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The role of topographic variability in river channel classification

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Abstract
To date, subreach-scale variations in flow width and bed elevation have rarely been included in channel classifications. Variability in topographic features of rivers, however, in conjunction with sediment supply and discharge produces a mosaic of channel forms that provides unique habitats for sensitive aquatic species. In this study we investigated the utility of topographic variability attributes (TVAs) in distinguishing channel types and dominant channel formation and maintenance processes in montane and lowland streams of the Sacramento River basin, California, USA. A stratified random survey of 161 stream sites was performed to ensure balanced sampling across groups of stream reaches with expected similar geomorphic settings. For each site surveyed, width and depth variability were measured at baseflow and bankfull stages, and then incorporated in a channel classification framework alongside traditional reach-averaged geomorphic attributes (e.g., channel slope, width-to-depth, confinement, and dominant substrate) to evaluate the significance of TVAs in differentiating channel types. In contrast to more traditional attributes such as slope and contributing area, which are often touted as the key indicators of hydrogeomorphic processes, bankfull width variance emerged as a first-order attribute for distinguishing channel types. A total of nine channel types were distinguished for the Sacramento Basin consisting of both previously identified and new channel types. The results indicate that incorporating TVAs in channel classification provides a quantitative basis for interpreting nonuniform as well as uniform geomorphic processes, which can improve our ability to distinguish linked channel forms and processes of geomorphic and ecological significance.

Keywords
Channel classification, river topography, nonuniform process, channel form

I Introduction
Building on the classic premise of Davis (1909), Thornbury (1954) stated that geomorphic...
processes create a characteristic assemblage of landforms. Through judicious use of inverse reasoning, investigation of landforms can provide an understanding of linked geomorphic processes. Over the past century, studies have shown that ecological structure and function of rivers are strongly influenced by channel type (e.g., Hack and Goodlett, 1960; Smith et al., 1995; Vannote et al., 1980). As a result of these strong foundations, channel classification has come to the forefront of river science and management as a central feature of methods for understanding, protecting, and restoring rivers in North America (Buffington and Montgomery, 2013; Kondolf, 1995; Rosgen, 1994), Europe (e.g., González del Tánago and García de Jalón, 2004; Orr et al., 2008), Australia (Brierley and Fryirs, 2005), and South Africa (Rowntree and Wadeson, 1998). Channel classification is of critical importance today for river management, because anthropogenic changes to flow regimes (Magilligan and Nislow, 2005; Molles et al., 1998), sediment regimes (Graf, 1980; Pitlick and Van Steeter, 1998; Wohl et al., 2015), and the physical structure of rivers (Price et al., 2012) have led to widespread degradation of river ecosystems worldwide (Arthington, 2012; Dynesius and Nilsson, 1994).

Reach-scale geomorphic settings (e.g., pool-riffle, step-pool (Montgomery and Buffington, 1997)) distinguished by attributes related to channel form and sediment transport and supply have been shown to influence ecosystem dynamics and biological diversity (Biggs et al., 2005; Meitzen et al., 2013; Milner et al., 2015; Montgomery and Bolton, 2003), highlighting channel reach classification as a critical step in river ecosystem management. Geomorphic attributes used in channel classification are often chosen to describe relevant, persistent reach-scale characteristics that influence hydraulics and sediment dynamics and in turn aquatic and riparian ecosystem functioning (Birkeland, 1996; Hupp and Osterkamp, 1996; Kasprak et al., 2016; Merritt and Wohl, 2003).

Considerable recent efforts have been invested in developing geomorphic attributes for river characterization, particularly in Europe through the implementation of the Water Framework Directive (e.g., Orr et al., 2008; Polvi et al., 2014; Raven et al., 1998; Sear et al., 2009). Common attributes considered include uniform metrics such as reach-averaged channel slope, width-to-depth ratio, entrenchment ratio, valley confinement, sinuosity, stream power, and dominant channel substrate (Brierley and Fryirs, 2005; Church, 1992; Kasprak et al., 2016; Knighton, 1999; Montgomery and Buffington, 1997; Rosgen, 1994).

However, nonuniform mechanisms not well characterized or indicated by reach-averaged uniform metrics have been identified as primary drivers of channel formation and maintenance in many channel settings (Dietrich and Smith, 1983; Lane and Carlson, 1953; Makaske, 2001; Paustian et al., 1992; Powell et al. 2005; Thompson, 1986; White et al., 2010; Wilcox and Wohl, 2006; Wohl and Thompson, 2000). For example, subreach-scale flow convergence routing has been shown to control riffle-pool formation and maintenance and the locations of sediment deposition and bar instability (MacWilliams et al., 2006). In meandering and alternate bar morphologies, nonuniformity is maintained primarily by the alternating converging and diverging secondary transverse flow cells in and between bends, respectively, which help to maintain sediment routing through the inside of meander bends (Thompson, 1986).

Topographic variability attributes (TVAs), defined here as any measure of subreach-scale variability (i.e., departures from average conditions in channel bed elevation, bankfull width, curvature, and floodplain width), are closely tied to nonuniform channel processes and likely offer more appropriate metrics for characterizing and comparing dominant channel processes and habitat dynamics than their far more common uniform counterparts used in many channel morphologies. For example, measures
of subreach-scale channel width and depth variance are expected to capture the frequency and magnitude distribution of flow expansions and contractions associated with flow convergence routing under a dynamic flow regime (MacWilliams et al., 2006). Furthermore, high within-reach topographic variability is often associated with heterogeneous habitat units available across a wider range of discharges that can support a variety of native biota and ecological functions (Murray et al., 2006; Scown et al., 2016), promoting high biodiversity (Fausch et al., 2002; Poff and Ward, 1990; Townsend and Hildrew, 1994) and ecological resilience (Elmqvist et al., 2003; McCluney et al., 2014).

Channel topographic variability exists naturally and is part of a dynamic equilibrium with other channel variables. At the valley scale, there are nested layers of topographic variability, including variations in the width of hillsides, terraces and floodplains along a corridor (e.g., Gangodagamage et al., 2007; White et al., 2010). When a flow of a set magnitude moves through a layered topographic boundary, it engages one or more of these controls and a specific scale of topographic steering is initiated. That specific type of steering then drives subreach variability in the hydraulic flow field that focuses erosion and deposition locally (Strom et al., 2016). For a dynamic flow regime, topographic steering changes with flow and this results in a diversity of stage-dependent hydraulic patch behaviors (Scown et al., 2016; Strom et al., 2016), each with a different capability to promote erosion or deposition (Brown and Pasternack, 2014; Grams et al., 2013).

As a result of these factors, rivers exhibit complex patterns of topographic change processes that promote strong longitudinal variation in width and depth (Wyrick and Pasternack, 2015). Variability itself is expected to differ between reaches, because many geomorphic processes control aspects of variability, such as flow convergence, avulsion, turbulence-driven scour, and meander bend cut-off. One might conjecture that variability is indicated by reach-scale homogenous metrics like specific stream power, and thus not needed to define channel classes, but if the processes that control channel form are governed by variability, then the reverse should be taken as the dominant conjecture: reach-scale homogenous metrics are the outcome of the interplay between channel variability and flow, not the controls on it.

In spite of the established geomorphic (Brown et al., 2014, 2015; Gostner et al., 2013a, 2013b; MacWilliams et al., 2006; Thompson, 1986; White et al., 2010) and ecological (Elmqvist et al., 2003; McCluney et al., 2014; Murray et al., 2006; Scown et al., 2016) significance of subreach-scale topographic variability, very few existing channel classifications consider TVAs. While the Rosgen (1994) and Montgomery and Buffington (1997) classifications both consider the spacing of individual channel-unit types along a reach (e.g., non-dimensional pool spacing measured in channel widths) in their suite of geomorphic attributes, no direct measure of channel width or depth variability is included. The limited consideration of TVAs in past channel classifications may be due to the preference by practitioners to conduct rapid field surveys (sometimes at only one cross-section per reach) in order to maximize the number of channel reaches surveyed in lieu of performing more in-depth surveys across fewer reaches (Buffington and Montgomery, 2013) given resource limitations. With the emergence of meter-scale remote sensing of rivers, datasets that support computing and analyzing TVAs will become more available, accurate, and useful (Gleason and Wang, 2015; Gonzalez and Pasternack, 2015). There has already been significant progress on the use of high resolution aerial imagery from drones to map river characteristics (e.g., Lejot et al., 2007; Rivas Casado et al., 2015, 2016).

