

RESEARCH ARTICLE

WILEY

Variability of stream extents controlled by flow regime and network hydraulic scaling

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Funding information

Natural Sciences and Engineering Research Council of Canada; Simon Fraser University

Abstract

Stream networks expand and contract through time, impacting chemical export, aquatic habitat, and water quality. Although recent advances improve prediction of the extent of the wetted channel network (L) based on discharge at the catchment outlet (Q), controls on the temporal variability of L remain poorly understood and unquantified. Here we develop a quantitative, conceptual framework to explore how flow regime and stream network hydraulic scaling factors co-determine the relative temporal variability in L (denoted here as the total wetted channel drainage density). Network hydraulic scaling determines how much L changes for a change in Q , while the flow regime describes how Q changes in time. We compiled datasets of co-located dynamic stream extent mapping and discharge to analyze all globally available empirical data using the presented framework. We found that although variability in L is universally damped relative to variability in Q (i.e., streamflow is relatively more variable in time than network extent), the relationship is elastic, meaning that for a given increase in the variability in Q , headwater catchments will experience greater-than-proportional increases in the variability of L . Thus, under anticipated climatic shifts towards more volatile precipitation, relative variability in headwater stream network extents can be expected to increase even more than the relative variability of discharge itself. Comparison between network extents inferred from the L - Q relationship and blue lines on USGS topographic maps shows widespread underestimation of the wetted channel network by the blue line network.

KEYWORDS

flow regime, hydrograph variability, hydrography, network hydraulic scaling, stream network extent, wetted channels

1 | INTRODUCTION

Headwater stream discharge and network extent—and their variability in time—impact aquatic habitat, carbon dioxide efflux, stream temperature, water transit times, and legal frameworks that define protected waters (Acuña et al., 2005; Allen & Pavelsky, 2018; Arismendi et al., 2017; van Meerveld et al., 2019; Acuña et al., 2014; A. S. Ward et al., 2018, e.g., the U.S. *Clean Water Act* and *Navigable Waters*

Protection Rule). While underlying physical drivers of stream discharge have been extensively studied, controls on time variation in wetted channel extent remain poorly understood.

Early studies of wetted channel extent dynamics showed that higher flows at the catchment outlet were associated with higher total wetted channel lengths (L , sometimes expressed as a drainage density, defined as L normalized by catchment area, and including both continuous and disconnected reaches), as revealed by plots of stream

discharge at the catchment outlet (Q , normalized by catchment area) as a function L (e.g., D. G. Day, 1978; Gregory & Walling, 1968; Roberts & Archibold, 1978; Roberts & Klingeman, 1972). Biswal and Marani (2010) then formalized the notion that L controls Q in an investigation on the hydrograph recession. They considered hillslopes with constant specific discharge to adjacent channels, such that variations in the total discharge at the catchment outlet arise solely from changes in L via its role in connecting and disconnecting contributing hillslopes.

Godsey and Kirchner (2014) proposed instead that the changes in L reflect—rather than determine—changes in observed Q at the catchment outlet. Based on extensive mapping of L across a wide range of discharge and catchments, Godsey and Kirchner (2014) observed a power-law scaling between L and Q ($L = \alpha Q^\beta$), where α is a positive constant, and $0 \leq \beta \leq 1$. For small values of β , L remains fairly constant with changes in Q , whereas for large values of β , L changes dramatically with changes in Q . Across diverse catchments, small values of β (ranging from 0.2–0.4) are typical (e.g., Godsey & Kirchner, 2014; Shaw, 2016), indicating that reductions in Q are primarily driven by declines in hillslope discharge, contradicting the constant hillslope discharge proposal of Biswal and Marani (2010) in which $\beta = 1$. The power law L - Q relationship is distinct from power law recession slope

analysis (that is, the slope of $\log(-dQ/dt)$ vs. $\log(Q)$). Whereas it is clear that recession slopes can be most accurately calculated on an event basis (Biswal & Marani, 2010; Shaw & Riha, 2012), data is not broadly available to compare L - Q log slopes calculated on an event vs. long-term basis.

Godsey and Kirchner (2014) pointed out that channels should be wetted if the supply of water from the upslope contributing area, A , exceeds the capacity of the channel to convey that supply in the subsurface, $Q_{sub,c}$, which is locally a function of the transmissivity, T , of the hyporheic zone and channel slope, S . Prancevic and Kirchner (2019) formalized this principle to quantitatively predict β using a set of contributing-area scaling relationships that describe how flowpath convergence (and therefore the extent of wetted channel for a given channel initiation contributing area), channel slope, and hyporheic transmissivity vary systematically throughout the channel network. These relationships, which we refer to as network hydraulic scaling (right side of Figure 1), capture spatial gradients in flow accumulating variables and the subsurface flow capacity of channels, which ultimately determine β .

The power-law relationship $L(Q)$ can be used to map a given value of Q at the catchment outlet to a particular value of L . While β may shift through time, for example due to sediment transport that alters

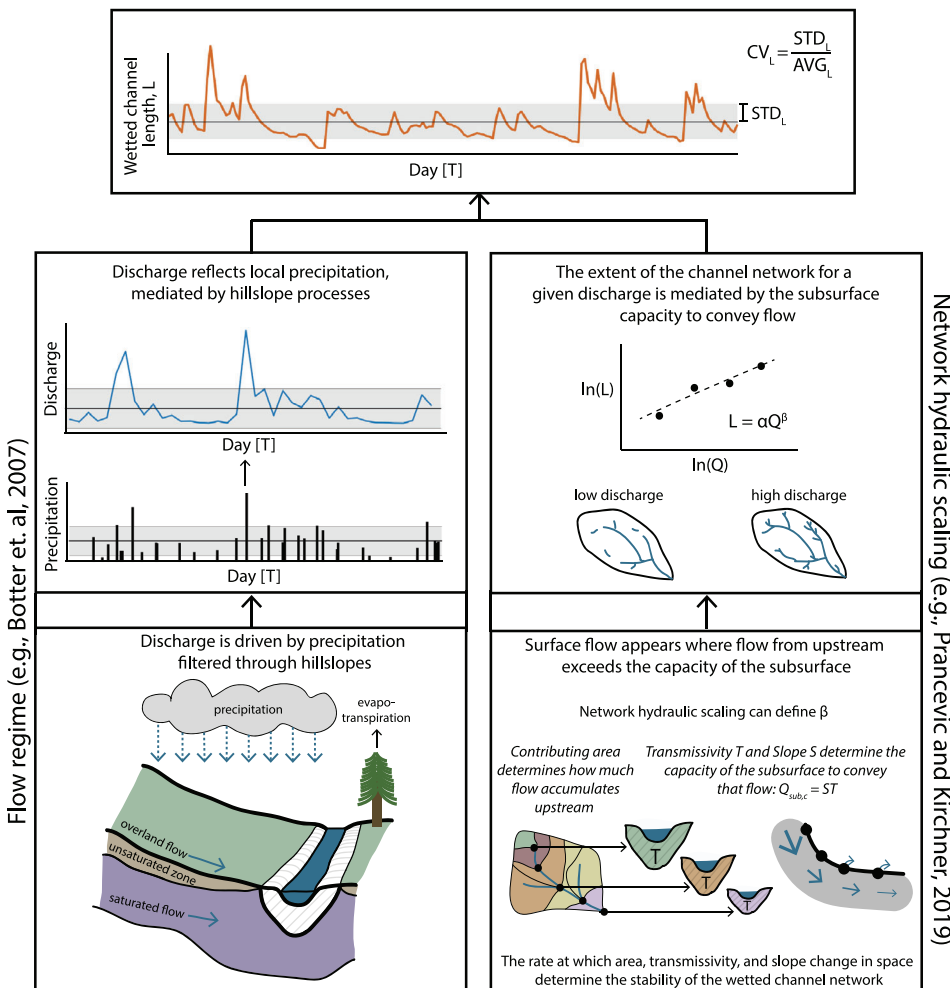


FIGURE 1 Flow regime (left) and network hydraulic scaling (right) co-determine the extent of and variation in wetted channel length through time (top). Hillslope runoff generation processes “filter” precipitation events leading to time variation in discharge (left), which is delivered to the channel network. The area-dependent scaling of discharge determines the magnitude of flow delivered to the channel at any point in the stream network, and transmissivity and slope determine the capacity of the channel subsurface to convey that flow (bottom right). Where discharge exceeds this subsurface capacity, surface flow emerges, resulting in a wetted channel. The relationship between flow and wetted channel length at the catchment mouth is observed to exhibit power law scaling: $L = \alpha Q^\beta$ (center right). The timeseries of Q and the power law relationship between Q and L result in a timeseries of L (top) and its associated relative variability, CV_L

hydraulic conductivity within the hyporheic zone (e.g., Godsey & Kirchner, 2014), it is likely a relatively static landscape feature over longer timescales. The temporal variability in L therefore arises from a separate driver: variability in catchment discharge, Q . Thus, while β explains how L varies with Q , it cannot fully explain the origins or magnitude of time variation in wetted channel extent. For example, variability in the length of the wetted stream channel network could remain low through time even if β were high, as long as the flow regime exhibited minimal variation about its mean value.

