Prediction of mountain stream morphology

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[1] We use a large and diverse data set from mountain streams around the world to explore relationships between reach-scale channel morphology and control variables. The data set includes 177 step-pool reaches, 44 plane-bed reaches, and 114 pool-riffle reaches from the western United States, Panama, and New Zealand. We performed several iterations of stepwise discriminant analysis on these data. A three-variable discriminant function using slope (*S*), D_{84}, and channel width (*w*) produced an error rate of 24% for the entire data set. Seventy percent of plane-bed reaches were correctly classified (16% incorrectly classified as pool-riffle and 14% incorrectly classified as step-pool). Sixty-seven percent of pool-riffle channels were correctly classified (31% incorrectly classified as plane-bed and 2% as step-pool). Eighty-nine percent of step-pool reaches were correctly classified (9% incorrectly classified as plane-bed and 2% as pool-riffle). The partial R^2 values and F tests indicate that *S* is by far the most significant single explanatory variable. Comparison of the eight discriminant functions developed using different data sets indicates that no single variable is present in all functions, suggesting that the discriminant functions are sensitive to the specific stream reaches being analyzed. However, the three-variable discriminant function developed from the entire data set correctly classified 69% of the 159 channels included in an independent validation data set. The ability to accurately classify channel type in other regions using the three-variable discriminant function developed from the entire data set has important implications for water resources management, such as facilitating prediction of channel morphology using regional S-w-D_{84} relations calibrated with minimal field work.

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1. Introduction

[2] We define mountain streams as occurring in mountainous areas and having an average gradient of $\geq$0.002 m/m [*Wohl*, 2000]. Stream channels formed at these steep gradients tend to have very coarse-grained and relatively immobile substrate and limited sediment supply. Under these conditions of high boundary roughness, flow is very turbulent relative to low-gradient river channels formed from finer-grained material [*Jarrett*, 1984; *Bathurst*, 1985, 1997; *Wohl and Thompson*, 2000; *Curran and Wohl*, 2003]. Bedrock and narrow valley bottoms can limit lateral channel mobility. Channel longitudinal profiles are likely to be segmented as a result of changes in underlying rock type or structure, tectonic activity, glacial history [*Wohl et al.*, 2004], beaver dams [*Butler*, 1995], or episodic introduction of wood [*Montgomery et al.*, 1995] or sediment from hillside and tributary mass movements [*Wohl and Pearthree*, 1991; *Benda et al.*, 2003; *Montgomery et al.*, 2003]. Channel classification systems that apply to the reach-scale, rather than entire catchments, most effectively describe spatially variable mountain streams [*Baker and Walford*, 1995]. We use "reach" to indicate a length of channel at least ten times the average channel width and having relatively consistent morphology.

[3] One of the more widely used systems classifies mountain streams into cascade, step-pool, plane-bed, and pool-riffle channels based on the presence and type of bed forms [*Montgomery and Buffington*, 1997]. Step-pool channels have longitudinal steps formed by bedrock, clasts, or wood organized into discrete channel-spanning accumulations that separate plunge pools. Plane-bed channels are planar channels formed in gravel-to-boulder-sized clasts. Pool-riffle channels have bars, pools and riffles that create lateral and longitudinal undulations in the channel.

[4] *Montgomery and Buffington* [1997] infer that bed form characteristics reflect a specific roughness configuration adjusted to the relative magnitude of sediment supply and transport capacity. Each channel type also has distinct responses to disturbance, including frequency of channel-forming discharges and response to increased water or sediment yield. Higher-gradient channel types are designated transport reaches, for example. These reaches are expected to

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transmit moderate increases in sediment yield downstream with relatively little channel change, whereas lower-gradient channel types are response reaches in which channel morphology is modified in response to increased sediment supply. We chose the Montgomery-Buffington classification system for use in this analysis because it is straightforward to apply in the field and because categories within the system reflect differences in channel processes that influence response to disturbance.

[5] *Montgomery and Buffington* [1997] initially developed this classification system using data from Alaska, Oregon, and Washington. Subsequent investigators have found the system to be useful in classifying steep stream channels around the world [*Wohl*, 2000]. Montgomery and Buffington's original data set indicated specific ranges of gradient, shear stress and relative roughness for each channel type: cascade channels are most common at gradients greater than 0.065, step-pool channels at 0.03–0.065, plane-bed channels at 0.015–0.03, and pool-riffle channels at gradients less than 0.015. Expanding the original data set to other geographic regions indicates greater variability in gradient range for each channel type, although the progression from cascade channels at the highest gradients to pool-riffle channels at the lowest gradients appears to be consistent [*Chin*, 1989; *Grant et al.*, 1990; *Chartrand and Whiting*, 2000].

[6] Most field investigators are well aware of these patterns in channel morphology in relation to gradient. However, it has not yet proven feasible to predict channel type a priori given information about gradient or other potential control variables in a drainage basin or a region. Such a capability would be extremely useful for: predicting channel response to disturbance [*Montgomery and Buffington*, 1997; *Miller and Benda*, 2000; *Benda et al.*, 2003; *Lancaster et al.*, 2003]; modeling river processes and landscape evolution [*Howard*, 1998; *Tucker et al.*, 2001]; and aspects of natural resources management from predicting flood discharges and designing culverts [*Jarrett and Costa*, 1982; *Jarrett*, 1989] to mapping habitat and explaining the spatial distributions of aquatic and riparian species or community types [*Harris*, 1988; *Gomi et al.*, 2002; *Moir et al.*, 2004]. In this paper we use a large and diverse data set from mountain streams around the world to explore correlations between channel morphology and control variables. We used discriminant analysis to develop a discriminant criterion that we then use to (1) infer controls on channel morphologic type and (2) develop methods of predicting location within a drainage basin for specific channel morphologic types.