A few exceptions include the studies by Trainor and Church (2003) and Jaeger (2015).
Trainor and Church (2003) included channel depth and width variability as key geomorphic attributes in a channel comparison study, but the focus on quantifying dissimilarity between channel reach pairs precluded an evaluation of the relative significance of individual attributes for distinguishing channel types. Jaeger (2015) considered the standard deviation of channel bed elevation (a measure of depth variability) in their classification of headwater streams. However, the set-up of the study as an analysis of the geomorphic significance of mountaintop mining again precluded any evaluation of attribute significance. This major gap in the channel classification literature indicates a need to test the value of incorporating TVAs into the suite of potentially significant geomorphic attributes distinguishing ecologically relevant channel types. This must be done before we can even begin to evaluate the geomorphic or ecological significance of these emerging attributes compared to the more traditional reach-averaged attributes described above.

The purpose of this study was to investigate how TVAs can be incorporated in a channel classification framework to improve the utility of morphological analysis to distinguish dominant channel processes and habitat dynamics along channel networks in varied landscapes. The specific study objectives were to test the use of TVAs in (i) distinguishing channel types across a landscape and (ii) characterizing dominant channel processes of interest. The utility and ecological implications of incorporating TVAs in a channel classification of montane and lowland streams of a Mediterranean basin are then discussed and evaluated in the context of the existing body of channel classification literature and current understanding of landscape form – process linkages.

II Methodology

The Rosgen channel classification (Level II, Rosgen, 1994), arguably the most commonly used channel classification system in North America and globally (Kasprak et al., 2016), was adopted and expanded on in this study to facilitate ease of application of the proposed methods in future channel classifications. The Rosgen channel classification is a stream-reach taxonomy that classifies channel types using field-collected geomorphic attributes (e.g., slope, entrenchment ratio, width-to-depth ratio, sinuosity, and median grain size). In an effort to support the incorporation of TVAs into field-based mapping for channel classification given the common constraint of resource limitations, the Rosgen channel classification procedure was extended in three ways: (1) the channel network was binned into hydrogeomorphically similar groups prior to field data collection using a stratified analysis of hydrologic and topographic data in a Geographic Information System (GIS); (2) four TVAs consisting of within-reach low flow and bankfull width and depth variance were measured in the field in addition to the traditional geomorphic attributes considered by Rosgen (1994); and (3) a heuristic refinement procedure was used to distinguish the most parsimonious set of physically interpretable channel types instead of associating the field-observed channel types with known Rosgen classes.

1. Study area

The study was conducted in the Sacramento Basin of California, USA, encompassing the largest river in the State of California by discharge (producing ~ 30% of California’s surface water runoff) and the second largest U.S. river draining into the Pacific Ocean (after the Columbia River) (Carter and Resh, 2005). This 70,000-km² basin lies between the Sierra Nevada and Cascade Range to the east and the Coast Range and Klamath Mountains to the west. From its headwaters in the volcanic plateau of northern California (Upper Sacramento, McCloud, and Pit Rivers), the Sacramento
River flows south for 715 km before reaching the Sacramento–San Joaquin River Delta and San Francisco Bay. The river has many small to moderate-sized tributaries (e.g., Clear, Cottonwood, Cow, Battle, Antelope, Mill, Deer, Stony, Big Chico, and Butte Creek) and two large tributaries, the Feather River and the American River. The basin primarily exhibits a Mediterranean climate with cold, wet winters (Oct–Apr) and warm, dry summers (May–Sep) (Leung et al., 2003).

The basin’s diverse physiographic settings range from the glacially-carved Sierra Nevada Mountains to lowland marshes and agricultural lands, with a total relief of about 4300 m (US Geological Survey, 2011). The Sacramento Basin is split into three overlying physiographic provinces: the Pacific Border, the Cascade-Sierra Mountains, and the Basin and Range provinces (Fenneman and Johnson, 1946) (Figure 1). These provinces exhibit distinct landscape units (sensu Brierley and Fryirs, 2005) based on differential tectonic uplift, lithology, and climate (California Geological Survey, 2002) and are therefore expected to account for major differences in geomorphic processes and resulting channel morphologies (Schmitt et al., 2007; Trainor and Church, 2003). For instance, the Basin and Range province consists primarily of a thick accumulation of lava flows and tuff beds, supporting low slope meandering streams and large marshlands with low sediment transport capacity. The Cascade-Sierra Mountains province consists of a massive tilted fault block; the western slope descends in a series of undulating low-relief upland surfaces punctuated by deeply incised river canyons, driving high sediment transport rates (Stock et al., 2005). The Pacific Border province delineates an alluvial basin that acts as a depositional trough (California Geological Survey, 2002). Relationships between contributing area and channel bed composition are expected to vary significantly between these provinces based on major differences in sediment regimes.

California’s legacy of intensive and widespread hydrologic and geomorphic alteration for water supply, flood control, land use change, hydropower, and mining has left the Sacramento Basin’s river ecosystems severely degraded (Hanak et al., 2011; Healey et al., 2008). The basin simultaneously supports 2.8 million people and numerous federally endangered and threatened aquatic species (e.g., winter-run Chinook salmon (Oncorhynchus tschawytscha), Sacramento splittail (Pogonichthys macrolepidotus)) (Lindley et al., 2007; Moyle et al., 2011). Most of the Sacramento Basin valley is intensively cultivated, with over 8100 km² of irrigated agriculture. Major reservoirs in the basin include Lake Shasta (5.6 km³, upper Sacramento, McCloud and Pit Rivers), Lake Oroville (4.4 km³, Feather River), Lake Folsom (1.2 km³, American River), and New Bullards Bar Reservoir (1.2 km³, Yuba River). In light of systemic anthropogenic alteration promoting channel homogenization and simplification (Arnold et al., 1982; Booth and Jackson, 1997; Walsh et al., 2005), one might expect that topographic variability would be suppressed. Therefore, if TVAs prove...
important here in the characterization of in-channel habitat dynamics, then they are likely even more important in undisturbed settings in which topographic variability is expected to be greater and thus influence habitat dynamics across a larger range of TVAs.

This study was constrained to one hydrologic regime found within the Sacramento Basin to help isolate factors that cause diverse hydrological and geomorphic effects. An existing regional hydrologic classification of California (Lane et al., 2017) was used to identify stream reaches exhibiting the low-volume snowmelt and rain (LSR) regime. The LSR hydrologic regime was chosen as it captures the transition from the montane snowmelt-driven to lowland rain-driven flow regime and has the largest spatial footprint of hydrologic regimes in the Sacramento Basin (47%); stream reaches in this hydrologic regime are expected to exhibit high geomorphic variability.

2. Channel network stratification

Given the large study domain with about 100,000 reaches and limited resources, the process of observing representative sites requires selecting a relatively small number of samples compared to the scope of the system. If sites were selected at random, then the odds are that different geomorphic settings would be observed in proportion to their frequency of occurrence, and that would bias the assessment of classification, especially if too few sites of rare yet important classes were sampled. Therefore, instead of random sampling, a stratified random approach was used to obtain an equal effort strategy mindful of process-based controls on river organization. Stratified random sampling and related variants using equal effort in each stratum have not been widely applied in channel classification studies to date to capture reach-scale geomorphic heterogeneity, but are well known in field ecology (Columbia Habitat Monitoring Program, 2016; Johnson, 1980; Manly and Alberto, 2014; Miller and Ambrose, 2000) and hydrology (Thomas and Lewis, 1995; Yang and Woo, 1999). Three landscape characteristics accounting for geologic structure, sediment availability, and sediment transport capacity were obtained from GIS data and analyses as described below and used to stratify the Sacramento Basin channel network into 15 subgroups or strata of potentially distinct reach-scale geomorphic characteristics.