Temporal variability in L has been considered using flow duration curves combined with $L(Q)$ (e.g., Jensen et al., 2017), and time series plots of L have appeared in the literature, either as individual point observations (e.g., Blyth & Rodda, 1973; L. D. Day et al., 1987; Durigetto et al., 2020), or via extrapolation by fitting a functional form between L and Q (e.g., Zimmer & McGlynn, 2017). Datry et al. (2007) summarized time variation in L for two small catchments using the coefficient of variation (CV_L), equal to the standard deviation of L divided by its mean. Botter and Durigetto (2020) explored how the persistency and spatial distribution of nodes within the channel network impact the stream length duration curve using a stochastic model; their framework allows for estimating average persistency and variation of a network where spatially explicit data are available. However, a framework unifying the role of β and Q as drivers of variability in L is lacking. Discerning the relative importance of these two drivers of wetted channel network stability would enable process-based predictions of the variability of L due to, for example, a shift in precipitation regime. This understanding is particularly relevant for ecological applications, since hydrologic variability over time is a principal driver of ecosystem processes (Datry et al., 2007). Linkages have been described between flow variability and food chain length (Sabo et al., 2010), life history trade-offs (Lytle & Poff, 2004), community diversity and structure (Clarke et al., 2010), and imperilled species survival (E. J. Ward et al., 2015), suggesting that improved mechanistic understanding of surface flow intermittency can offer insight into the drivers and conditions that control how ecological variables might respond to environmental change. By decoupling the climatic and landscape influences on wetted channel variability, headwater stream networks can be classified according to their hydrologic stability, and in turn, long-term ecological stability.

Here, we present a conceptual, quantitative framework that reveals how the flow regime and network hydraulic scaling collectively govern variability in wetted channel extent, shown graphically in Figure 1. The flow duration curve, or equivalently the probability distribution of flows, encapsulates the catchment flow regime, whose variability can be succinctly summarized by the coefficient of variation (Botter et al., 2013). Our framework enables attribution of variability in the extent of the wetted channel network to network hydraulic scaling (β) and variability in discharge (CV_Q). We compile the globally available datasets of sites for which both flow regimes (i.e., hydrographs) and network hydraulic scaling values (i.e., β) exist and place them within our framework. Our results reveal that an

increase in flow regime variability, which is likely to occur with projected increases in rainfall volatility and extremes (e.g., Swain et al., 2018), will result in an even greater increase in the relative variability of headwater wetted channel extents. We also use publicly available USGS hydrography data to calculate the extent of perennial and intermittent channels, as portrayed by mapped “blue lines”, within the study watersheds. Such regional streamline delineations are used extensively to direct conservation and management efforts (Paybins, 2003). While many studies report that USGS hydrography underestimates empirical channel length since the hydrography is based on landscape topology alone (Colson, 2006), these studies are based on remote sensing data, single field surveys, or isolated USGS gauges (e.g., Avcioglu et al., 2017; Fritz et al., 2013; Hansen, 2001; Paybins, 2003; Svec et al., 2003). Our dataset uniquely allows us to determine what fraction of dynamic channel extent is captured across a range of US sites. Results confirm that hydrographic datasets show stream network extents that are much smaller than the typical extent of wetted channels, and overlook the magnitude of temporal variation one might infer from mapped perennial and intermittent channels.

2 | METHODS

2.1 | Data acquisition

We compiled a globally comprehensive database composed of 14 sites where wetted channel length survey data and corresponding stream hydrographs are available (see Table 1). Prancevic and Kirchner (2019) recently collected available wetted channel survey data. We sought additional sources and identified sites where streamflow timeseries are also accessible. Some sites (marked by a dagger in Table 1) did not have streamflow timeseries, but hydrographs were available by proxy from either nearby watersheds (Pioneer) or a larger watershed of which the study watershed was a subcatchment (Upper Studibach, Yellow Barn). In the former case, the regression calculated by Whiting and Godsey (2016) was used to infer Pioneer Creek discharge, and in the latter case, discharge from proxy watersheds normalized by area was assumed representative of the study catchment.

Streamflow statistics were calculated from flow timeseries, and additional watershed characteristics were collected from the original publications and distributed sources. While β was nearly always reported (except Zimmer & McGlynn, 2018), α was not generally reported, so we used DataThief III (<https://datathief.org/>) to digitize L - Q data from the original scatterplots to calculate α values and associated uncertainty, as well as to confirm reported values of β . Since total wetted channel length was the most commonly reported metric from surveys, we reported statistics and measures of total wetted channel extent only, rather than continuous wetted channel extent. The full compilation of data, including metadata and standardized streamflow timeseries, are available in the data supplement (will be available on HydroShare at time of publication).

TABLE 1 Watershed characteristics: Metadata for all sites included in this study

Catchment	Location (°)	Climate	Area (km ²)	# Surveys	L (km/km ²)	Q (mm/day)	α	β	R ²	CV _L	CV _Q
Bull Creek ¹	36.97, –119.06	Csa	3.58	4	0.79 ± 0.21	1.79 ± 3.52 ⁹	2.95 ± 0.08	0.19 ± 0.02	0.98	0.27	1.97
Caspar Creek ¹	39.34, –123.73	Csb	8.48	4	0.17 ± 0.07	1.36 ± 4.32 ¹⁰	1.27 ± 0.09	0.31 ± 0.04	0.99	0.62	3.18
CWT12 ²	35.05, –83.44	Cfb	0.12	7	39.6 ± 4.6	2.72 ± 2.55 ¹¹	4.70 ± 0.14	0.08 ± 0.01	0.77	0.12	0.94
Duke Forest ³	36.04, –79.08	Cfa	0.033	41	65.2 ± 54.7	1.18 ± 5.35 ¹²	3.79 ± 0.18	0.18 ± 0.02	0.78	0.84	4.54
Elder Creek ⁴	39.73, –123.64	Csb	16.97	4	0.21 ± 0.07	3.58 ± 8.22 ¹³	2.33 ± 0.15	0.17 ± 0.04	0.92	0.32	2.29
FNW37 ²	39.05, –79.69	Cfb	0.37	7	4.44 ± 1.69	1.74 ± 3.14 ¹⁴	1.80 ± 0.06	0.17 ± 0.02	0.91	0.38	1.80
HB13 ²	43.95, –71.74	Dfb	0.13	5	57.4 ± 13.9	2.58 ± 5.13 ¹⁵	7.68 ± 0.45	0.14 ± 0.03	0.88	0.24	1.99
HB42 ²	43.96, –71.72	Dfb	0.42	7	13.2 ± 4.2	2.39 ± 4.89 ¹⁵	5.58 ± 0.19	0.20 ± 0.03	0.94	0.32	2.04
Pioneer Creek ^{5,†}	45.07, –114.82	Dfb	15.8	3	0.041 ± 0.005	0.32 ± 0.28 ¹⁶	0.83 ± 0.01	0.20 ± 0.03	0.98	0.11	0.88
Providence ¹	37.06, –119.21	Csb	4.01	4	0.36 ± 0.19	0.94 ± 1.70 ¹⁷	1.79 ± 0.11	0.39 ± 0.06	0.96	0.53	1.82
River Ray ⁶	51.88, –1.01	Cfb	18.6	46	0.080 ± 0.044	0.44 ± 1.26 ¹⁸	2.40 ± 0.09	0.15 ± 0.02	0.71	0.55	2.86
Sagehen Creek ¹	39.43, –120.24	Dsb	27.2	4	0.013 ± 0.005	1.07 ± 1.97 ¹⁹	1.12 ± 0.07	0.32 ± 0.08	0.91	0.41	1.85
Upper Studibach ^{7,†}	47.04, 8.73	Cfb	0.13	3	82.1 ± 36.5	4.81 ± 7.88 ²⁰	6.13 ± 1.67	0.31 ± 0.14	0.85	0.44	1.64
Yellow Barn ^{8,†}	42.4, –76.44	Dfb	1.5	11	0.45 ± 0.05	1.51 ± 2.32 ²¹	5.40 ± 0.16	0.10 ± 0.03	0.85	0.11	1.54

