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Channel-reach morphology dependence on energy, scale, and hydroclimatic processes with implications for prediction using geospatial data

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[1] Channel types found in mountain drainages occupy characteristic but intergrading ranges of bed slope that reflect a dynamic balance between erosive energy and channel boundary resistance. Using a classification and regression tree (CART) modeling approach, we demonstrate that drainage area scaling of channel slopes provides better discrimination of these forms than slope alone among supply- and capacity-limited sites. Analysis of 270 stream reaches in the western United States exhibiting four common mountain channel types reveals that these types exist within relatively discrete ranges of an index of specific stream power. We also demonstrate associations among regional interannual precipitation variability, discharge distribution skewness, and means of the specific stream power index of step-pool channels. Finally, we discuss a conceptual methodology for predicting ecologically relevant morphologic units from digital elevation models at the network scale based on the finding that channel types do not exhibit equal energy dissipation.

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1. Introduction

[2] Aquatic ecology is undergoing a shift from the conventional paradigm of continuous one-dimensional downstream change to a more dynamic and discontinuous view of aquatic systems that encompasses complex interactions between channel networks and the landscape [*Fisher et al.*, 2001; *Fausch et al.*, 2002; *Wiens*, 2002; *Benda et al.*, 2004]. This evolving paradigm in aquatic science has also brought to the forefront the need to link ecologically relevant aquatic habitat units with their formative processes acting at multiple spatial and temporal scales in fluvial systems. At the channel-reach scale, water discharge volume and timing are set by climatic forcing and upstream watershed (hillslopes and valley-channel network) geometry and material characteristics. Erosion and transport of hillslope and upstream channel-bed material, together with water discharge characteristics, determine the sediment flux into a channel reach. The resulting water and sediment regimes act within a particular geologic and historical setting, along with recruitment and retention of woody debris, to influence the local habitat template over which aquatic community structure is imposed [*Southwood*, 1977; *Poff*, 1997; *Montgomery et al.*, 1999]. Field studies frequently focus on the channel-reach scale largely because variables of interest within a reach several channel widths in length remain relatively homogeneous [*Grant et al.*, 1990; *Montgomery and Buffington*, 1997]. The channel reach is therefore an important scale of focus when considering how processes at multiple spatial and temporal scales drive geomorphic form and structure physical habitat.

[3] Most existing fluvial classifications are intended to relate measurable reach-scale elements of channel form such as channel bed slope, bankfull dimensions, bed forms, and substrate size to stream processes and functions. Channel bed slope, in particular, is consistently used in fluvial classifications as indicative of local flow energy dissipation [e.g., *Rosgen*, 1994; *Montgomery and Buffington*, 1997]. Reach-scale channel bed morphology arises as a function of local shear stress and specific stream power, which are determined by both channel slope and unit discharge. The flow regime (and thus unit discharges) imposed locally depends on, among other variables, climatic forcing and network position (scale). Fluvial classifications have been criticized for not incorporating scale [e.g., *Juracek and Fitzpatrick*, 2003], although scale-dependence of some channel-reach characteristics has been well established, for example, by work on downstream hydraulic geometry [e.g., *Leopold and Maddock*, 1953], punctuated downstream fining [e.g., *Rice*, 1998; *Rice*, 1999], and vegetative control of channel width [*Anderson et al.*, 2004].

[4] *Montgomery and Buffington* [1998] provide a description of key processes operating at various spatiotemporal scales that could be used to stratify channel networks and argue that knowledge of how these processes affect the spatial distribution of channel classes aids in predicting

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Table 1. Summary of the Data Sets Used in This Meta-Analysis, With the State, Region, and Number of Reaches Surveyed for Each Data Set Indicated

Source	State	Region	Number of Reaches
This study	Colorado	Front Range	12
Chin [1989]	California	Santa Monica	14
Curran [1999]	Washington	Cascades	20
MacFarlane and Wohl [2003]	Washington	Cascades	20
Madsen [1995]	Montana	Northern Rockies	88
Montgomery and Buffington [1997]	Washington	Cascades	34
Southerland [2003]	Washington	Cascades	57
Wohl et al. [2004]	Colorado	Front Range	25
Total			270

channel response to disturbance. At the coarsest spatiotemporal scales, for instance, they suggest stratification along geomorphic provinces that are bound spatially by significant physiographic, climatic, and geological features to minimize variability in relationships among drainage area, discharge, sediment supply, and substrate size. However, fluvial classifications rarely include quantifiable metrics of climatic and hydrologic (hydroclimatic) influence [*Poff et al.*, 2006], particularly related to long-term characteristics of discharge timing, duration, and frequency, and associated climatic forcing, to aid in identification of such provinces. In part, the fact that classifications are rarely informed by hydroclimatology arises from competition between the need to assess channel types and aquatic habitats over large regions (e.g., ecoregions) and the relative sparseness of discharge data over these scales. Invoking drainage area as a surrogate for channel-forming discharge is a common way to compromise between these competing factors and introduces an element of scale into classification. However, doing so is predicated on homogeneity in the relationship between discharge and drainage area (and implicitly in climatic forcing) over the region of interest. Thus, over large regions the assumption of interchangeability between drainage area and discharge can be confounded by gradients in hydroclimatic behavior.

[5] In the present study we examine the hypothesis that mountain channel-reach types occupy distinct ranges of specific stream power. This hypothesis is a logical integration of previous studies which reported that (1) combining substrate size with drainage area significantly improves models predicting bed slope as a function of drainage area only [*Hack*, 1957], and (2) mountain channel types occupy fairly distinct ranges of both substrate size and bed slope [*Grant et al.*, 1990; *Montgomery and Buffington*, 1997; *Wohl and Merritt*, 2005]. Because our data set consists of ungaged sites from several regions of the western United States spanning a hydroclimatic gradient, we used an index of specific stream power based on contributing area and local channel slope. We specifically examine whether channel types [after *Montgomery and Buffington*, 1997] occupy characteristic ranges of the drainage area–dependent index of specific stream power and in doing so, exhibit scale dependence. To assess the adverse impact of using drainage area as a surrogate for discharge characteristics on our ability to discern different channel types, we investigate whether variability in the index of specific stream power of step-pool channels is related to regional discharge and climate variables. Finally, we comment on potential implications in the fields of geomorphology and aquatic ecology, especially regarding the development and use of fluvial classification systems, and discuss future research possibilities that may facilitate an ability to predict attributes of channel-reach morphology using digital geospatial data.

2. Methodology

[6] We compiled a database of 270 alluvial stream reaches from the Washington Cascades [*Montgomery and Buffington*, 1997; *Curran*, 1999; *MacFarlane and Wohl*, 2003], the Northern Cascades [*Southerland*, 2003], the northern Rocky Mountains of Montana [*Madsen*, 1995], the Colorado Front Range [this study; *Wohl et al.*, 2004], and the Santa Monica Range of California [*Chin*, 1989] (Table 1). The channel reaches in the database have observations of the following variables of interest: (1) channel-reach type comparable to *Montgomery and Buffington* [1997], (2) reach-scale bed slope measured with field survey equipment, and (3) drainage area upstream of the channel reach. Of these channel reaches, 15 were classified as cascade, 135 were classified as step-pool, 15 were classified as plane-bed, and 115 were classified as pool-riffle. Bed material at all sites is gravel or larger. Watershed areas were digitized or measured with a digital planimeter from 7.5-min topographic quadrangle maps in all studies except that of *Chin* [1989], which did not report how watershed areas were determined.

[7] The process-based channel classification of *Montgomery and Buffington* [1997] is used because (1) the channel types they delineate are collections of spatially connected channel units that are widely known in fluvial geomorphology, and (2) *Montgomery and Buffington* [1997] hypothesize that the roughness configurations or energy-dissipating features that distinguish these channel types reflect downstream changes in sediment supply relative to capacity. Large woody debris (LWD) was present at some of the sites used in this study, but no sites with bed morphology forced by LWD influence were included in the database.

