



Groundwater hysteresis increasingly decouples flowing network length from streamflow as snow shifts to rain

Elijah N. Boardman^{1,2}, Mark S. Wigmosta³, Nicole M. Fernandez⁴, John A. Whiting², and Adrian A. Harpold^{2,5}

¹Mountain Hydrology LLC, Reno, Nevada, 89503, USA

²Graduate Program of Hydrologic Sciences, University of Nevada, Reno, Reno, Nevada, 89557, USA

³Energy and Environment Directorate, Pacific Northwest National Laboratory, Richland, WA, 99354, USA

⁴Department of Earth and Planetary Sciences, ETH Zürich, 8092 Zürich, Switzerland

⁵Department of Natural Resources and Environmental Science, University of Nevada, Reno, Reno, Nevada, 89557, USA

Correspondence: Elijah N. Boardman (eli.boardman@mountainhydrology.com)

Received: 17 December 2025 – Discussion started: 12 January 2026

Revised: 28 June 2026 – Accepted: 6 August 2026 – Published: 14 August 2026

Abstract. Flowing stream networks expand and contract in response to dynamic groundwater levels. Field studies generally associate greater flowing network length (L) with higher streamflow (Q), but this neglects potential hysteresis caused by nonequilibrium groundwater flow after rain and snowmelt. Using a new version of the Distributed Hydrology Soil Vegetation Model (DHSVM), we predict that groundwater hysteresis may decouple L from Q across large ($> 100\%$) variations in Q . Groundwater hysteresis contributes to the spatial reconfiguration of active flowpaths and changes to hillslope-riparian hydrological connectivity, which can manifest as a network length scaling anomaly relative to the best-fit power law. In a 27 km² snowy volcanic watershed, seasonal anomalies in measured stream ionic concentration indicate an outsized contribution from longer subsurface flowpaths during recession, supporting our L - Q hysteresis hypothesis and refining our model calibration. The model can reproduce observed stream network elasticity (from field surveys), and the predicted network length anomaly mirrors seasonal anomalies in measured stream ionic concentration ($r = -0.92$), suggesting that the model can capture seasonal changes in the spatial configuration of groundwater convergence and streamflow generation. A warmer climate is expected to cause a partial transition from snow to rain resulting in flashier streamflow, but our simulations predict that seasonal groundwater hysteresis would dampen storm-scale stream network elasticity, thereby significantly increasing L - Q hysteresis on daily to monthly timescales ($p < 0.01$). Conceptual models of stream networks should consider the

potential effects of groundwater hysteresis, especially in a changing environment. More broadly, our investigation highlights how spatially distributed process-based hydrological modeling can reveal emergent hydrological behaviors that are not necessarily apparent from sparse field data.

1 Introduction

Flowing stream networks interconnect global biogeochemical cycles across all timescales (Aufdenkampe et al., 2011; Castro and Thorne, 2019; Allan et al., 2021; Liu et al., 2022). Headwaters streams account for the majority of network length (Downing et al., 2012; Lane et al., 2026) and fulfill a unique environmental role (Clarke et al., 2008; Wondzell, 2011; Von Schiller et al., 2017) characterized by expansion, contraction, and disconnection in response to patterns of landscape wetting and drying (Gregory and Walling, 1968; Prancevic et al., 2025). Climate-mediated streamflow regime changes can have cascading effects on fluvial systems and stream ecology (Dhungel et al., 2016), including reducing the total extent and spatial connectivity of flowing stream networks in ways that are challenging to predict and manage (Jaeger et al., 2014; Ward et al., 2020; Botter et al., 2021). Changes to the extent and persistence of flowing stream networks can have large-scale consequences for freshwater ecosystems, carbon fluxes, nutrient cycles, and other fluvial processes such as erosion, sedimentation, and contam-

inant transport (Alexander et al., 2007; Freeman et al., 2007; Meyer et al., 2007; Marx et al., 2017).

Flowing stream networks are coupled to local groundwater (GW) conditions (Freeze and Cherry, 1979; Winter et al., 1999). Although intense precipitation can cause ephemeral streamflow over dry soil (Kampf et al., 2016), on longer timescales (days to years), flowing stream network variability is the surface expression of varying GW levels (De Vries 1995). As GW converges from hillslopes to valley bottoms, streamflow (Q) initiates where the total down-valley flow exceeds the subsurface conveyance capacity (Carlston, 1963; Hewlett and Hibbert, 1967; Godsey and Kirchner, 2014; Ward et al., 2018), which is controlled by spatial patterns of upslope wetness, down-valley topography (valley bottom width and slope), and hydrogeological properties (transmissivity). Numerous studies have mapped flowing stream network variability by visual observation (e.g., Godsey and Kirchner, 2014; Whiting and Godsey, 2016; Jensen et al., 2017; Durigetto et al., 2020; Senatore et al., 2021), distributed sensors (e.g., Jensen et al., 2019; Zanetti et al., 2022), and remote sensing (e.g., Dugdale et al., 2022; Dralle et al., 2023).

Many observational studies suggest a strong proportional scaling relationship between Q and the length of the upstream flowing network (L), often expressed as a power law, i.e., $L \sim Q^\beta$, with β varying from near zero to greater than 0.5 largely depending on topography (Prancevic and Kirchner, 2019). The β exponent is also referred to as the “elasticity coefficient” since it describes the flowing network elasticity in response to changing catchment wetness (Prancevic et al., 2025). As GW levels rise, flowing streams also receive additional inflow due to changing hydraulic gradients (Zimmer and McGlynn, 2017a), and thus Q increases proportionally faster than L ($\beta < 1$ in most circumstances). Although L - Q scaling has been observed to fit a power law across several orders of magnitude in Q (e.g., Godsey and Kirchner 2014), flattening behaviors are common in the lowest- and highest-flow regimes as the network reaches its minimum or maximum extent (Durigetto et al., 2025). The power law exponent (β) describes the relative scaling between fractional changes in Q and L under the assumption that Q and L are instantaneously coupled. In this study, we challenge the assumption of instantaneous hydrological coupling that is implicit in simple L - Q scaling relationships such as the power law and exponential or gamma functions (Durigetto et al., 2025). Simple L - Q scaling approximations are typically assessed with a handful of labor-intensive stream network surveys, which do not constrain the full range of hydrological variability on daily to decadal timescales. For example, the hysteresis behavior analyzed in the present study only becomes apparent from many years of daily stream network length estimates, which cannot realistically be reproduced by manual field surveys (walking the length of the network each day). From the current sparse field observations, it thus remains unclear whether a fixed L - Q scaling relationship

is suitable for analysis in nonstationary environments. Conversely, process-based hydrological reasoning gives us a reason to doubt that the L - Q relationship would hold nonequilibrium conditions; for example, climate change may reconfigure spatial patterns of hydrological connectivity (Abhervé et al., 2025).

Groundwater responds to terrestrial water inputs more slowly than streamflow due to threshold-like soil saturation processes (Beven, 2006; Spence, 2010), producing hysteretic relationships (temporally lagged responses) between GW and Q (Andermann et al., 2012; Sproles et al., 2015; Gu et al., 2023). Observations of the water table after rainfall or snowmelt runoff events indicate that hillslope GW generally lags Q (McGlynn et al., 2004; Allen et al., 2010; Camporese et al., 2014). This hysteresis can also reverse direction in riparian areas with shallow antecedent water tables (Q lags riparian GW) before hillslopes reach saturation (Kendall et al., 1999; McGlynn and McDonnell, 2003). Antecedent wetness similarly decouples GW flow directions from topography (van Meerveld et al., 2015) and mediates GW- Q hysteresis across runoff events (Detty and McGuire, 2010b; Penna et al., 2011). GW hysteresis also may emerge from the convergence of flowpaths in higher-order valleys, and GW flowpaths interact with topography to control the dynamics of catchment-scale hydrological connectivity (Abhervé et al., 2025). In regions where GW levels predominantly control L (De Vries, 1995), the GW- Q hysteresis suggests a potential L - Q hysteresis grounded in well-established process-based reasoning and GW observations.

The hysteretic relationship between GW and Q is not considered by simple L - Q scaling approximations such as power law equations, which implicitly assume that all stream channels respond instantly and proportionally to the overall wetness of the entire watershed (Eq. 2 of Prancevic and Kirchner, 2019). Prancevic et al. (2025) note this limitation in their extrapolation of the L - Q power law to 14 765 watersheds, but they assume that the decoupling of Q from headwaters wetness is probably only relevant at scales $> 10\,000\text{ km}^2$. On the contrary, observations indicate a hysteretic relationship between L and Q even in small watersheds, with a longer network (shallower GW) during recession at catchment scales as small as 3.3 ha (Zimmer and McGlynn, 2017b) and 2.6 km^2 (Zanetti et al., 2022). Moreover, catchment-scale observations at scales of 0.67 km^2 (Senatore et al., 2021) and 1.5 km^2 (Shaw, 2016) show that Q sometimes varies substantially at constant L . Streamflow travel times can even introduce a reverse L - Q hysteresis during storms, with the network expanding rapidly while outlet streamflow increases gradually (Roberts and Archibold, 1978; Jensen et al., 2019). Hysteresis effects are not necessarily limited to storm-event timescales though, as partial decoupling of L and Q is observed even at seasonal timescales (Blyth and Rodda, 1973; Jensen et al., 2019). For example, the measured value of β nearly doubles (0.287 to 0.502) between winter and summer in a 0.41 km^2 catchment (Gregory and Walling, 1968, reana-

lyzed by Godsey and Kirchner, 2014). Anomalies in the L - Q relationship are thus apparent across a range of catchment sizes and timescales, in contrast to a bijective (1 : 1) scaling law. However, a lack of long-term timeseries data describing the L - Q relationship precludes precise estimation of the temporal lag between L and Q , and how that lag might vary with different environmental conditions. It thus remains unclear whether L - Q hysteresis is significant on the timescales (days, months, seasons) that matter for fluvial and riparian environmental processes.

Although the original understanding of L - Q scaling resulted from empirical curve-fitting to field data, “bottom-up” approaches based on our physical hypotheses of how the system works at small scales can also be a useful means to explore the implications of our conceptual understanding (Hrachowitz and Clark, 2017). Physically based, spatially distributed hydrological simulations are useful to investigate potential deviations from simple scaling relationships because mechanistic simulations enable process attribution, emergent spatial reorganization, and perturbation of climate conditions. Previous mechanistic approaches to simulating L - Q dynamics have spanned a range of complexity, from “perceptual” models limited to the hyporheic zone (Ward et al., 2018), to semi-distributed models with lumped down-valley flow implicitly partitioned between Q and GW (Mahoney et al., 2023), to grid-scale distributed GW- Q models based on linear reservoirs (Gao et al., 2021). However, all of these approaches assume static GW pressure gradients based on the surface topography, in contrast to the time-varying behavior of observed GW levels (Zimmer and McGlynn, 2017a; van Meerveld et al., 2015). Fully dynamic GW- Q models that solve the three-dimensional Richards equation can successfully reproduce observed GW- Q hysteresis for individual wells (Camporese et al., 2014), but at the time of our investigation this type of highly sophisticated model has only been applied to investigate the L - Q scaling dynamics of idealized theoretical catchments (Zanetti et al., 2024). Here, we implement a new medium-complexity bidirectional surface-groundwater coupling scheme within an existing spatially distributed physically based hydrology model to predict how GW modulates the effect of short- and long-term climate variability on flowing stream networks. We contrast our simulation results with the L - Q power law scaling relationship since it is widely used as the basis for empirical conceptualizations. Our simulation platform is based on the Distributed Hydrology Soil Vegetation Model (DHSVM, Wigmosta et al., 1994; Wigmosta and Perkins, 2001), which is notable for representing mountain forest ecohydrological processes with high physical fidelity (Beckers et al., 2009) and is widely applied to examine the climate sensitivity of mountain streams (Cristea et al., 2014; Lee et al., 2020; Ridgeway and Surlleet, 2021; Hasan et al., 2023). Since spatially distributed hydrological and land surface models notoriously struggle to represent non-perennial streamflow behavior (e.g., Price and Kaiser, 2026), our updated version of DHSVM provides a

uniquely successful example of ephemeral streamflow simulation within a medium-complexity framework (i.e., spatially distributed dynamic water table routing without a full 3D groundwater flow solver).

Mountain catchments are expected to undergo extreme changes in places where precipitation shifts substantially from snow to rain, altering soil moisture, vegetation phenology, and streamflow timing (Thackeray et al., 2019; Harpold and Molotch, 2015; Klos et al., 2014). The compounding effects of this change on L - Q dynamics remains uncertain, limiting our ability to predict and manage the future trajectory of fluvial systems. In general, a shift from snow to rain caused by warming is expected to increase streamflow “flashiness”, with brief but frequent rainfall-runoff events replacing more gradual seasonal snowmelt (Foster et al., 2016; Kampf and Lefsky, 2016; Patterson et al., 2022). However, prior stream network analyses have not generally permitted spatial reorganization of flowing networks or changes to streamflow generation and flow routing in nonstationary environmental conditions. Instead, prior studies of network scaling have assumed a fixed hierarchical network activation sequence (Botter et al., 2021), which does not permit emergent spatial reorganization of hydrological connectivity, or a fixed power law relationship between spatially distributed wetness and outlet Q (Ward et al., 2020; Lapides et al., 2021), which does not permit hysteresis or changes to L - Q scaling. Although some studies have recognized the potential for disruptions of L - Q dynamics subject to nonstationarity, these previous numerical investigations of L - Q scaling in idealized catchments have not identified significant L - Q hysteresis despite variable weather simulations (Zanetti et al., 2024). Thus, the integrated network effects in real-world catchments remain uncertain, despite growing awareness of climate-mediated disruptions to groundwater and hydrological connectivity (Abhervé et al., 2025).