Note: Climate zone was indicated based on the Köppen Climate Classification. L and Q are given as the mean value ± the standard deviation. α and β are reported with 1 standard deviation of uncertainty. R² is reported for the power law fit between L and Q. Sites marked with a dagger (†) used a nearby watershed or a larger catchment as a proxy for hydrograph data. Data source for each site was marked next to the catchment name: [1] Godsey and Kirchner (2014), [2] Jensen et al. (2017), [3] Zimmer and McGlynn (2018), [4] Lovill et al. (2018), [5] Whiting and Godsey (2016), [6] Blyth and Rodda (1973), [7] van Meerveld et al. (2019), [8] Shaw (2016). Data sources for hydrographs are marked: [9] Hunsaker (2019a), [10] US Forest Service (1998a) and US Forest Service (1998b), [11] Miniati et al. (2016), [12] Zimmer (2017), [13] U.S. Geological Survey (2020a), [14] Edwards and Wood (2011), [15] USDA Forest Service, Northern Research Station (2020), [16] U.S. Geological Survey (2020b), U.S. Geological Survey (2020c), U.S. Geological Survey (2020d), U.S. Geological Survey (2020e) and U.S. Geological Survey (2020f), [17] Hunsaker (2019b), [18] UK Centre for Ecology and Hydrology (2020), [19] U.S. Geological Survey (2020g), [20] Stahl (2018), [21] U.S. Geological Survey (2020h).

2.2 | Watershed characteristics

Climate grouping are reported using the Köppen classification system (Defrance et al., 2020; K. Wladimir, 2011; W. Köppen & Geiger, 1930; Stern et al., 2000), as classified by Chen and Chen (2013). All study sites were either in temperate (zone C) or continental (zone D) zones; polar, monsoonal, tropical, and dry climates were not represented in the available datasets. Within the temperate and continental groups, a variety of seasonal precipitation regimes were present. Watersheds in the temperate group (zone C) included: (1) Mediterranean climates (Csa and Csb), located along the west coast of North America, which experience precipitation maximum out of phase with maximum temperatures; and (2) humid subtropical/oceanic climates (Cfa and Cfb), located along the east coast of North America and in parts of Europe, which have fairly consistent precipitation throughout the year. Watersheds in the continental group (zone D) included: (1) humid

continental climates (Dfb), located along the east coast of North America, which receive ample precipitation distributed across the year; and (2) Mediterranean-influenced continental climates (Dsb), located on the west coast of North America, which have colder winters than Mediterranean climates but with rainfall still temporally out of phase with the warm season (Table 2).

The soil and bedrock characteristics of the studied sites varied significantly, ranging from well- to poorly-draining soils and single geologic units (D. G. Day, 1983) to complex multi-unit basements consisting of bedrock of marine origin, moraine, sandstone, and volcanic material (Durigetto et al., 2020). The catchment areas of the studied sites also ranged across 3 orders of magnitude, as shown in Table 1. Detailed soil, bedrock, and slope data are available in the data supplement (Leclerc et al., 2020d).

Across all study sites, L was typically mapped from above the 80th to below the 20th flow exceedence percentile. Elder Creek

TABLE 2 Summary of survey differences among study sites

Catchment	Seasonality	Springs?	Survey timing	min. Q mapped (P_{exd})	max. Q mapped (P_{exd})
Bull Creek	Snowmelt pulse and Mediterranean		Spring/Fall, any flow	99	10
Caspar Creek	Mediterranean		Spring/Fall, any flow	89	33
CWT12	Most rain in winter/spring	yes	Summer/Fall, any flow	96	0.1
Duke Forest	Negligible		All year, any flow	42	0.2
Elder Creek	Mediterranean	Yes	Summer recession	99	61
FNW37	Summer thunderstorms		Summer/Fall, any flow	85	7
HB13	Snowmelt pulse		Summer/Fall, any flow	67	2
HB42	Snowmelt pulse		Summer/Fall, any flow	81	9
Pioneer Creek	Snowmelt pulse	Yes	Summer recession	3	0.2
Providence	Snowmelt pulse and Mediterranean		Spring/Fall, any flow	98	18
River Ray	Snowmelt pulse	Yes	All year, any flow	83	2
Sagehen Creek	Snowmelt pulse and Mediterranean		Spring/Fall, any flow	93	16
Upper Studibach	Snowmelt pulse, wet summer		Summer/Fall, any flow	96	18
Yellow Barn	Snowmelt pulse	Yes	Storm recession events	93	12

and Caspar Creek data did not include the highest flow percentiles (all above 60th exceedance percentile), and Duke Forest and HB13 did not include low flow data (above 42nd, and 67th percentiles, respectively). Pioneer Creek appears to have been surveyed only from the 0-3rd flow exceedance percentiles (Table 2); however, this may be due to the fact that the Pioneer Creek hydrograph is constructed as a regression from nearby gauges and may not be accurate.

2.3 | Empirical determinations of the variability in streamflow and network extent

With the full set of available hydrographs and wetted channel surveys, we extrapolated values of L for the full available hydrograph using the relationship $L = \alpha Q^\beta$. This procedure resulted in a timeseries of L equivalent in length to the period of record of discharge. The relative variability of streamflow and network extent, described by their coefficients of variation CV_Q and CV_L , can be calculated directly from the standard deviation and mean of the respective time series. Uncertainties in the timeseries of L and its coefficient of variation were calculated using Gaussian error propagation from the uncertainties reported on α and β , which are depicted throughout the figures. Where not visible, the error bars were either not relevant (since neither β nor α was required for the plot) or smaller than the scatter plot points. We present timeseries of Q and L of representative years for each site, as well as exceedance probability plots for the entire timeseries of record. The exceedance probability of L is equivalent to one minus the stream length duration curve recently described by Botter and Durighetto (2020), although that study specifically focuses on reaches with flowing water rather than wetted extents that may or may not exhibit clear flow.

2.4 | Analytical method for determining relative variability in wetted channel length and its sensitivity to a shift in streamflow variability

Assuming a power law relationship between L and Q , relative variability of L (that is, its coefficient of variation, $CV_L = \sigma_L/\mu_L$) can be defined as a function of the flow regime and the network hydraulic scaling terms:

$$CV_L = \frac{\sigma_L}{\mu_L} = \frac{\sqrt{\mathbb{E}[L^2] - \mathbb{E}[L]^2}}{\mathbb{E}[L]} = \frac{\sqrt{\int_0^\infty \alpha^2 Q^{2\beta} \cdot pdf(Q) dQ - \left(\int_0^\infty \alpha Q^\beta \cdot pdf(Q) dQ\right)^2}}{\int_0^\infty \alpha Q^\beta \cdot pdf(Q) dQ} \quad (1)$$

where σ_L and μ_L are the standard deviation and mean of L , $pdf(Q)$ is the probability distribution function of streamflow, and $\mathbb{E}[\cdot]$ represents the expectation (mean) of the random variable. Many hydrological models and empirical studies of hydrographs describe the probability distribution of discharge as a two-parameter gamma distribution (e.g., Botter et al., 2007; Deal et al., 2018; Muneeppeerakul et al., 2010), in which case CV_L was obtained as a function of β and CV_Q :

$$CV_L = \frac{\sqrt{\Gamma\left(\frac{1}{CV_Q^2}\right)\Gamma\left(2\beta + \frac{1}{CV_Q^2}\right) - \Gamma\left(\beta + \frac{1}{CV_Q^2}\right)^2}}{\Gamma\left(\beta + \frac{1}{CV_Q^2}\right)} \quad (2)$$

Here, $\Gamma(\cdot)$ is the gamma function (Abramowitz & Stegun, 1948) (Note: the gamma function has one parameter and is not the same as the 2-parameter gamma distribution). To directly explore the sensitivity of CV_L with respect to changes in CV_Q , we calculated the elasticity of CV_L with respect to CV_Q for the case of gamma-distributed Q :

$$E(CV_L(CV_Q)) = \frac{CV_Q \partial CV_L}{CV_L \partial CV_Q} \approx \frac{\% \Delta CV_L}{\% \Delta CV_Q}$$

$$= \frac{\Gamma\left(2\beta + \frac{1}{CV_Q^2}\right) \Gamma\left(\frac{1}{CV_Q^2}\right) \psi\left(\beta + \frac{1}{CV_Q^2}\right) - \psi\left(2\beta + \frac{1}{CV_Q^2}\right) \Gamma\left(\frac{1}{CV_Q^2}\right)}{CV_Q^2 \Gamma\left(2\beta + \frac{1}{CV_Q^2}\right) \Gamma\left(\frac{1}{CV_Q^2}\right) - \Gamma\left(\beta + \frac{1}{CV_Q^2}\right)^2} \quad (3)$$

where $\psi(x)$ is the 0^{th} order polygamma function (Abramowitz & Stegun, 1948); integration and simplification of Equations (2) and (3) were performed in the mathematical programming language Mathematica. Elasticity can be interpreted as the percent change in CV_L relative to a percent change in CV_Q for a particular value of CV_Q (e.g., Harman et al., 2011). When elasticity is 1, then CV_L changes to the same degree (proportionally) as CV_Q . Values larger than 1 indicate that CV_L has heightened sensitivity to changes in CV_Q , and values smaller than 1 indicate that CV_L has diminished sensitivity to changes in CV_Q .