Geologic structure (i.e., tectonic uplift and lithology), derived from the overlying physiographic provinces (California Geological Survey, 2002; Fenneman and Johnson, 1946) (Figure 1), was used in conjunction with sediment availability and transport capacity to distinguish 15 geomorphic strata. Sediment supply and transport capacity were represented using contributing area to a reach \( (A_c) \) and the channel bed slope of a reach \( (S) \). These were obtained through analysis of the National Hydrography Dataset (HUC 1802) (US Geological Survey, 2013) in conjunction with a 10-m digital elevation model (DEM) of the study area (US Geological Survey, 2009). \( A_c \) is a common topographically-derived surrogate for channel-forming discharge (e.g., Hack, 1957; Rosgen, 1994; Schumm et al., 1984) and \( S \) is consistently used in classifications to characterize local flow energy dissipation (e.g., Gartner et al., 2015; Montgomery and Buffington, 1997; Rosgen, 1994). The combination of the two variables is also prominent in hydrogeomorphic classification, as it is often conjectured that channel bed morphology arises as a function of reach-scale shear stress and/or specific stream power, which are determined by both unit discharge and channel slope (Flores et al., 2006). Indices combining \( A_c \) and \( S \) as a measure of stream power (Lane, 1957; Leopold and Wolman, 1957; Sklar and Dietrich, 1998) have been used to distinguish braided from meandering rivers (Carson, 1984), to identify thresholds for channel incision (Schumm et al., 1984) and sediment transport capacity (Bledsoe et al., 2002), and in reach-scale channel classification (e.g., Schmitt et al., 2007).
The channel network was derived from the 10-m DEM and dissected into equidistant segments of 250 m length; S and A_c were subsequently derived from the DEM for each segment. Within each physiographic province, channel segments were binned according to GIS-derived S and A_c thresholds to aid with sampling – the results of the study are not sensitive to the exact number of bins or thresholds between bins, as long as the procedure aids with sampling the diversity in the system with equal effort. Five S bins were considered based on Rosgen’s (1994) channel classification thresholds for ease of comparison: <0.1%, 0.1–2%, 2–4%, 4–10%, and >10%. Three A_c bins were established based on estimated A_c threshold transitions for prevalent sediment sizes: (1) bedrock/boulder, (2) cobble/gravel, and (3) sand/silt. The A_c thresholds assigned to distinguish channel bed composition classes were unique for each of the three physiographic provinces within the Sacramento Basin. This decision was based on the expected differences in A_c required to transition from boulder- to cobble- and from gravel- to sand- dominated channels arising from large-scale differences in geology, topography, and climate driving distinct sediment regimes. The physiographic provinces provide bounds on what channels are potentially comparable in terms of relations between drainage area and discharge, sediment supply, and substrate size (Montgomery and Buffington, 1993). Within each province, A_c bin thresholds were estimated based on identified channel composition transition locations reported in available literature combined with expert knowledge relating A_c and sediment composition in the region (e.g., Gasparini et al., 2004; Montgomery and Buffington, 1993) (Table 1). Fifteen geomorphic strata were then distinguished as all possible combinations of topographically-derived A_c and S bins (Figure 2, top-left), and each stream segment in the channel network was assigned to a stratum based on its particular GIS-based A_c and S values (Figure 2a).

<table>
<thead>
<tr>
<th>Physiographic province</th>
<th>Contributing area threshold (km²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pacific Border</td>
<td>50 to cobble/gravel</td>
</tr>
<tr>
<td></td>
<td>5,000</td>
</tr>
<tr>
<td>Cascade-Sierra Mountains</td>
<td>300 to sand/silt</td>
</tr>
<tr>
<td></td>
<td>9,000</td>
</tr>
<tr>
<td>Basin and Range</td>
<td>300</td>
</tr>
<tr>
<td></td>
<td>10,000</td>
</tr>
</tbody>
</table>

Of the 15 geomorphic strata distinguished across the Sacramento Basin by A_c and S combinations, 13 strata were exhibited by LSR reaches, indicating that LSR-dominated hydrologic regimes were 87% representative of the full range of geomorphic variability in the Sacramento Basin as expressed by the geomorphic strata. The two geomorphic strata not found within LSR reaches consisted of the combinations of the highest A_c bin and 4–10% or >10% slope bins. Based on reach accessibility and expected variability of geomorphic attributes, 10 to 12 field surveys were performed within each of the 13 geomorphic strata exhibited by LSR reaches for a total of 161 field survey reaches representing a large range of A_c–S combinations (Figure 3). Note that DEM-derived S was not used further in this study, as it is not highly accurate at representing reach-scale channel slope.

3. Data-driven geomorphic channel classification

Field surveys. Geomorphic field surveys were performed for each study reach identified through the stratified random sampling scheme described above. Surveys of 64 reaches were conducted by the authors' crew and data from another 97 reaches were obtained from the Surface Water Ambient Monitoring Program.
of the California State Water Resources Control Board. Both field campaigns used the same sampling protocols, outlined in Ode (2007) and briefly summarized below. Depending on whether the average wetted channel width was less than or greater than 10 m, a stream reach was surveyed over a length of 150 or 250 m, respectively (Ode, 2007), corresponding to 10 – 100 bankfull widths. Eleven evenly spaced cross-sectional transects were surveyed along each stream reach to quantify variability in 22 geomorphic attributes listed in Table 2 (Ode, 2007). These decisions were intended to balance geomorphic (Grant et al., 1990; Montgomery and Buffington, 1997) and ecological (Frissell et al., 1986) relevance with the practical time and resource limitations of field surveying. The choice of reach length and transect spacing also enabled incorporation of the existing SWAMP geomorphic dataset for the study region that uses the same values. Channel morphology and reach characteristics for the 161 surveyed reaches were measured using a surveying level and stadia rod (Topcon AT-B, 0.01m). Longitudinal streambed profiles were surveyed at consecutive transects along the thalweg for the entire length of the reach.

Figure 2. Map of geomorphic strata (a) across the Sacramento Basin and (b) across the low-volume snowmelt and rain (LSR) reaches of the Sacramento Basin. Yellow dots indicate the randomly chosen field survey locations across the 15 strata. The geomorphic strata are defined in the top-left table based on the combination of contributing area ($A_c$) and slope ($S$) bins, which are derived based on thresholds stated in the bottom-left table and Table 1.

Figure 3. The stratified random field survey locations ($n = 161$) represent a large range of GIS-based reach slopes ($S$) and contributing areas ($A_c$). Colors and shading indicate the distinct $S$ and $A_c$ bins that correspond to the geomorphic strata listed in Figure 2 based on the Cascade-Sierra Mountains physiographic province $A_c$ thresholds in Table 1.
Wolman pebble counts (Wolman, 1954) of 110 pebbles were performed at each reach such that 10 pebbles were randomly selected from each of 11 transects to balance sampling precision and effort across a range of sediment material variability assuming normally distributed sediment size (Bunte and Abt, 2001; Edwards and Glysson, 1999).

Reach-scale geomorphic attributes. Twenty-two geomorphic attributes (Table 2) were chosen to describe relevant, persistent reach-scale geomorphic characteristics that influence hydraulics and sediment dynamics and in turn aquatic and riparian ecosystem functioning (Birkeland, 1996; Hupp and Osterkamp, 1996; Merritt and Wohl, 2003). The field-measured and computed attributes included traditional reach-averaged diagnostic variables (e.g., slope (slope), contributing area (Ac), sinuosity (sin), entrenchment (e.ratio), shear stress (shear), relative roughness (d,D50), sediment composition (i.e., D50, D84, and Dmax) and base flow and bankfull depth (dBF, wBF), and

<table>
<thead>
<tr>
<th>Geomorphic Attribute</th>
<th>Code</th>
<th>Description</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>wetted depth</td>
<td>d</td>
<td>average across 11 transects; 0 if dry channel</td>
<td>m</td>
</tr>
<tr>
<td>wetted width</td>
<td>w</td>
<td>average across 11 transects; 0 if dry channel</td>
<td>m</td>
</tr>
<tr>
<td>wetted width-to-depth</td>
<td>w.d</td>
<td>ratio of channel width to depth</td>
<td>–</td>
</tr>
<tr>
<td>wetted depth-to-D50</td>
<td>d.D50</td>
<td>low water roughness; channel depth standardized by median grain size</td>
<td>–</td>
</tr>
<tr>
<td>bankfull depth</td>
<td>dBF</td>
<td>average across 11 transects</td>
<td>m</td>
</tr>
<tr>
<td>bankfull width</td>
<td>wBF</td>
<td>average across 11 transects</td>
<td>m</td>
</tr>
<tr>
<td>bankfull width-to-depth</td>
<td>w.dBF</td>
<td>ratio of bankfull width to depth</td>
<td>–</td>
</tr>
<tr>
<td>bankfull depth-to-D50</td>
<td>dBF.D50</td>
<td>roughness; bankfull depth standardized by median grain size</td>
<td>–</td>
</tr>
<tr>
<td>entrenchment ratio</td>
<td>e.ratio</td>
<td>manually estimated from high resolution aerial imagery (&lt;1m) (Rosgen, 1994)</td>
<td>–</td>
</tr>
<tr>
<td>shear stress</td>
<td>shear</td>
<td>depth–slope product approximation</td>
<td>Pa</td>
</tr>
<tr>
<td>shields stress</td>
<td>shields</td>
<td>non-dimensionalization of shear stress (Shields, 1936)</td>
<td>–</td>
</tr>
<tr>
<td>contributing area</td>
<td>Ac</td>
<td>drainage area to downstream end of reach</td>
<td>km²</td>
</tr>
<tr>
<td>slope</td>
<td>slope</td>
<td>average water surface slope over 11 transects</td>
<td>%</td>
</tr>
<tr>
<td>sinuosity</td>
<td>sin</td>
<td>straightline distance/actual channel distance along ~ 2000 m</td>
<td>–</td>
</tr>
<tr>
<td>sediment distribution variance</td>
<td>CV_sed</td>
<td>variance of transect sediment distribution (n=10) across 11 transects</td>
<td>–</td>
</tr>
<tr>
<td>D50</td>
<td>D50</td>
<td>median grain size across reach (n=110)</td>
<td>mm</td>
</tr>
<tr>
<td>D84</td>
<td>D84</td>
<td>84th percentile grain size across reach (n=110)</td>
<td>mm</td>
</tr>
<tr>
<td>Dmax</td>
<td>Dmax</td>
<td>maximum grain size across reach (n = 110)</td>
<td>mm</td>
</tr>
<tr>
<td>wetted depth variance</td>
<td>CV_d</td>
<td>std/mean across 11 transects; 0 if no water in channel</td>
<td>–</td>
</tr>
<tr>
<td>wetted width variance</td>
<td>CV_w</td>
<td>std/mean across 11 transects; 0 if no water in channel</td>
<td>–</td>
</tr>
<tr>
<td>bankfull depth variance</td>
<td>CV_d.BF</td>
<td>std/mean across 11 transects</td>
<td>–</td>
</tr>
<tr>
<td>bankfull width variance</td>
<td>CV_w.BF</td>
<td>std/mean across 11 transects</td>
<td>–</td>
</tr>
</tbody>
</table>

