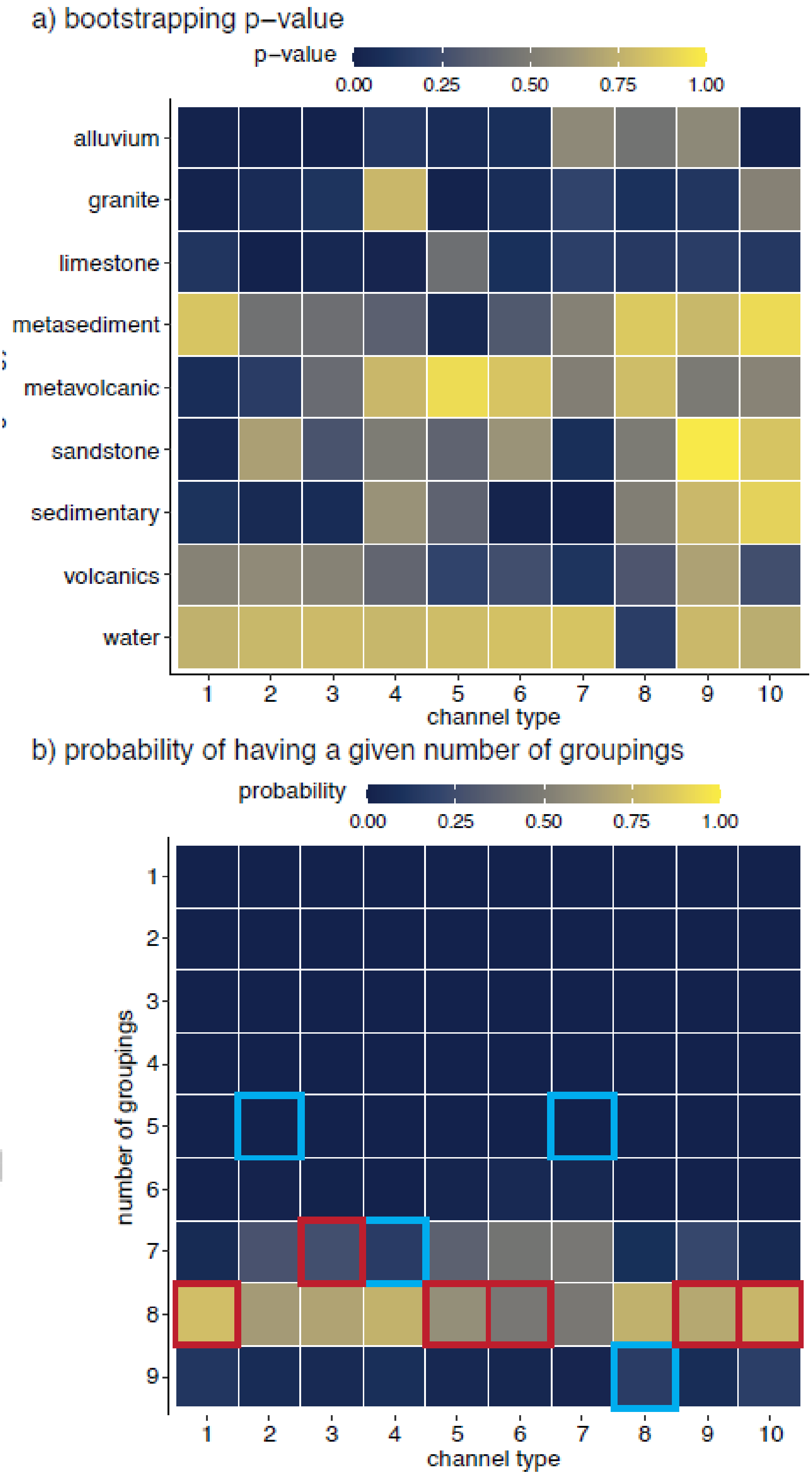

Figure 7. (a) Probability that the proportion of field sites in a channel type that falls in each lithology category deviates from random. (b) Probability that each channel type falls in a given number of lithology categories. Outlined boxes indicate the number of categories observed in each channel type (row value), and a teal outline indicates that the outcome was significant (p<0.05).