Equations (2) and (3) enabled an exploration of the sensitivity of CV_L to shifts in CV_Q for particular values of β . If discharge is gamma-distributed, and if a power-law relationship is used to obtain L from Q , then Equation (2) should exactly match the empirically calculated CV_L . Comparison between empirical and theoretical CV_L therefore assesses the degree to which discharge is gamma-distributed.

While other functional forms of $pdf(Q)$ may be used to obtain an expression for CV_L , an advantage of using a gamma probability distribution for discharge is that existing model frameworks enable interpretation of CV_Q in terms of physical landscape and climate parameters. Botter et al. (2007) demonstrate that gamma-distributed discharge may arise from a simple, process-oriented description of rainfall-runoff processes within a catchment. In this way, variability in the flow regime may be used to directly explore the dependence of CV_L on the climatic and hydrogeologic attributes of a watershed.

For a more general description of CV_L that does not rely on the assumption that discharge is gamma-distributed, we also derived a formula using Taylor expansions of the mean and standard deviation of L ; however, error in the truncated Taylor series proved too large to capture CV_L for values of CV_Q greater than approximately 2.

Costigan et al. (2016) introduced a framework underscoring the importance of meteorologic, geologic, and land use factors in influencing non-perennial stream dynamics. Our model incorporated each aspect of the framework, with meteorologic and climatic information included in CV_Q , and geologic aspects of the basin included in β . Land use was implicitly included in both CV_Q and β . Land use changes can affect the way hillslopes filter precipitation with dramatic impacts on the hydrograph and along-channel flow dynamics. For example, changes in evapotranspiration with changing plant communities, an increase in impermeable surface cover, or removal of in-channel wood can affect the runoff frequency, the hillslope recession constant, and the capacity of the channel to convey flow in a way that causes shifts in CV_Q and β .

2.5 | Assessing the ability of the gamma distribution to describe the flow regime

Since our analysis is predicated on the assumption that discharge is gamma-distributed, we explored the extent to which this assumption held for each site. For this analysis, hydrographs were analyzed in their entirety and also separated by northern hemisphere season (i.e., winter is December–February, spring is March–May, summer is June–August, and fall is September–November) since a gamma fit may be more appropriate on a seasonal basis in some climates. For each site and each season, we fit a gamma distribution to the discharge timeseries using Maximum Likelihood Estimation (MLE). We use the R^2 between (1) the relationship between empirical and fitted quantiles of Q and (2) a 1:1 line. This is mathematically equivalent to the Nash-Sutcliffe model efficiency coefficient (NSE) of flow quantiles, which we will use to refer to this metric throughout the text. We use a threshold of 0.65, which has identified as a threshold for acceptable fit using the NSE (Ritter & Muñoz-Carpena, 2013) and fits well within the fit categories used by Müller et al. (2014) and Castellarin et al. (2004) for NSE of flow quantiles ([0.75–1]: good, [0.5–0.75]: fair, [−inf,0.5]: poor). Since full hydrographs were generally fit well by a gamma distribution in this study, results that employ Equations (2) and (3) are only shown for full timeseries for simplicity.

2.6 | USGS blue line comparison

We determined the blue stream line drainage density from Geo-PDFs of the most recently published 7.5' U.S. Geological Survey (USGS) topographic maps for the study watersheds in the United States. We collected this data to compare the topographic map definitions of perennial stream (solid blue lines) and intermittent stream (dashed blue lines) to the wetted channel extents determined from the $L(Q)$ relationships. The USGS defines a perennial stream as a stream that normally has water at all times except during rare droughts. The USGS defines an intermittent stream as one that flows only when it receives water from a spring or from rainfall but flows more than an ephemeral stream, which only flows in response to precipitation. Busch et al. (2020) recommend using the term “non-perennial” for streams that have interruptions in surface expression, so we use that term throughout in general, but intermittent is used specifically according to the USGS definition.

The blue line network in the National Hydrography Dataset (NHD), included in the 7.5' USGS topographic maps, was inherited from the USGS and the U.S. Environmental Protection Agency (USEPA) (Fritz et al., 2013). Stream segments are included in the blue line network based on distance from features such as saddles or divides rather than field surveys (U.S. Geological Survey, 2020w).

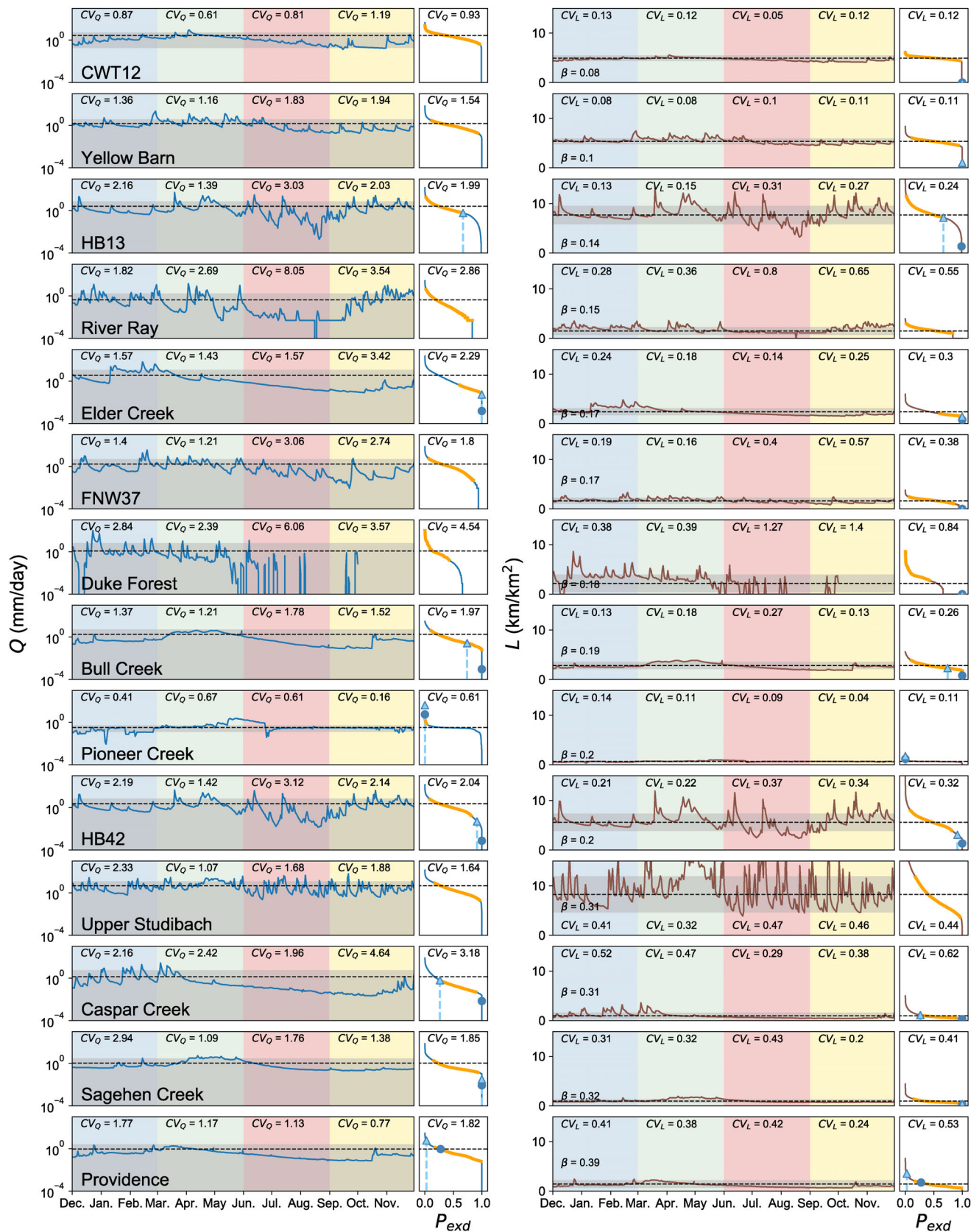


FIGURE 2 Legend on next page.