[8] Prior to conducting the statistical analyses described below, we examined log-log plots of channel slope versus drainage area by channel type for study reaches in the five regions (Figures 1 and 2). Slope-area plots are used extensively to detect transitions from diffusive to fluvial erosion process dominance [*Montgomery and Dietrich*, 1989; *Tarboton et al.*, 1991; *Montgomery and Foufoula-Georgiou*, 1993] and in modeling as a diagnostic to distinguish between orogenic regime [*Tucker and Whipple*, 2002]. *Chin* [2002] was able to discriminate between cascade, step-pool, and pool-riffle channels using slope-area plots

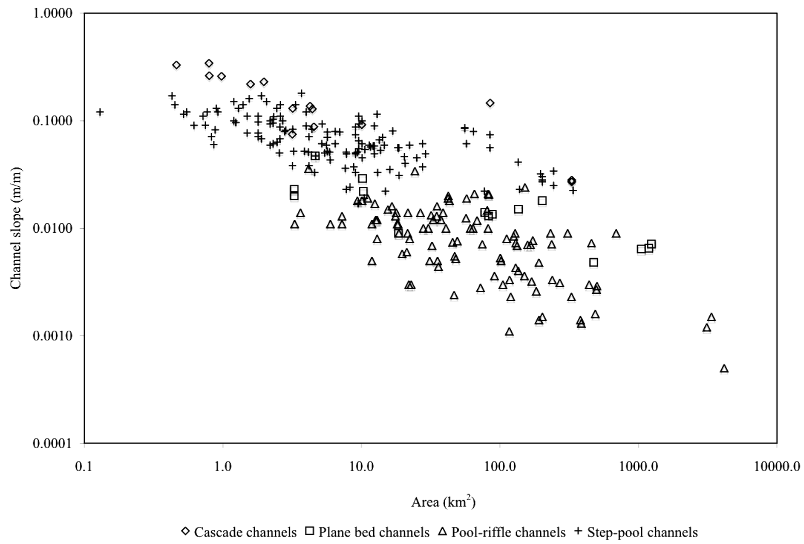

Figure 1. Channel slope (m/m) versus upstream drainage area (km^2) for each site considered in the CART analysis. Markers indicate the channel types considered in the analysis. A sharp transition in channel slope exists between step-pool and pool-riffle streams, although both of these channel types occupy a broad range of upstream area. Cascade and plane-bed channels are also difficult to discriminate from step-pool and pool-riffle channels, respectively.

for channel reaches in the Santa Monica Mountains, California. *Montgomery et al.* [1996] had some success distinguishing between bedrock and alluvial channels in forested drainages using a similar plot. However, the data of *Montgomery et al.* [1996] exhibit overlap in channel slope between bedrock and alluvial stream types as well as considerable variation in slope conditioned on drainage area. The slope-area plots exhibit a degree of scatter, but scaling appears consistent with fluvial erosion that in the mean sense, could reasonably be described using one power law relationship (Figures 1 and 2). A sharp transition between the channel slope of step-pool and pool-riffle channels is evident, although both of these channel types are observed over a broad range of basin area with a high degree of overlap (Figure 1). The slope-area relationship does little to stratify cascade channels from step-pool channels and plane-bed from pool-riffle channels (Figure 1). Moreover, the channel slope-area relationship does not adequately discriminate between the different regions within the data set (Figure 2). When taken alone, these slope-area plots are insufficient to disaggregate step-pool versus cascade and pool-riffle versus plane-bed channels. With the possible exception of the Colorado Front Range data, variability in channel types within a hydroclimatic region makes it difficult to use

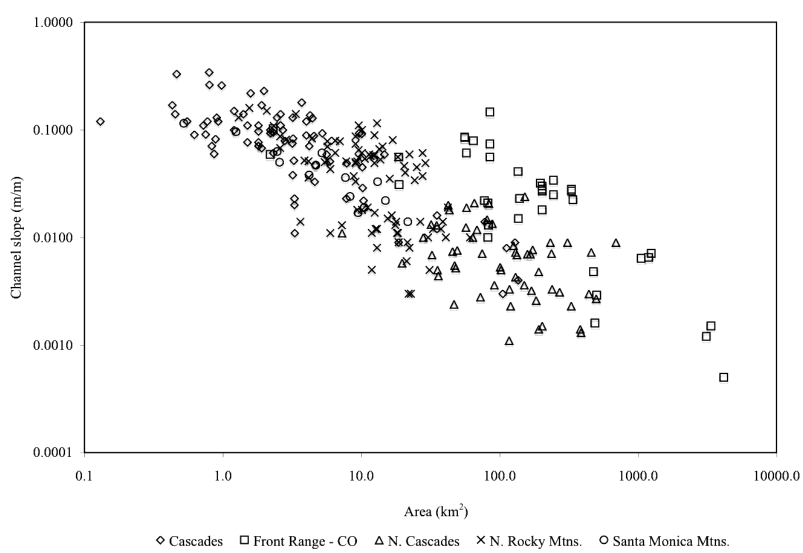

Figure 2. Channel slope (m/m) versus upstream drainage area (km^2) for each site considered in the CART analysis. Markers indicate the regions considered in the analysis. The channel slope-drainage area relationship alone is unable to provide a systematic discrimination between the regions.

slope-area plots as a means to distinguish hydroclimatic regions from one another.

2.1. Examination of Scale Dependence of Channel-Reach Types

[9] Previous work has been successful in discriminating different channel types using only channel-reach bed slope within a hydroclimatic region or among watersheds of similar size [*Grant et al.*, 1990; *Montgomery and Buffington*, 1997]. A reasonable extension of previous work is to consider watersheds across diverse hydroclimatic regions and basin sizes to determine whether channel-reach types are sensitive to hydroclimatic variables and basin scale, respectively. To investigate whether channel-reach morphology depends on basin scale, we seek a combination of channel-reach slope and upstream drainage area that reflects the balance between eroding and resisting forces at a site. While local streambed slope approximates the average rate of flow energy dissipation per unit channel length for a given total discharge, streambed slope is less useful as a measure of erosive capacity if not scaled by unit discharge, depth, or a corresponding surrogate measure.

[10] Sediment transport capacity along a stream is related to the energy dissipation per unit area per time or specific stream power (ω) in a channel reach [*Bagnold*, 1980]:

$$\omega = \frac{\gamma Q S_f}{w}, \tag{1}$$

where γ is the specific weight of the water-sediment mixture, Q is volumetric discharge, S_f is friction slope, and w is channel width. In equation (1) it is often assumed that friction slope is equivalent to bed slope (S_0), although such an assumption assumes steady uniform flow at discharge (Q).

[11] Channel width has been shown to be a function of discharge as [*Leopold and Maddock*, 1953]

$$w = c_0 Q^b, \tag{2}$$

where the exponent (b) has a typical value near 0.5 for single-thread gravel channels [*Hey and Thorne*, 1986; *Knighton*, 1998]. Furthermore, the upstream drainage area (A) is often related to discharge (Q) as

$$Q = c_1 A^d. \tag{3}$$

Combining equations (1), (2), and (3) yields

$$\omega \propto S_0 A^{d(1-b)}. \tag{4}$$

Values of d have been reported to vary between 0.6 and 1.0 [*Cathcart*, 2001; *Eaton et al.*, 2002; *Jennings et al.*, 1994; *Knighton*, 1987], and we assume the midpoint of this range (i.e., d = 0.8) for the present work. Setting b and d equal to 0.5 and 0.8, respectively, yields an index of specific stream power ($S_0A^{0.4}$) for all 270 reaches in the database. Channel bed slope and specific stream power index values for each stream are plotted against channel morphology on box-whisker plots. While the values of b and d we used are consistent with previously reported values, these parameters exhibit some variability that we did not incorporate into the analysis of specific stream power that follows. The sensitivity of specific stream power to b is

$$\frac{\partial \omega}{\partial b} = -d\ln(A)S_0A^{d(1-b)} = -d\ln(A)\omega, \tag{5}$$

while the sensitivity to d is

$$\frac{\partial \omega}{\partial d} \propto (1-b)\ln(A)S_0A^{d(1-b)} = (1-b)\ln(A)\omega. \tag{6}$$

Equations (5) and (6) imply that for slope and area given, the sensitivity of specific stream power to b and d is linearly proportional to those parameters and to the value of specific stream power. Hence the specific stream power index is more sensitive to parameter uncertainty in environments of high specific stream power.