We test the updated DHSVM model in the 27 km² Sagehen Creek Basin (SCB, California, USA). Prior research on SCB has revealed an extensive GW system that interacts with the underlying volcanic bedrock on multi-decadal timescales (Rademacher et al., 2001, 2005; Blumhagen and Clark, 2008; Manning et al., 2012), though streamflow also responds rapidly to variations in shallow riparian aquifers (Kirchner et al., 2020). SCB has a long legacy of ecohydrological monitoring, including a 16-year record of daily specific electrical conductivity (EC) data at the streamflow gauge location. Stream water EC reflects the accumulation of dissolved ions from mineral weathering processes along upstream GW flowpaths, which makes EC a useful tracer of temporally variable GW contributions from different parts of the landscape (Stieglitz et al., 2003; Brown et al., 2007; Cano-Paoli et al., 2019; Warix et al., 2023). By synthesizing EC observations and physical modeling, we address the following questions:

- To what degree might GW hysteresis modulate spatial patterns of hydrological connectivity and the resulting relationship between L and Q in mountain catchments, and over what time scales is this hysteresis effect significant?
- How could GW mediate the sensitivity of L and Q during a partial snow-rain climate transition, and are static topographic water routing assumptions valid under changing runoff generation mechanisms?

2 Materials and Methods

2.1 Model Development

We substantially overhaul the water routing module of a well-established process-based hydrological model to enable simulation of the GW- L - Q interactions considered in this study. The original version of DHSVM (Wigmosta et al., 1994) assumed a topographic approximation for subsurface routing following the transmissivity parameterization from Beven (1982), and a later update implemented an explicit stream channel routing scheme based on linear storage reservoirs and Manning's equation (Wigmosta and Perkins, 2001). Key changes to the version used for this study include (1) recalculating saturated hydraulic gradients (and hence GW flow directions) based on the spatially distributed dynamic water table at each timestep, (2) permitting lateral subsurface flow in grid cells containing channels, (3) instantiating a bidirectional surface-groundwater coupling based on the dynamic hydraulic gradient between stream water depth and the local water table elevation, (4) recalculating channel hydraulic routing parameters at each timestep, and (5) implementing evaporation routines for flowing and dry channels.

Figure 1 gives an overview of geometrical relationships used to define stream and GW connectivity and the key surface-subsurface fluxes. Figure S1 in the Supplement shows how these relationships compare to the original model.

The core algorithmic implementations of subsurface flow and channel routing remain substantively unchanged, and the relevant equations were originally described by Wigmosta et al. (1994) and Wigmosta and Perkins (2001). However, in some cases these equations have been repurposed to describe additional fluxes. No additional parameters are required by the new version of the model; instead, we simply leverage the existing parameters describing vertical and lateral subsurface heterogeneity within and between grid cells.

2.1.1 Dynamic Flow Directions and Gradients

The original model assigned flow to one or more of four neighbors (rook case), which has been revised to eight neighbors (queen case). The fraction of flow from one grid cell to any of its eight neighbors is proportional to the slope between the water table elevation of each pair of cells, defined

by subtracting the water table depth, $WTD(t)$, from the grid cell digital elevation model (DEM). Flow directions are recalculated each timestep based on the updated water table map. On a given timestep, a particular cell may contribute flow to any number of neighbors between zero and eight depending on which (if any) neighbors have lower water tables. This update replaces the original topographic hydraulic gradient ($\beta_{i,j,k}$ between cells i and j in the k direction, cf. Wigmosta et al., 1994) with the dynamic (time-variable) water table slope, $\beta(t)_{i,j,k}$:

$$GWL(t)_i = DEM_i - WTD(t)_i \quad (1)$$

$$\beta(t)_{i,j,k} = \frac{GWL(t)_j - GWL(t)_i}{DX} \quad (2)$$

GWL represents the ground water level (above sea level), $WTD(t)$ represents the time-varying water table depth (below the surface), DEM represents the model surface elevation, and DX represents the grid cell resolution, following the schematic in Fig. 1. The flow width between cells is distributed radially (i.e., the circumference of an inscribed circle divided among eight neighbors), so the saturated GW flow between cells is given by $q(t)_{i,j,k}$:

$$q(t)_{i,j,k} = T(t)_i \cdot \beta_{i,j,k}(t) \cdot \frac{\pi \cdot DX}{8}, \quad \beta_{i,j,k}(t) < 0$$

$$q(t)_{i,j,k} = 0, \quad \beta_{i,j,k}(t) \geq 0 \quad (3)$$

The transmissivity of each cell, $T(t)_i$, is calculated following the original parameterization for an exponential decrease in transmissivity with increasing WTD (Eq. 48 of Wigmosta et al., 1994), reproduced in Eq. (4) here, taking K_{lat} as the surface lateral saturated hydraulic conductivity and f as an empirical shape parameter controlling the vertical profile:

$$T(t)_{d_0,d_1} = \frac{K_{lat}}{f} \cdot (e^{-f \cdot d_1} - e^{-f \cdot d_0}) \quad (4)$$

Critically, $T(t)$ can be calculated for any vertical section of the soil profile between lower depth d_0 and upper depth d_1 (positive downward from the DEM surface), which makes it trivial to calculate the transmissivity of the appropriate soil column associated with channel-subsurface fluxes or hyporheic outflow from mounded GW at the sub-grid-scale (Sect. 2.1.3). For the transmissivity used to calculate inter-cell GW fluxes in Eq. (3), d_0 is the total “soil” depth, SD (actually the depth to an impermeable layer, potentially including both soil and regolith/fracture zone material), and d_1 is $WTD(t)$.

Flow leaving a cell is negative, so cell i contributes to any and all of its eight neighbors for which $\beta(t)_{i,j,k} < 0$. Just as in the original version of DHSVM (Wigmosta et al., 1994), the change in WTD between timesteps is determined by the net inflow and outflow to each cell and the amount of pore space that must be filled to saturate the soil, i.e., the differ-

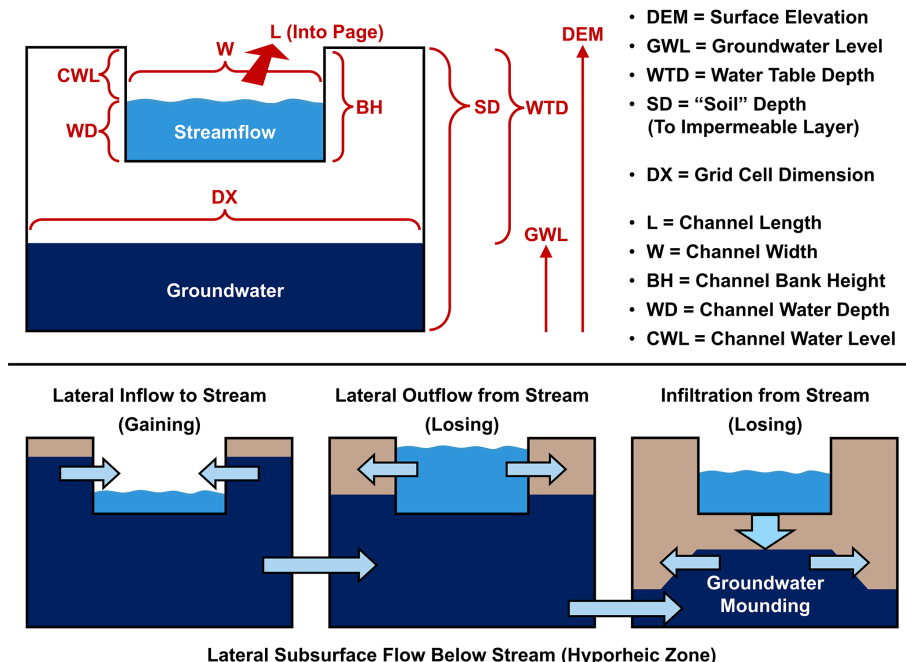


Figure 1. Cross-sectional view of the new dynamic surface-groundwater coupling mechanism in DHSVM. Lateral and vertical exchanges between the channel and groundwater are determined by the hydraulic gradient between the channel water level and the local water table. Channels can switch between gaining or losing water to the subsurface over both time and space.

ence between porosity, ϕ , and the current soil moisture, $\theta(t)$:

$$\text{WTD}(t+1) \cong \text{WTD}(t) + \sum_k q(t)_k \cdot \frac{1}{\phi - \theta(t)} \cdot \frac{1}{\text{DX} \cdot \text{DY}} \cdot \Delta t \quad (5)$$

In Eq. (5), the relationship is only given approximately since the model implementation requires iterative consideration of the depth-variable porosity and soil moisture on a discrete layer-by-layer basis as the water table rises through the soil column. In summary, the dynamic $\text{WTD}(t)$ is a strong control on emergent GW dynamics in the updated version of DHSVM, since it both controls the GW fluxes between cells (Eqs. 1–3) and responds to these same GW fluxes (Eq. 5).

2.1.2 Hyporheic Flow

The original model assumed that the water table never falls below the bottom of the channel in grid cells intersected by the channel network, and cell-to-cell (down-valley) GW was prohibited from leaving cells containing channels by an “if” statement in the subsurface routing code. The updated version permits down-valley hyporheic flow following the same water table-based subsurface routing scheme applied to non-channel grid cells. Unlike dedicated hyporheic models, which explicitly parameterize near-channel subsurface parameters that differ from the surrounding subsurface material (e.g., Ward et al., 2018), we apply the same grid cell average parameters to the hyporheic zone in DHSVM, which im-

proves model parsimony since hyporheic channel fill thickness and conductivity data are sparsely available. Our approach requires no additional parameters (beyond what was previously required to operate DHSVM) and subsumes hyporheic zone heterogeneity within the “effective” parameters of the calibrated model, fitting with the approach to other lumped subsurface parameters in typical distributed model calibration frameworks (e.g., Boardman et al., 2025). However, this simpler approach may contribute to network length overestimation if the real-world hydraulic conductivity of the alluvial channel fill is substantially higher than the effective model grid cell conductivity. Additionally, the model does not account for equilibrium hyporheic exchange that may occur within a single stream reach, i.e., the model only considers the effective net exchange between the subsurface and channel based on differences in water elevation (Sect. 2.1.3).

2.1.3 Surface-Groundwater Coupling

The original model did not permit losing streams, i.e., streamflow could only leave the network at the watershed outlet, and there was no mechanism for channels to infiltrate back into the subsurface. Thus, the original version of the model is not capable of simulating riparian GW recharge or riparian ET subsidies from losing streams. This assumption may be more appropriate for the humid climate of Vancouver Island, where the DHSVM channel routing scheme was developed (Wigmosta and Perkins, 2001), but in more arid climates, not all stream reaches are continually gain-

ing water. In the updated version, channels gain or lose water to the subsurface depending on whether the water level in the channel ($CWL(t)$, analogous to $WTD(t)$) is above or below the grid cell water level. The $CWL(t)$ is calculated each time step based on the storage, $V_c(t)$, (related to $Q(t)$ through a linear reservoir model, Eq. (18) of Wigmosta and Perkins, 2001) and the channel segment length, width, and bank height, BH , which collectively determine the mean water depth, $WD(t)_{\text{mean}}$, in the channel as shown in Sect. 2.1.4:

$$CWL(t) = BH - WD(t)_{\text{mean}} \quad (6)$$

If the $CWL(t)$ is larger than the $WTD(t)$ (lower elevation below the surface), the channel gains water via lateral inflow from GW, and if the $WTD(t)$ is below the $CWL(t)$ but above the channel bottom, the channel loses water via lateral outflow to GW. In both cases, the hydraulic gradient is calculated on each timestep based on the channel geometry (midpoint between channel edge and grid cell edge, with W being the channel width) and the difference in elevation between the $CWL(t)$ and the $WTD(t)$. Transmissivity of the channel bank, $T(t)_c$, is determined by integrating the depth-variable conductivity in each grid cell over the vertical distance between the $CWL(t)$ and the $WTD(t)$ according to Eq. (4). The amount of water flowing into the channel (positive) or out from the channel (negative), $q(t)_c$, is thus calculated as follows, with the channel length multiplied by two representing both sides of the channel:

$$q(t)_c = T(t)_c \cdot (2 \cdot L) \cdot \frac{CWL(t) - WTD(t)}{(DX - W) \cdot \frac{1}{4}} \quad (7)$$

Individual stream reaches may alternately gain or lose GW at different times, as the channel bank hydraulic gradients are recalculated on each time step in response to the current $WTD(t)$ and $CWL(t)$. The predicted net flow between channel and groundwater (Eq. 7) is restricted on each timestep such that the maximum magnitude of $q(t)_c$ can equilibrate (but not reverse) the gradient on any single timestep, reducing spurious numerical oscillations.