2. Data Set and Methods

[7] The data set analyzed here consists of stream reaches from mountainous regions of the United States (Alaska, Arizona, Colorado, Idaho, Montana, Washington, Wyoming), New Zealand, and Panama (Table 1). Most of the data were originally collected by Wohl and her graduate students for other research projects. Peter Whiting provided data from Idaho and David Montgomery provided data from Washington. The validation data set comes from streams in New Mexico and Montana; these data were provided by Mark Fonstad and Matt O'Connor. We visually identified channels as step-pool, plane-bed or pool-riffle based on the dominant bed forms. Natural channels exhibit a continuum of morphology, with gradations between the channel types distinguished here. We predominantly chose channel reaches with a consistent bed form type. We also chose study sites in which channel parameters appeared to reflect dominantly fluvial processes (e.g., no recent evidence of debris flows present at the study site). Channel reaches with direct human effects (e.g., adjacent roads or timber harvest) were avoided. Presence and abundance of wood in the channel varied widely.

[8] Because the data were originally collected for other purposes, the level of information varies between regional subsets. The most complete subsets include reach gradient (S); drainage area (A); bank-full discharge (Q), width (w), depth (d) and velocity (v); streambed grain size distribution (D_{50}, D_{84}); bed form type and dimensions; and channel type. We then used these parameters to calculate hydraulic and form variables, including shear stress (τ), Darcy-Weisbach friction factor (f), stream power per unit area (ω), total stream power (Ω), relative grain roughness (R/D_{84}), and relative form roughness (R/H, where R is hydraulic radius and H is bed form amplitude).

[9] "Bank-full" in this context represents a fairly frequent discharge that recurs on average every 1–2 years. We estimated bank-full channel dimensions using field indicators that included changes in bank geometry or vegetation, organic debris, or stains on the clasts or bedrock along the channel margins. We indirectly estimated bank-full discharge and velocity using the Manning equation with a visually estimated roughness coefficient, n:

$$v = (1/n)R^{0.67}S^{0.5} \tag{1}$$

where v is reach-averaged mean velocity (m/s), R is hydraulic radius (m), and S is bed gradient (m/m). We constrained field estimates of discharge with discharge-drainage area relations developed from systematic gage records where possible. More than half of the study sites had multiple stream gages within the drainage basin. We used these records to develop discharge-drainage area regression curves for the mean annual peak flow. Field estimates of bank-full discharge that deviated substantially (>50%) from the regression line were reexamined and adjusted to more closely match the regression if uncertainty in field estimates warranted such adjustment.

[10] We obtained streambed grain size distribution with a random walk clast count [*Wolman*, 1954]. Counts were conducted on riffles for pool-riffle channels, and across the entire streambed for the other channel types; the depth of pools in pool-riffle channels generally precluded access to the streambed.

[11] We calculated hydraulic variables using bank-full values of relevant parameters:

$$\tau = \gamma RS \tag{2}$$

$$f = (8gRS)/v^2 \tag{3}$$

$$\omega = \tau v \tag{4}$$

$$\Omega = \gamma QS \tag{5}$$

Table 1. Characteristics of Data Subsets Used in Analyses[a]

Data Set	Drainage Area, km^2	Bank-full Discharge, m^3/s	Number of Reaches	Geology	Mean Annual Precipitation, mm;	Flow Regime	Description	Data Source
Alaska (AK)	10–3105	2.8–130.7	14: step-pool and pool-riffle	Precambrian and Paleozoic metamorphic	250–500	spring snowmelt with secondary summer rainfall peaks	Chena River drainage, central Alaska	*Wohl* [2004]
Arizona	1–2994	0.7–356	14: plane-bed	Precambrian granites, Tertiary basalts	150–500	summer rainfall	Agua Fria River drainage, central Arizona	*Wohl* [2004]
Colorado 1 (CO1)	2–245	5.4–19.4	25: step-pool and plane-bed	Precambrian granite	360–710	spring snowmelt	North St. Vrain Creek drainage, north-central Colorado	*Wohl et al.* [2004]
Colorado 2	10–1470	0.6–12.9	6: step-pool	Precambrian granite and gneiss	400–600	spring snowmelt	Fraser River drainage, north-central Colorado	E. Wohl (unpublished data, 2005)
Idaho	1–308	0.1–28.6	22: step-pool, pool-riffle, and plane-bed	Mesozoic intrusive igneous and Cenozoic volcanics	500–1500	spring snowmelt; occasional winter rainfall	Central Idaho	P. J. Whiting (unpublished data, 2003)
Montana (MT)	1–61	0.2–10.7	89: step-pool and pool-riffle	slightly metamorphosed Precambrian sedimentary rocks	380–2540	spring snowmelt; occasional winter rainfall	Kootenai and Clark Fork River drainages, northwestern Montana	*Madsen* [1995]
New Zealand east (NZe)	1–30	1.3–62.2	21: step-pool and plane-bed	Paleozoic-Mesozoic greywacke; 2.5–3.5 mm/yr uplift	750–1000	spring snowmelt and winter rainfall	Porter and Kowai River drainages, east side, South Island	*Wohl and Wilcox* [2005]
New Zealand west (NZw)	0.5–70	3.2–193.8	13: step-pool and plane-bed	Mesozoic schist; 6 mm/yr uplift	6000–8000	winter rainfall	Crooked River drainage, west side, South Island	*Wohl and Wilcox* [2005]
Panama (PAN)	1–407	10–2620	40: step-pool and pool-riffle	Tertiary intrusives and volcanics	3000–5000	monsoonal rainfall	Rio Chagres drainage	*Wohl* [2004]
Washington 1 (WA1)	1–10	0.1–0.3	40: step-pool	Tertiary volcanics, sandstone, schist	800–3600	spring snowmelt and winter rainfall	southern & central Cascade Range	*Curran* [1999] and *MacFarlane* [2001]
Washington 2 (WA2)	0.5–135	0.1–23.4	48: step-pool, pool-riffle, and plane-bed	Phyllite, schist, sandstone	1500–4500	spring snowmelt and winter rainfall	western Washington	D. R. Montgomery (unpublished data, 2003)
Wyoming (WY)	13–64	1.8–8.6	20: pool-riffle	Eocene andesites and basalts	450–1350	spring snowmelt	N. Fork Shoshone River drainage, nw Wyoming	*Zelt* [2002]
New Mexico	0.1–60	0.1–1.0	107: step-pool, pool-riffle, and plane-bed	Precambrian granite and Tertiary intrusives	630–890	spring snowmelt	Costilla basin, northern New Mexico and southern Colorado	*Fonstad* [2003]
Montana 2	—	—	52: step-pool, pool-riffle, and plane-bed	—	—		—	M. O'Connor (unpublished data, 2004)