[12] Classification and regression trees (CARTs) [*Breiman et al.*, 1984] were used to develop models for predicting stream type with channel bed slope, drainage area, total stream power (estimated as S_0A), and $S_0A^{0.4}$ included as potential splitting variables. CART analysis yields binary decision trees created from learning data where the response variable is partitioned into groups (nodes) with minimized variance, maximized similarity, and increasing purity [*De'ath and Fabricus*, 2000]. Each node is a decision that leads to a branch of the tree, and either to another decision node or to a terminal node. Terminal nodes (predicted results) are a class from the learning data set.

[13] Classification trees have several benefits over other classification techniques. Data can be categorical, continuous, or mixed; there are no required assumptions regarding the underlying distribution of the data; the errors have no assumed or required distributions; and missing data do not require exclusion of records [*Breiman et al.*, 1984]. Furthermore, CART analysis is well suited to identifying thresholds, interactions, and nonlinear relationships between predictor and response variables [*Iorgulescu and Beven*, 2004]. Because variables can be used repeatedly to split data, CART can illuminate scenarios where, for example, the associated change in a response variable conditioned on a change in a predictor variable is scale dependent. This is in contrast to discriminant analysis (DA), which may suggest that such a variable is an insignificant predictor of the response variable.

[14] Ideal classification trees are those with a small relative cost (R_C) and a low misclassification rate. In addition to these criteria, we endeavored to minimize the number of predictor variables, maintain an ability to physically interpret models, and focus on variables that are easily measured or estimated. We used the Gini index as the splitting criteria because it is the only splitting rule that is a direct measure of node impurity and is typically preferred in situations where computational burden is not limiting [*Breiman et al.*, 1984]. To aid in model selection, we tested the robustness of classification trees using a tenfold cross validation.

[15] For comparative purposes, we also used discriminant analysis to predict channel types using channel bed slope and $S_0A^{0.4}$ as predictor variables. Discriminant analysis will often outperform CART when predictor-predictand relationships are highly linear. Minitab® R14.1 (http://www.minitab.com) was used to create linear discriminant

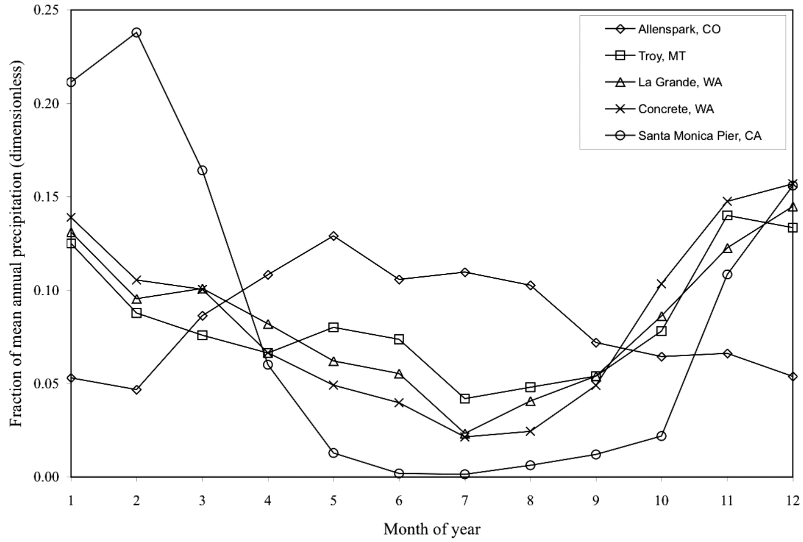

Figure 3. Long-term mean monthly precipitation (mm) normalized by mean annual precipitation (mm) for each of the regions considered. The seasonal distribution of precipitation throughout the calendar year varies between regions. January corresponds to month 1.

functions using a leave-one-out cross validation to test for robustness and ensure results are not overly optimistic. Both predictor variables were log-transformed using a perturbation of one before analysis to improve compliance with model assumptions.

2.2. Dependence of Channel-Reach Morphology on Hydrology and Climate

[16] At the watershed scale, *Zaprowski et al.* [2005] demonstrate a positive correlation between profile concavity, maximum annual discharge, and precipitation intensity in a tectonically stable region, demonstrating a connection between climatic forcing and sediment transport as modulated by hydrology. Provided that gradient is an important (but not exclusive) determinant in the distribution of channel types, long-profile sensitivity to hydroclimatology suggests channel type sensitivity to hydroclimatology.

[17] The assumption that drainage area upstream of a channel reach is a surrogate measure of some geomorphically significant discharge in a manner following equation (3) is complicated, in part, by hydroclimatic variation among channel reaches in the data set. For example, the constant of proportionality in equation (3), c_1, varies with many factors including climate, soils and lithology, and regional vegetation characteristics, and has been shown to vary among hydroclimatic regions [*Eaton et al.*, 2002]. Assuming the slope and area scaling remains the same, this would nevertheless imply that the estimate of reach-scale specific stream power derived in equation (4) would vary among regions through differences in the constants of proportionality. For these reasons, we hypothesize that variation in hydroclimatic characteristics among watersheds is a significant source of loss in predictive power in the classification tree approach outlined above. For example, hydroclimatic regions with comparable annual precipitation may have distinctly different seasonal runoff patterns that result in higher discharge magnitudes per basin area where the bulk of annual runoff is compressed within a relatively narrow window of time.

[18] In the present study we investigate whether scaling channel slope by $A^{0.4}$ to produce an estimate of specific stream power may be limited by interregional hydroclimatic variability. However, because the majority of available study sites lack spatial coordinates and are not located at discharge gaging stations, we must infer the role of hydroclimatic processes indirectly. An implication of our hypothesis that channel types occupy distinct ranges of specific stream power and that drainage-area-based indices of specific stream power indirectly incorporate hydroclimatic processes is that specific stream power for a particular alluvial channel type within a relatively homogeneous hydroclimatic region should be narrowly distributed about a mean value. Given imprecise knowledge of study site locations, our stratification according to hydroclimatic region makes the necessary assumption that the geographic proximity of sites within a particular region are influenced by similar climatic forcing and exhibit similar characteristics of runoff response.

[19] The data set we examine contains at least nine step-pool channels (the most frequently occurring channel type within the data set) for each hydroclimatic region, making step-pool channels an appropriate subset of the data for investigating the influence of hydroclimatic gradients on the efficacy of drainage-area scaling in stream classification. For each hydroclimatic region, monthly precipitation data were obtained for a continuous period no less than 10 years in length from the gauging station nearest to the approximate locations of the study reaches from the National Climatic Data Network (NCDC). We first verified that the precipitation process in each region is approximately stationary over the period of record. The nondimensional seasonal cycle (long-term mean monthly precipitation normalized by mean annual precipitation) suggests that the timing of precipitation delivery throughout the year varies significantly by region (Figure 3). We use two variables computed from the precipitation records that represent the magnitude and variance in the seasonal cycle of precipita-

Table 2. Summary of Hydroclimatological Data Used in the Analysis

National Climate Data Center Cooperative Identification	National Climate Data Center Gage Name	U.S. Geological Survey Gage	U.S. Geological Survey Gage Name	Region	P_{ma}, mm	CV_p	Mean Channel Slope, m/m	Mean Specific Stream Power, $km^{0.8}$	Discharge Skewness
50183	Allenspark, Colorado	06721500	North Saint Vrain, near Allen's Park, Colorado	Front Range, Colorado Rockies	531.30	0.33	0.0487	0.260	2.20
248390	Troy, Montana	12304500	Yaak River near Troy, Montana	Northern Rocky Mountains	623.24	0.39	0.0695	0.170	2.68
454360	LaGrande, Washington	12087000	Mashel near La Grande, Washington	Cascades	980.31	0.45	0.1038	0.143	4.34
451679	Concrete, Washington	12161000	SF Stillaguamish River near Granite Falls, Washington	Cascades (Finney Creek)	1713.88	0.58	0.0542	0.123	5.14
047953	Santa Monica Pier, California	11104000	Topanga Creek Near Topanga Beach, California	Santa Monica Mountains	327.09	1.07	0.0478	0.076	36.73

tion. The mean annual precipitation (P_{ma}) is simply the sum of the seasonal cycle and physically represents the long-term averaged volume of annual precipitation delivered to a basin. The coefficient of variation in mean monthly precipitation (CV_p) provides insight into the seasonality of precipitation delivery to the basin throughout the year.