If the water table is below the bottom of the geomorphic channel, Q recharges GW through vertical infiltration, determined by the vertical hydraulic conductivity and the gradient between the $CWL(t)$ and the $WTD(t)$. Unlike analogous gradients used in other functions, the infiltration gradient is along a diagonal direction to account for variations in the relative importance of vertical or lateral flow paths from the channel bottom to the rest of the grid cell. As a simple approximation that takes these factors into account, the gradient is proportional to the vertical difference in water elevations divided by the diagonal flow distance. The vertical channel infiltration flux, $q(t)_{cv}$, is thus calculated from the vertical hydraulic conductivity (K_v) of the soil layer in which the channel bottom occurs, the channel width and length, and

the dynamic water elevations introduced previously:

$$q(t)_{cv} = K_v \cdot L \cdot W \cdot \frac{WTD(t) - CWL(t)}{\sqrt{(WTD(t) - CWL(t))^2 + \left(\frac{DX - W}{4}\right)^2}} \quad (8)$$

During routing of the streams and subsurface, the predicted infiltration flux (Eq. 8) is limited during each timestep so that the total flux cannot exceed the amount that would equilibrate the water level immediately below the channel, $WTD(t)_c$, with the stream $CWL(t)$. To reduce the dependence of surface-groundwater coupling dynamics on the (arbitrary) grid scale resolution, the water table directly below the channel, $WTD(t)_c$, can rise above the grid cell mean water table, $WTD(t)$, with lateral conveyance away from the recharge zone calculated using the same approach to lateral hydraulic gradients and transmissivity introduced previously. Specifically, the transmissivity of the sub-channel GW mound, $T(t)_m$, is determined by substituting $WTD(t)$ and $WTD(t)_c$ into Eq. (4), and the decrease in $WTD(t)_c$ due to lateral flow from the mound into the surrounding cell is calculated analogously to Eq. (5). The total change in height of the sub-channel GW mound level, $WTD(t)_c$, is thus the sum of the sub-grid lateral redistribution, which lowers $WTD(t)_c$ towards $WTD(t)$, and the (negative) vertical channel infiltration, $q(t)_{cv}$, which raises $WTD(t)_c$ towards $CWL(t)$. The change in WTD_c between time steps thus depends on the balance between infiltration and lateral conveyance away from the GW mound (immediately below the channel) into the rest of the grid cell. In simpler words, channel infiltration builds up a local GW mound, which dissipates outwards into the grid cell over time.

$$\begin{aligned} WTD_c(t+1) = & WTD_c(t) + [(T(t)_m \cdot (2 \cdot L) \\ & \cdot \frac{WTD(t) - WTD_c(t)}{(DX - W) \cdot \frac{1}{4}}) \\ & - q(t)_{cv}] \cdot \frac{1}{\phi - \theta(t)} \cdot \frac{1}{L \cdot W} \cdot \Delta t \end{aligned} \quad (9)$$

Although this implementation (Eq. 9) is a relatively crude approximation to variably saturated flow in the hyporheic zone below a losing stream reach, this linkage preserves the computational efficiency of DHSVM (i.e., no Richards equation solver, all processes resolved step-wise at the grid scale) while nevertheless permitting the emergence of transient and/or steady-state groundwater mounding at the sub-grid-cell scale and constraining the rate of infiltration (Eq. 8) to a maximum limited by the rate of lateral equilibration within the hyporheic zone (Eq. 9).

2.1.4 Dynamic Stream Routing

The original model assumed static values for the hydraulic radius and slope required by Manning's equation, based on

an arbitrary reference flow (nominally 75 % of bank height in the legacy model version) and the topographic slope, respectively (Wigmosta and Perkins, 2001). In the original DHSVM channel paper, Wigmosta and Perkins (2001) showed a strong sensitivity to the choice of static reference flow and stated that it “must be selected with care”, but in practice, the reference flow is buried in the model source code and seldom (if ever) considered during model application. The updated version of the model used here addresses this hidden sensitivity by replacing the static reference flow with the actual time-varying flow calculated by the model. In the new version, the hydraulic radius, $R_r(t)$, is recalculated each timestep based on the predefined channel geometry and dynamic water depth, which accounts for the way that channels become relatively more rough as water increasingly interacts with the textured channel bed at low flows. The hydraulic radius follows the standard definition, with the mean water depth in the channel, WD_{mean} , calculated from the reach storage, $V(t)$, which is time averaged to smooth unphysical oscillations, and the channel bottom area:

$$WD_{\text{mean}}(t) = \frac{V_c(t) + V_c(t-1)}{2 \cdot L \cdot W} \quad (10)$$

$$R_r(t) = \frac{WD_{\text{mean}}(t) \cdot W}{2 \cdot W D_{\text{mean}}(t) + W} \quad (11)$$

Additionally, the stream surface slope, also used in Manning’s equation, is now calculated on each timestep, which permits the model to develop transient backwater effects. The water depth at the lower end of each reach is assumed to match the water depth at the top of the downstream reach, and the water depth at the top of each reach is calculated from mass conservation assuming a uniform slope within each reach. The difference in channel water depth (WD, Fig. 1) between the top and bottom of each channel reach (length L) thus determines a transient gradient that is added to the channel bed (topographic) slope, S_{topo} , to determine the time-varying water slope, $S_o(t)$, used in Manning’s equation:

$$S_o(t) = S_{\text{topo}} + \frac{WD_{\text{top}}(t) - WD_{\text{bottom}}(t)}{L} \quad (12)$$

Stream water depths and slopes are propagated uphill starting with a uniform depth at the outlet, so that the water depth at the bottom of each reach is equal to the water depth at the top of the next-lower reach, where i indicates the channel routing order starting from one (channel initiation point) and increasing towards the outlet:

$$WD_{\text{bottom}}(t)_i \equiv WD_{\text{top}}(t)_{i+1} \quad (13)$$

The water depth at the top of a reach is determined from the reach storage (Eq. 10) after fixing the bottom water depth:

$$WD_{\text{top}}(t)_i = 2 \cdot WD_{\text{mean}}(t)_i - WD_{\text{bottom}}(t)_i \quad (14)$$

Collectively, these modifications alter the original linear reservoir stream routing (Eqs. 18–19 of Wigmosta and

Perkins, 2001) by introducing time dependencies into several terms, such that the streamflow, $Q(t)$, depends on the current reach storage, $V(t)$, the current hydraulic radius, $R_r(t)$, the current reach water surface slope, $S_o(t)$, the Manning’s roughness coefficient, n , and the reach length, L :

$$Q(t) = V_c(t) \cdot \frac{R_r(t)^{2/3} \cdot \sqrt{S_o(t)}}{n \cdot L} \quad (15)$$

The updated stream routing scheme enables emergent interactions between flow rates and downstream ponding in flatter reaches, which smooths streams over subtle knick-points and permits a more realistic relationship between Q and GW levels throughout the flowing network. In particular, the water depth within the stream (Eq. 10) is particularly important in this updated version of DHSVM, since it directly controls whether the stream is gaining or losing water relative to the grid cell WTD (Eqs. 6–7).

2.1.5 Stream Channel Evaporation

The original model did not parameterize evaporation from stream networks. In the updated version, the existing Penman-Monteith implementation of potential evapotranspiration (PET) is applied to calculate evaporation from flowing stream channels, assuming that open water channel evaporation occurs at the potential rate, with surface area defined by the channel width and reach length:

$$ET_{\text{channel}} = PET \cdot W \cdot L \quad (16)$$

For channels that are dry, soil evaporation is implemented based on the extant soil desorption process in DHSVM. In grid cells with channels, understory fractional coverage is reduced in proportion to the channel surface area, but overstory fractional coverage is unchanged since riparian trees may overhang the channel. Although evaporation from flowing streams is usually a small fraction of the water balance (e.g., 0.4 % of total ET in our SCB simulation), we find that it can nevertheless be an important process that can determine the persistence or drying of very small streams (on the order of 0.001–0.1 L s^{-1}).

2.1.6 Technical Considerations

Several nuances of the actual programmatic implementation are relevant for understanding our L - Q coupling simulations. DHSVM defines stream networks with reaches of arbitrary length, set at 30 m in this study, though most studies use much longer reaches defined only by the network topology (i.e., each tributary is a single reach). Importantly, the stream network topology is independent of the grid scale resolution (10 m in this study); one reach frequently spans multiple cells, and cells at confluences can have two or more reaches. Thus, the many-to-many relationship between streams and cells is nontrivial. These relationships are tracked carefully in the updated model, such that (1) water added to a stream

from the subsurface is only available for recharge or evaporation in cells downhill of where it entered the channel, and (2) all incoming streamflow in a particular channel segment is fully available for recharge or evaporation in grid cells ordered sequentially downstream (i.e., a stream can recharge its entire flow into a single grid cell if that cell has sufficient dry pore space).

DHSVM equations are implemented using an “operator splitting” approach (Clark and Kavetski, 2010), with all processes assumed constant over the (arbitrary) discrete time step, but real hydraulic gradients vary continuously through time. Although this approach may provide a less exact solution for some groundwater configurations compared to a more sophisticated 3D flow solver, the operator splitting approach has the benefit of reduced computational overhead (no iterative convergence-seeking algorithms) and the ability to work with complex sub-grid routing and discrete flow constraints (Sect. 2.1.4) that may not be easily expressible by a single parametric governing equation. However, this approach relies on the assumption that time varying behaviors can be expressed using sufficiently small linearizations (with respect to time steps and grid cells). The updated version of the model only permits GW flow to the extent that would bring water tables into equilibrium within a single time step (i.e., water cannot continue flowing from cell *A* to cell *B* during a single time step if that would raise the water table of cell *B* above cell *A*). This reduces unphysical oscillations caused by the reversal of flow directions as minor water table variations propagate through low-relief areas. Additionally, for grid cells where the change in $WTD(t)$ across a given time step is greater than either the elevation separation ($\Delta DEM_{i,j}$) and/or the water table separation ($\Delta GWL_{i,j}$) from its down-gradient neighbors, the respective hydraulic gradients are averaged between the current and previous time steps on the basis that the hydraulic gradient changes continuously over time, not instantaneously. An analogous approach is applied to the channel water level. This implies that the average flow rate within a single time step is equal to a linearized approximation of the continuously time-varying flow rate between the beginning and end of the time step. Note that the time-averaging of hydraulic gradients is only applied in areas with very low gradients at times in which the water table is changing rapidly; under other conditions, the instantaneous water table is assumed to be a reasonable approximation over whole time steps. This approach is congruent with a similar strategy applied to vertical unsaturated flow in the original version of DHSVM (Eq. 42 of Wigmosta et al., 1994).

A video animation of simulated GW flow in SCB (Supplement) shows remarkably complex patterns of GW activation that intuitively match expectations for the way that water would flow over complex topography. Repeated visualization and manual tracking of water through the model helped identify many of the complex nuances addressed above. We suggest that animated visualizations are underutilized to help elucidate whether complex models are (or are not) match-

ing intuition for the way that water does (or does not) move. Additionally, this visualization provides insight into how antecedent conditions create emergent streamflow generation patterns, but of course we do not expect the animation to match the actual spatial locations of GW flowpaths due to uncertain subsurface heterogeneity.

2.2 Model Application

We apply the updated version of DHSVM to simulate L - Q dynamics in SCB. The model is discretized at 10 m horizontal resolution, with stream segments of 30 m maximum length, and at a 3 h time step. Some stream segments are shorter (near confluences or initiation points) since natural stream lengths are not evenly divisible by 30 m. Initiation points of the geomorphic channel network are determined from the National Hydrography Database (NHD, U.S. Geological Survey, 2019). Compared to the standard DHSVM setup approach, which initiates channels based on a minimum upslope contributing area, the NHD-based approach better represents the heterogeneity of channel density: for example, the western edge of the basin has a denser channel network compared to the northern edge (Fig. S2). Prior studies indicate that map-based stream databases tend to underestimate stream network extent (e.g., Fritz et al., 2013; Lapides et al., 2021). However, in our specific SCB study watershed, the NHD-based network is much more extensive than the largest observed flowing network (compare Fig. 1 of Godsey and Kirchner, 2014 with Fig. S2), though some of the channels and confluence locations are imprecise. For the sake of greater generality, we do not manually refine the SCB stream network, preferring instead to test the ability of existing datasets (i.e., NHD) to reproduce key aspects of stream network elasticity in DHSVM in order to build towards large-domain modeling. Reach-scale transmissivity variations are uncertain regardless, so we prefer to treat the simulated streams as representative counterparts of the actual network without expecting a 1 : 1 correspondence between individual modeled and measured stream reaches. The watershed modeling domain is extended approximately 2 km below the stream gauge (USGS site 10343500) to reduce the effect of unknown boundary conditions on the partitioning of down-valley flow between Q and GW at the calibration point (Fig. S2).