3 | RESULTS

3.1 | Data synthesis

Figure 2 shows timeseries of Q (as discharge per catchment area) and L (as total wetted channel length per catchment area) for a representative year for each site where Q , α , and β values are available. All data are plotted on the same vertical axes for comparison, with logarithmic scaling for Q and linear scaling for L . There was a large range in hydrograph behaviour among the sites, from relatively smooth and seasonal hydrographs like Sagehen Creek to highly variable flashy hydrographs like Duke Forest. There is a corresponding large range in observed CV_Q values calculated for the entire timeseries among these sites, from a minimum of 0.88 for Pioneer Creek to a maximum of 4.54 for Duke Forest, with the most common CV_Q around 2. Values of CV_Q were also calculated within seasons and in most cases tend to bracket values of annual CV_Q . Relative variability in Q necessarily exceeds relative variability in L because β is everywhere less than one, which damps the impact of variation in Q on the timeseries of L . Moving down Figure 2, β increases, and CV_L generally increases with increasing β . It is important when considering the mean stream conditions to note that, as β results in a nonlinear transformation from the timeseries of Q to that of L , the exceedence probability of the mean flow μ_Q (15%–37%) is distinct from that of the mean wetted channel network extent μ_L (32%–53%). In all cases, μ_L occurs at a flow rate lower than μ_Q .

3.2 | How does variability in Q impact variability in L for different values of β ?

Equation (2) is plotted in the contour plot of Figure 3, which shows that where the network hydraulic scaling term β is small, CV_L is also generally small. As β increases, much larger values of CV_L are possible. This means that a greater amount of the temporal variability in Q is translated to L for larger values of β . Scatter points in Figure 3 show the relationship between β and the empirically calculated CV_Q from the entire timeseries for all sites in the dataset acquired for this study. The majority of our sites have $0.2 \leq \beta \leq 0.4$ and $1.5 \leq CV_Q \leq 2.5$. In this part of the space, values of CV_L are generally below 1.

Figure 3 enables prediction of how network hydraulic scaling (β) and a given flow regime (defined by its relative variability CV_Q) determine CV_L . While β is a relatively static landscape property, CV_Q may

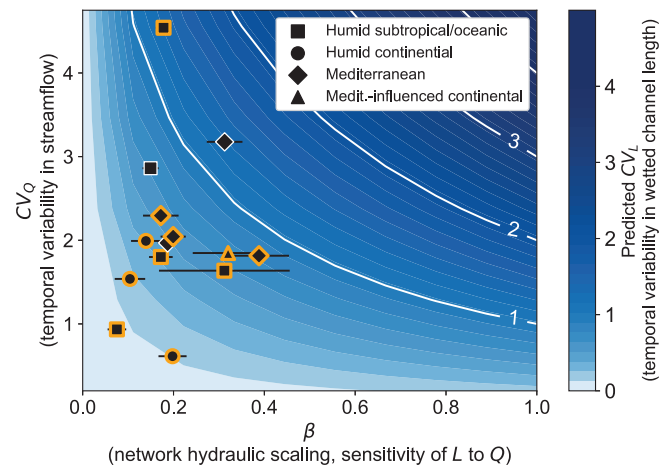


FIGURE 3 Relative variability in flow regime (CV_Q) and network hydraulic scaling (β) govern relative variability in wetted channel extent (CV_L) under simplifying model assumptions (i.e., gamma-distributed Q). Points show flow regime and network hydraulic scaling of actual catchments, with symbol shape denoting climate zone. Gold outlines indicate that flow is fit well by a gamma distribution ($NSE > 0.65$)

change over time due to, for instance, changing climate or patterns of anthropogenic surface water use. Given a shift in CV_Q , what is the impact on CV_L ? Shifting points up or down vertically along the CV_Q axis in Figure 3 results in a new value of CV_L . As CV_Q increases, CV_L increases. Figure 4a more clearly reveals how change in CV_Q impacts CV_L using elasticity. Elasticity can be interpreted as the fractional change in CV_L relative to a small fractional change in CV_Q for a given value of CV_Q and β . If elasticity is 1, then CV_L and CV_Q change at the same relative rate. As elasticity increases, changes in CV_L will be proportionally larger than changes in CV_Q . As elasticity decreases, changes in CV_L will be proportionally smaller than changes in CV_Q . Elasticity is at least 1 everywhere throughout the space (i.e., when $0 < \beta \leq 1$). While elasticity is nearly 1 for $\beta > 0.4$, when β is smaller, changes in CV_L have heightened sensitivity to changes in CV_Q (elasticity > 1). Thus, changes in variability in Q have a larger impact on variability in L when β is small. Surprisingly, our studied sites lie in the region of the plotting space most sensitive to changes in CV_Q ($\beta < 0.4$). Elasticity describes the “instantaneous” change in CV_L for a change in CV_Q ; however, similar relative changes would be exhibited with larger changes in CV_Q because vertical shifts in CV_Q do not cause points to cross many contour lines of elasticity. For example, as shown

FIGURE 2 Representative annual hydrographs (left) and corresponding wetted channel length L timeseries (right) given $L = \alpha Q^\beta$ for all sites included in this study, listed in order of increasing β . Data are plotted for one representative year, with shading marking northern hemisphere seasons: Blue (DJF), green (MAM), red (JJA), and yellow (SON). Dashed black lines indicate the mean for the full timeseries, and the shaded grey region covers the interval of one standard deviation around the mean (note log scale for hydrographs). CV_Q and CV_L are reported by season in each coloured region and for the total timeseries in the flow-duration/length-plots. Marked points indicate USGS 7.5' perennial channel extent/associated discharge (dark blue) and combined perennial and intermittent channel extent/associated discharge (light blue). All CV values are calculated overall years of available data. Site name is found on the discharge timeseries, and β is marked on the L timeseries. Exceedance probabilities P_{exd} are shown to the right of each timeseries. Bold orange sections of exceedance probability functions show the range of flows/wetted channel extents covered by surveys

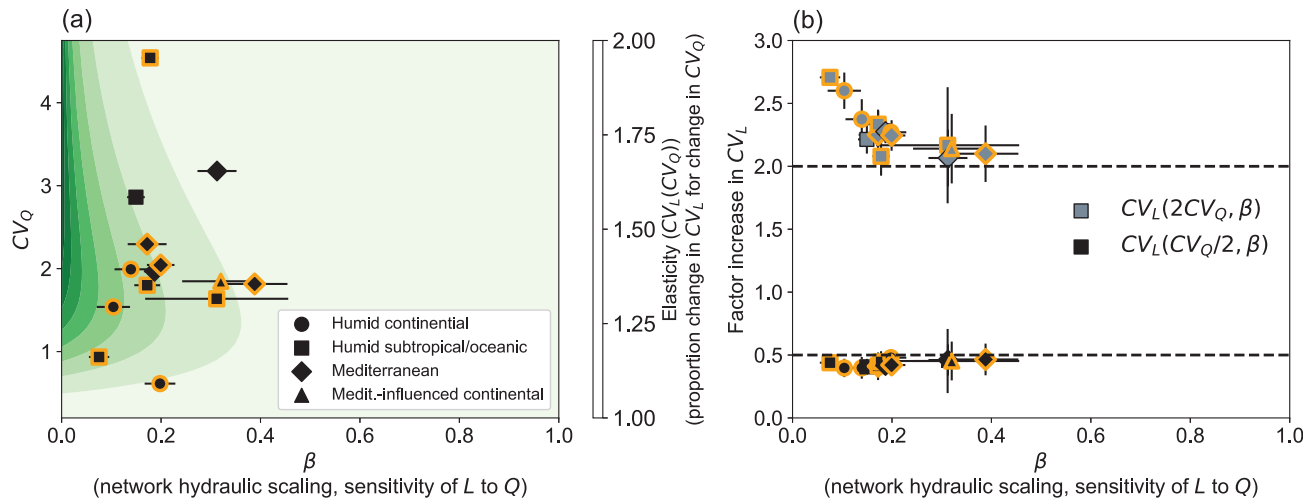


FIGURE 4 (a) There is exaggerated sensitivity of CV_L to changes in CV_Q (elasticity > 1) for small values of β and moderate values of CV_Q , where nearly all study sites lie. (b) For either a doubling (grey) or halving (black) of CV_Q , the fractional change in CV_L as calculated from Equation (2) is more extreme; points lie beyond the dashed lines that indicate a 1–1 change. Gold outlines in both panels indicate that flow is fit well by a gamma distribution ($NSE > 0.65$)

in Figure 4b, if CV_Q doubles, then all of the points lying in regions of darker green in Figure 4a will experience more than a doubling in CV_L (average 2.30 for all sites). A halving of CV_Q similarly results in more than a halving in CV_L for many sites in this study (average factor less than half, 0.43).