[20] Characteristics of streamflow in each region are determined through analysis of a streamflow record of at least 10 years in length from a U.S. Geological Survey (http://waterdata. usgs.gov/nwis/sw) reference gage on an unregulated river nearest to the approximately known locations of the study reaches. The mean annual discharge (Q_{ma}), the discharge corresponding to the 2-year recurrence interval (Q_2), and the coefficient of skew of daily discharges are estimated for each flow record. An estimate of runoff per unit basin area is computed for each hydroclimatic region by normalizing Q_{ma} and Q_2 by the upstream drainage area at the gage. Normalizing Q_2 by Q_{ma} gives a measure of the spread in the distribution of floods and is interpreted to reflect the degree of hydrologic flashiness. Coefficients of skew of daily streamflow data obtained from the records represent the asymmetry of the daily discharge distribution and can be interpreted as a measure of the relative frequency of occurrence of low- and high-magnitude flows. For a unimodal distribution, a higher skew coefficient implies greater probability density in the left tail (below mean flows) relative to the right tail (above mean flows). These data, along with mean values of $S_0A^{0.4}$ by physiographic region, are presented in Table 2.

[21] Recurrence intervals of step-forming events in mountain channels have been reported to range from approximately 10 years to greater than 50 years [*Sawada et al.*, 1983; *Grant et al.*, 1990; *Chin*, 1989, 1998; *Ergenzinger*, 1992]. The flow record lengths considered in our analysis of hydroclimatology preclude estimation of extreme events in all hydroclimatic regions without extrapolation. Hence, while we would expect a correlation between regional mean values of the specific stream power index for step-pool channels and, for example, the ratio in magnitudes of 25-year and 2-year recurrence interval events, the lengths of the flow records do not adequately capture this relationship for all hydroclimatic regions. It should be noted that this analysis, while isolating step-pool channels for additional analysis, is not intended to suggest that the variability introduced via drainage area scaling is only relevant to the step-pool channel type. Furthermore, we hypothesize that surrogate measures of specific stream power for other channel types are likely to exhibit correlation with different statistics of the climate and discharge distributions.

3. Results

3.1. Scale Dependence of Channel-Reach Types

[22] Channel-reach types exist within intergrading ranges of bed slope and the index of specific stream power; scaling channel bed slope by $A^{0.4}$ improves separation in inner and outer quartile ranges between pool-riffle and plane-bed channels, and step-pool and cascade channels (Figures 4 and 5). Separation in inner and outer quartile ranges between plane-bed and step-pool channel types, however, decreases as a result of scaling bed slope by $A^{0.4}$. The tenfold cross-validated classification tree with the lowest relative cost

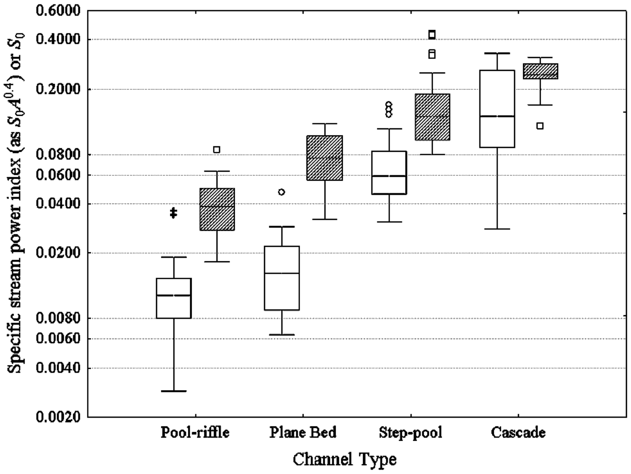

Figure 4. Channel slope (m/m) and specific stream power index (km$^{0.8}$) versus channel type for all regions. Hatched data represent specific stream power, open boxes represent channel slope. Boxes correspond to the inner and outer quartiles, and whiskers correspond to inner and outer tenths. Open circles are outliers of channel slope, crosses are extreme values of channel slope, and open squares are outliers of specific stream power. High outliers are 1.5–3 times the inner quartile range above the 75th percentile, while low outliers are 1.5–3 times the inner quartile range below the 25th percentile. Extreme values are greater than 3 times the inner quartile range above or below the 75th and 25th percentiles, respectively.

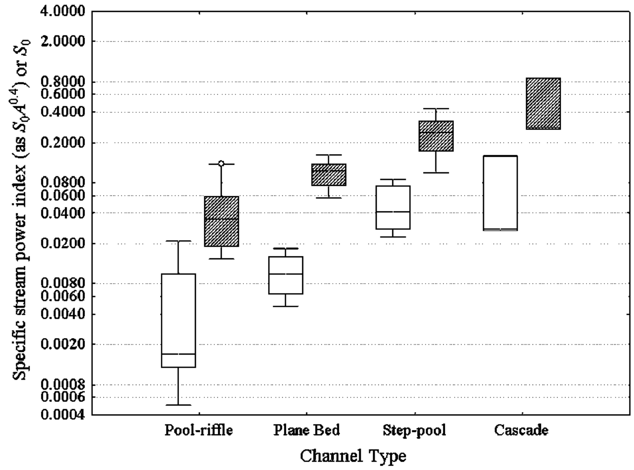

Figure 5. Channel slope (m/m) and specific stream power index (km$^{0.8}$) versus channel type for the North Saint Vrain data. Hatched data represent specific stream power, open boxes represent channel slope. Boxes correspond to the inner and outer quartiles, and whiskers correspond to inner and outer tenths. The open circle is an outlier of channel slope. High outliers are 1.5–3 times the inner quartile range above the 75th percentile, while low outliers are 1.5–3 times the inner quartile range below the 25th percentile. Extreme values are greater than 3 times the inner quartile range above or below the 75th and 25th percentiles, respectively.

(R_C = 0.365) resulting from the CART analysis (Figure 6) has a correct classification rate of 76.3% (Table 3). Channel bed slope and $S_0A^{0.4}$ emerged as the most significant predictor variables in this tree with variable importances of 100 and 98.9, respectively. Watershed drainage area and S_0A had variable importances of 32.1 and 29.9, respectively. Linear DA resulted in a maximum 74.8% overall correct classification rate using channel bed slope and $S_0A^{0.4}$. The discriminant function predicts pool-riffles (Table 4) with better accuracy than CART, but overall model performance was not as robust.

3.2. Variability of Step-Pool Energy Levels and Hydroclimatic Influence

[23] Although, as expected, P_{ma} correlates well with Q_{ma} (and less well with Q_2), there is little correspondence between mean values of the specific stream power index and P_{ma}, Q_{ma}, or Q_2 among regions. However, there appear to be significant relationships between climatic variability, hydrologic variability, and regional means of the specific stream power index for step-pool channels. Discharge skew coefficient demonstrates power law dependence on CV_p with a coefficient of determination (r^2) of 0.97 ($p < 0.003$; Figure 7). When the Santa Monica Mountains, which demonstrate a higher discharge skew relative to other regions, are excluded from the plot, r^2 decreases to 0.92 ($p < 0.05$; Figure 7). Regional mean of the specific stream power index decreases nonlinearly as discharge skew coefficient increases with an r^2 of 0.85 ($p < 0.07$; Figure 8). When data from the Santa Monica Mountains, which demonstrate a low mean value of $S_0A^{0.4}$ relative to the other regions in addition to a relatively high discharge skew coefficient, are removed, r^2 increases to approximately 0.87 ($p < 0.06$; Figure 8). Power law dependence also exists between regional means of the specific stream power index and s_p. When all regions are considered together, this power law scaling produces an r^2 value of 0.85 ($p < 0.03$; Figure 9), and when the Santa Monica Mountains are excluded, r^2 increases to 0.90 ($p < 0.05$; Figure 9). Analysis showed no significant correlation between discharge skew and drainage area for the streamflow gages.