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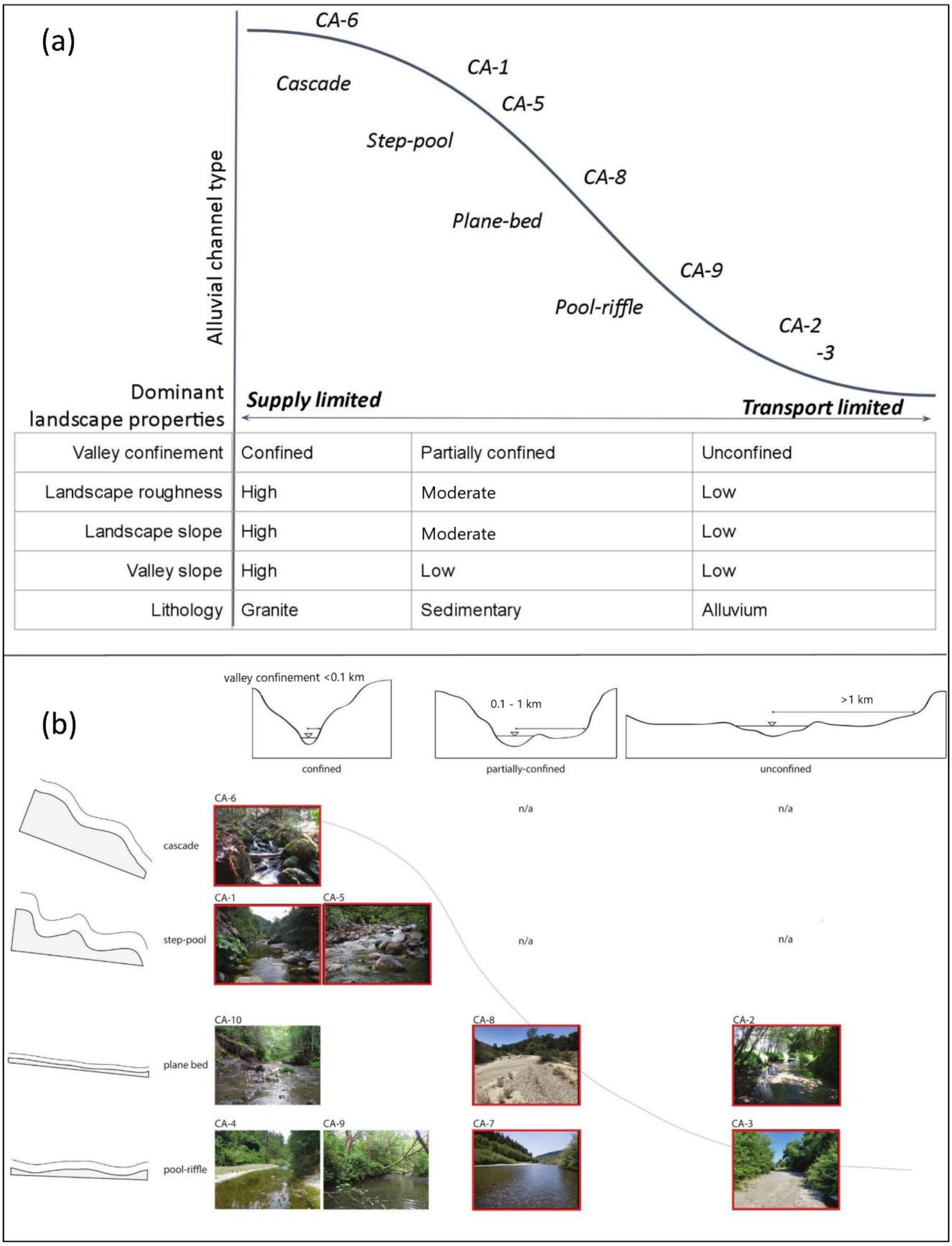

Figure 8. Channel types identified for the study area visualized using (a) an established conceptual model adapted from Montgomery & Buffington (1997) and (b) an alternative framework capable of including all statewide channel types. Red outlines indicate channel types that roughly map onto the downstream conceptual model in Figure 8a.

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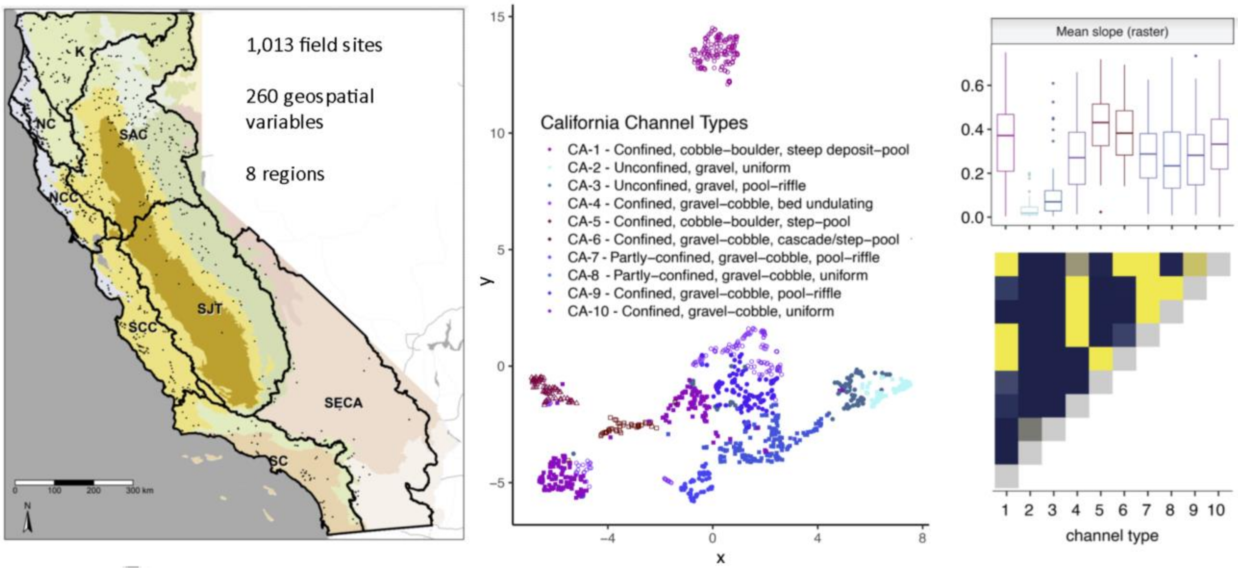
Channel reach morphology and landscape properties are linked across a large heterogeneous region

Belize Lane*, Herve Guillon, Colin Byrne, Gregory Pasternack, Alan Kasprak, & Samuel Sandoval



Data-driven methods were used to evaluate multivariate patterns in channel morphology and linkages with landscape properties based on a large field dataset spanning heterogeneous physio-climatic settings.

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