† Topographic variability attributes (TVAs)
width-to-depth ratio ($w_d_{BF}$)) as well as four TVAs capturing within-reach variability in base flow and bankfull channel width ($CV_w$) and bed elevation ($CV_d$) (Table 2).

 Reach-scale estimates of geomorphic attributes were computed from field surveys by averaging values across the eleven surveyed cross-sections within each reach. Entrenchment was calculated as flood-prone width divided by bankfull width (Rosgen, 1994), where flood-prone width was measured manually from sub-meter resolution aerial imagery. Sinuosity was calculated as the linear valley distance divided by the actual channel distance along 2 km of channel straddling the field site (Elliott et al., 2009). The coefficient of variation (CV) of base flow and bankfull width and depth was calculated among the eleven cross-sections of each survey reach as a measure of within-reach variability. CV is a non-dimensional measure of standard deviation that provides a useful but not exclusive metric of variability (Schneider, 1994) that is commonly used in spatial analysis of ecological patterns (Gostner et al., 2013a; Gubala et al., 1996; Palmer et al., 1997; Rossi et al., 1992; Simonson et al., 1994; Thoms, 2006). A list of geomorphic attributes considered and their methods of measurement or calculation is provided in Table 2. When possible, these attributes were made non-dimensional for application in a range of physiographic and climatic settings (Parker, 1979; Parker et al., 2003). Given the dual aims of adapting the Rosgen classification to incorporate TVAs and comparability with existing field data for the study region, the present study omitted several potentially significant metrics (e.g., channel vegetation, bank material, dominant flow types (Raven et al., 1998), and stream power (Knighton, 1999; Orr et al., 2008)) that could be considered in future studies.

**Statistical analyses.** The geomorphic attributes (Table 2) were initially re-scaled to range from 0 to 1 and examined for correlation to identify and remove highly correlated attributes (Pearson’s correlation coefficient > 0.8) to meet the assumption of lack of multicollinearity. Five of the original 22 attributes were highly correlated ($\bar{d}$, $\bar{\omega}$, $D_{50}$, $\bar{D}_{50}$, $CV_{sed}$), reducing the dataset to 17 geomorphic attributes (Table 2).

A hierarchical clustering analysis using Ward’s algorithm (Murtagh and Legendre, 2013; Ward, 1963) was used to examine the clustering structure of the uncorrelated, standardized geomorphic attributes describing the 161 study reaches. The dataset also was analyzed by $k$-means cluster analysis stipulating 2 to 15 ($k$) clusters that maximize the between-group variation (Hartigan and Wong, 1979; Kaufman and Rousseauw, 1990). Slope breaks in the $k$-means scree plot of the within-group sum of squares for each clustering solution were interpreted as numbers of clusters at which information content of the clustering process changed. Scree plot slope breaks and the Davies–Bouldin internal clustering index ($DBI = 0.91$) indicated that 12 clusters created distinct groups of study reaches, similar to the hierarchical clustering results.

A combination of univariate and multivariate statistical methods was then applied to (i) examine the strength of variables for distinguishing identified channel types, (ii) test the hypothesis that channel types exhibit significantly different values of geomorphic attributes, (iii) examine the potential range of values for variables of interest between channel types, and (iv) validate the basis of the channel classification by predicting the channel type using geomorphic attributes. These statistical methods included nonmetric multidimensional scaling (NMDS) (Clarke, 1993), one-way analysis of variance (ANOVA) with Tukey’s honestly significant differences (HSD) test, nonparametric permutational multivariate analysis of variance (PerMANOVA) (Anderson, 2001), and classification and regression trees (CART) (Breiman et al., 1984; De’ath and Fabricius, 2000).
An exploratory NMDS analysis (Clarke, 1993; Oksanen, 2011) of the surveyed reaches based on the uncorrelated geomorphic attributes was performed to visually represent the structure of the multivariate dataset and evaluate the relative significance and correlation of attributes. NMDS is common in ecological studies, including those identifying differences in biological communities based on geomorphic variables (e.g., Virtanen et al., 2010; Walters et al., 2003) and is increasingly included in dedicated geomorphic studies (e.g., Jaeger, 2015; Merriam et al., 2011; Sutfin et al., 2014; Varanka et al., 2014). Histograms of each geomorphic attribute were also used to evaluate the density distributions of attribute values across the survey reaches and lend insight into the multivariate clustering structure.

Individual one-way ANOVAs were conducted to compare geomorphic attribute means between channel types. A post-hoc Tukey’s HSD test at the 95% confidence level indicated the best attributes for distinguishing between channel types. A PerMANOVA analysis (Anderson, 2001) (Euclidean distance, 9999 permutations (Oksanen, 2011)) was performed to test the hypothesis that the channel types distinguished through clustering analysis exhibit significant differences ($p < 0.01$) in geomorphic attributes.

Toward the primary goal of the study, CART (Breiman et al., 1984) was then used to identify the most explanatory geomorphic attributes distinguishing channel types and their threshold values. CART yields a binary decision tree where the response variable (study reach) is partitioned into groups (channel types) with minimized within-group variance (based on ten-fold cross-validation, Therneau et al., 2010) and increasing purity (based on the Gini index, De’ath and Fabricus, 2000).

**Heuristic refinement of inductive clustering solution.**
The final number of clusters distinguished was determined heuristically based on a combination of statistical analysis interpretation and physical understanding of the region. First, potential splitting solutions were identified based on the structure of the hierarchical clustering and the shape of the scree-plots from the non-hierarchical $k$-means clustering. Each potential splitting solution was assessed iteratively from largest to smallest splitting distance (based on Ward’s hierarchical clustering). Heuristic (dis)aggregation of clusters was subsequently performed based on the physical distinction and interpretability of the resulting clusters with the objective of minimizing the final number of physically interpretable channel types. For instance, if a particular splitting solution distinguished only some empirical clusters to a level of reasonable physical interpretability, the remaining clusters would be iteratively disaggregated based on the next potential splitting solutions until the minimal number of physically meaningful clusters was identified.

**III Results**

1. **Relative significance of geomorphic attributes**

The two-dimensional NMDS ordination illustrated the significance of TVAs and the relative roles of geomorphic attributes in structuring the multivariate dataset. The NMDS minimized mean stress at 0.08 for 161 study reaches (Figure 4); stress values of <0.1 are considered to be a good ordination with little risk of drawing false inferences (McCune and Grace, 2002). NMDS indicated that the first axis (NMDS1) is dominated by $CV_{d,BF}$, $CV_{w,BF}$, slope, and $A_c$, while the second axis (NMDS2) is dominated by cross-sectional geomorphic attributes (e.g., $D_{84}$, $D_{50}$, $d_{BF}$, $w_{d_{BF}}$) as well as $CV_{w,BF}$. As these axes represent gradients of maximum variation, dominant attributes on each axis control the structure of the multivariate dataset.