4. Discussion

4.1. Prediction of Channel-Reach Type

[24] These results demonstrate potential benefits of using drainage-area scaling, specifically the index of specific stream power computed via equation (4), in classifying and predicting channel types and their associated habitat characteristics across landscapes. The classification tree model

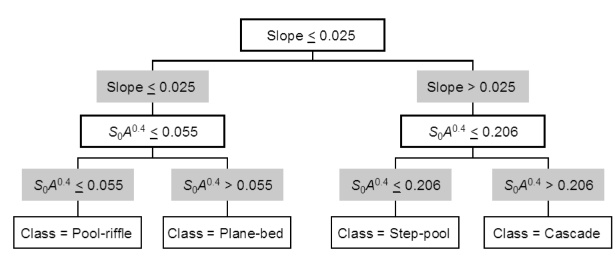

Figure 6. Tenfold cross-validated classification tree that predicts channel-reach morphology with 76% accuracy (R_C of 0.365).

Table 3. CART Model Classification Performance for Four Stream Types

Actual Class	Cascade	Plane-Bed	Pool-Riffle	Step-Pool	Total Cases	Total Correct	Percent Correct
Cascade	13	0	0	2	15	13	86.7
Plane-bed	0	10	3	2	15	10	66.7
Pool-riffle	0	22	81	2	105	81	77.1
Step-pool	25	5	3	102	135	102	75.6
Total					270	206	76.3

indicates that channel slope is a strong indicator of transport versus supply-limited channels (using the terminology of *Montgomery and Buffington* [1997] for convenience). However, consideration of some metric of local-flow energy such as specific stream power, shear stress, or flow resistance appears necessary for accurately distinguishing between channel types within supply- and transport-limited regimes. The index of specific stream power discriminates between cascade and step-pool channels better than slope (Figures 4 and 5). Cascade channels exhibit the highest correct classification rate in the CART model (Table 3). This indicates that the CART model can largely resolve cascade and step-pool channels, in spite of the significant overlap in channel slope and drainage area in these two channel types seen in Figure 1 and the relatively small number of cascade channel types within the data set.

[25] The same conclusion is reached for comparisons of plane-bed and pool-riffle streams. Figures 4 and 5 suggest that plane-bed channels and step-pool channels have similar values of $S_0A^{0.4}$, yet plane-bed channels are closer to pool-riffle channels in terms of channel slope. In both the CART and linear DA models, plane-bed channels exhibit the lowest correct classification rate (Tables 3 and 4). Perceptual differences in what constitutes a plane-bed channel undoubtedly affect model accuracy in classifying plane-bed streams, although this is largely an irreducible source of uncertainty in this study. Another possible interpretation of this result lies in the hypothesized origins of plane-bed channels. *Montgomery and Buffington* [1997] suggest that plane-bed channels, in which rhythmic occurrence of bed forms is absent and which can serve as sediment sources or sinks, represent a transition from supply- to transport-limited conditions. It is in these reaches of the channel network where channel response is increasingly dependent on downstream divergence in boundary shear stress or specific stream power in addition to magnitude. The drainage areas of step-pool and plane-bed channels in our data set average 23.8 and 306 km^2, respectively, and are statistically different ($p < 0.02$) in a t test with unequal variance. Thus plane-bed channels may occur where values of the specific stream power index are comparable to values for step-pool channels, but a lack of step-forming clasts of sufficient size relative to channel width [*Curran and Wilcock*, 2005] resulting from downstream fining and/or diminished hillslope coupling [*Church*, 2002] inhibits step formation.

[26] The CART model slightly outperformed DA in classification accuracy and provides a basis for straightforward physical interpretation. Our ability to predict channel-reach morphology would not be substantially diminished using DA alone, but understanding the physical influences and delineating quantitative thresholds would be more difficult. Furthermore, the subtle differences between results of CART and linear DA analysis suggest the presence of nonlinear interactions between predictor and response variables that is better captured in the CART model structure. The CART results indicate a process shift associated with slopes in the vicinity of 2.5% and also lend support to the argument that channel types represent configurations that are suited to fairly discrete ranges of energetic conditions. Our results are consistent with those of *Montgomery et al.* [1999] and *Buffington et al.* [2004], who suggest that this shift in process dominance occurs at channels slopes in the vicinity of 3%, and use this criterion in predicting network-wide distributions of spawning substrates.

[27] Our results suggest that channel types delineated by *Montgomery and Buffington* [1997] do not satisfy the hypothesis of equal energy expenditure per unit bed area (Figures 4 and 5) suggested in the optimal channel network (OCN) model of *Ijjasz-Vasquez et al.* [1993]. In fact, it is this apparent departure from optimality, as defined in the OCN framework, which gives rise to the utility of stratifying channel types according to a specific stream power index. It should be noted, however, that the OCN and other models that hypothesize equal energy expenditure per unit bed area assume that channel slope is the principal degree of freedom that adjusts to meet the extremal state. However, in natural channel networks, channel-bed configuration and substrate size represent two of many additional degrees of freedom that may adjust to satisfy the governing equations.

4.2. Regional Variation in the Specific Stream Power Index and Hydroclimatic Influences

[28] The investigation of whether hydroclimatic variables are correlated with the index of specific stream power used in the channel-type models is motivated by two considerations. First, most of the stream reaches that comprise our

Table 4. Linear Discriminant Analysis Model Classification Performance for Four Stream Types

Actual Class	Cascade	Plane-Bed	Pool-Riffle	Step-Pool	Total Cases	Total Correct	Percent Correct
Cascade	10	0	0	5	15	10	66.7
Plane-bed	0	10	5	0	15	10	66.7
Pool-riffle	0	18	87	0	105	87	82.9
Step-pool	17	19	4	95	135	95	70.4
Total					270	202	74.8

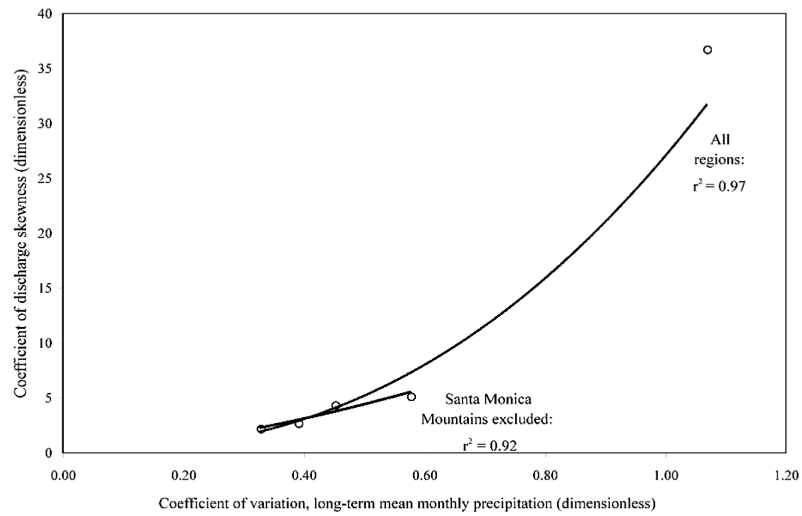

Figure 7. Discharge skew coefficient (dimensionless) versus coefficient of variation in mean monthly precipitation (dimensionless). Each point represents one region corresponding to a subset of the step-pool data. The Santa Monica Mountains exhibit a large coefficient of discharge skew relative to the other regions. Discharge skew coefficient is positively correlated with the coefficient of variation in mean monthly precipitation. Using a power law fit, r^2 = 0.97 when all regions are considered and r^2 = 0.92 when the Santa Monica Mountains are excluded.

data set are on ungaged streams, streams with inadequate discharge records, or are on an altitudinal gradient along the same stream. This consideration necessitates the use of drainage area as a surrogate of geomorphically significant discharges. Second, these data span a range of climatic regions in terms of both volume and timing of precipitation delivery, and a range of hydrologic response. Together, these considerations suggest that the predictive power of our CART and DA models are reduced because climate and hydrology are sources of variability lumped into the values of drainage area used to estimate specific stream power. Our selection of step-pool channels to address this concern is an artifact of having at least nine step-pool channels per hydroclimatic region. We underscore that we cannot estimate the amount of predictive power lost in the CART models owing to hydroclimatic trends existing within the data set, for lack of adequate numbers of each channel type within each hydroclimatic region.