3.3 | How applicable is the theoretical model to actual catchments?

Sites in this study generally exhibit gamma-distributed flow, so the theoretical model presented should accurately capture the relationships between CV_L , CV_Q , and β . Figure 5a shows the NSE (R^2 between empirical and fitted quantiles of Q and a 1:1 line) and % error in CV_Q when estimated using a gamma distribution. The shaded region denotes $NSE > 0.65$, the chosen threshold for acceptable fit. The majority of the sites fall within this region, with the exceptions of Bull Creek ($NSE = 0.48$), River Ray ($NSE = -1.29$), and Caspar Creek ($NSE = 0.58$). In Figure 5b, the relationship between CV_L empirical and CV_L predicted using Equation (2) is shown for each site. The points fit well by a gamma distribution ($NSE > 0.65$, outlined in orange) lie close to the dotted 1:1 line, confirming that the model is appropriate in describing CV_L for the full timeseries. For a discussion of model fit on a seasonal basis, see Appendix 8 in Data S1.

The other consideration for applying the theoretical model is the applicability of the power law relationship $L = \alpha Q^\beta$ for different catchments. As shown in Table 1, the R^2 value for the fit between survey data and the power law is always greater than 0.7 and typically above 0.85. We also plot the residual distribution around the power law fit (see Appendix C in Data S1), which is generally evenly distributed with some negative bias in residuals at low-flow at some sites.

3.4 | Stream network extents in relation to USGS blue line stream mapping

The USGS 7.5' solid blue line network does not capture the inferred wetted channel network extents in this study, plotted along the flow-duration and L -duration curves in Figure 2. As shown in dark blue in Figure 6a the drainage density of the perennial stream network (solid blue lines on USGS maps) is systematically smaller (median 53% difference, average 1.4 factor difference) than the empirically inferred wetted channel network from the $L = \alpha Q^\beta$ relationship at the lowest recorded flow (100% exceedance probability) in all except two cases. Furthermore, the difference between the empirically calculated wetted channel drainage density and the USGS blue line drainage density is highly inconsistent between sites, such that there is not an obvious way to infer perennial wetted channel extents from the USGS solid blue line network.

A similar relationship holds between the drainage density of the total stream network mapped by the USGS (solid and dashed blue lines) and the highest (0% exceedance probability) empirically inferred wetted channel network extent (Figure 6); the highest inferred L (0% exceedance probability) is always greater than the USGS total network extent with a median percent difference of 79% and an average factor difference of 3.6. This is not particularly surprising, as the USGS excludes ephemeral stormflow by definition, which the flow regime would capture. However, only just over half of the total USGS network extents even exceed the lowest wetted channel network extent inferred from $L = \alpha Q^\beta$ (100% exceedance probability), shown in the grey region of Figure 6b. Pioneer Creek is an outlier among these sites as the only site for which both USGS perennial and combined perennial and intermittent are far greater than the lengths inferred from $L = \alpha Q^\beta$. The individual USGS stream network extents may therefore

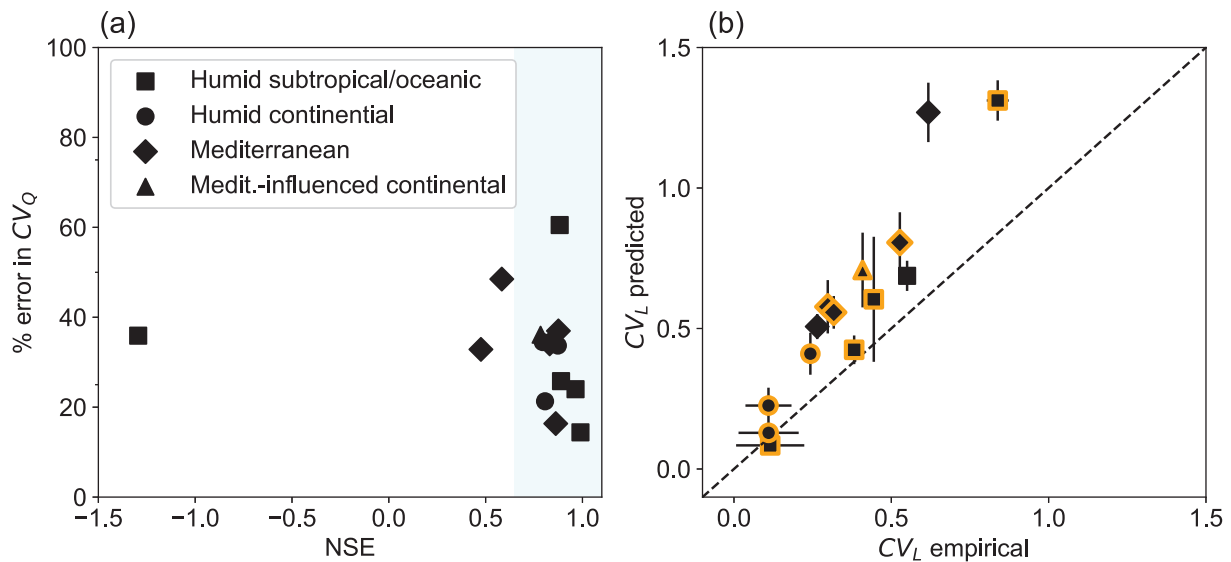


FIGURE 5 How well does the gamma distribution describe actual hydrographs, and how does this affect predictions of CV_L ? (a) plots the percentage difference between model-predicted and empirically derived CV_Q vs. the NSE goodness-of-fit criteria for gamma distribution and actual hydrograph percentiles for $NSE > 0$. Shaded region indicates $NSE > 0.65$. (b) Comparison between CV_L calculated from the empirical hydrograph timeseries and the predicted value based on CV_Q and β (from the model in (a)). The dashed line shows one-to-one correspondence for reference. Error bars incorporate the uncertainty in α and β . Points outlined in gold meet the selection criteria for the gamma fit

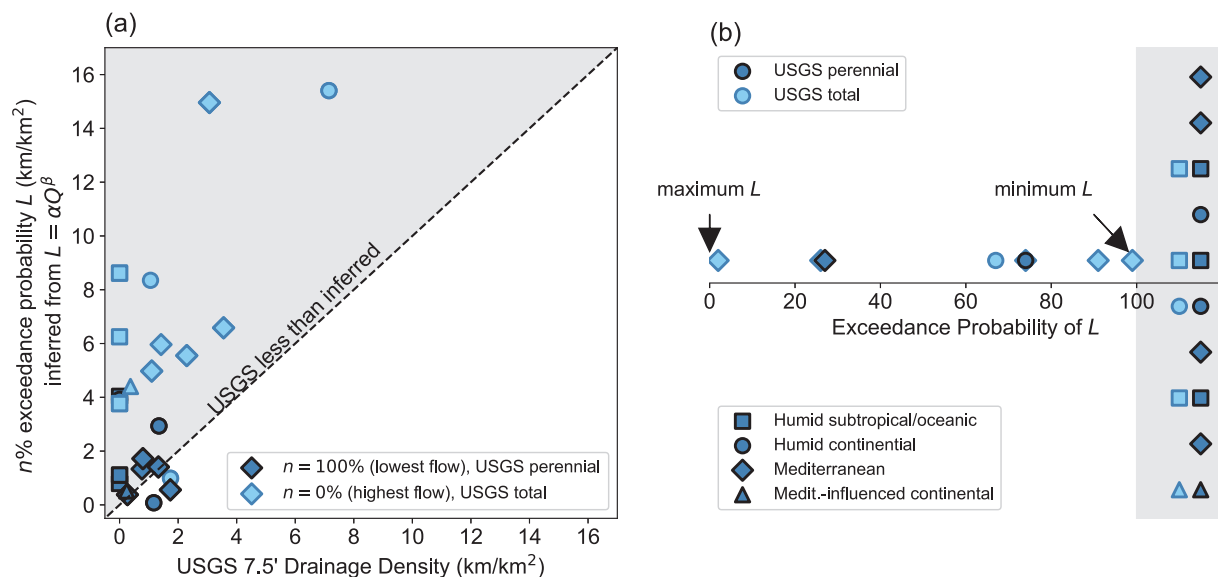


FIGURE 6 (a) USGS 7.5' blue line stream extent is nearly always less than both perennial and dynamic stream extents inferred from the $L(Q)$ relationship. (b) the exceedance probability for USGS 7.5' blue line channel extents is often greater than 100%. Points in the grey region beyond 100% have values well below the smallest inferred L , and total stream lengths fall along the full spectrum of possible exceedance probabilities

capture some, none, or all of the dynamic variability inferred from the wetted channel mapping campaigns.