Histograms of rescaled geomorphic attributes lend insight into how the density distributions of geomorphic attribute values control the
multivariate data structure (Figure 5). If an attribute is normally distributed with a predominance of its values within a narrow band of its full range for most study reaches, then that attribute will likely yield a single grouping, so it cannot explain differences between those reaches; it may instead distinguish the few statistical outlier reaches. In contrast, an attribute with a more uniform distribution will tend to produce more, equally weighted groupings and thus be a dominant factor explaining differences among many reaches. Upon visual assessment of the geomorphic attribute distributions, most attributes exhibited highly skewed distributions towards lower values (e.g., $\sin$, $e.\text{ratio}$, and $w_{BF}$). In contrast, the TVAs ($CV_{d,BF}$ and $CV_{w,BF}$) and slope exhibited more uniform

Figure 4. Nonmetric dimensional scaling (NMDS) for the first two axes with channel types of individual study reaches indicated. Vectors of attributes are plotted based on the strength of their correlation to the axis (e.g. longer vectors are more strongly correlated to an axis).

Figure 5. Histograms of geomorphic attributes (re-scaled from 0 to 1) across the 161 study reaches illustrate the distribution of each attribute. In contrast to the highly skewed distributions exhibited by most attributes about a small range of values, the TVAs ($CV_{d,BF}$ and $CV_{w,BF}$) and slope exhibit more uniform distributions.
distributions, helping to explain their dominant roles in structuring the multivariate dataset.

2. **Distinguishing channel types**

Agglomerative hierarchical clustering with Ward’s linkage (Murtagh and Legendre, 2013; Ward, 1963) illustrated the clustering structure of the 161 study reaches across the re-scaled uncorrelated geomorphic attributes (Figure 6). The first split occurs at a distance of 20, distinguishing reaches of high (∼0.2–1.7) and low (∼0–0.2) bankfull width variance. Splitting groups at a distance of eight distinguished 12 groups that were then reduced to nine physically meaningful groups by applying the heuristic clustering refinement procedures explained in Section II.3. The nine resulting groups represented physically distinct channel types containing between 4 and 57 study reaches each (average of 18 reaches).

Individual one-way ANOVA results indicated that group means of 12 of 17 geomorphic attributes varied significantly between the nine channel types ($p < 0.05$) (all attributes except $\bar{w}$, $\bar{d}$, $D_{50}$, $D_{max}$, and shields) (Table 3). Multiple comparisons of group means of each attribute using Tukey’s HSD post-hoc test at the 95% confidence level indicated particularly significant channel types for specific attributes (Figure 7). For example, $\bar{w}.d_{BF}$ is significantly higher for type 2 reaches than all

![Figure 6](image).

**Table 3.** ANOVA results show that mean geomorphic attribute values differ between the nine channel types. Statistically significant attributes ($p < 0.05$) are indicated in bold.

<table>
<thead>
<tr>
<th>Geomorphic attribute</th>
<th>Mean square</th>
<th>F</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$A_{c}$</td>
<td>334.59</td>
<td>106.28</td>
<td>0.00</td>
</tr>
<tr>
<td>$d_{BF}.D_{50}$</td>
<td>121.09</td>
<td>26.96</td>
<td>0.00</td>
</tr>
<tr>
<td>$CV_{w}.BF$</td>
<td>0.25</td>
<td>19.90</td>
<td>0.00</td>
</tr>
<tr>
<td>slope</td>
<td>37.06</td>
<td>18.63</td>
<td>0.00</td>
</tr>
<tr>
<td>$w_{BF}$</td>
<td>76.26</td>
<td>15.98</td>
<td>0.00</td>
</tr>
<tr>
<td>$CV_{d}.BF$</td>
<td>0.24</td>
<td>15.90</td>
<td>0.00</td>
</tr>
<tr>
<td>$d_{BF}$</td>
<td>59.50</td>
<td>12.20</td>
<td>0.00</td>
</tr>
<tr>
<td>e.ratio</td>
<td>20.43</td>
<td>10.27</td>
<td>0.00</td>
</tr>
<tr>
<td>$w_{BF}$</td>
<td>42.36</td>
<td>8.50</td>
<td>0.00</td>
</tr>
<tr>
<td>$\sin$</td>
<td>28.36</td>
<td>5.59</td>
<td>0.02</td>
</tr>
<tr>
<td>$D_{84}$</td>
<td>9.86</td>
<td>4.96</td>
<td>0.03</td>
</tr>
<tr>
<td>shear</td>
<td>9.28</td>
<td>4.66</td>
<td>0.03</td>
</tr>
<tr>
<td>$D_{max}$</td>
<td>17.66</td>
<td>3.43</td>
<td>0.07</td>
</tr>
<tr>
<td>shields</td>
<td>0.74</td>
<td>0.14</td>
<td>0.71</td>
</tr>
</tbody>
</table>
other channel types. Conversely, $CV_{w,BF}$ differs significantly between channel types 4 and 7 and channel types 6, 8, and 9 while there is no significant difference in the attribute within those groups. Box-and-whisker plots illustrate relative differences in geomorphic attributes within and across the nine identified channel types (Figure 7). Finally, a map of the spatial distribution of classified channel types across LSR-dominated reaches in the Sacramento Basin is provided in Figure 8.

Multivariate analyses revealed that the data-driven channel types identified exhibit significantly different geomorphic settings and identified the geomorphic attribute ranges across each channel type in the study basin. PerMANOVA results indicated that multivariate mean geomorphic setting is not equal for all nine channel types ($p = 0.0001$; F-statistic = 13), allowing for the rejection of the null hypothesis that channel types were identical. The CART analysis identified the most explanatory geomorphic

---

**Figure 7.** Box-and-whisker plots and Tukey’s honestly significant differences (HSD) test indicate differences in geomorphic and topographic variability attributes across the nine identified channel types: 1. confined headwater small boulder cascade, 2. partly-confined expansion pool – wide bar, 3. unconfined upland plateau large uniform, 4. confined cascade/step-pool, 5. partly-confined pool-riffle, 6. partly-confined large uniform, 7. unconfined anastomosing plateau small pool-riffle, 8. unconfined large uniform boulder, and 9. unconfined large meandering sand.

\* indicates significantly different from 1+ other reach types (95% confidence level)

\# indicates significantly different from all other reach types based on Tukey’s HSD test (95% confidence level)
attributes distinguishing channel types and their threshold values, providing potential ranges of attribute values expected for each channel type (Figure 9). The classification tree model determined the relative strength of non-dimensional variables to be as follows: $CV_{w.BF}$, $\sin$, $\text{slope}$, $e.ratio$, $CV_{d.BF}$, $w.d_{BF}$. This indicates that two of the six explanatory attributes identified by the model were TVAs (i.e., $CV_{w.BF}$, $CV_{d.BF}$), while slope played a lesser role. The non-dimensional classification tree correctly classified 85% of survey reaches based on their reach-averaged geomorphic attribute values (Figure 9(a)). Alternatively, 93% of reaches could be correctly classified by the classification tree considering all attributes (Figure 9(b)). When both dimensional and non-dimensional attributes were considered ($n = 17$, Table 2), $D_{94}$, $A_c$, and $w_{BF}$ emerged as additional significant attributes for distinguishing channel types. Separate classification tree models using only the author’s field sites ($n = 64$) and using both the author’s and SWAMP field sites ($n = 161$) both identified $CV_{w.BF}$, $\sin$, and $\text{slope}$ as the three primary attributes distinguishing channel types, emphasizing their persistent significance independent of individual field sites. Furthermore, $CV_{w.BF}$ emerged as a dominant attribute above traditional Rosgen (1994) geomorphic attributes in both models.

3. Physical interpretation of channel types

Physical interpretation of the above statistical analyses (summarized in Table 4) was used in combination with expert evaluation and existing channel classification literature to name the nine channel types based on their valley setting and distinguishing channel attributes (this nomenclature is used for the remainder of this study): 1. confined headwater small boulder cascade, 2. partly-confined expansion pool – wide bar, 3. unconfined upland plateau large uniform, 4. confined cascade/step-pool, 5. partly-confined pool-riffle, 6. partly-confined large uniform, 7. unconfined anastomosing.
Table 4. Descriptive name, literature analogs, key channel form characteristics, and physical process interpretation of identified channel types are provided.