[a]Values for drainage area and discharge represent the range within each data subset from a region. Abbreviations for regional data set names are used in Figure 1. Of the data sets listed, only Colorado 2, Washington 1 and 2, and Montana 2 included channels with substantial wood.

Table 2a. Classification Error Rates in Stepwise Discriminant Analysis: Test 2, Three-Variable Discriminant Function From Entire Data Set Applied to Regional Subsets

Regional Subset	Overall Error Rate	Step-Pool	Plane-Bed	Pool-Riffle
Montana	15%	8% as plane-bed	—	17% as plane-bed, 6% as step-pool
Panama	46%	31% as plane-bed, 19% as pool-riffle	—	42% as plane-bed
Washington 2	21%	0%	25% as step-pool	39% as plane-bed
New Zealand east and west	12%	4% as plane-bed	20% as pool-riffle	—

Columns without data indicate that these channel types were not present in this regional data subset.

where g is gravitational acceleration (9.8 m/s^2), and γ is the specific weight of water (9800 N/m^2).

[12] We developed two variables to represent the ratio of driving forces (ω and Ω) to substrate resistance (D_{84}). Variables ω, Ω, and D_{84} were standardized (mean = 0 and standard deviation = 1), and the ratios of the standardized variables (composite variables) were used to compute unit driving force to substrate resistance (ω/D_{84}) and total driving force to substrate resistance (Ω/D_{84}). Standardization was used in this case, because ω and Ω are in different units than D_{84}. Standardization makes the scaling of units irrelevant by adjusting the means of all variables to 0 and retaining the variability in the data. These composite variables were also used in the analyses.

[13] The initial data set used for discriminant analysis includes 177 step-pool reaches, 44 plane-bed reaches, and 114 pool-riffle reaches (some reaches were subsequently dropped because of missing variables). These data are drawn from a larger composite data set that *Wohl* [2004] used to examine the spatial limits of downstream hydraulic geometry.

[14] We first conducted stepwise discriminant analysis on the entire data set to determine the subset of the hydraulic and morphologic variables that best discriminate between channel types. We then developed discriminant functions for a subset of individual regions to detect differences in driving variables in geographically separated, geologically and climatically distinct regions. The four largest regional subsets of the data set are reaches sampled in Montana (n = 88, step-pool and pool-riffle), Panama (n = 40, step-pool and pool-riffle), Washington (n = 50, all 3 channel types), and New Zealand (n = 31, step-pool and plane-bed). Discriminant functions from Montana, Panama, and Washington were each used to classify reaches in the other regions in pairwise fashion. In addition, we used each of these three discriminant functions to classify reaches in the New Zealand data set.

3. Statistical Analyses

[15] We used stepwise discriminant analysis to derive a discriminant criterion based on the combination of morphologic, hydraulic, and composite variables that best separate streams into the independently classified reach types (pool-riffle, plane-bed and step-pool). Variable entry into and retention in the discriminant model were based upon the significance of the F statistic from analysis of covariance between the groups (variables already in the model serving as covariates [*Johnson and Wichern*, 1992]). Variables with $p < 0.1$ were entered into the model; only those contributing to the explanatory power of the model (significant at $p < 0.1$ after entry of covariates) were retained in the final model. The function was then used to assign membership of each of the stream reaches to one of the three morphological types using the best subset of variables.

[16] After plotting frequency distributions and examining a number of transformations, the following data were $\log_{10}$ transformed to more closely comply with the assumptions of within group multivariate normality: reach gradient (S); drainage area (A); bankfull discharge (Q), bankfull width (w), bankfull depth (d) and bankfull velocity (v); streambed grain size distribution (D_{50}, D_{84}), shear stress (τ), Darcy-Weisbach friction factor (f), stream power per unit area (ω), total stream power (Ω), and relative grain roughness (R/D_{84}).

[17] We evaluated the explanatory strength of the discriminant function by determining the cross validation error rate. In cross validation, each data point is successively removed from the data set, a discriminant function is fitted to the remaining data, the function is used to classify the

Table 2b. Classification Error Rates in Stepwise Discriminant Analysis: Test 3, Discriminant Function Developed From Three Regional Data Subsets and Applied to a Fourth Regional Subset

Regional Subsets	Subset Tested	Variables in Discriminant Function	Overall Error Rate	Step-Pool	Plane-Bed	Pool-Riffle
Montana, Panama, New Zealand	Washington 2	S	13%	13% as plane-bed	13% as step-pool	0% error
Montana, Panama, Washington 2	New Zealand	R/D_{84}, f, S, v, w	60%	100% as plane-bed	20% as pool-riffle	—
Panama, New Zealand, Washington 2	Montana	R/D_{84}	33%	21% as pool-riffle, 79% as plane-bed	—	33% as plane-bed
Montana, New Zealand, Washington 2	Panama	R/D_{84}	13%	44% as plane-bed, 56% as pool-riffle	—	13% as plane-bed