4 | DISCUSSION

We have formalized the joint control on the temporal variability in wetted channel extent (CV_L) by network hydraulic scaling relationships

(in the form of β , which determines how much L changes for a change in Q , as suggested by Godsey & Kirchner, 2014; Prancevic & Kirchner, 2019) and the flow regime (described by CV_Q , e.g., Botter et al., 2007). Our approach is summarized in Figure 1. The collection of all sites with jointly available streamflow and β values from the literature (Figure 2; Table 1) reveals that relative variability in discharge greatly exceeds (often by a factor of >5) relative variability in wetted channel extent. By assuming that flow is well-approximated by a

gamma distribution, we predicted CV_L as a function of CV_Q and β (Figure 3). An increase in the relative variability of streamflow (CV_Q) results in an even greater increase in the relative variability in wetted channel extents (CV_L). Perhaps surprisingly, this elasticity is greatest for small β . The location of sites from around the world within this plotting space suggests that for most places, an increase in the relative variability of discharge under a shifting climate regime will result in an even greater increase in the relative variability of wetted channel extents.

This study provides a framework for assessing the controls on CV_L between different sites under current conditions as well as a way to predict changes in CV_L under a shifting climate. Climate change is projected to result in more volatile precipitation regimes with more frequent extreme events in many locations globally, without necessarily changing mean precipitation totals (Seneviratne et al., 2012; Swain et al., 2018). We can understand how a change in the variability in precipitation will affect variability in the wetted channel network extent under the assumptions of a simplified stochastic hydrologic model. Botter et al. (2007) show that $CV_Q = \sqrt{\frac{k}{\lambda_Q}}$, where k is the linear flow recession constant that describes the rate of flow decrease during rainless periods and λ_Q is the frequency of catchment runoff generating events, which depends on vegetation water use, vegetation-available water storage capacity in the unsaturated zone, and rainfall patterns. Within this model, climate is embedded within CV_Q via λ_Q . Increasing precipitation volatility with a constant or decreasing mean will result in a decrease in the frequency of rainfall events. A decrease in the frequency of rainfall events translates into a decrease in the frequency of runoff events, as the Botter et al. (2007) model indicates, so higher precipitation volatility would be expected to result in larger CV_Q . In parallel to increased precipitation volatility, rising temperatures will increase evapotranspiration demand (Kingston et al., 2009). This could increase actual evapotranspiration, resulting in vegetation withdrawing more moisture from the vadose zone and increasing the threshold amount of rainfall required to then initiate a streamflow event. This suggests that greater potential evapotranspiration could also lead to a decreased frequency of runoff events (i.e., smaller λ_Q) and therefore larger CV_Q . Thus, the projected shifts in climate could result in a significant increase in CV_Q , which our findings indicate would result in an even greater relative increase in CV_L for headwater stream networks.

4.1 | Implications for physical and chemical streamwater dynamics

Variability in wetted channel extent should impact variability in solute export dynamics. Wigington Jr et al. (2005) showed that nitrate concentrations scaled with stream network length in western Oregon, and Hale and Godsey (2019) showed that variability in L impacts dissolved organic carbon (DOC) concentrations. Both Wigington Jr et al. (2005) and Hale and Godsey (2019) suggested that connection to source areas is the likely mechanism by which variation in L regulates these solute concentrations.

The total surface area of water is important for determining chemical exchange between water and the atmosphere, including the process of CO_2 evasion. This is not only important for chemical cycling but also for energy flux to the channel. Studies that have attempted to estimate the global surface area of rivers have done so by extrapolating channel areas observed at mean annual discharges (Allen & Pavelsky, 2018). Our findings suggest that the average length of headwater streams is about 20% less than that predicted using the mean annual discharge. Barefoot et al. (2019) found that increases in headwater stream surface area with increasing runoff were equally contributed by longitudinal and lateral expansion, so surface area of streams should scale with longitudinal extent, indicating that average river area in headwater streams may be overestimated at mean discharge.

Understanding the availability of surface water is critical, as it impacts several physicochemical processes, including evaporative cooling of the local atmosphere as well as in-stream temperatures. Drier conditions result in a contraction of the wetted stream area, leading to much greater daily variability in channel water temperature than would occur under wet conditions (since water has a greater specific heat than air). Rapidly changing water temperatures can be unsuitable or lethal for aquatic species (Beitinger et al., 2000), and swings in temperature also dictate available energy for chemical reactions in the water and chemical exchange with the atmosphere. As an increase in variability in L leads to increased variability in temperature, an increase in variability, even at the same mean, could increase stress on aquatic organisms and alter stream chemistry.

4.2 | Ecological impacts

The inter- and intra-annual variability of streamflow are critical components of the natural flow regime to which biota both respond and adapt (Stubbington et al., 2017). Based on the model presented by Larned et al. (2010), aquatic biodiversity may be heavily controlled by the wetting and drying dynamics in non-perennial streams. While many species are attuned to variation in discharge and wetted channel length, they rely on certain phenological conditions for survival. For example, organisms' life history strategies use metrics like average timing of winter floods, spring recession, and summer low flows as cues to initiate certain developmental stages (Lytle & Poff, 2004). Looking at the seasonal differences in CV_Q and CV_L (Figure 2) can provide insights into how reliable these cues are and how these may impact phenological bottlenecks in survival.

An overarching concern for predicting the fate of aquatic ecosystems is that while hydrologic variability has been identified as a control on ecological processes, many of the current empirical relationships that are used to govern management decisions are rooted in climatic stationarity (Horne et al., 2019). These assumptions fail to incorporate a shifting baseline climate regime, with already variable regions predicted to become even more volatile. For example, in California, which experiences a highly variable Mediterranean climate, future climate is projected to have an exacerbated seasonal cycle,

with rapidly alternating drought and flood periods (Swain et al., 2018). This has direct implications for the ecological dynamics within these systems, where intermittency of headwater river networks is typically the norm rather than the exception, and aquatic species rely on wetted channel reach refuges during network contraction (Bogan et al., 2019; Hwan et al., 2018). Our study addresses recent calls for novel strategies to adaptively manage river ecosystems, with a focus on process based models that incorporate increasing climatic variability (Tonkin et al., 2019). For headwater stream networks that are expected to exhibit greater variability based on their location within the elasticity plotting space of Figure 4a, a shift in community composition may occur (Brooks, 2009), resulting in a new composition of species that are resistant or resilient to increased variability (Poff et al., 1996). Networks that are relatively more buffered from potential increases in streamflow variability can act as a refuge for aquatic species. These refugial networks may harbour keystone communities (Mouquet et al., 2013), and become a focus for management efforts.

4.3 | Management implications

Correct classification of streams is essential for effective management, as perennial and non-perennial streams function differently and provide different ecosystem services. Stream classification also determines which governing body is in charge of regulation (e.g., federal or state). Waters of the United States (WOTUS) defines stream categories in the US for management purposes, including categories of flow persistency (perennial, intermittent, and ephemeral similar to the USGS definitions). A 2020 ruling in the United States redefined WOTUS in a way that reduces waterway protection (Harvard EELP, 2020). The 2020 *Navigable Waters Protection Rule* (NWPR) specifically excludes ephemeral streams from protection (U.S. Engineers Corps and U.S. Environmental Protection Agency, 2020). This stands in contrast to the previous definition (U.S. Engineers Corps and U.S. Environmental Protection Agency, 2015) of WOTUS which recognized that ephemeral streams and pools support imperilled species and biodiversity and play an important role in the global carbon and nutrient cycles (Marshall et al., 2018). The NWPR also neglects to acknowledge that disconnected surface reaches are often still connected hydrologically through the hyporheic zone, which acts as an important interface between the surface and subsurface, mediating biogeochemical processes (Boulton, 2007) and acting as a refuge for invertebrates (Stubbington, 2012). Particularly with reduced protection for some classes of nonperennial streams, it is important that streams be classified properly to maintain the maximal legal protection to which streams are entitled.

In the US, USGS maps are often one of the main tools used for preliminary distribution of surface water resources for both management and conservation purposes. Our results demonstrate that the USGS 7.5' blue line stream network under-represents both the perennially wetted stream extent and the dynamic wetted stream extent in nearly all US sites included in this study (excluding Pioneer Creek, which is over-represented). That is, both perennially and non-

perennially wetted channel segments are generally either underestimated, or, in many cases, totally absent from the map. van Meerveld et al. (2019) also compared surveyed stream extents to topographic maps and found similarly that topographic maps showed much smaller stream extents than they observed. If this pattern holds elsewhere, then the solid blue line USGS stream network is systematically smaller than the perennially wetted channel network and dynamically active non-perennial network across the US. By assuming area thresholds for channel initiation based on field studies across the conterminous US, Fesenmyer et al. found that the USGS stream network may be missing nearly 75% of ephemeral stream channels. Since legislative categories are based on specification of channel segments as perennial or non-perennial (Acuña et al., 2014), misidentification of stream segments will cause legislation to be applied differently than intended or not at all, where stream segments are missing from USGS maps.