The rectangular geometry of each channel reach (depth and width) is estimated from regional power law regressions related to contributing area developed by Bieger et al. (2015). We refine the estimation of channel width by adjusting the parameters to more closely match stream widths measured at 17 locations across five representative reaches in Google Earth, which span a per-reach mean range of 0.8 to 3.4 m (contributing area 1 to 31 km²). The refined equation relates channel width to contributing area with a power law scale of 0.85 and exponent of 0.41, which achieves $R^2 = 0.98$ across the five representative stream reaches. Channel depths pre-

dicted by the Bieger et al. (2015) data generally match with our expectations from field experience in SCB, e.g., 0.2–0.5 m bank cut height. We constrain the channel depth and width to minimums of 0.1 and 0.25 m, respectively, roughly congruent with field observations. Note that we do not consider small soil rills as part of the geomorphic channel network. Channel roughness (Manning's N coefficient) is estimated from a regression equation compiled by Limerinos (1970) and a d84 particle size of 0.25 m, roughly representative of small mountain streams in the study region. Manual sensitivity tests with DHSVM in varied settings have indicated minimal sensitivity to channel roughness on the daily streamflow. Although the channel geometry is undoubtedly a source of uncertainty in our analysis, we emphasize that the dynamic water table gradients are adaptable to over- or under-estimation of the channel geometrical proportions, since the water table will dynamically rise to the level necessary to interact appropriately with the stream, which is constrained by calibration at the outlet gauge, network field surveys, and geochemical timeseries.

Considerable spatial information (e.g., Fig. S2) and other parameters are required to operate DHSVM. Baseline parameters are estimated from prior literature reviews, as documented in Boardman et al. (2025). Land surface cover, vegetation type, and fractional cover are estimated from NLCD, LANDFIRE, and RCMAP, respectively (Dewitz and U.S. Geological Survey, 2019; LANDFIRE, 2022; Rigge et al., 2021). Subsurface heterogeneity is represented by disaggregating regional soil survey data from SSURGO (Soil Survey Staff, 2022) and water retention data (Gupta et al., 2022) based on topographic metrics using Random Forest (Breiman et al., 2002). The relative pattern of bedrock depth is estimated by combining disaggregated SSURGO data with a curvature-based approach (Patton et al., 2018), and up to 20 m of sediment fill is added in low-gradient areas following the approach of Essaid and Hill (2014) in SCB. We emphasize that maps of subsurface properties are not expected to match actual spatial heterogeneity, but as in the case of the imperfect channel network, introducing a representative degree of spatial variability (inferred from regional databases) should help increase the physical realism of our simulations even if the spatial patterning is inexact. Daily gridMET meteorological data (Abatzoglou, 2013) are disaggregated to the 3 h model timestep using the MetSim preprocessing routine (Bennett et al., 2020).

Key model parameters with high uncertainty are refined via calibration in a multi-objective Bayesian optimization framework (Jones et al., 1998; Boardman et al., 2025). The calibration period is water years 2015–2024, and the validation period is 2001–2014 (overlapping the available EC measurements from 2001–2016). A five-year spin-up period is used to control for unknown initial conditions. A total of 14 parameters are calibrated simultaneously, including additive or multiplicative adjustment factors applied to bias-correct the gridded temperature and precipitation data, respectively

(Boardman et al., 2025). The following parameters are determined by spatially variable maps calibrated relative to a mean value: soil depth, hydraulic conductivity, the exponential decrease in conductivity with depth, porosity, field capacity, overstory leaf area index, and overstory fractional cover. The following parameters are calibrated based on look-up tables: minimum stomatal resistance (variable across vegetation types, calibrated relative to mean), the maximum air temperature for snowfall, the accumulation- and melt-season snow albedo decay rates, and the threshold to increase albedo with new snow. Calibration is implemented using six objective functions: daily Nash-Sutcliffe Efficiency (NSE), daily log-scale NSE, mean absolute yearly percent error, mean absolute percent error between April and July (snowmelt season), root mean square error in > 95th-percentile high flows, and mean absolute yearly peak flow percent error. Due to parameter interactions that reduce the effective dimensionality of the parameter space and a highly efficient sampling algorithm that rapidly improves the Pareto frontier using surrogate model optimization procedures, we can calibrate DHSVM using many fewer optimization runs than might be expected given the dimensionality of the search space (cf. correlograms in the Supplement to Boardman et al., 2025). Additionally, we accelerate the calibration through pre-calibration at coarser resolutions of 30 and 90 m (Sun et al., 2020). Among 760 total tested models (360 tested at 10 m resolution), we select 30 calibrated models with diverse parameter values that all achieve < 20 % mean absolute error for the annual water yield. Although all six objective functions are used during calibration, we include several models with sub-optimal streamflow NSE and log-scale NSE (relative to the best values achieved by the model, i.e., 0.87 for both) in this 30-member ensemble to ensure sufficient parameter diversity to appropriately evaluate the sensitivity of L - Q scaling dynamics within the model (Figs. S4 and S5).

To refine our final model selection, we evaluate the seasonality of a potential hysteresis signal (network length anomaly) that will be introduced in more detail subsequently (Sect. 3.2). We simulate daily L - Q scaling dynamics for 30 parameter subsets and compare the simulated power law network length anomaly (L_A) with measured anomalies in electrical conductivity (EC_A). Only a few parameter sets achieve both satisfactory NSE and reasonably high seasonal L_A - EC_A correlation, indicating skill at simulating both surface streamflow variability and GW flowpath variability. We select the model with the highest seasonal L_A - EC_A correlation since the L_A anomaly is our primary focus in this study. The selected parameter set has several other desirable characteristics compared to other tested parameters, including reasonably high NSE and log-scale NSE on both calibration and validation periods (calibration: 0.78, 0.82 log, validation: 0.61, 0.76 log, overall: 0.71, 0.79 log). Additionally, the selected parameter set has a relatively small median network size that is closer to field-surveyed L compared to other tested parameter sets (Fig. S5). Although it would

theoretically be possible to directly calibrate the L_A - EC_A correlation, each L_A evaluation generates approximately 2 GB of data, making it computationally intensive to evaluate L_A - EC_A for more than a handful of parameter sets. Our prior work with DHSVM has also suggested that it may be preferable to not directly calibrate metrics related to the research questions (i.e., L_A - EC_A correlation) to avoid overfitting (Boardman et al., 2025).

The relationship between parameter uncertainty and L - Q scaling is illustrated in Figs. S4–S5. In general, higher transmissivity is associated with smaller, more dynamic networks. Most of the acceptable parameter sets (total NSE and log NSE > 0.7) produce L - Q power law exponents (β) within the range of uncertainty from field surveys (Godsey and Kirchner, 2014). Only three tested parameter sets have acceptable NSE and an L_A - EC_A correlation stronger than -0.8 . Of these, the selected parameter set is closest to the field-measured β with the smallest median length (closest to field surveys). Thus, we use this parameter set for our primary L - Q simulations.

We evaluate L - Q dynamics by saving maps of Q for each of 2382 unique stream reaches within SCB at noon on every day between 1 October 2000 and 30 September 2024 (8766 d). This results in a total of 2×10^7 datapoints (number of reaches times number of days) describing the spatiotemporal evolution of the flowing stream network. In contrast to the four datapoints available in the same catchment from field surveys, we hypothesize that the massive scale of data generated by process-based models may provide different insights from rare field surveys. Additionally, our process-based modeling approach is conducive to exploring nonstationarity (Milly et al., 2008, 2015). In this study, we implement a simple uniform-warming experiment ($+4^\circ\text{C}$) to explore the potential sensitivity of L - Q dynamics to an increased fraction of precipitation falling as rain, but this should not be interpreted as a realistic future climate “scenario.”

2.3 Statistical Analysis

All significance values are calculated using the one sample two-sided t -test, or the Pearson’s product-moment correlation test, implemented in the R statistical programming language.

We define the outlet streamflow, Q , as the daily modeled flow rate in units of specific discharge (area normalized). We define the flowing network length, L , as the sum of lengths of all upstream reaches with non-zero simulated outflow. We also test an alternate definition of L using a minimum flow threshold of 0.01 L s^{-1} to define “flowing” reaches. This alternate definition provides a nearly identical timeseries of L ($r = 0.9997$). For simplicity, we adopt the simple non-zero streamflow definition (arbitrarily low streamflow still counts as “flowing”) for the remainder of this study.

The crux of our study is a comparison between DHSVM-simulated L and a power law function, $L_P(Q)$, defined as follows:

$$L_P = \alpha Q^\beta \quad (17)$$

We estimate α and β through least-squares regression of L and Q in log-log space, where Eq. (17) is linear. We only consider L - Q pairs with $Q < 2 \text{ mm d}^{-1}$ to control for the asymptotic behavior of L at high Q , as L approaches the maximum geomorphic network extent (subsequently illustrated in Fig. 4). In our study, the best-fit values are $\alpha = 45.54$, $\beta = 0.2705$. Although we acknowledge that the power law formulation is arbitrary, it is widely used by prior research (e.g., Godsey and Kirchner, 2014; Prancevic et al., 2025) as the default scaling assumption. Moreover, our analysis merely treats the power law as a reference approximation against which the time-varying anomaly is calculated, so our conclusions should be robust to other formulations of a bijective L - Q scaling law (Durighetto et al., 2025).

The residual between L (simulated by DHSVM) and L_P (power law prediction from the same DHSVM-simulated Q) defines the network anomaly, L_A :

$$L_A = L - L_P \quad (18)$$

We calculate the autocorrelation of L and L_P to evaluate the degree of hysteresis that is not explained by a bijective relationship between L and Q (Fig. S10). The sample autocorrelation $R_L(k)$ of the discrete $L(t)$ timeseries at a lag k (in days) is estimated as follows (Venables and Ripley, 2002), where n is the number of samples in L , σ^2 is the sample variance, and μ is the sample mean:

$$R_L(k) = \frac{1}{(n-1)\sigma^2} \sum_{t=1}^{n-k} (L(t) - \mu)(L(t+k) - \mu) \quad (19)$$

The “hysteresis effect” is defined as the difference in DHSVM-simulated autocorrelation relative to the power law autocorrelation (R_{LP}), defined analogously to R_L by replacing $L(t)$ with $L_P(t)$. The network length hysteresis effect, HE_L , is thus:

$$HE_L(k) = R_L(k) - R_{LP}(k) \quad (20)$$

Defining the hysteresis effect this way provides a metric with an easily interpretable range of values (same scale as $[0, 1]$ range of autocorrelation) that can directly quantify hysteresis at various discrete time lags.

We calculate R_L , R_{LP} , and HE_L at lags of $k = 0$ to 180 for the entire 24-year timeseries as well as separately within 24 “block bootstrap” subsets defined by each water year (1 October through 30 September), extended backwards and forwards 90 d to reduce the impact of the arbitrary start date for longer values of k . Thus, each of the 24 block bootstrap samples overlap a total of 180 d, with the exception of the

first and last water years, which only overlap 90 d in one direction. We use these 24 estimates of HE_L to evaluate the statistical significance of HE_L at different lags using a one sample two-sided t -test.

Analogously to Eqs. (17)–(20), we use measured EC data to calculate a best-fit power law (EC_P), anomaly (EC_A), autocorrelation (R_{EC}), power law autocorrelation (R_{ECP}), and hysteresis effect (HE_{EC}). For EC, we only consider block bootstrap periods with no more than 25 % missing data, which yields 15 usable bootstrap periods.

To relate variations in HE_L and HE_{EC} to variations in snow and rain partitioning, we aggregate DHSVM-simulated watershed-average snowfall and precipitation within each of the same block bootstrap periods. The snow fraction is defined as the fraction of watershed-average precipitation falling as snow. Finally, we apply the Pearson's product-moment correlation test to estimate the correlation between the snow fraction and either HE_L or HE_{EC} at lags of 10, 20, and 30 d.

3 Results

3.1 Flowing Stream Network Dynamics

Simulated flowing stream networks expand, contract, and disconnect in response to variable wetness in SCB (Fig. 2). The model reproduces observed daily, seasonal, and inter-annual variations in Q across the 24-year simulation period, with a Nash-Sutcliffe Efficiency (NSE) of 0.79 for log-transformed daily Q . Importantly, the model also reproduces the network elasticity observed by field surveys (Godsey and Kirchner, 2014), with a model estimate of $\beta = 0.27$ and a field estimate of $\beta = 0.31 \pm 0.09$. There is considerable uncertainty in field-based validation of the absolute network length due to model variability in L at constant Q , but the model likely overestimates L due to a combination of network digitization artifacts and uncertain transmissivity in the hyporheic zone (i.e., channel fill, which is not explicitly parameterized: Sect. 2.1.2). To maintain simplicity in our definition of a “flowing stream,” we calculate L wherever Q is nonzero (cf. sensitivity test in Sect. 2.3), which makes L sensitive to small Q that might not be detected in the field (Sarah Godsey, personal communication, October 2025). The survey dates from Godsey and Kirchner (2014) are only reported to the nearest month, and personal communication with the first author of that study (Sarah Godsey, December 2024) indicates that the channel network survey data have likely not been preserved outside of the figures from that study, rendering an exact comparison impossible. Furthermore, the absolute stream network length is ill-defined because stream networks have a fractal dimension greater than one (Mandelbrot, 1982; La Barbera and Rosso, 1989), so network length depends on the resolution of measurement. In our study, the 3 m DHSVM grid cells may provide a smaller “measuring

stick” than the (unspecified) resolution used to measure channels by Godsey and Kirchner (2014), perhaps contributing to the discrepancy in absolute channel length. Regardless, for our sensitivity analysis of stream network elasticity, the absolute magnitude of L (power law scale) is less important than β (power law exponent), which matches field observations. Indeed, Godsey and Kirchner (2014) only report the best-fit power law exponent and do not report the best-fit power law scale, supporting our contention that the power law scale is relatively unimportant for overall hydrological understanding. Our model simulations predict frequent stream disconnection, i.e., dry channel gaps that interrupt the flowing network (Fig. 2), which is also in qualitative agreement with the mapped network behavior (Godsey and Kirchner, 2014), although exact disconnection locations are imprecise due to uncertain fine-scale heterogeneity. In our simulations, flowing channel disconnection occurs when the subsurface transmissivity exceeds the total down-valley flow, and channels re-activate on the surface when the total flow exceeds the subsurface capacity, which is consistent with the conceptual models of Godsey and Kirchner (2014) and Ward et al. (2018).