Table 2c. Classification Error Rates in Stepwise Discriminant Analysis: Test 4, Discriminant Function From a Single Regional Subset Tested Against Entire Data Set and Various Other Subsets[a]

Regional Subset	Variables in Discriminant Function	Montana	Panama	Washington 2	New Zealand	Entire Data Set
Montana	S (λ = 0.21, $p < 0.0001$) D_{84} (λ = 0.17, $p < 0.0001$), d (λ = 0.16, $p < 0.0001$), ω (λ = 0.16, $p < 0.0001$)	2% (3% pool-riffle as step-pool; 2% step-pool as pool-riffle)	41% (0% pool-riffle; 81% step-pool as pool-riffle)	12% (6% pool-riffle as step-pool; 69% plane-bed as pool-riffle, 31% as step-pool; 19% step-pool as pool-riffle)	12% (100% plane-bed as pool-riffle; 12% step-pool as pool-riffle)	19% (3.5% pool-riffle as step-pool; 82% plane-bed as pool-riffle, 18% as step-pool; 35% step-pool as pool-riffle)
Panama	w (λ = 0.43, $p < 0.0001$)	50% (100% pool-riffle as step-pool)	19% (13% pool-riffle as step-pool; 25% step-pool as pool-riffle)	28% (56% pool-riffle as step-pool; 12% plane-bed as pool-riffle, 88% as step-pool)	12% (20% plane-bed as pool-riffle, 80% as step-pool; 12% step-pool as pool-riffle)	36% (68% pool-riffle as step-pool; 11% plane-bed as pool-riffle, 89% as step-pool; 4% step-pool as pool-riffle)
Washington 2	R/D_{84} (λ = 0.33, $p < 0.0001$) f (λ = 0.17, $p < 0.0001$) τ (λ = 0.07, $p < 0.0001$) v (λ = 0.05, $p = 0.0001$) D_{50} (λ = 0.04, $p = 0.0056$)	100% (87% pool-riffle as plane-bed, 13% as step-pool; 100% step-pool as plane-bed)	100% (21% pool-riffle as plane-bed, 79% as step-pool; 94% step-pool as plane-bed, 6% as pool-riffle)	16% (28% pool-riffle as plane-bed; 19% plane-bed as pool-riffle)	48% (96% step-pool as plane-bed)	62% (45% pool-riffle as plane-bed, 35% as step-pool; 20% plane-bed as pool-riffle; 75% step-pool as plane-bed, 10% as pool-riffle)

[a]Overall or cross-validation error rate.

removed data point, and finally the classification error rate is determined.

[18] We performed several iterations of stepwise discriminant analysis.

[19] 1. Using the entire data set, we (1) selected the subset of variables that best discriminated channel type (this produced a subset of 8 variables), (2) used stepwise discriminant analysis to further reduce this subset to 4 variables that still produced effective discrimination and low error rates, and (3) manually removed one additional variable to arrive at the most parsimonious model for the entire data set.

[20] 2. We tested the three-variable discriminant function developed from the entire data set against four regional subsets (Montana, Panama, New Zealand, Washington 2).

[21] 3. We developed a discriminant function using three regional subsets and tested this function against a fourth regional subset. We performed this iteration of analysis four times.

[22] 4. We developed a discriminant function from a single regional subset and tested this function against that subset, against other regional subsets, and against the entire data set. We performed these analyses for three regional subsets (Montana, Panama, Washington 2).

[23] 5. Finally, we tested the discriminant function developed from the entire data set against independent data not used in the original discriminant analysis (validation data set from New Mexico and Montana 2). Our intent in performing these multiple iterations was to evaluate consistency in the variables chosen for the discriminant function when using different data sets, and consistency in the error rate associated with various discriminant functions.

[24] Following discriminant function analysis, we performed canonical discriminant analysis (CDA) so that the classified reaches could be plotted and examined relative to the independent variables used in the function. In CDA, linear combinations of the independent variables are derived and, through maximizing multiple correlations between groups, maximum separation between groups is achieved. SAS version 9.1 was used for all statistical analyses (SAS Institute, Cary, NC).

4. Results

[25] 1. In analyses of the entire data set (44 plane-bed, 114 pool-riffle, and 177 step-pool reaches), we fitted a quadratic discriminant function (within covariance matrices) using the eight variables selected in stepwise analysis. We dropped 62 reaches (21 pool-riffle and 41 step-pool) from the stepwise analysis because of missing data in one or more of the variables included in model selection; we then included these reaches in the development of a final discriminant function. Variables included in the most inclusive discriminant function for the entire data set include (Wilks' Lambda (λ) and p value in parentheses): S (λ = 0.52, $p < 0.0001$), D_{84} (λ = 0.45, $p < 0.0001$), w (λ = 0.38, $p < 0.0001$), f (λ = 0.35, $p < 0.0001$), τ (λ = 0.34, $p < 0.0001$), Ω/D_{84} (λ = 0.32, $p < 0.0001$), d (λ = 0.32, $p < 0.0001$), and R/D_{84} (λ = 0.30, $p < 0.0001$). The overall discriminant function is significant in that it does a good job of classifying the three channel types (Wilks' Lambda = 0.29, $p < 0.0001$, df = 16/526). Seventy-seven percent of the reaches are correctly classified by the eight variable dis-

Table 3. Correlation Coefficients (r), p Values, and Number of Observations (n) From Spearman Rank Correlations for Variables Used in the Stepwise Discriminant Analysis[a]