[29] Our analysis of step-pool streams suggests that hydroclimatic factors may be related to interregional variation in the specific stream power index. Specifically, climate is associated with characteristics of discharge distribution (Figure 7), and variation in discharge skewness is also related to regional mean $S_0A^{0.4}$ (Figure 8). Moreover,

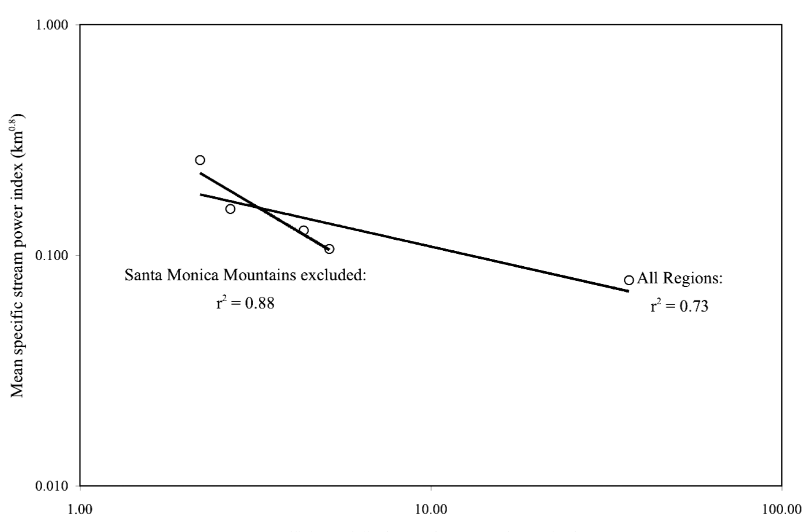

Figure 8. Regional mean of specific stream power index (km$^{0.8}$) of step-pool channels is negatively related to discharge skew coefficient (dimensionless). A power law fit yields a value of r^2 = 0.73 when all regions are considered and r^2 = 0.88 when the Santa Monica Mountains, which demonstrate a large discharge skew coefficient, are excluded.

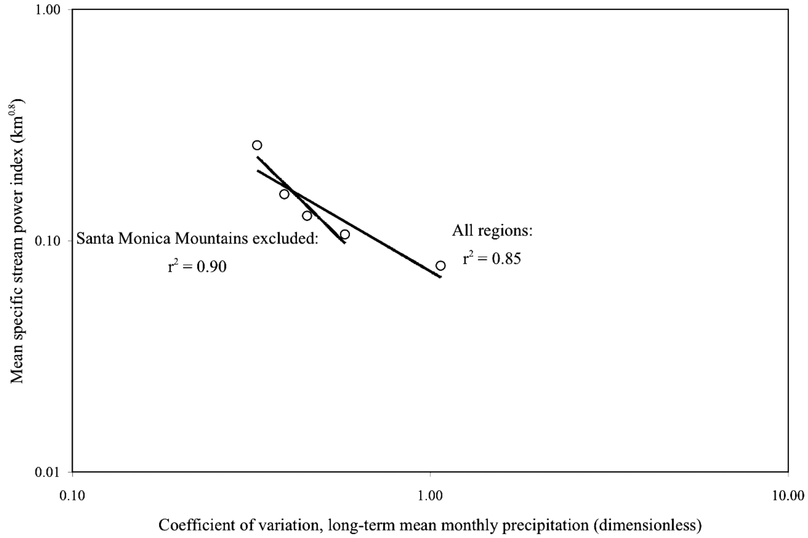

Figure 9. Regional mean of specific stream power index ($km^{0.8}$) of step-pool channels is negatively related to coefficient of variation in mean monthly precipitation (dimensionless). A power law fit yields a value of $r^2 = 0.85$ when all regions are considered and $r^2 = 0.90$ when the Santa Monica Mountains are excluded.

increasing nonuniformity in the seasonal distribution of precipitation is associated with decreasing regional mean $S_0A^{0.4}$ (Figure 9). Hence these results indicate that scaling bed slope by $A^{0.4}$ to yield an index of local specific stream power and, more generally, using drainage area as a surrogate for geomorphically significant discharge characteristics introduce variability associated with climate. The variability introduced by assuming drainage area as a discharge surrogate appears to be related to the degree uniformity of the seasonal precipitation distribution, although apparently not the total mean annual precipitation.

[30] While the present investigation does not establish causal links between climate and regional spatial distributions of local-channel morphology, the influence of seasonal variation in precipitation within the data set raises some intriguing questions regarding linkages between climate, basin hydrologic response, and geomorphic processes. One interpretation of the positive correlation between the coefficient of variation of the seasonal precipitation cycle and discharge skew coefficient is that a more seasonally variable distribution of precipitation leads to a distribution of flows with high outliers significant enough to result in a high discharge-skew coefficient. Increasing CV_p (i.e., increasing seasonality) generally implies narrower windows of time over which annual runoff production may occur. As the window of time each year during which runoff occurs narrows, the frequency distribution of flows is increasingly dominated by base flow, and the skew of the discharge distribution can be expected to increase. Therefore increasing seasonality is expected to be associated with increasing discharge skew (Figure 8), which in turn is associated with greater runoff per unit area during flood flows. For example, *Sanborn and Bledsoe* [2006] found that the ratio of precipitation in the wettest three months to the driest three months is of first-order importance to discharge skew in several regions of the Pacific Northwest and Rocky Mountains.

[31] Equilibrium channel response models [e.g., *Lane*, 1955] suggest an inverse relationship between slope and dominant discharge for a given sediment load. Because step-pool channels adjust to high-magnitude flows, increasing runoff per unit area is expected to be associated with decreasing slope for a particular drainage area, implying an inverse relationship between both precipitation seasonality and discharge skew, and the mean index of specific stream power for a region. The inverse relationship could potentially arise because step formation is most influenced by flow conditions ranging in recurrence interval from approximately 10 years to greater than 50 years [*Sawada et al.*, 1983; *Grant et al.*, 1990; *Chin*, 1989, 1998; *Ergenzinger*, 1992]. This hypothesis, however, could not be tested given that the hydroclimatic records available are insufficient to estimate the magnitude of step-forming events, given the relatively long recurrence intervals associated with such events.

[32] If the channel-forming flow magnitude is taken to be the effective discharge [*Wolman and Miller*, 1960; *Emmett and Wolman*, 2001], our finding also appears consistent with previous studies that find an association between increasing flow distribution skew and effective discharge [*Baker*, 1977; *Andrews*, 1980; *Andrews and Nankervis*, 1995]. *Goodwin* [2004] shows analytically that effective discharge magnitude is linearly proportional to the product of skew and standard deviation of the flow distribution for a gamma distribution (it should be noted that skew and variance are not independent). This suggests that in addition to uncertainty in hydraulic reconstruction techniques [e.g., *Grant et al.*, 1990], and other factors such as supply and size of clasts [*Curran and Wilcock*, 2005] and geologic context, a degree of the variability in recurrence intervals of step-forming events observed in the literature could result from variability in hydroclimatic regimes. In the present study the fact that skew coefficient is calculated from daily flows (and thus with substantially more data points than events with a given annual maximum recurrence interval) may be a secondary reason for its significance in relation to regional values of $S_0A^{0.4}$.