In our simulations, higher-order stream reaches (downstream of confluences) are more stable over time, but the relationship between topography and L - Q scaling is nuanced. Streamflow persistence, defined as the fraction of time that a given reach is flowing, generally increases at larger Strahler order (Strahler, 1957), as seen in Fig. S6 and similarly reported by Mahoney et al. (2023). Nevertheless, some first-order streams are perennial (persistence = 100 %), and some third-order streams have persistence as low as 36 % (Fig. S6). (In this context, we consider a static Strahler order based on the geomorphic channel network, not the flowing network.) Further, there is only a loose relationship between simulated stream persistence and the topographic wetness index (Fig. S7), challenging prevailing contributing area assumptions (Prancevic and Kirchner, 2019; Ward et al., 2018; Mahoney et al., 2023). In an alternate configuration of DHSVM with static hydraulic gradients defined by the surface topography (kinematic assumption as opposed to fully dynamic grid cell water table gradients), streamflow persistence is overestimated by a mean of 11 % ($p < 0.01$) and watershed-average warm-season (July–October) evapotranspiration (ET) is underestimated ($p < 0.01$) by a mean of 8 % overall and up to 25 % on some days (Fig. S8). Topography-based routing schemes fail to account for the dispersion of GW recharge from streams into adjacent riparian corridors and broad valley bottoms, which subsidizes root-zone soil water (Tague and Peng, 2013; Graup et al., 2022). Prevailing models used for prior L - Q analyses assume static topographic hydraulic gradients and flow directions (Gao et al., 2021; Mahoney et al., 2023), but our sensitivity analysis indicates that time-varying gradients and flow directions are more appropriate for L - Q analysis in the groundwater-driven SCB study watershed.

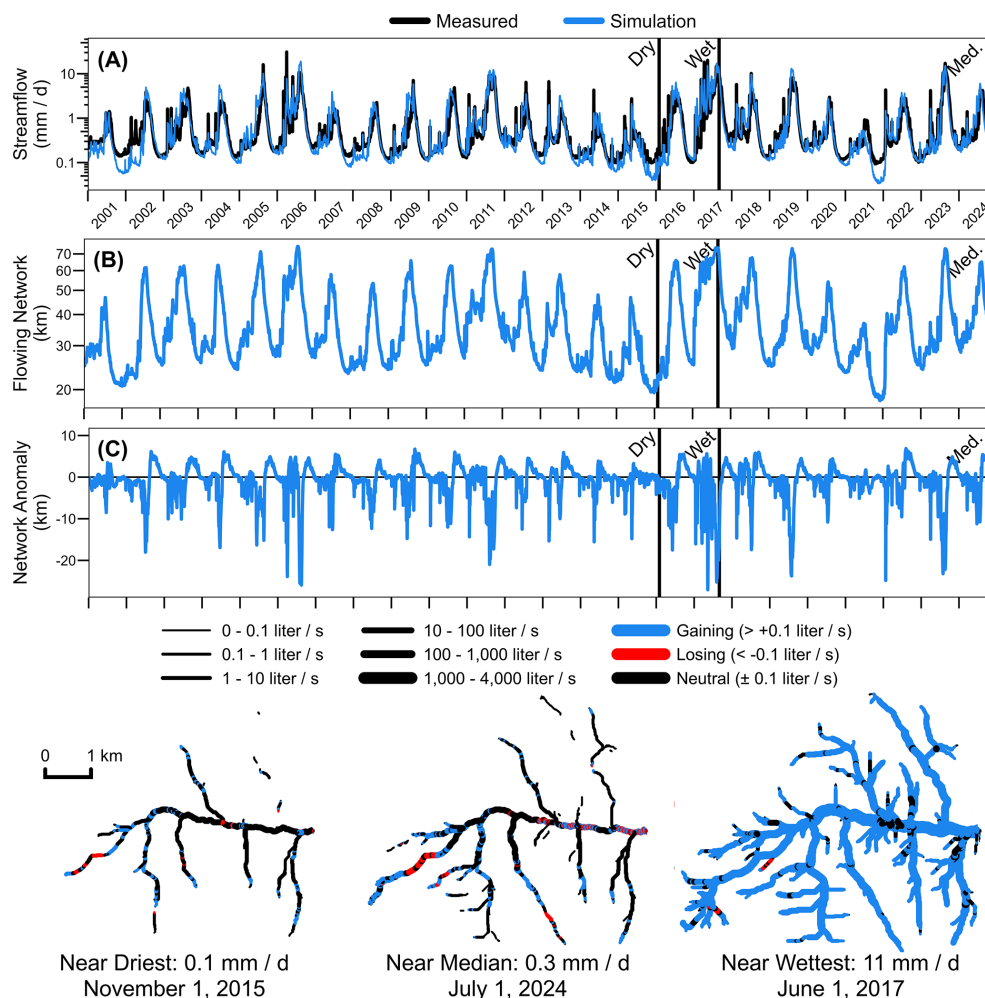


Figure 2. Daily timeseries over the 24-year study period: (A) measured and modeled streamflow, Q , (B) modeled flowing stream network length, L , and (C) modeled anomaly in L relative to a power law scaling assumption. Example maps of the modeled flowing network show the spatial arrangement and variable Q (line width) of flowing stream reaches at 1st, 50th, and 99th-percentile flows. Stream reaches that are gaining Q from GW are illustrated in blue, reaches that are recharging Q back to GW (losing) are illustrated in red, and reaches with an approximately neutral balance of inflows and outflows are illustrated in black.

Lateral redistribution and convergence of GW into higher-order valley bottoms on seasonal timescales partially decouples the fractional contribution of different Strahler orders from the magnitude of outlet Q in our simulations (Figs. 3 and S9). Longer subsurface flowpaths in third-order valleys contribute a larger fraction of network-total lateral inflow (24 %–55 %) in the late recession season (August–September) compared to the April–May snowmelt season (12 %–37 %), when the shorter and faster hillslope flowpaths connected to first-order streams are more dominant. In our DHSVM simulations, GW recharge rarely exceeds 1 % from fourth-order stream reaches (in contrast to smaller tributaries, where recharge is substantial), indicating that most higher-order valley bottom segments are consistently gaining water from the riparian aquifer (Fig. 3). This model prediction (which was not considered during model selection) is sup-

ported by observations of riparian water table levels from wells in the fourth-order SCB valley bottom (Kirchner et al., 2020), which likewise indicate that two particular locations along the fourth-order section of Sagehen Creek are consistently gaining water. In our simulations, most GW recharge is concentrated at the second and third Strahler orders of the geomorphic network, and there is only negligible recharge from the fourth-order reaches where the Kirchner et al. (2020) wells are located (Figs. 3 and S9).

3.2 Flowing Network Length Anomalies

Simulated L - Q scaling dynamics broadly reproduce the postulated proportional scaling relationship within the low- to medium-flow range, albeit with substantial scatter (Fig. 4). We determine the best-fit power law function, $L_P(Q)$, using only days with simulated $Q < 2 \text{ mm d}^{-1}$, because the notion

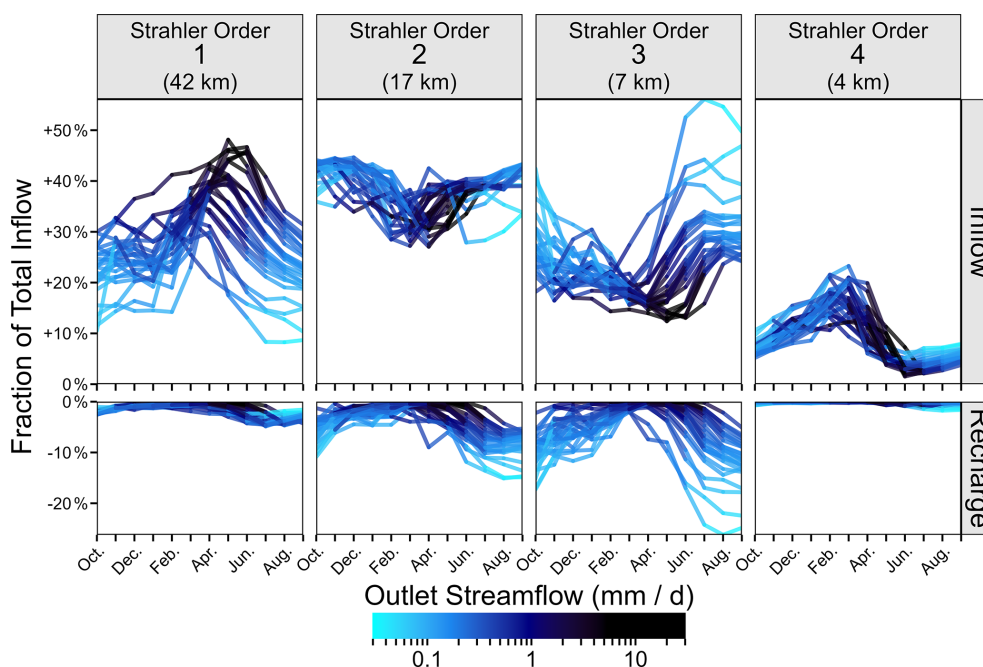


Figure 3. Seasonal variation in the inflow and groundwater recharge from stream reaches organized according to Strahler order (Fig. S6). Each line represents a single water year, and all values are aggregated to the monthly median. Lines are colored according to the log-scaled outlet streamflow, and the vertical axes are scaled in proportion to the total network inflow. First-order streams contribute relatively more inflow during the snowmelt period, and third-order streams contribute disproportionately in the late summer. Most recharge from streams to groundwater occurs in second- and third-order streams. Relative seasonal network dynamics are partially decoupled from the absolute magnitude of outlet streamflow.

of “flowing stream network” becomes ambiguous when surface flow exceeds the geomorphic channel network (imposed in DHSVM, Fig. S4). This approach is consistent with other modeling studies that have used an upper threshold on Q to define the relevant power law scaling range for channelized flow (Gao et al., 2021; Mahoney et al., 2023), and field surveys in SCB suggest that the power law holds at least as high as 1.76 mm d^{-1} (Godsey and Kirchner, 2014). The fitted power law has $R^2 = 0.91$ (below 2 mm d^{-1}), similar to the range of high R^2 values reported in field studies, e.g., 0.82–0.99 (Jensen et al., 2017). Nevertheless, this high R^2 hides a systematic structure in the power law residuals, $L - L_P$, hereafter called the “network anomaly” or L_A (Fig. 2C). Similar scatter in the L - Q relationship has been predicted by prior modeling studies (Gao et al., 2021; Mahoney et al., 2023), though it is unclear whether the scatter arises for the same or different reasons in those other modeling frameworks, and these prior authors do not investigate or comment on the source of the scatter.

Anomalous large stream networks for a given Q (positive L_A) are associated with a decreasing antecedent streamflow trend (recession period), whereas anomalously small networks for a given Q (negative L_A) are associated with an increasing or neutral antecedent streamflow trend. To explore this anomaly (on days with $Q < 2 \text{ mm d}^{-1}$), we apply the Mann-Kendall trend test (Mann, 1945; Kendall,

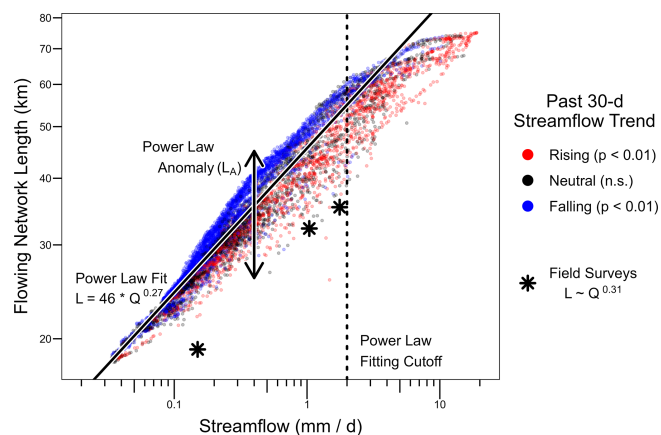


Figure 4. Logarithmically scaled scatterplot between simulated daily streamflow (Q) and flowing stream network length (L). Each point represents one day over water years 2001–2024. Red (blue) colors indicate a rising (falling) streamflow trend over the 30 d prior to each point (Mann-Kendall test). Three field surveys are shown, and a fourth survey falls below the lower vertical axis limit ($Q = 0.24 \text{ mm d}^{-1}$, $L = 15.4 \text{ km}$), which Godsey and Kirchner (2014) identify as a potential outlier because of practical difficulties in following the entire network on the first field survey.