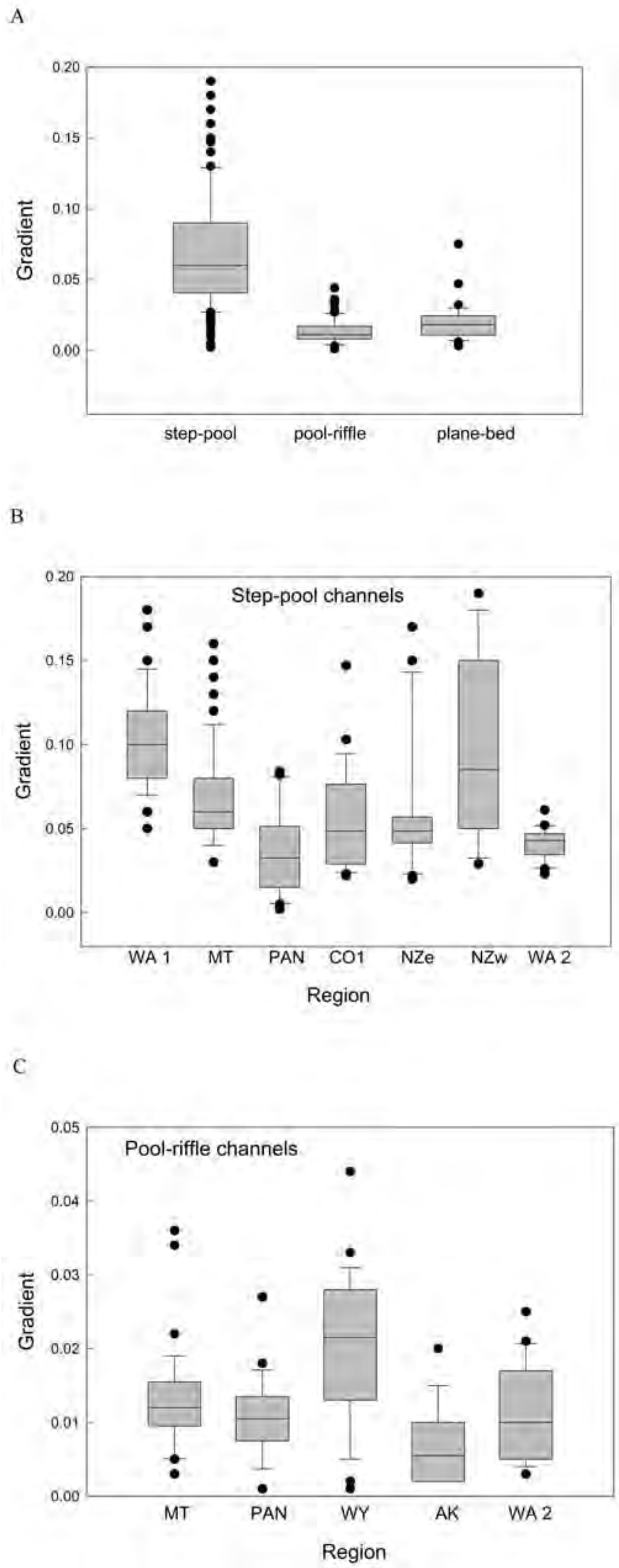
	Q	S	d	w	v	D50	D84	R/D84	f	τ	ω	Ω	ω/D84	Ω/D84
A														
r	0.64	−0.67	0.58	0.73	0.43	0.08	−0.01	0.49	−0.47	−0.18	−0.07	0.45	−0.13	0.26
p	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	0.1394	0.8162	<0.0001	<0.0001	0.0011	0.2687	<0.0001	0.0496	<0.0001
n	276	334	334	334	276	331	331	331	276	334	236	334	236	294
Q														
r	1.00	−0.53	0.91	0.88	0.83	0.46	0.32	0.51	−0.62	0.29	0.56	0.92	0.11	0.84
p		<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	0.0827	<0.0001
n	276	276	276	276	276	273	273	273	276	276	236	276	236	236
S														
r	−0.53	1.00	−0.49	−0.63	−0.33	0.20	0.28	−0.69	0.63	0.52	0.47	−0.15	0.41	0.01
p	<0.0001		<0.0001	<0.0001	<0.0001	0.0003	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	0.0056	<0.0001	0.8945
n	276	335	335	335	276	332	332	332	276	335	236	335	236	295
d														
r	0.91	−0.49	1.00	0.82	0.72	0.42	0.34	0.52	−0.51	0.33	0.55	0.81	0.19	0.64
p	<0.0001	<0.0001		<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	0.003	<0.0001
n	276	335	335	335	276	332	332	332	276	335	236	335	236	295
w														
r	0.88	−0.63	0.82	1.00	0.58	0.36	0.30	0.43	−0.55	0.07	0.20	0.72	−0.14	0.53
p	<0.0001	<0.0001	<0.0001		<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	0.2022	0.0019	<0.0001	0.0349	<0.0001
n	276	335	335	335	276	332	332	332	276	335	236	335	236	295
v														
r	0.83	−0.33	0.72	0.58	1.00	0.45	0.30	0.38	−0.73	0.37	0.78	0.85	0.33	0.75
p	<0.0001	<0.0001	<0.0001	<0.0001		<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
n	276	276	276	276	276	273	273	273	276	276	236	276	236	236
D50														
r	0.46	0.20	0.42	0.36	0.45	1.00	0.93	−0.43	−0.11	0.52	0.74	0.60	0.00	0.43
p	<0.0001	0.0003	<0.0001	<0.0001	<0.0001		<0.0001	<0.0001	0.0724	<0.0001	<0.0001	<0.0001	0.987	<0.0001
n	273	332	332	332	273	332	332	332	273	332	236	332	236	295
D84														
r	0.32	0.28	0.34	0.30	0.30	0.93	1.00	−0.57	−0.03	0.53	0.65	0.53	−0.12	0.28
p	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001		<0.0001	0.6515	<0.0001	<0.0001	<0.0001	0.0753	<0.0001
n	273	332	332	332	273	332	332	332	273	332	236	332	236	295
R/D84														
r	0.51	−0.69	0.52	0.43	0.38	−0.43	−0.57	1.00	−0.47	−0.22	−0.18	0.21	0.28	0.30
p	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001		<0.0001	<0.0001	0.0044	<0.0001	<0.0001	<0.0001
n	273	332	332	332	273	332	332	332	273	332	236	332	236	295
f														
r	−0.62	0.63	−0.51	−0.55	−0.73	−0.11	−0.03	−0.47	1.00	0.06	−0.13	−0.50	0.21	−0.25
p	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	0.0724	0.6515	<0.0001		0.3567	0.0453	<0.0001	0.0013	<0.0001
n	276	276	276	276	276	273	273	273	276	276	236	276	236	236
τ														
r	0.29	0.52	0.33	0.07	0.37	0.52	0.53	−0.22	0.06	1.00	0.79	0.55	0.44	0.44
p	<0.0001	<0.0001	<0.0001	0.2022	<0.0001	<0.0001	<0.0001	<0.0001	0.3567		<0.0001	<0.0001	<0.0001	<0.0001
n	276	335	335	335	276	332	332	332	276	335	236	335	236	295
ω														
r	0.56	0.47	0.55	0.20	0.78	0.74	0.65	−0.18	−0.13	0.79	1.00	0.85	0.56	0.70
p	<0.0001	<0.0001	<0.0001	0.0019	<0.0001	<0.0001	<0.0001	0.0044	0.0453	<0.0001		<0.0001	<0.0001	<0.0001
n	236	236	236	236	236	236	236	236	236	236	236	236	236	236
Ω														
r	0.92	−0.15	0.81	0.72	0.85	0.60	0.53	0.21	−0.50	0.55	0.85	1.00	0.33	0.84
p	<0.0001	0.0056	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001		<0.0001	<0.0001
n	276	335	335	335	276	332	332	332	276	335	236	335	236	295
ω/D84														
r	0.11	0.41	0.19	−0.14	0.33	0.00	−0.12	0.28	0.21	0.44	0.56	0.33	1.00	0.53
p	0.0827	<0.0001	0.003	0.0349	<0.0001	0.987	0.0753	<0.0001	0.0013	<0.0001	<0.0001	<0.0001		<0.0001
n	236	236	236	236	236	236	236	236	236	236	236	236	236	236
Ω/D84														
r	0.84	0.01	0.64	0.53	0.75	0.43	0.28	0.30	−0.25	0.44	0.70	0.84	0.53	1.00
p	<0.0001	0.8945	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	
n	236	295	295	295	236	295	295	295	236	295	236	295	236	295