Additionally, since we found no systematic pattern in the under-representation of streams in USGS maps, legislation would be applied differently in different locations, leading to inconsistent management. This finding adds urgency to the development of adaptive large-scale wetted channel maps that incorporate the variability and likely non-stationarity exhibited by the sites in this study. The USGS developed PROSPER, a probability model that predicts stream permanence probability for the Pacific Northwest region of the United States, in response to this need. This model has been shown to be 80% accurate with regard to dry and flowing stream reach classification (Jaeger et al., 2019). Pate et al. (2020) employed a random forest to gain even higher accuracy in predicting stream permanence and connectivity in their study sites along the west coast of the US. These tools (along with the present study) demonstrate that accurately predicting stream permanence is a data-intensive task. One way forward would be to focus on addressing the data requirements needed to build and assess the reliability of such tools.

4.4 | Limitations of model and analysis

4.4.1 | Extrapolation where mapped network extents do not cover the full range of flows

The power law relationship between L and Q enables calculation of timeseries of wetted channel length from timeseries of discharge. Although this relationship has been observed to be robust in studies that span nearly the entire range of flows on record (e.g., Godsey & Kirchner, 2014; Jensen et al., 2017; van Meerveld et al., 2019), some studies of wetted channel extent span highly limited ranges in flow. Lovill et al. (2018), for example, focused on dry season recession dynamics in Elder Creek, and their highest-flow survey occurred at only the 55th exceedance percentile of flow. Constructing the timeseries of L from the hydrograph using the empirical relationship $L = \alpha Q^\beta$ therefore requires, in some cases, significant extrapolation beyond the empirically observed range of flows. The calculations of CV_L in this study are contingent on the validity of this extrapolation,

which could be validated with future mapping at targeted flow percentiles.

4.4.2 | Hysteresis in relationship between wetted channel length and Q

The relationship between L and Q may exhibit hysteresis. Blyth and Rodda (1973) suggested distinct relationships between L and Q by season, which was observed at one site by Godsey and Kirchner (2014) in their reanalysis of data from Gregory and Walling (1968). Distinct α and β values between winter and summer surveys were observed. For some studies included in the compiled dataset, surveys were conducted in particular seasons (e.g., Lovill et al., 2018). Using the same relationship throughout the year may not be justified, and fitting a single relationship for surveys taken throughout the whole year may alter measured variability in CV_L . Hysteresis in the relationship between Q and L may also occur on an event basis (Shaw, 2016). Bhamjee and Lindsay (2011) noted that distinct modes of expansion and contraction (e.g., upstream or downstream) could occur during wetting and drying. Roberts and Archibold (1978) and Zimmer and McGlynn (2017) found that distinct wetted channel lengths can be associated with the same value of Q , depending on whether the survey is done on the rising or falling limb of the hydrograph.

In the case of significant hysteresis, scatter around an L - Q relationship would be expected to be large. For the sites included in this study, though, L - Q scatter is relatively small; however, a number of sites exhibit non-uniqueness (hysteresis) in the L - Q relationship at low flows. Future improvements on the analyses presented here could incorporate time-varying relationships between Q and L .

4.4.3 | Differences in study methodology

Although survey methodology varies between studies, we find no apparent systematic relationship between methodological particulars and values of β . However, sites with fewer surveys tend to have larger values of β . For example, all sites with $\beta > 0.3$ have 4 or fewer surveys. Given the small number of sites included in this study and the sparse survey data, it is unclear whether this is coincidental or whether the dates surveyed do not accurately capture the relationship between L and Q .

4.4.4 | Alternative metrics to total wetted channel extent

In this study, we examine and report on parameters related to the total extent of wetted channels, since this was the most commonly reported metric in the literature. Some studies also mapped and reported the continuously wetted channel network extent, which may be a more relevant metric in certain contexts. For example, the extent of continuously wetted channels likely dictates mobility and food

delivery downstream for many aquatic organisms, and Vander Vorste et al. (2020) found that the extent of non-fragmented (continuous) habitat is a strong control on fish survival. Wetted extent is also a coarse ecological metric, standing in for relevant reach-scale variables like water depth, width, and flow rate. The flowing channel network may also be distinct from the wetted channel extent explored in this study since standing water does not count toward flowing channel length. Flowing channels may be more important for some ecological applications and are often referred to in legislation about streams. Future studies could exploit empirically determined scaling relationships between these variables and L to predict their variability as well, although some of these other variables may scale with L used in this study (e.g., number of independent channel segments and L ; Shaw, 2016), yielding qualitatively similar results.

4.4.5 | Data is limited in geographic and temporal extent

Headwater streams have been called *aqua incognita* due to their relative lack of study (Bishop et al., 2008). While ubiquitous, many headwater streams are simply absent from maps or receive little attention, despite their importance for a variety of ecological, geochemical, and geomorphological processes and downstream impacts (Nadeau & Rains, 2007), although interest and research attention are growing fast (Leigh et al., 2015). Non-perennial streams can constitute the majority of the total stream length across many regions (Goodrich et al., 2018); thus, changes in variability or length of wetted stream networks have an enormous impact on total stream habitat availability and quality. These understudied reaches are also vulnerable to climate change, as suggested by the amplified impact in CV_L of increases in CV_Q demonstrated in this study.

As shown in the map in Appendix A in Data S1, there is a strong geographic bias towards North America in the data sets available for inclusion in this study, with only 2 sites in Europe and none in Australia, South America, Africa, or Asia. While the majority of these headwater catchments have $0.2 < \beta < 0.4$, the true distribution of β globally is still unknown, given the geographic concentration and small number of surveyed dynamic stream extents. Another important consideration is that over a third of sites included in this study have prominent springs, which tend to stabilize wetted channel extents. This may nevertheless be captured by a small slope in the power-law L - Q relationship. For example, a channel network that is permanently anchored to springs (that is, constant L for all values of Q) would have a slope $\beta = 0$.

One particularly promising avenue for increasing the number of datasets exploits advances in drone-based mapping technologies that could rapidly enable repeat, high resolution mapping of wetted channel extents (e.g., Hooshyar et al., 2015). In order to expand the present study to more sites, continuous discharge timeseries and wetted channel surveys across a large range of discharge values are required. Reporting both α and β in wetted channel studies would facilitate further research along these lines. To learn more from a data compilation,

it would be useful to have information about total connected stream extent (in addition to total extent) and dates associated with each surveyed channel extent so that a seasonal analysis would be possible.

5 | CONCLUSIONS

We developed a conceptual model for how the flow regime and network hydraulic scaling collectively determine the extent of the wetted channel network. Using our conceptual framework, we explored empirical variability in wetted channel extent and employed a modeling framework for predicting changes in CV_L assuming gamma-distributed streamflow. A compilation of all available data from 14 sites around the world revealed that headwater stream extents were significantly less variable than streamflow because network hydraulic scaling dampens variability in Q through the relationship $L = \alpha Q^\beta$, where $\beta < 1$ always. Although variability in L is damped, the relationship is elastic, such that for a given change in CV_Q , headwater streams will experience an even more extreme change in CV_L . Therefore, headwater stream network extents are very sensitive to a shift in climate toward less frequent runoff events, as projected in many places around the world. We compared the wetted channel extents determined from the $L(Q)$ relationship to USGS stream delineations, and found that published stream networks are persistently underestimated. Given its use in making legislative, management, and conservation decisions, we recommend that hydrographic datasets incorporate the variability in wetted channel extent.

DATA AVAILABILITY STATEMENT

All data is available for download from HydroShare at (<https://www.hydroshare.org/resource/23fc96f7517247babb83f7d5418e3023/>) (Leclerc et al., 2020b, 2020c, 2020d, 2020e). Supporting code is available on GitHub (<https://zenodo.org/record/4057320>; Leclerc et al., 2020a). A preprint of this study is available in the public domain (Lapides et al., 2020).

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of this article.

How to cite this article: Lapidés DA, Leclerc CD, Moidu H, Dralle DN, Hahm WJ. Variability of stream extents controlled by flow regime and network hydraulic scaling. *Hydrological Processes*. 2021;35:e14079. <https://doi.org/10.1002/hyp.14079>