1975) over the prior 30 d of Q with a significance threshold of $p < 0.01$ to determine the antecedent streamflow trend (Fig. 4). Days with antecedent Q trends that are not significant (n.s.) are considered neutral. As seen in Fig. 4, days with a rising streamflow trend have anomalously small flowing networks (mean $L_A = -7.8\%$, $p < 0.001$), and the opposite is true during a falling streamflow trend (mean $L_A = +3.5\%$, $p < 0.001$). Neutral streamflow trends are associated with anomalously small networks (mean $L_A = -3.0\%$, $p < 0.001$) because recession periods are relatively prolonged compared to periods of rising Q , which biases the power law to underestimate L during neutral flow periods in the least-squares fit. Essentially identical results are also obtained from calculating the streamflow trend using the Sen's slope of Q (Sen, 1968) categorized as increasing, decreasing, or neutral depending on whether the trend has a magnitude of at least $1\% \text{ d}^{-1}$ relative to the current day's Q .

By comparing the simulated network on specific days, we illustrate how (1) similar networks could produce widely varying Q , and (2) different network configurations with variable L could produce similar Q (Fig. 5). In the early recession season after seasonal snowmelt (June of 2013 and 2018), the simulated flowing network is anomalously large relative to the power law prediction, i.e., $L_A > 0$. In the late recession season (December), when antecedent conditions are relatively dry, rainfall-runoff events can elevate streamflow with only small increases in the flowing network. The 150% increase in Q between 11 June 2013, and 18 December 2023, would be associated with a 28% increase in L based on the best-fit L - Q power law, but our simulation shows a decrease of 0.4% instead since the two dates have different spatial water table configurations. In another example, an extra 10 km (+33%) of streams are flowing on 12 June 2018, compared to 18 December 2023, despite near-identical outlet Q on both days. Streamflow originating from high-elevation snowmelt in a relatively small first-order reach may propagate down channels that would otherwise be dry, losing Q back to GW over lengths in excess of 0.5 km (Fig. 5) before reaching a downstream confluence. Thus, wetting of outlying first-order reaches can have a disproportionate impact on the overall network extent without affecting outlet streamflow. This behavior is still fundamentally tied to GW hysteresis, because the activation of distal streams is caused by the transient shallowing of the water table as nonequilibrium groundwater flow gradually converges into higher-order valley bottoms. In other words, if groundwater instantaneously equilibrated across the catchment, the most distal headwaters streams would not flow.

However, seasonal L - Q scaling anomalies are important for larger streams as well, not just trickling rivulets. Considering the additional flowing stream reaches on 12 June 2018, that are dry during the storm event on 18 December 2023, these “extra” streams span a wide range of flow magnitudes, from near zero ($< 0.01 \text{ L s}^{-1}$) to as much as 39 L s^{-1} (22% of outlet Q on both dates). This large relative contri-

bution from different streams at different times indicates that the same downstream Q can derive from substantially different parts of the landscape depending on antecedent wetness and the resulting transient spatial GW configuration. In other words, the scaling anomaly is also predicted to manifest in sizable streams.

3.3 Chemical Signature of Groundwater Hysteresis

Stream electrical conductivity (EC) data provide observational evidence supporting a GW hysteresis behavior in the study catchment, and these observations further support the seasonality of our DHSVM predictions. Measured daily EC at the SCB stream gauge generally correlates inversely with Q (more dilute concentrations of total dissolved ions at higher discharge), interpreted as an increased contribution from newer water (shorter subsurface residence time) during high flows. A power law fit between measured EC and Q gives a similarly high R^2 of 0.94 (Fig. S3), and the power law residuals (EC_A) exhibit a similar pattern to L_A . Days with a rising Q trend have anomalously high EC (mean $EC_A = +2.9\%$, $p < 0.001$), and days with a falling Q trend have anomalously low EC (mean $EC_A = -2.3\%$, $p < 0.001$). Anomalously high EC indicates an outsized contribution from longer subsurface flowpaths (older, more chemically evolved GW) during the rising hydrograph limb, consistent with the model prediction of anomalously small L under similar conditions.

Measured EC and simulated GW both show seasonal hysteresis loops with Q , which largely matches the seasonal pattern of L_A (Fig. 6). The modeled area-average catchment water table depth (WTD) is relatively deep (less GW storage) on the rising limb of the seasonal hydrograph (increasing Q), and relatively shallow (more GW storage) on the falling limb of the hydrograph (decreasing Q). Similar smaller loops are superimposed from individual rainfall or snowmelt runoff events. Again, measured EC shows a similar hysteretic relationship with Q , supporting the model results.

Measured EC_A mirrors simulated L_A , especially after aggregating the data over longer time periods to reduce the effect of uncertain model forcing and other sources of noise (Fig. 7). Across the 2001–2016 period of continuous EC monitoring, there are 4750 d with available EC data and $Q < 2 \text{ mm d}^{-1}$. Across this daily dataset, lower measured EC is strongly correlated with longer modeled L ($r = -0.87$, $p < 0.01$), but this correlation primarily reflects the mutual relationship with Q . After decorrelating L and EC from Q by subtracting the best-fit power law, EC_A and L_A are still significantly correlated, albeit more weakly ($r = -0.38$, $p < 0.01$). On daily timescales, other geochemical processes, random noise, and errors in the DHSVM forcing data would be expected to dilute the underlying GW hysteresis effect, potentially explaining this relatively weak daily correlation. Aggregating both EC_A and L_A to the monthly median using only days with available EC data (176 months with at least

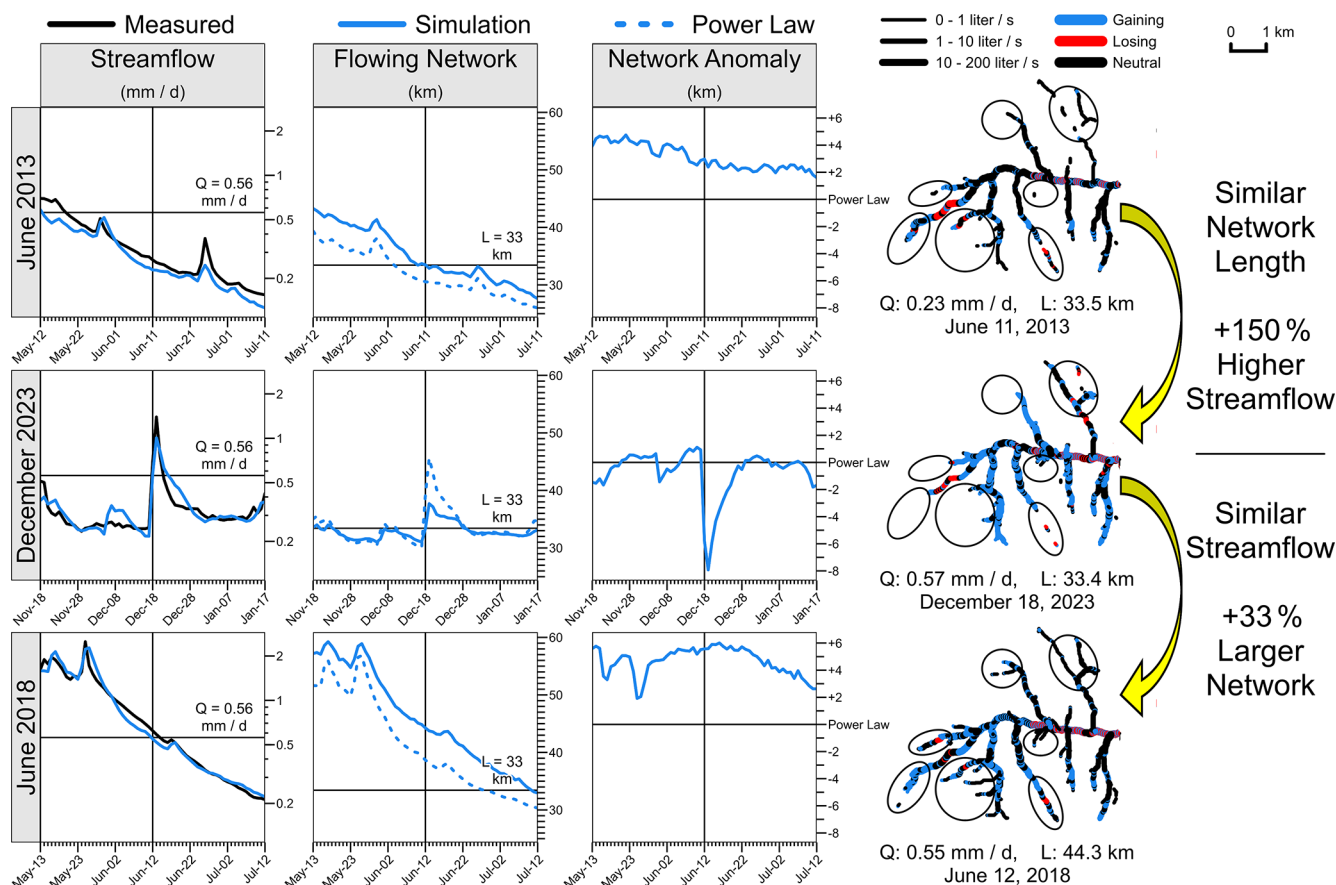


Figure 5. Examples of different streamflow magnitudes associated with the same flowing network size (June 2013–December 2023) and different network sizes associated with equivalent streamflow (December 2023–June 2018). Circled regions highlight parts of the flowing network that are particularly variable across these examples.

2 d of data) produces a stronger correlation of $r = -0.47$ ($p < 0.01$). Still, each year may have unknown and variable meteorological forcing biases that propagate into simulated GW, Q , and L , diluting the EC- L correlation. To further control for noise in the EC- L correlation, we also consider the overall seasonality of scaling anomalies in both EC and L by calculating the median for each month across all available years (Fig. 7). In this case, the seasonal pattern of EC closely mirrors L ($r = -0.95$, $p < 0.01$) and EC_A closely mirrors L_A ($r = -0.92$, $p < 0.01$). However, it is important to note that the monthly median L_A - EC_A correlation is considered as part of our model selection procedure (Sect. 2.2 and Fig. S4), so it is not independent evidence of the model's predictive skill. Nevertheless, the strong match between modeled network dynamics and measured stream chemistry supports our process-based GW hysteresis interpretation, and selecting the model that best matches observations (Fig. S4) increases the realism of our analysis.

3.3.1 Sensitivity to Snow-Rain Transition

In a warming climate, a partial snow-rain transition alters the spatiotemporal organization of liquid water inputs to the catchment, and simulating the cascading hydrological effects of this change (without untested assumptions of stationarity) requires a spatially distributed physical model such as DHSVM. We compare simulations of flowing stream network dynamics in the historical climate (Abatzoglou, 2013) with a uniform $+4^\circ\text{C}$ warming scenario applied to the same baseline climatology (2001–2024) to investigate the potential effects of a partial precipitation phase change. The $+4^\circ\text{C}$ increase is within the plausible range of cold-season anthropogenic warming in the SCB region (Null et al., 2010; Huang et al., 2018; Sun et al., 2019), but does not account for potential changes in other aspects of climate (e.g., precipitation timing and magnitude) or nuanced spatiotemporal controls on climate trends (Lundquist and Cayan, 2007). Thus, the warming scenario implemented here should not be understood as a prediction of actual future climate sensitivity. Instead, we are concerned with the broad sensitivity of L - Q scaling assumptions to a transition from snow to rain, which

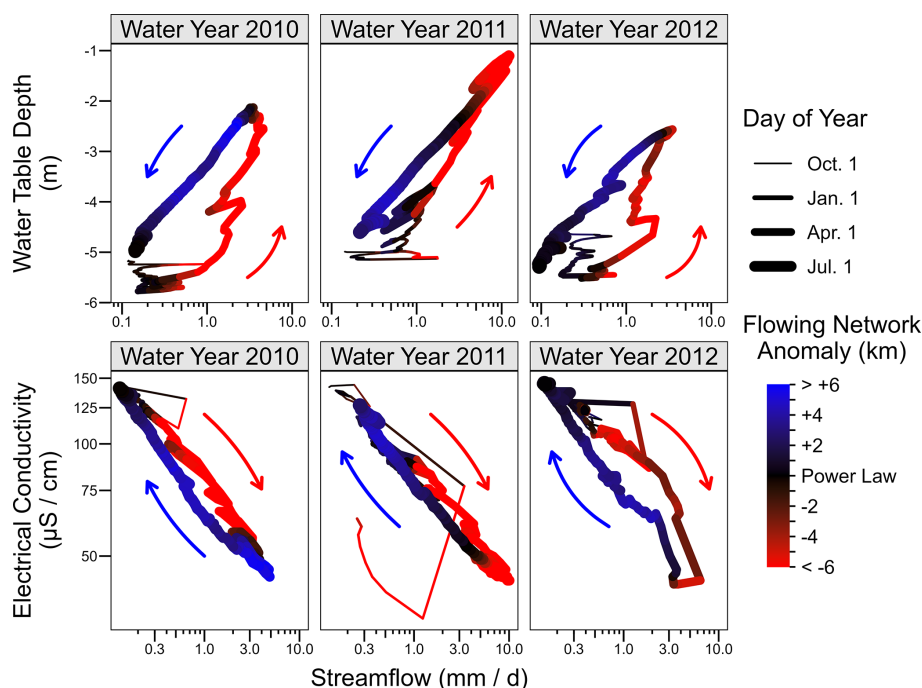


Figure 6. Hysteresis relationships in three example years, showing (top panels) simulated water table depth and simulated streamflow, (bottom panels) measured stream electrical conductivity, reflecting total dissolved ion content (correlated to groundwater age, Rademacher et al., 2001), and measured streamflow. Each line traces a path beginning on 1 October of a given water year, and line width is scaled proportionally to the day of year. Color indicates whether the simulated flowing stream network is larger (blue) or smaller (red) than predicted by a power law relationship with streamflow on a given day.