[a]Variables shown include drainage area (A), bankfull discharge (Q), reach gradient (S), depth (d), width (w), velocity (v), streambed grain size distribution (D50, D84), relative grain roughness (R/D84), Darcy-Weisbach friction factor (f), shear stress (τ), stream power per unit area (ω), total stream power (Ω), and the ratio of unit driving force to substrate resistance (ω/D_{84}) and total driving force to substrate resistance (Ω/D_{84}).

criminant function (cross validation classification error rate 23%). Thirteen percent of plane-bed reaches were incorrectly classified (2% as pool-riffle, 11% as step-pool), 20% of pool-riffle reaches were incorrectly classified (all as plane-bed), and 34% of step-pool reaches were incorrectly classified (29% as plane-bed, 5% as pool-riffle).

[26] If the four least significant variables (τ, Ω/D_{84}, d, and R/D_{84}) are dropped from the discriminant function, the

function is reduced to the four variables S, D_{84}, w, and f. Of these, f is the only variable not directly measured in the field data used here. For the sake of parsimony and greater accuracy, we also removed f to arrive at a discriminant function using only S ($\lambda = 0.42$, partial $R^2 = 0.58$), D_{84} ($\lambda = 0.36$, partial $R^2 = 0.13$), and w ($\lambda = 0.34$, $R^2 = 0.07$). The partial R^2 values indicate that S is by far the most significant single explanatory variable. The simplified discriminant function with three variables produced an error rate of 24%, which compares very favorably with the error rate obtained using the discriminant function with eight variables. Seventy percent of plane-bed reaches were correctly classified (16% incorrectly classified as pool-riffle, 14% incorrectly classified as step-pool). Sixty-seven percent of pool-riffle channels were correctly classified (31% incorrectly classified as plane-bed, 2% as step-pool). Eighty-nine percent of step-pool reaches were correctly classified (9% incorrectly classified as plane-bed, 2% as pool-riffle).