<table>
<thead>
<tr>
<th>Channel number</th>
<th>Valley setting</th>
<th>Channel type</th>
<th>Descriptive name</th>
<th>Literature analog</th>
<th>Morphological characterization</th>
<th>Physical process interpretation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Confined headwater</td>
<td>Small boulder-cascade</td>
<td>Type A(^a); Bedrock or Cascade(^b); Steep headwater(^c)</td>
<td>Very steep, straight</td>
<td>Low w-to-d, highly entrenched</td>
<td>Poorly sorted boulder-dominated</td>
</tr>
<tr>
<td>2</td>
<td>Partly-confined expansion</td>
<td>Pool-wide bar</td>
<td>Moderate gradient alluvial fan channel (Paustian et al., 1992)</td>
<td>Variable slope, high sinuosity</td>
<td>Wide and shallow, entrenched</td>
<td>Poorly sorted pebble- to cobble-sized</td>
</tr>
<tr>
<td>3</td>
<td>Unconfined upland plateau</td>
<td>Large uniform</td>
<td>Low slope, straight</td>
<td>Large channel dimensions, low entrenchment</td>
<td>Homogenous pebble- to cobble-sized</td>
<td>Low variability</td>
</tr>
<tr>
<td>4</td>
<td>Confined Cascade / Step-pool</td>
<td>Cascade or Steep-pool(^d); Type G1-2 or A(^e); Gorge(^f)</td>
<td>Steep, moderate sinuosity</td>
<td>Low w-to-d, entrenched</td>
<td>Boulder-dominated</td>
<td>Extremely high variability;(-)covariance</td>
</tr>
<tr>
<td>5</td>
<td>Partly-confined Pool-riffle</td>
<td>Pool-Riffle(^g); Type C(^h)</td>
<td>Mid- to high-slope, moderate sinuosity</td>
<td>Moderate w-to-d, moderate entrenchment</td>
<td>Gravel- to cobble-sized</td>
<td>High d variance, moderate w variance; (+) covariance</td>
</tr>
<tr>
<td>6</td>
<td>Partly-confined Large uniform</td>
<td>Plane-bed(^i); Type B(^j)</td>
<td>Mid slope, straight</td>
<td>Moderate w-to-d, moderate entrenchment</td>
<td>Cobble- to boulder-sized</td>
<td>Low variability</td>
</tr>
</tbody>
</table>

(continued)
Table 4. (continued)

<table>
<thead>
<tr>
<th>Channel number</th>
<th>Valley setting</th>
<th>Channel type</th>
<th>Literature analog</th>
<th>Channel slope and planform</th>
<th>Cross-sectional attributes</th>
<th>Bed material</th>
<th>TVAs</th>
<th>Physical process interpretation</th>
</tr>
</thead>
<tbody>
<tr>
<td>7</td>
<td>Unconfined anastomosing plateau</td>
<td>Small pool-riffle</td>
<td>Type DA; Type E</td>
<td>Low slope, moderately sinuous</td>
<td>Small channel dimensions, low entrenchment</td>
<td>Poorly sorted pebble- to cobble-sized</td>
<td>High variability; $+/-$ covariance</td>
<td>Anastomosing channels formed by avulsion driven by rapid channel aggradation (Makaske, 2001). High channel depth variance and poorly sorted sediment may be indicative of rapid, heterogeneous channel deposition triggering avulsion.</td>
</tr>
<tr>
<td>8</td>
<td>Unconfined</td>
<td>Large uniform boulder</td>
<td></td>
<td>Low slope, moderate sinuosity</td>
<td>Large channel dimensions, entrenched</td>
<td>Cobble- to boulder-sized</td>
<td>Low variability</td>
<td>Underlying bedrock geology constrains formation of meander bends and determines sediment supply and composition.</td>
</tr>
<tr>
<td>9</td>
<td>Unconfined</td>
<td>Large meandering sand bed</td>
<td>Labile channel (Church 2006); Meandering sand (Lane 1957)</td>
<td>Low slope, high sinuosity</td>
<td>Very large channel dimensions, highly entrenched</td>
<td>Sand</td>
<td>Low variability</td>
<td>Meanders maintained by secondary transverse flow cells that drive sediment routing through inside of bends (Thompson, 1986); <em>live bed</em> sediment transport (Henderson, 1963).</td>
</tr>
</tbody>
</table>

†Rosgen (1994).
‡Montgomery and Buffington (1997).
*Brierley and Fryirs (2005).
The order of the identified channel types represents an idealized upstream to downstream progression in the landscape from montane to lowland streams; however, some channel types are less predictable along such a progression (e.g., partly-confined expansion pool – wide bar, unconfined upland plateau large uniform).

Four of the identified channel types (i.e., 2, 3, 6, and 8) were not commonly identified by previous classifications. The geomorphic characteristics of each channel type are described below, organized and interpreted with respect to presumed dominant channel processes and related to TVAs where applicable.

The confined headwater small boulder-cascade channel type (1) (sensu Hassan et al., 2005; Montgomery and Buffington, 1997; Sullivan, 1986) is characterized by the highest slopes and lowest $A_c$ of any channel type. These channels exhibit high entrenchment, low width-to-depth, low sinuosity, and a boulder-dominated bed. High stream power combined with variable topography drive high sediment transport and high subreach-scale variability in scour and fill (Powell et al., 2005) indicated by high $CV_{d,BF}$.

The confined cascade/step-pool channel type (4) is distinguished from the boulder-cascade by slightly lower slopes and larger $A_c$, as well as slightly increased channel dimensions and a reduction in $w,d_{BF}$ and dominant sediment size. These changes are indicative of a downstream progression from hillslope- to channel-dominated processes. Cascade/step-pool channels are also characterized by the highest $CV_{d,BF}$ and $CV_{w,BF}$ of any channel type and generally negatively co-varying bed and width undulations, indicating complex subreach-scale flow resistance dynamics. Flow resistance in these channels is hypothesized to be generated by the form drag of constricting step-forming roughness features and by tumbling flow regimes in which critical or supercritical flow over narrow step crests plunges into wider pools.

Figure 10. Example images of channel types distinguished by classification from field and Google Earth® imagery.
abruptly decreasing velocity and generating substantial turbulence (Montgomery and Buffington, 1997; Peterson and Mohanty, 1960; Wilcox and Wohl, 2006; Wohl and Thompson, 2000; Wyrick and Pasternack, 2008).

The partly-confined pool-riffle channel type (5) exhibits the next highest slopes and shear stress and slightly larger $A_c$ than the cascade/step-pool channel. Pool-riffle channels are constrained by valley and floodplain topographic controls and characterized by positively co-varying bed and width undulations that generate subreach-scale width and depth constrictions and expansions (indicated by high $CV_{w,BF}$ and $CV_{d,BF}$) which drive localized flow convergence. Topographically-driven convective accelerations have been shown to reinforce these nonuniform convergent and divergent flow patterns, and thus pool-riffle morphogenesis (Dietrich and Smith, 1983; Dietrich and Whiting, 1989; Nelson and Smith, 1989). The pool-riffle channel type is morphologically similar in many regards to the partly-confined large uniform channel type (6) except for significantly higher topographic variability and smaller sediment composition. This is interpreted as a difference in sediment transport mechanisms. In pool-riffle channels, topographic variability has been shown to control sediment transport through mechanisms such as topographic steering (MacWilliams et al., 2006; Whiting and Dietrich, 1991), flow convergence (MacWilliams et al., 2006; Sawyer et al., 2010), and recirculating eddies (Lisle, 1986; Rathburn and Wohl, 2003; Thompson and Wohl, 2009; Woodsmith and Hassan, 2005). Alternatively, in large uniform channels largely devoid of any organized or rhythmic bedforms, at the time of transport the whole bed is expected to move as a conveyor belt (Lane and Carlson, 1953; Montgomery and Buffington, 1997). As there are no topographic steering controls on where deposition or erosion takes place in large uniform channels, the presumed result is maintenance of uniform width and depth with energy dissipation dominated by grain and bank roughness (Montgomery and Buffington, 1997). The well-armored bed indicated by the large $D_{50}$ and $D_{84}$ suggests relative channel stability and a supply limited sediment transport regime (Dietrich et al., 1989).

Partly-confined expansion pool – wide bar channels (2) generally occur at abrupt valley widenings and exhibit very high $w \cdot d_{BF}$ and heterogeneous sediment composition ($CV_{sed}$). Alluvial fans develop by the accumulation of sediment where a channel exits an upland drainage area (Drew, 1873). These lower-gradient type 2 channels running through alluvial fan style valley expansions likely have limited transport capacity due to reduced stream power and lateral flow divergence, driving rapid deposition of unsorted alluvial sediment (Paustian et al., 1992). These channels are distinguished by pool-wide bar morphology in which positively co-varying bed and width variability combine with mobile sediment and limited lateral confinement to generate extremely wide, entrenched bars between constricted troughs.