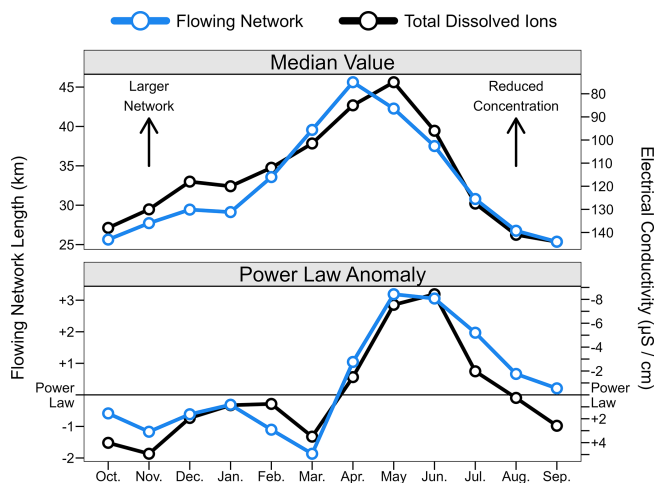


Figure 7. Comparison of monthly median simulated stream network dynamics with measured stream water electrical conductivity (EC), a proxy for total dissolved ion concentrations. Note that the vertical axis is reversed for EC (positive down) to highlight the similar shape of the seasonal signals. The seasonality of anomalously large flowing networks matches the seasonality of anomalously low EC, indicative of a greater fractional contribution from relatively fast, chemically dilute subsurface flowpaths during the snowmelt season.

is sufficiently captured by an easily interpretable uniform warming experiment. Over the 2001–2024 simulation period in SCB, a $+4^{\circ}\text{C}$ warming scenario reduces the total fraction of precipitation falling as snow (“snowfall fraction”) from 49 % to 26 %, i.e., total snowfall is reduced by 47 % with the same total precipitation. Total streamflow is reduced by 8 %, and annual peak flows change by -25% to $+116\%$ (median $+5\%$), consistent with general expectations for reduced water yield and increased flood risk as mountains transition away from snow dominance (Berghuijs et al., 2014; Huang et al., 2018; Gordon et al., 2022).

Figure 8 illustrates salient characteristics of the snow-rain transition scenario using a single representative water year (2022). In this particular year of the $+4^{\circ}\text{C}$ warming scenario, the predicted annual peak flow is 93 d earlier, 77 % higher, and associated with a discrete storm event in December rather than a gradual snowmelt period in March and April. The annual median and minimum flows decrease by 28 % and 35 %, respectively. Based on the model simulation, the minimum, median, and maximum flowing network length each decrease by 13 %, 10 %, and 2 %, respectively (in this example year), comparable to the 9 %, 9 %, and 3 % reductions predicted for 1st-percentile, median, and 99th-percentile flowing network lengths across the full 24-year period. In contrast to the 2 % decrease in maximum L predicted by the warming simulation in this year, the pre-warming L -

Q power law predicts a 22 % increase in maximum L , synchronous with the higher maximum Q . Naïve application of the power law assumption to simulated streamflow timeseries in a warming climate could thus misrepresent the directionality of changes in the maximum network extent. Even more dramatically, the power law predicts a maximum L during an October storm that is 77 % larger than predicted by the simulation model ($L = 37$ km, $L_P = 66$ km). The power law L_P still overestimates the DHSVM-simulated maximum L during this late-recession-season storm by 45 % in the historical climate, but the near-complete transition to rain for this storm (2 % vs. 35 % snow fraction) increases the importance of considering the spatial configuration of antecedent GW levels. In the 2022 example year (Fig. 8), and throughout the longer simulation period, the power law systematically underestimates DHSVM-simulated L during seasonal recession periods (panels B–C). In the warmer climate, the power law underestimates DHSVM-simulated L ($p < 0.01$) by a median of 7 % (interquartile range: 5 % to 11 % underestimation) over the 137 d period from maximum L (January 15) through the end of May. This underestimation is even more apparent during the snowmelt recession period in the historical climate, when snow is more dominant: over the 98 d period from maximum L (25 April) through the end of July, the median underestimation relative to DHSVM is 11 % ($p < 0.01$, interquartile range: 9 % to 13 % underestimation).

In the warming scenario, flowing streams become overall less persistent, but static topographic assumptions fail to capture the magnitude – and sometimes even the direction – of DHSVM-predicted climate change effects. The mean decrease in stream persistence (fraction of flowing days) for all stream reaches is 2 % ($p < 0.01$), but the persistence of some reaches decreases by as much as 15 % or increases by as much as 6 % (Fig. 8). We compare these simulation results with a simpler approach based on the power law and a fixed hierarchical ranking (Botter et al., 2021) that distributes L among stream reaches based on the topographic wetness index, analogous to prior L - Q modeling approaches (Beven and Kirkby, 1979; Mahoney et al., 2023). This simpler approach predicts the same 2 % mean decrease in persistence, but all reaches decrease or remain unchanged (Fig. 8). Moreover, the fixed hierarchical approach leads to a 40 % overestimation of the number of reaches with at least a 10 % decrease in persistence. A fixed hierarchical approach to streamflow persistence does not account for the potential spatial variability and nonlinearity in the climate sensitivity of different streams. In SCB, the stream reaches with increased persistence in a warmer climate occur at the highest elevations, where earlier snowmelt permits a longer runoff season. We expect that the nonuniformity of interactions between climate and flowing stream networks could be even more pronounced over climate gradients that extend beyond the 700 m elevation range in SCB.

3.4 Relevant Timescales for L - Q Hysteresis

Quantifying the timescales over which GW decouples L and Q is important for understanding whether these effects are relevant for fluvial and riparian processes. The autocorrelation of L at different time lags (in days) provides a metric quantifying the temporal stability of flowing stream networks. At progressively longer lags, the autocorrelation of L_P (estimated by the power law) tends to decrease more rapidly compared to the autocorrelation of L (simulated by DHSVM), indicating that simple scaling laws may overestimate the elasticity of the stream network in some circumstances. We define the flowing network “hysteresis effect”, HE_L , as the difference in autocorrelation between the time-series of L simulated by the distributed model or estimated by the power law. Positive HE_L indicates a stronger autocorrelation in L than would be expected from temporal persistence in Q alone, i.e., damped elasticity of L relative to Q . Based on the autocorrelation within 24 yearly bootstrap samples over the historical simulation period (Fig. S11), we find that HE_L is significantly greater than zero at lags of 1–95 d ($p < 0.01$). Across the full 24-year period, the hysteresis effect is largest at a lag of 47 d, at which point the simulation predicts an autocorrelation of 0.60 and the power law predicts an autocorrelation of 0.51 ($HE_L = 0.09$). An analogous hysteresis effect, HE_{EC} , is detectable in the EC timeseries. An EC- Q power law similarly underestimates the measured EC autocorrelation, but HE_{EC} is only statistically significant at shorter lags of 1–5 d ($p < 0.01$) and 6–7 d ($p < 0.05$), potentially due to measurement noise or confounding sources of EC variability.

Greater rain dominance causes a flashier hydrograph, but DHSVM predicts that GW hysteresis would buffer changes in L (Fig. 8), so the power law approximation increasingly overestimates the sensitivity of the flowing network in the warmer climate relative to DHSVM simulations (Fig. S11). The increase in HE_L between historical and +4 °C simulations is significant at time lags of 1–36 d ($p < 0.01$). Across the full 23-year period, the change in HE_L is largest at a lag of 9 d, at which point the power law autocorrelation decreases from 0.92 to 0.89 in the warmer climate, while the simulation autocorrelation remains nearly unchanged at 0.96. Although HE_L overall peaks at 47 d, and remains significant beyond three months, the mediating role of hysteresis on a snow-rain transition is most pronounced at much shorter lags, which intuitively matches the shorter hydrological response time after individual storms compared to the longer snowmelt period. The power law matches the DHSVM prediction of reduced below-median network lengths but does not account for an increase in upper-quartile lengths associated with hysteresis after rain (Fig. S12).

The flowing network hysteresis effect (HE_L) is larger in years with reduced snow dominance (Fig. 9). Considering HE_L calculated for 24 bootstrap annual periods in each of the historical and warmer climates, a smaller simulated an-

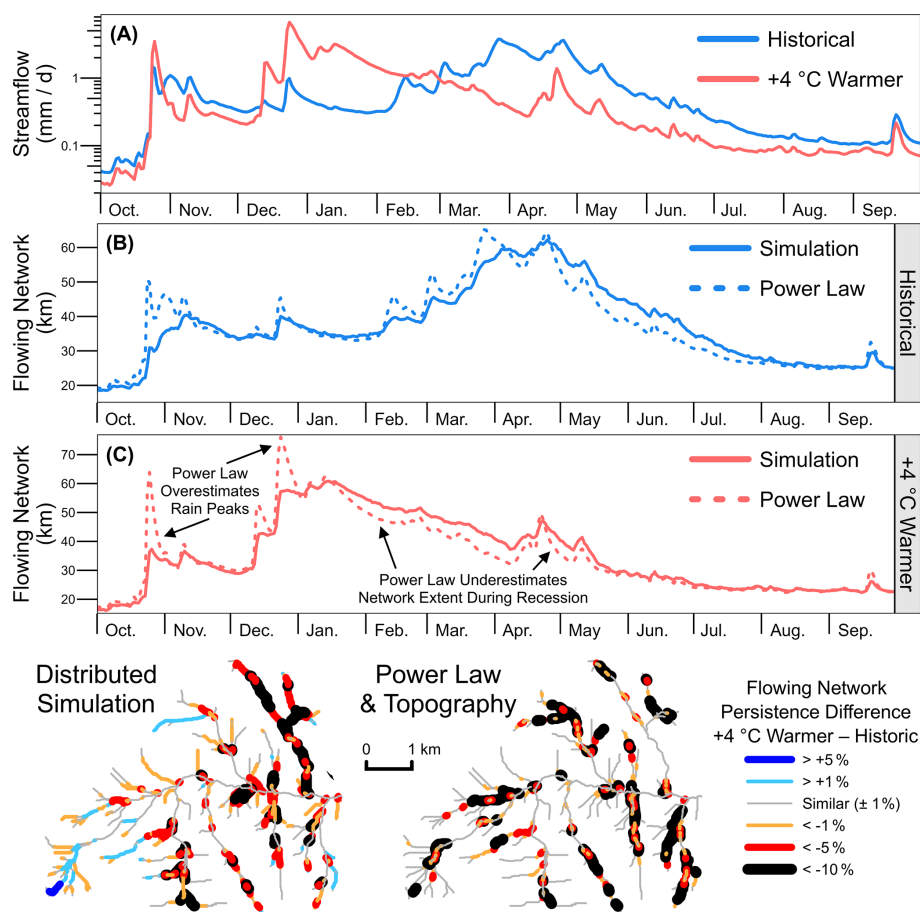


Figure 8. Example timeseries for one year of the simulation under historical or +4 °C warmer climate scenarios, showing (A) simulated streamflow and (B–C) flowing network length simulated directly or estimated from a power law in the historical (B) or warmer (C) scenarios. Maps show the change in streamflow persistence (fraction of flowing days across 24 years) between warmer and historical model simulations (left) or inferred from the combination of a power law and static topographic flow routing assumptions (right).

nual snowfall fraction correlates with a larger hysteresis effect at lags of 10, 20, and 30 d ($r = -0.69, -0.65, -0.52$; $p < 0.01$). Considering just the historical years, the correlation between HE_L and the annual snowfall fraction remain significant at 10, 20, and 30 d lags ($p < 0.01$). Analogously for measured EC data across 15 bootstrap periods, a larger hysteresis effect (HE_{EC}) significantly correlates with a smaller snowfall fraction at lags of 10, 20, and 30 d ($r = -0.61, -0.58, -0.58$; $p < 0.05$). Excluding the two years with negative HE_{EC} , the measured correlation at a 10 d lag rises to $r = -0.65$ ($p < 0.05$). Although the mean value of HE_{EC} itself is not significantly different from zero at lags beyond 7 d, the correlation of HE_{EC} with the snow fraction is significant even at a 30 d lag. This suggests that noise in the EC signal may obscure longer-term hysteresis within individual years, but the month-scale hysteresis effect becomes apparent when comparing across 14 years with different degrees of snow or rain dominance.