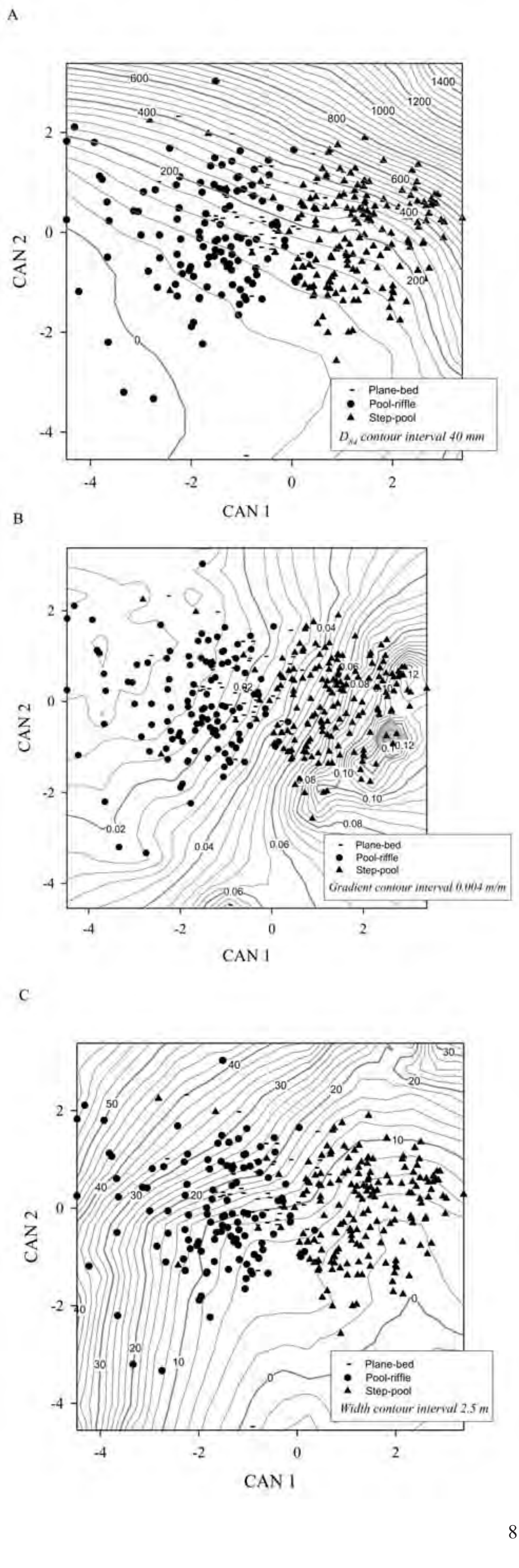


[27] 2. Table 2a summarizes the results of applying the three-variable discriminant function to regional data subsets (test 2). The overall error rate using this approach was good ($\leq$21%) for three of the four regional subsets tested. The fourth subset, Panama, had a 46% overall error rate, largely as a result of pool-riffle channels misclassified as plane-bed reaches.

[28] 3. Table 2b lists the results of applying discriminant functions developed from three subsets of regional data against another regional subset (test 3). Of the four discriminant functions developed using this approach, only two included the variable of S, which was by far the most significant variable in the discriminant function developed for the entire data set. Three of the four subset discriminant functions included R/D_{84}, which did not appear in the discriminant function based on the entire data set. Three of the four subset discriminant functions had acceptable overall error rates (<33%), whereas one function had an overall error rate of 60%, largely because this function misclassified all of the step-pool reaches in the test subset.

[29] 4. Table 2c summarizes the results for discriminant functions developed from individual regional subsets of data (test 4). The Montana linear discriminant function included four variables and had a very low error rate (2%) when tested against Montana data. The model was statistically significant ($\lambda = 0.16$, $p < 0.0001$, df = 4/84). The error rates remained fairly low when the function was tested against the Washington (12%), New Zealand (12%), and entire (19%) data sets, but was high (41%) when tested against the Panama data set. The Panama linear discriminant function, although having a higher error rate (19%) when tested against the Panama data, was also significant ($\lambda = 0.43$, $p < 0.0001$, df = 1/38) and contained only one variable. The error rates varied from fairly high when tested against the Montana (50%) data set, to reasonable against Washington (28%), New Zealand (12%), and the entire (36%) data set. The Washington linear discriminant function was significant ($\lambda = 0.04$, $p < 0.0001$, df = 10/86) and included five variables. This function had a 16% error rate for Washington data, but the error rate rose to 48% for the New Zealand data, 62% for the entire data set, and 100% for the Montana and Panama data.

Figure 1. (a) Gradient by channel type. (b) Gradient by region for step-pool channels. (c) Gradient by region for pool-riffle channels. Abbreviations for regions are as in Table 1. The line within each box indicates the median value, box ends are the 25th and 75th percentiles, whiskers are the 10th and 90th percentiles, and solid dots are outliers.



[30] It is important to note that several of the variables used in all of the discriminant analyses were highly correlated. If two variables are highly correlated, the first one entered into the discriminant function may prevent the other from being included even though it would have contributed to the model in a similar way. For example, whereas only w was included in the Panama discriminant function, width is correlated with A ($r = 0.73$, $p < 0.001$), Q ($r = 0.88$, $p < 0.001$), S ($r = -0.63$, $p < 0.001$), d ($r = 0.58$, $p < 0.001$), L ($r = 0.70$, $p < 0.001$), f ($r = -0.55$, $p < 0.001$), and Ω ($r = 0.72$, $p < 0.001$). Therefore w in the Panama discriminant function represents these other variables and the discriminant function should be interpreted as such. A complete correlation matrix is provided in Table 3.

[31] 5. Of the 159 reaches (62 plane-bed, 41 pool-riffle, and 56 step-pool) in the validation data set, 69% of reaches were correctly classified by the discriminant function developed from the original data set. Twenty-six percent of plane-bed reaches in the validation data set were classified as step-pool and 18% were incorrectly classified as pool-riffle. Thirty-nine percent of pool-riffle reaches were misclassified as plane-bed and 7% as step-pool. Step pool channels had the lowest classification error rate, with only 7% misclassified as plane-bed and 2% as pool-riffle.

5. Discussion

[32] Comparison of the eight discriminant functions developed using different data sets indicates that no single variable is present in all discriminant functions. This suggests that the discriminant functions are sensitive to the specific stream reaches being analyzed. In several cases, the subsets used for analyses did not include all three channel types that are present in the entire data set. The Panama subset, for example, has only pool-riffle and step-pool reaches, whereas the New Zealand subset has only step-pool and plane-bed reaches. However, discriminant functions developed from a data subset with only two channel types do not have consistently higher overall error rates when applied to the entire data set than functions developed from subsets with all channel types (Table 2c). No single channel type is consistently misclassified at a higher rate than the other types. Of course, discriminant functions developed from a data subset having only two channel types can only classify new data into one of the two reach types for which the function was created. As might be expected, the discriminant function developed using the entire data set generally has the lowest overall error rate when applied to individual data subsets.