The unconfined upland plateau large uniform channel type (3) exhibits very low entrenchment due to moderate-sized channels bordered by vast floodplains. The laterally unconfined upland plateau valleys through which these channels run are low-energy (low slope and $A_c$) depositional environments in which sediment supply is presumed to exceed transport capacity (Nagel et al., 2014). The uniform topography, low sinuosity, and homogenous sediment composition are indicative of uniform geomorphic processes (e.g., sediment transport as a uniform sheet (Miller and Burnett, 2008)). The unconfined anastomosing plateau small pool-riffle channel type (7), also characterized by low entrenchment and a laterally unconfined valley setting, is distinguished from the large uniform channel type by much smaller channel dimensions and higher topographic variability and sinuosity. Similar to partly-
confined pool-riffle channels, these channels are expected to maintain nonuniform morphology through nonuniform mechanisms such as topographic steering, flow convergence, and eddy recirculation. At the valley scale, these channels appear to connect to create multi-thread channels that diverge and converge around vegetated, rarely inundated islands cut from the floodplain (Knighton and Nanson, 1993). The high channel depth variability that distinguishes this channel type from the upland valley uniform channel may be indicative of past avulsion triggered by rapid, heterogeneous channel deposition (Makaske, 2001).

Finally, unconfined large uniform boulder (8) and large meandering sand bed (9) channels are characterized by very large $A_c$, large channel dimensions, low slopes, high sinuosity, and very low width and depth variability. Large uniform boulder bed channels are distinguished by boulder-dominated beds and lower bankfull depths, while the large meandering sand bed channels are sand-dominated and exhibit extremely high sinuosity and entrenchment typical of meandering morphologies (Hickin, 1974). These differences likely indicate a difference in underlying geology and sediment supply constraining the formation of meanders by lateral migration and influencing channel bed composition. The large meandering sand channel type distinguished in this study appears similar to the meandering sand bed channel described by Lane (1957) and the labile channel distinguished by Church (2006). Meanders are hypothesized to be maintained primarily by the alternating converging and diverging secondary transverse flow cells in and between bends, respectively, which help to maintain sediment routing through the inside of meander bends (Thompson, 1986). Mobile bedforms provide the primary hydraulic resistance in these channels (Kennedy, 1975), driving “live bed” sediment transport (Henderson, 1963).

IV Discussion

1. Lessons learned from channel classification modifications

Channel network stratification. The initial GIS-based stratification of the channel network based on catchment DEM-derived $S$ and $A_c$ proved effective at distinguishing underrepresented geomorphic settings in the landscape that would likely otherwise have been overlooked. While some channel types (e.g., pool-riffle, plane-bed, cascade/step-pool) spanned many $S$–$A_c$ bins, indicating their limited dependence on $S$ or $A_c$, others were almost exclusively found in one bin (e.g., pool–wide bar, large uniform boulder, large meandering sand). Bins with the largest representation across the landscape unsurprisingly captured the largest number of channel types. Bins 2, 3, and 4 (Figure 2) represented 28, 16, and 20% of the channel network in the study domain and contained 7, 6, and 5 channel types, respectively, compared with 3 channel types per bin on average. Geomorphic bins 1–5 with the smallest $A_c$ accounted for 78% of LSR-dominated reaches in the Sacramento Basin while bins 11–13 with the largest $A_c$ accounted for less than one percent of the study domain combined. However, field sites classified as large uniform boulder and large meandering sand channels fell almost exclusively in bins 11–13, emphasizing the value of stratified sampling for revealing naturally underrepresented channel types. Slope bins were more evenly distributed, but very low (<0.1%) and very high (>10%) slopes each accounted for less than 10% of the study domain. The identification of low slope dominated channel types by the classification (e.g., anastomosing, large uniform boulder, and large meandering sand) highlights the value of stratified sampling as these channel types would likely not have been sampled sufficiently to distinguish distinct classes in a uniform random sampling scheme given their limited representation in the basin.
The stratified sampling scheme enabled a large proportion of the full range of geomorphic variability present in the study domain to be captured by the field sites. For example, bankfull channel width across all surveyed sites ranged from 1.1 to 98.8 m. The smallest and largest channels evident in the system from visual inspection are 0.8 and 100 m, respectively, indicating that the sampling scheme captured 98% of the total range of bankfull widths. Similarly, the sampling scheme captured 78% of the total range of $A_c$ and 65% of the total range of $S$. The maximum $A_c$ for a surveyed site was 7760 km$^2$ while the maximum $A_c$ of any reach in the LSR channel network was closer to 10,000 km$^2$. The maximum surveyed $S$ of 14.3% was substantially less than the estimated 22% maximum reach $S$. Overall, these results indicate that, while not entirely representative, stratifying field data collection by GIS-based landscape characteristics accounting for geologic structure, sediment availability, and sediment transport capacity enabled the resulting field sites to capture a large range of geomorphic variability. Splitting the channel network into further bins with more refined $A_c$ and $S$ requirements could increase the proportion of the total range of geomorphic variability captured by field surveys. Alternatively, stratifying the network across other GIS-based characteristics such as bankfull width or adjusting the $A_c$ and $S$ thresholds for bin membership could potentially improve results.

**Heuristic refinement of classification results.** The nine channel types identified in this study capture a diverse range of reach-scale geomorphic settings including channel types previously identified by existing channel typologies and new, thus far unidentified, channel types. These findings emphasize the value of the *a posteriori* heuristic refinement of inductive classification results by suggesting that the resulting channel types retain a physical basis (deductive component) but are capable of capturing the unique context of the landscape under study (inductive component).

Identified channel types with strong analogs in the classification literature highlight the physical basis of the classification results achieved after heuristic classification refinement. For example, cascade channels as defined by Montgomery and Buffington (1997) generally occur on steep slopes, are narrowly confined by valley walls, and are characterized by longitudinally and laterally disorganized bed material typically consisting of cobbles and boulders. This channel type corresponds strongly to our identified *confined cascade/step-pool* channel, characterized by valley-confined channels with steep slopes, low width-to-depth, high bankfull width and depth variance, and cobble/boulder dominated sediment. Montgomery and Buffington’s (1993) plane-bed channel type refers to mid-slope planar gravel- and cobble-bed channels generally lacking discrete bars or in-channel features. This channel type is similar to our *partly-confined large uniform* channel, characterized by a moderate slope, cobble-dominated bed, and very low bankfull width and depth variance (indicating absence of bars and planar longitudinal morphology).

Some identified channel types have no analog in the Montgomery and Buffington classification designed for the mountains of the Pacific Northwest of the US, particularly those channel types associated with non-mountain environments. In these cases (e.g., *unconfined anastomosing plateau small pool-riffle*), the more descriptive Rosgen (1994) channel types may provide a better analog (Table 4). Alternatively, the *large meandering sand bed* (9) channel type, while not present in the Montgomery and Buffington (1993) or Rosgen (1994) channel classifications, has been distinguished in numerous other channel classification frameworks (e.g., Church, 2006; Lane, 1957; Schumm, 1963). The *partly-confined expansion pool – wide bar* channel type seems to only have an analog in the
moderate gradient alluvial fan channel as described by Paustian et al. (1992). This similarity of our results with the process-based channel types distinguished by Paustian et al. (1992) indicates that the classification framework as applied in this study is similarly capable of revealing distinct associations between channel morphology and processes.

Channel types with no clear analog in the literature were also identified (e.g., unconfined upland plateau large uniform, unconfined large uniform boulder), suggesting that the addition of TVAs to the classification framework combined with channel network stratification and heuristic refinement enabled the resulting channel classification to reveal the unique context of the landscape under study. For instance, upland plateau large uniform channels were distinguished from anastomosing plateau small pool-riffle channels primarily on the basis of topographic variability. Distinct geomorphic channel formation and maintenance processes and associated ecosystem functions were thus revealed from otherwise similar channel types and valley settings based on differences in subreach-scale topographic variability.

2. Value of topographic variability attributes

Distinguishing channel types. With respect to the first study objective, TVAs were found to play a major role in distinguishing channel types across the landscape. Numerous univariate and multivariate statistical analyses all identified bankfull width and depth variability as first-order predictors of geomorphic channel type. Even though $S$ and $A_c$ – frequently identified as dominant variables controlling channel form and geomorphic processes (Church 2002; Dietrich et al., 1992; Dunne and Leopold, 1978; Leopold and Maddock, 1953; Montgomery and Buffington, 1997) – were used to stratify the channel network prior to random sampling, they were not identified as the primary attributes distinguishing geomorphic channel types, though they were significant attributes in CART. The hierarchical clustering structure (Figure 6) and classification tree (Figure 9) both identified $CV_{w,BF}$ as the primary splitting variable distinguishing channel types for LSR streams of the Sacramento Basin.