[33] Higher moments of the underlying distribution of the discharge regime such as discharge skew coefficient may account for some variation in the energy dissipation characteristics of step-pool channels, but this may not be generally true of energy-dissipation characteristics of other channel types. For example, pool-riffle channels generally adjust more readily to imposed water and sediment-discharge characteristics, and often have effective discharges with recurrence intervals of 1–2 years [*Whiting et al.*, 1999; *Emmett and Wolman*, 2001]. A similar analysis conducted with pool-riffle channels may reveal that, for example, $Q_{1.5}$ correlates better than discharge skew with central tendencies in specific stream power of this type among hydroclimatic regions.

[34] Formation of cascade-type channels is sensitive to stochastic sediment delivery [*Nanson*, 1974; *Griffiths*, 1980; *Ashida et al.*, 1981; *Whittaker*, 1987b], implying that the signature of hydroclimatic processes lumped in drainage area (and thus a drainage area–dependent index of specific stream power) is less detectable. For these channels, the influence of climate may be in the initiation of landslides and debris flows, and estimates of local specific stream power may more directly relate to recurrence intervals of mass movement–inducing precipitation events. This argument, however, is contrary to our findings indicating that drainage area–dependent indices of specific stream power are useful in identifying cascade-type channels. Further, in environments where freeze-thaw processes, seismic disturbance, or volcanism are primary agents of mass movement initiation, there may be no detectable dependence on hydroclimatology.

[35] Large variations in local geomorphic attributes over relatively short timescales can exist [*Benda and Dunne*, 1997a, 1997b; *Benda et al.*, 2004], even when a watershed approximates a state of dynamic equilibrium with respect to sediment fluxes. This results, in part, from internal variability in driving processes, spatiotemporal variations in the response, and external stochastic drivers such as wood, fire, and volcanism. Because this implies that reach-scale geomorphic attributes are likely correlated with both long-term hydroclimatic trends and individual hydrologic events, caution must be exercised when interpreting trends between hydroclimatic and geomorphic data from sampling intervals shorter than reach-scale response times of the system. This is especially true of channel types having morphologies that primarily reflect rare events with large recurrence intervals. Geologic context and historical setting particular to the data set being studied are thus critical considerations when investigating interactions between climate, hydrology, topography, and regional spatial distributions of channel types.

4.3. Implications for Fluvial Classification

[36] Our findings underscore the need for caution when using drainage area as a discharge surrogate in scaling channel slopes. We suggest that the influence of hydroclimatic gradients be directly investigated when possible and normalized out of drainage area in comparisons of watersheds across heterogeneous regions. For example, *Eaton et al.* [2002] find significant regional variability in proportionality constant of power law relationships between 20-year flood magnitude and drainage area in British Columbia. They attribute much of this variability to spatial patterns in hydroclimatic regimes within the province. Hence it is likely that correlations between slope-drainage area surrogates for flow energy and landscape distributions of channels types will reflect region-specific hydroclimatic signatures and thus necessitate regional calibration of predictive models. Despite these complications, the association between the annual distribution of precipitation and regional mean values of the index of specific stream power identified in this study suggests that combining slope-drainage area scaling with appropriate climate descriptors could potentially improve interregional models for predicting mountain channel types. This could be especially advantageous where hydrologic data are sparse relative to climatic data.

[37] The ability to increase discrimination among channel-reach types by scaling slope with drainage area, properly normalized for hydroclimatic influence as necessary, also underscores potential benefits for existing classification systems. For example, the complexity of the widely used classification system of *Rosgen* [1994] is substantially increased through the introduction of channel subtypes (e.g., B3a, B3, B3c) to account for within-class variability in slope. Scaling slopes with drainage area or incorporating hydroclimatic variables in developing surrogate measures of specific stream power can potentially reduce variability, and improve the physical basis and parsimony of existing classifications. There is currently no unified channel typology that explicitly links climate, hydrology, and reach-scale geomorphic processes, although recent work represents a move toward such a classification [*Poff et al.*, 2006].

[38] Regional stratification of channel-type data based on existing biophysical classifications (e.g., ecoregions) may be inappropriate because these classifications poorly resolve hydroclimatic variation present at finer spatial scales in some regions. For example, mechanisms driving hydrologic regime can vary from snowmelt to rain-on-snow to frontal rain within a mountainous ecoregion. Such classifications also may not adequately account for geologic influences on discharge associated with heterogeneity in basin lithology [*Tague and Grant*, 2004]. Furthermore, bank vegetation and materials can substantially influence downstream hydraulic geometry relationships [*Andrews*, 1984; *Hey and Thorne*, 1986; *Anderson et al.*, 2004] and therefore indirectly affect specific stream power.

[39] Mapping of network- or regional-scale distributions of stream physical habitat could also benefit from refinements of this approach. Assuming that channel-reach types represent equilibrium forms to dissipate energy supplied by a range of flow conditions as suggested by *Montgomery and Buffington* [1997], a map bracketing the ranges of specific stream power over which particular channel-reach types exist throughout a channel network could be used to predict geomorphic attributes of putative ecological significance and potentially link spatial distributions of these attributes with landscape patterns of biotic variation. Such an approach could also be used to map the relative sensitivity of channel types to human influences [*Montgomery and Buffington*, 1998; *Montgomery and MacDonald*, 2002]. A map based solely on network specific stream power would, however, represent possible channel types only in the absence of external forcing due to such factors as LWD input, debris flow deposit, and tributary influence. For

example, in their effort to predict locations of reaches suitable to salmon spawning, *Lunetta et al.* [1997] reported that tributary confluences are problematic.

[40] In the present study, a lack of accurate locations for the majority of field sites prevented us from incorporating information related to valley confinement, LWD loading, and lithology. Including these variables could potentially yield substantial improvements in models for predicting channel types with geospatial data. Connectivity and proximity of channels to valley walls, for instance, affect the amount and frequency of colluvial material delivery to channels. Additionally, others have noted that valley characteristics directly influence the effectiveness of channel-forming events [*Costa and O'Connor*, 1995; *Miller*, 1995]. Measures of valley entrenchment and hillslope connectivity in the vicinity of a sample location estimated from digital elevation models (DEMs) could be used with CART modeling to stratify portions of the channel network where floods are confined and the potential of forcing due to colluvial input from adjacent hillslopes exists.

[41] Similarly, identifying regions of the network where LWD locally affects channel dimensions may also prove useful in predicting local-channel morphology using geospatial data. *Lunetta et al.* [1997] used forest seral stage spatial data in the vicinity of channels to infer loading rates of LWD and demonstrate an ability to predict reaches preferential for salmonid spawning beds. New high-resolution data (light detection and ranging (lidar)) have also been successfully used to infer LWD loading rates [*Buckley et al.*, 2000]. These techniques could potentially be combined with elements of the present study to identify locations within channel networks where recruitment of LWD would have significant effects on energy dissipation characteristics and morphology.

[42] Both basin-wide and local lithology influence local-channel morphology as well as stream substrate size [*Hack*, 1957; *Werritty*, 1992; *Kodama*, 1994]. *Chin* [1989] notes that the mobility of steps is largely a function of particle size. Lithology also constrains the influence of groundwater on hydrograph shape [*Tague and Grant*, 2004] and plays a crucial role in sediment supply, although sediment supply is difficult to assess using geospatial data. Accounting for lithology, both locally and basin-wide, is likely to better inform efforts to predict local-channel morphology. Doing so within the CART framework may be especially straightforward since CART predictor variables may be categorical.

[43] Formation of characteristic morphologies in mountain channels may also depend on the time rate of change of flow conditions in addition to some sustained high flow. For instance, anecdotal reports suggest that step formation in Pacific Northwest streams may be influenced by the steepness of the receding limb of the annual maximum hydrograph (G. Grant, personal communication, 2002), and previous work suggests that step formation occurs during the falling limb of hydrographs of extreme events [*Sawada et al.*, 1983; *Whittaker*, 1987a; *Warburton*, 1992]. In some hydroclimatic regions, channel adjustment is strongly forced by colluvial sediment inputs (and thus an imposed sediment size distribution) to channels through landsliding and debris flows. In these regions the influence of climate on the network-wide distribution of step-pool channels may be more closely linked with climatological events that deliver sediment to channels through mass movement. This hints at an additional realm of processes that could better inform development and application of fluvial classifications.