Figure 2. Canonical discriminant analysis (CDA) of channel type classified by reach gradient, D_{84}, and channel width. Plot of first two axes from CDA with contours constructed from (a) D_{84}, at an interval of 40 mm, (b) reach gradient, at an interval of 0.004 m/m, and (c) channel width, at an interval of 2.5 m. Contour plots were constructed using the inverse distance weighting method. Canonical loadings (weights) of the three variables D_{84}, reach gradient, and channel width are 0.53, 0.94, and −0.58 on canonical axis 1, respectively. Canonical loadings of D_{84}, reach gradient, and channel width are 0.79, −0.32, and 0.49 on canonical axis 2, respectively.

[33] Slope and R/D_{84} are present in half of the eight discriminant functions. Functions that include S as one of the variables tend to have lower error rates when applied to the entire data set or to another data subset (Tables 2a–2c). Slope in this data set can be regarded as an independent variable imposed on the channel at the reach scale. None of the reaches included in these data sets were sinuous, and most of the drainage basins from which data were drawn had abrupt downstream changes in slope associated with glacial history, lithology, or structure. Given the importance of slope in the discriminant analyses, comparison of slope ranges for each channel type between the different data subsets helps to explain some of the classification errors. Although the mean gradient of each channel type is significantly different when combining all channels of each type for the entire data set (Figure 1a), there are significant differences between the mean gradient of step-pool reaches (Figure 1b) or pool-riffle reaches (Figure 1c) from different regions.

[34] Interregional differences could reflect differences in (1) site selection criteria (e.g., targeted stream size) and/or differences in methods of collecting field data among the regional data sets, (2) flow regime (differences in magnitude, frequency, and duration of flows capable of mobilizing the streambed may create systematic differences among step-pool channels in Panama and Arizona, for example, although this has not been examined), or (3) wood loading. Wood loading was sparse in most of the regional data sets (e.g., Arizona, New Mexico, Panama, New Zealand), but some of the channels in Washington and Montana, in particular, included abundant wood that could be forcing specific channel morphologies at a lower gradient than they would otherwise be present [*Montgomery et al.*, 1995].

[35] Plotted results from the canonical discriminant analysis indicate consistent trends with respect to channel type. Step-pool channels tend to have the largest values of D_{84} (Figure 2a) and S (Figure 2b), and the lowest values of w (Figure 2c). Pool-riffle channels have the smallest D_{84} and S values, and the greatest w, and plane-bed channels are intermediate between the other two channel types.

[36] We initially hypothesized that some measure of hydraulic driving force would be included in the final discriminant function. The absence of such a variable could reflect the fact that the bank-full hydraulic variables used in this analysis are largely estimated, rather than directly measured. Because the roughness coefficient is very difficult to estimate in steep, coarse-grained streams [*Jarrett*, 1984, 1990; *Wohl*, 2000], there is probably at least twenty percent uncertainty in the estimates of hydraulic variables, which contrasts with the higher accuracy of other variables, such as those included in the discriminant function. Alternatively, the lack of hydraulic variables in the final discriminant function could reflect the fact that hydraulic variables are truly not as effective in discriminating among the three channel types that we analyzed. Resolution of this question requires collection of bankfull hydraulic data for mountain streams.

[37] The ability to accurately classify channel type in other regions using the three-variable discriminant function developed from the entire data set has important implications for water resources management. Slope, the single most dominant variable, can be mapped using topographic map or high-resolution digital elevation model (DEM) coverage of a basin, although it is difficult to accurately estimate the slope of shorter channel reaches (<approximately 500 m long). Grain size distribution is likely to correlate strongly with slope within a region, and channel width is likely to correlate strongly with discharge or drainage area [*Wohl et al.*, 2004], allowing calibration of regional S-w-D_{84} relations with minimal field work. Prediction of channel type distribution has the potential to facilitate numerous resource management decisions. Spawning Atlantic salmon, for example, preferentially use pool-riffle and transitional pool-riffle/plane-bed reaches, and avoid plane-bed and step-pool reaches [*Moir et al.*, 2004]. Accurate maps of channel type within a drainage basin using GIS base coverage of channel-reach slope could thus serve as surrogate habitat availability maps where the relations between reach-scale geomorphic features and gradient are well established. The structure and composition of riparian vegetation are also highly related to fluvial features and reach-scale channel morphology [*Harris*, 1988; *Hupp and Simon*, 1991; *Bendix and Hupp*, 2000]. Studies of channel response to flow diversion in the southern Rocky Mountains indicate that pool-riffle channels are more likely than step-pool channels to have altered width/depth ratios as a result of flow diversion [*Ryan*, 1994]. Maps of channel sensitivity to land use such as flow diversion or timber harvest could thus be developed from maps of channel type based on distribution of reach-scale channel slope.

[38] The methods presented here for testing the ability of specific variables to predict channel morphology might also be applicable to other types of independent variables that can be extracted from DEMs of a basin. Discriminant functions constructed of variables such as valley attributes (e.g., width, side slope angle, tributary inputs to a main channel, and valley slope) could be used within a GIS platform to classify pertinent aspects of reach-scale channel morphology for a particular region. Not only could reach-scale channel morphology be classified from such a simple analysis, but confidence bounds could be placed upon such classifications, and functions could be refined a posteriori with information obtained during field verification.

[39] In this analysis, the inclusion of data from a broad range of climatic and tectonic regimes suggests that the discriminant function developed here for distinguishing step-pool, plane-bed, and pool-riffle channel types may be more broadly applicable to mountain streams in other parts of the world.

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