Unlike most geomorphic attributes, which had overlapping value ranges across all but one channel type (e.g., $\bar{w}.d_{BF}$, $e.ratio$, $sin$, $shear$), $CV_{w,BF}$ and $CV_{d,BF}$ exhibited more uniform density distributions (Figure 5) and expressed a continuum of value ranges across all nine channel types (Figure 7). Thus, TVAs were found to be very important because they show that some rivers have substantial channel bed and width variability and some do not – it is the variability in the variability that makes them powerful classifiers compared to $A_c$ and many other reach-average metrics. For example, the channel classification distinguished four channel types with very low, one with moderate, and four with high topographic variability. Of the highly variable channel types, two exhibited primarily positive width and depth covariance, one exhibited primarily negative covariance, and one exhibited a mixture of both.

It may be possible that the significance of TVAs in this study is influenced by the specific positioning or frequency of cross-sections along each study reach. Topographic variability is often structured with quasi-periodic undulations, so how sample locations align with those structures is very important and probably should not be left to chance when designing observation protocols. Future studies with more cross-sections per reach or using near-census channel width measurements based on high-resolution remote sensing data would reduce the likelihood that the variability being measured is a function of the cross-section locations. However, the statistically distinct clustering solution and physical interpretability of results indicate that the significance of TVAs in the channel classification is fundamentally based on differences in subreach-scale channel forms and processes.
Furthermore, study results indicate that the history of land use and anthropogenic alterations in the Sacramento Basin are not artificially inflating the importance of TVAs in the landscape. If any reaches with small degrees of variability stood out given the simplified nature (e.g., dredged and straightened) of many parts of the basin, one would expect to see a highly skewed distribution of TVA values towards low variability. However, the uniform distributions exhibited by $CV_{w,BF}$ and $CV_{d,BF}$ (Figure 5) negate this hypothesis, indicating instead a large, relatively evenly distributed range of width and depth variability across the landscape.

**Characterizing dominant channel processes.** With respect to the second study objective, TVAs were found to be extremely useful for characterizing dominant channel processes that have been reported extensively in the literature but which have been neglected from quantitative classification studies prior to this. Most studies only consider processes in terms of reach-average erosive potential, sometimes relative to sediment supply. They have no basis for describing channel types in terms of the actual specific processes that occur in reaches, such as knickpoint migration, bank erosion, and island formation. By incorporating TVAs in a channel classification framework, we were able to characterize and distinguish the type and magnitude of topographic variability within reaches. In doing so, this study provided a quantitative basis for interpreting the resultant classes in terms of a diversity of mechanisms for fluvial landform formation and maintenance that rely on both nonuniform and uniform channel morphology (Dietrich and Smith, 1983; Lane and Carlson, 1953; Makaske, 2001; Paustian et al., 1992; Powell et al., 2005; Thompson, 1986; White et al., 2010; Wilcox and Wohl, 2006; Wohl and Thompson, 2000). As hypothesized, TVAs – closely tied to nonuniform processes – improved the ability to characterize and compare dominant channel processes in many channel types. For example, differences in TVAs and their covariance as distinguished by the channel classification appeared to be indicative of different sediment transport mechanisms in partly-confined pool-riffle and large uniform channels. Similarly, the high channel depth variance distinguishing unconfined plateau small pool-riffle channels from large uniform channels supported the interpretation of the dominant channel forming process as avulsion and the dominant channel maintenance processes as topographic steering, flow convergence, and eddy recirculation in spite of very similar valley settings and traditional geomorphic attributes (e.g., slope, $w.d_{BF}$, $e.ratio$, $D_{84}$). Alternatively, unconfined large uniform boulder and meandering sand bed channel types were differentiated on the basis of underlying geology rather than TVAs.

**Ecological implications.** The spatial variability or lack thereof of channel morphology and associated geomorphic processes as distinguished by TVAs has important ecological implications. For example, differences in spatial patterns of hyporheic exchange (Kasahara and Wondzell, 2003; Tonina and Buffington, 2009) drive differences in local biogeochemistry (Poole et al., 2008) and habitat dynamics (Geist, 2000). Channels with high subreach topographic variability and associated heterogeneous sediment scour and deposition (e.g., our pool-riffle and cascade/step-pool channels) may exhibit highly localized hyporheic exchange (Kasahara and Wondzell, 2003; Poole et al., 2006, 2008), creating local nutrient hotspots associated with algae or macrophyte growth (Fisher et al., 1998) and preferential spawning habitat (Geist 2000). In contrast, the uniform flow and sediment transport processes exhibited by very low topographic variability (e.g., upland valley uniform channels) are associated with long hyporheic flow paths that modify the reach’s mean daily temperature (Poole et al., 2008) and
biogeochemistry (Findlay, 1995) from average channel conditions, in turn affecting habitat quality (Poole et al., 2008; Tonina and Buffington, 2009) and salmonid population structure (e.g., Burnett et al., 2003) throughout the reach. Unconfined uniform channels with the propensity for these long hyporheic flow paths have also been shown to provide low-velocity refugia for biota during periods of high flow (e.g., Wenger et al., 2011) and support wider riparian zones (Polvi et al. 2011).

Incorporating TVAs in channel classification is also expected to inform river restoration efforts. For example, riparian species richness has been shown to increase with subreach-scale bed elevation variability (Pollock et al., 1998), suggesting that characterizing TVAs in addition to more traditional geomorphic attributes may help predict the impact of disturbances on the biotic community across the channel network. Targeting high variability channel types (e.g., cascade/step-pool, pool-riffle) for riparian restoration efforts may increase the likelihood of success by increasing the range of hydrogeomorphic and thus ecological responses to disturbance. Alternatively, channel change associated with channel unit to reach scale (e.g., 10 – 100 channel widths) changes in TVAs may indicate changes in flow regimes, sediment regimes, or land use (Montgomery and Bolton, 2003), indicating critical locations for larger-scale restoration efforts. For example, the conversion of fully forested riparian zones to grasslands has been associated with a significant reduction in within-reach width variability (Jackson et al., 2015). By identifying channels with rapidly changing $CV_{BF,W}$, practitioners may more easily define management objectives and prioritize restoration activities. Characteristic TVA values of ecologically functional reaches could provide practitioners with a baseline level of channel and floodplain variability to incorporate into restoration efforts for degraded reaches.

3. Future research
With the aim of characterizing dominant process regimes of distinct channel types as differentiated by TVAs, we speculated as to the physical processes associated with each identified channel type. We suggest direct measurement of these hypothesized dominant subreach-scale processes and their co-occurrence with distinct TVA settings as an important direction for future work. For instance, measurement of hydraulic flow fields, hyporheic exchange, or sediment transport rates across channel types would bolster physical understanding of the differences in processes regimes between distinct TVA settings.

With the emergence of meter-scale remote sensing of rivers, datasets that support computing and analyzing TVAs will become more available, accurate, and useful (Gleason and Wang, 2015; Gonzalez and Pasternack, 2015). In the meantime, by considering TVAs in addition to more traditional channel classification attributes, we hope to encourage future research into how a stream reach is influenced by its surrounding landscape at various scales based on hierarchical topographic variability relationships. This could enable the application of increasingly available larger-scale topographic datasets to distinguishing differences in multi-scale process controls on channel morphology and predicting reach-scale geomorphic settings. Further understanding of relationships between TVAs and multi-scale geomorphic processes is critical to developing insight into sediment transport and formative processes in these diverse channel types.

V Conclusion
This study found that measures of subreach-scale topographic variability provided improved information on river geomorphic landforms and processes in channel networks of varied landscapes. When incorporated in a channel classification framework among a suite of more
traditional geomorphic attributes, TVAs improved the ability to distinguish dominant channel types and associated geomorphic processes in LSR-dominated streams of a Mediterranean region. Bankfull width variance was identified as the primary attribute distinguishing channel types over common attributes such as channel slope, width-to-depth ratio, confinement, sinuosity, and dominant substrate. The nine channel types distinguished for the Sacramento Basin included both channel types with strong analogs in existing geomorphic literature and novel channel types. By reenvisioning channel classification through the incorporation of TVAs, distinct channel landforms and processes were revealed from otherwise similar geomorphic settings with limited additional resource requirements. Results indicate that incorporating TVAs in channel classification may improve river restoration efforts by revealing ecologically-significant differences in channel form and function.

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