[44] Ultimately, comparability of field investigations of channel reaches and watershed processes is of fundamental importance to classification and in determining the primary drivers influencing channel morphologies within a drainage network. For example, steps can be alluvial features that exhibit discernible signatures in the longitudinal frequency domain that imply structured periodicity [*Chin*, 2002], but may also be the result of local geologic controls or input of colluvial material [*Zimmerman and Church*, 2001], local-bed roughness impeding transport of step-forming grains [*Curran and Wilcock*, 2005], or low channel width-to-depth ratio [*Grant et al.*, 1990]. Restricting classification of step-pool sequences to those channels in which steps occur rhythmically at the intervals reported by *Grant et al.* [1990] may imply a narrower range of basin scale and consequently a narrower range in specific stream power. Hence the notion of what constitutes a step-pool channel, for instance, partially determines the efficacy of using drainage-area scaling. Field reconnaissance will undoubtedly continue to reveal that maps of putative channel types poorly reflect actual conditions in some contexts, despite the inclusion of variables describing geology, valley form, and LWD forcing as model inputs. Departures of the map from the territory are instructive in both efforts to refine methods of prediction of channel morphology and targeting of field campaigns where predictions are least certain.

4.4. Future Research Needs

[45] Several avenues of future research that extend this work hold promise for fluvial classification, and the prediction of reach-scale channel geomorphology from geospatial data. Our findings suggest that models including slope-area scaling, hydroclimatic influences (e.g., seasonal precipitation variability and discharge skew), and other pertinent information about the channel and valley network upstream of a reach may facilitate the prediction of channel-reach types using geospatial data in a geographic information system (GIS). This assertion, however, must be qualified. First, using only specific stream power and hydroclimatic information as independent variables to predict channel-reach types neglects the potentially significant roles of LWD, local geologic control, and inputs of nonalluvial sediment from adjacent hillslopes in forcing channel morphology. Second, using a combination of bed slope and drainage area as a surrogate measure of specific stream power for prediction of channel-reach types necessitates an estimate of slope from a DEM that can serve as a reliable substitute for a channel-bed slope obtained through on-the-ground surveying.

[46] Several previous studies have demonstrated the utility of using DEMs to estimate channel slopes in the development of predictive models at the drainage network scale [*Lunetta et al.*, 1997; *Montgomery et al.*, 1998; *Dalla Fontana and Marchi*, 2003; *Reinfelds et al.*, 2004]. Using the findings of this work, we attempted to predict the spatial arrangement of channel types within the North Saint Vrain watershed, where spatial coordinates of sample locations were available. However, values of specific stream power computed with local-channel slopes obtained from a 10-m

DEM were unable to resolve heterogeneity in channel types within the network. Although qualitative inspection of longitudinal profiles reveals that currently available DEMs are able to depict a degree of structural variation in channel networks [*Reinfelds et al.*, 2004], DEM resolution remains a significant source of error in estimating local channel slope. New DEMs such as those derived from lidar reflectance data will undoubtedly serve to increase the accuracy of slope estimates.

[47] These challenges aside, the ability to reliably and accurately predict attributes of channel morphology from readily available digital geospatial data would have many useful applications. For instance, development of biomonitoring networks and protocols for biomonitoring activities could be improved through hydrogeomorphic stratification. Investigating the correspondence between biotic and geomorphic heterogeneity, or lack thereof, could be facilitated by assessing the spatial connectivity and redundancy of channel types throughout channel networks using a GIS. Models for predicting the spatial arrangement of channel types throughout a drainage network would also be informative in qualitatively describing channel response to changes in variables acting at coarser scales. For instance, the ability to identify linkages between channel morphology and precipitation acting through hydrology could provide insight into the sensitivity of the spatial arrangement of channel types and habitats to climate change.

[48] Finally, some degree of uncertainty in the data can be attributed to channel-type classification and field techniques for estimating slope in channels with complex topography. Inevitably, these factors translate to a degree of uncertainty in the observed results that remains largely irreducible within the constraints of this meta-analysis. Future studies may see improved results through a concerted effort to explicitly cope with uncertainty due to these factors, yielding maps of the spatial distribution of channel types that communicate uncertainty in channel-type predictions. Moreover, designing field data-collection protocols around known gradients in hydrologic and climatic processes may make accounting for hydroclimatic factors more straightforward in future studies.

5. Conclusions

[49] In a data set of 270 mountain channel reaches from five regions of the western United States, variance in a surrogate measure of specific stream power is less than the corresponding variance in channel slope among reaches within a particular mountain channel type. Scaling channel slope by $A^{0.4}$ also reduces the occurrence of extreme observations within a channel type. These factors result in a net improvement in the ability to discriminate among channel types, and thus improved the performance of CART and DA models for predicting channel type. CART analysis also revealed that channel slope can be used to delineate transport- from supply-limited channel types, while the index of specific stream power further separates channel types within transport- and supply-limited conditions. We argue that using specific stream power to discriminate between channel types has added benefits of (1) introducing an element of scale into an existing fluvial classification, and (2) including a physically meaningful variable closely related to sediment-transport capacity. However, estimates of specific stream power based on drainage-area scaling introduce additional variability when considering channel reaches across a gradient of hydroclimatic influence. An investigation of the influence of regional hydroclimatic factors on the specific stream power index of step-pool channels indicates a positive trend between seasonal precipitation variability and the skew coefficient of daily discharges, and an inverse trend between the specific stream power index and discharge skew. This suggests that climate, modulated by hydrology, may influence the drainage network positions of mountain channel types. We hypothesize that the association with discharge skew reflects the sensitivity of step-pool channels to hydrologic events with recurrence intervals ranging from 10 to 100 years. Although other channel types are influenced by climate (acting through hydrology), the nature of the influence probably varies with the sensitivity of a particular channel type to hydrologic events of different return intervals.

[50] Finally, a conceptual approach for predicting channel-reach types using digital geospatial data is described. This approach makes use of specific stream power estimated from topographic data with expected channel-reach types assigned on the basis of bracketed values of specific stream power over which each channel-reach type exists. Information about local valley characteristics, LWD loading and retention, and local and basin-wide lithology can then be employed to modify the predicted classes and/or assess uncertainty in the predicted spatial arrangement of channel types. Ground inspection of predicted channel types can then be carried out at locations throughout the channel network to verify and adjust the model to more accurately assign channel-reach types. The ecological significance of channel types or coarse geomorphic patches can then be inferred by the systematic analysis of spatial arrangements of these units throughout a channel network. Finally, suggestions for future research include quantification of the effect of valley configuration on channel types, addressing LWD loading, accurate estimation of channel slope and specific stream power from DEMs, and inclusion of variables to account for the role of basin lithology.

Notation

- A upstream drainage area (km^2).
- b exponent.
- c coefficient.
- c_1 function of climate, soils and lithology, and regional vegetation characteristics.
- CV_p coefficient of variation in mean monthly precipitation.
- d exponent.
- P_{ma} mean annual precipitation.
- Q volumetric discharge (m^3/s).
- $Q_{1.5}$ discharge corresponding to the 1.5-year recurrence interval (m^3/s).
- Q_2 discharge corresponding to the 2-year recurrence interval (m^3/s).
- Q_{ma} mean annual discharge (m^3/s).
- R_C relative cost.
- r^2 coefficient of determination.
- S_0 channel bed slope.
- S_0A surrogate measure of total stream power (km^2).

$S_0A^{0.4}$ surrogate measure of specific stream power ($km^{0.8}$).
S_f friction slope.
w channel width (m).
γ specific weight of the water-sediment mixture (N/m^3).
ω specific stream power (W/m^2).

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