4 Discussion

Our simulations and water chemistry data support the hypothesis that groundwater (GW) hysteresis partially decouples the flowing stream network length (L) from streamflow (Q) in a mountain catchment on daily to seasonal timescales, and this decoupling becomes more pronounced in years with relatively less snow and more rain. Model simulations predict that the degree of the hypothesized L – Q decoupling may be surprisingly large: simulated Q can vary by more than 100 % at a constant network length, and networks varying by 33 % or more can produce the same Q (Fig. 5). Moreover, the hypothesized effect manifests in stream reaches ranging from small trickles to as large as 22 % of streamflow at the gage, indicating a substantial reorganization of spatial streamflow generation patterns. A simple scaling law, in which L is perfectly coupled to Q , would underestimate the autocorrelation of simulated L variability on daily to > 2 month timescales. Put simply, Q is not necessarily a good proxy for L in certain circumstances. Similar power law de-

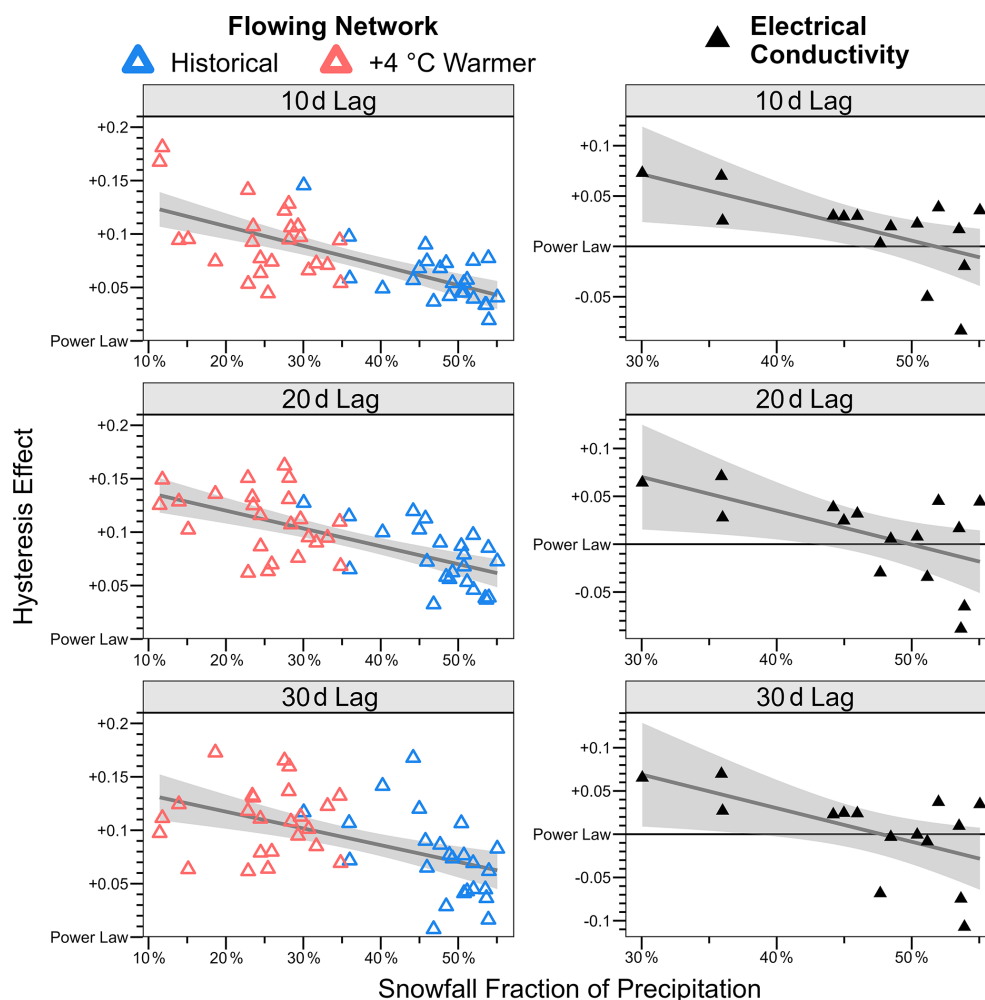


Figure 9. A stronger flowing network hysteresis effect (difference in simulated autocorrelation relative to a power law assumption) is associated with a smaller fraction of precipitation falling as snow. A similar relationship is detected in timeseries of measured stream electrical conductivity, which is related to groundwater age. Shaded gray regions show the 95 % confidence range for the best-fit linear trendline.

viations are detected in observational records from the same watershed. Using measured electrical conductivity as a proxy for solute-rich streamflow derived from slower groundwater flowpaths, the seasonal hysteresis effect diagnosed here provides a physical explanation for why stream chemistry differs between the rising and falling hydrograph limbs at the same streamflow level (Fig. 6). Importantly, our results suggest that anomalies in the L - Q scaling relationship are likely to be significant over the spatiotemporal timescales that matter for fluvial and riparian biogeochemical processes (Alexander et al., 2007; Meyer et al., 2007; Aufdenkampe et al., 2011; Marx et al., 2017; Liu et al., 2022).

We expect that GW hysteresis causes anomalously small flowing networks during autumn and early winter rainfall-runoff events and anomalously large flowing networks during spring and summer snowmelt recession, summarized in Fig. 10. These GW- L - Q hysteresis relationships (Fig. 6) re-

sult from the extensively documented spatiotemporal variability of hydraulic gradients and flow directions in response to antecedent conditions (e.g., McGlynn et al., 2004; Detty and McGuire, 2010a; Rodhe and Seibert, 2011; von Freyberg et al., 2014). As the catchment “wets up” after the growing season, streamflow rises rapidly due to decreased riparian evapotranspiration and steepening hydraulic gradients during early winter storms. However, raising the catchment-average GW level (which controls stream network expansion) requires a substantial increase in the spatially distributed dynamic water storage, which is accumulated over time. Conversely, as GW declines during recession, valley-bottom hydraulic gradients become increasingly parallel to streams, reducing channel inflow (Rodhe and Seibert, 2011; van Meerveld et al., 2015). Flowing streams can persist “on top” of the receding water table even if inflow from GW to

Q is minimal. Hence, catchment-average GW and L both lag Q (Fig. 6).

Measured hysteresis in the stream EC- Q relationship supports our interpretation of GW- L - Q hysteresis on daily to seasonal timescales (Figs. 6–7). Chemical weathering of the underlying volcanic bedrock in SCB creates a positive correlation between EC and GW residence time, as measured by multiple geochemical tracers across springs of varying age (Rademacher et al., 2001). Additional observations across other Sierra Nevada catchments of varying lithology show that longer flowpaths and older GW sources similarly tend to have higher EC (Holloway and Dahlgren, 2001; Ahearn et al., 2004; Meyers et al., 2022). The daily EC measurements in SCB reveal that stream EC remains elevated as Q begins to rise, interpreted as an outsized contribution from riparian aquifers connected to relatively long valley-bottom GW flowpaths with longer residence times. Conversely, stream EC remains suppressed during the falling hydrograph limb as Q decreases, consistent with the transient activation of relatively fast, shallow, chemically depleted GW flowpaths in hillslope and headwater regions. Notably, the hysteresis effect in EC (HE_{EC}) is significantly positive at short time lags of 1–7 d and its inverse correlation with the annual snowfall fraction remains significant even at time lags of 30 d (Fig. 8). This behavior suggests that EC may record not only event-scale runoff dynamics, but also broader seasonal GW memory effects. In more rain-dominated years, stream EC is relatively stable compared to a power law relationship with streamflow, possibly reflecting inputs from older, slowly responding GW sources after each rainfall-runoff event. Together, these findings suggest that EC, and by extension other geochemical tracers of GW residence times (Marçais et al., 2018; Druhan and Benettin, 2023), could be useful complementary proxies for detecting shifts in GW ages under changing climate conditions, though EC is not always conservative, limiting its potential application as a tracer in some circumstances. Moreover, these observations further support our model-based hypothesis that GW hysteresis will become more important for mediating the flowing stream network as rain replaces snow, even on monthly timescales. The volcanic lithology of our SCB study area is particularly notable for the importance of old GW (e.g., Rademacher et al., 2005), and catchments with different subsurface characteristics may have weaker or stronger L - Q hysteresis, which might be detectable through analysis of EC- Q relationships.

Our simulations predict that a partial shift from snowmelt-driven to rainfall-driven runoff generation would heighten the importance of GW hysteresis as a mediator of flowing network length (Fig. 10). Compared to the distributed simulation model, a simple scaling law overestimates L during storm runoff events when the watershed is dry and GW is concentrated in higher-order convergence zones (Figs. 3–4). Conversely, the power law approximation consistently underestimates simulated L during seasonal recession when GW is distributed more evenly throughout the catchment

(Figs. 3–4). Although both types of biases are present in both simulated climate scenarios (Fig. 8), the recession underestimation becomes relatively less important with a declining snowmelt season, and the storm peak overestimation becomes relatively more important with increasing cold-season rainfall-runoff events.

Flowing stream network studies may need to account for the pervasive hysteretic character of hydrological storage and runoff generation processes to avoid systematically biased predictions of change. Hysteresis is an emergent property of threshold-like behavior in hydrological systems, and this recognition heralds a “paradigm shift” in conceptual models of streamflow generation (Spence, 2010). Still, hysteresis is missing from the widely accepted empirical model of flowing stream network dynamics (Godsey and Kirchner, 2014; Prancevic et al., 2025) and likewise ignored by most prior mechanistic simulations (Ward et al., 2018; Gao et al., 2021; Mahoney et al., 2023). However, recent numerical modeling is beginning to account for these considerations (Zanetti et al., 2024). In particular, Abhervé et al. (2025) recently predicted a similar hysteresis behavior between groundwater and the saturated fraction of the catchment area, and since their results come from a different model lineage (MODFLOW) in a different mountain environment (French Pyrenees), this parallel finding supports the generalizability of our conclusions. Although DHSVM lacks the 3D groundwater flow in MODFLOW, the spatially detailed channel interactions with the water table in our study (Figs. 1 and 10) provide a synergistic approach to understanding the impacts of GW hysteresis on flowing networks.

Although our fully dynamic simulations are limited to one watershed, our conceptual understanding (Fig. 10) is generalizable to other mountain catchments where GW mediates streamflow generation. Anecdotally, we observe similar seasonal EC hysteresis signals in other watersheds, especially in groundwater-dominated basins with volcanic lithologies such as the Madison River in Yellowstone National Park, Wyoming, USA (Payton Gardner et al., 2010; McCleskey et al., 2012), though a comprehensive multi-basin investigation is beyond the scope of the current study. Future research could investigate the variability of EC as a proxy for L - Q hysteresis across multiple catchments to constrain the role of topography, lithology, land surface cover, and climate. Our model results indicate that L - Q hysteresis may be nonnegligible at scales ranging from first-order streams up to the 27 km² SCB catchment, and future simulations could quantify this effect at even larger watershed scales. Finally, long-term spatially explicit monitoring of stream networks could validate or refine our understanding of the relevant time lags and predicted changes in L - Q hysteresis, though such monitoring may be unrealistic given the many-year timescales and daily sampling frequencies required to quantify the hysteresis effect (HE_L) defined here.

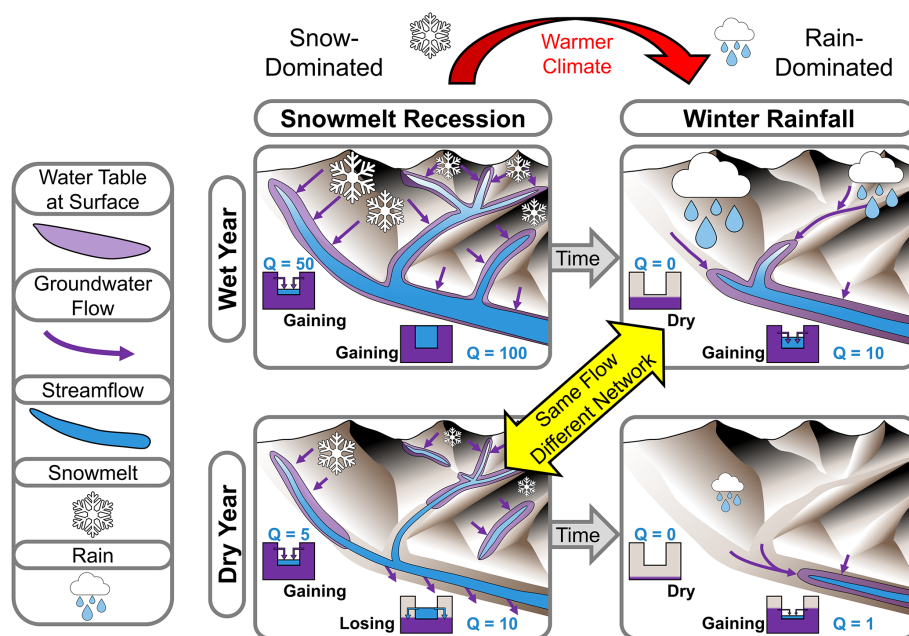


Figure 10. Revised conceptual model of stream-groundwater interactions in a mountain catchment, illustrating the emergence of stream network hysteresis caused by transient groundwater flow between hillslopes and riparian zones. Contrast with conceptual model illustrated in Fig. 7 of Godsey and Kirchner (2014), which assumes equilibrium groundwater flow. Channel cross-sections show how this conceptual model is simulated at the grid scale (cf. schematic in Fig. 1). Antecedent groundwater priming from snowmelt and rain activates a relatively large flowing stream network during the seasonal recession period, but rainfall during periods with a low antecedent water table can cause a rapid increase in streamflow even though the flowing network remains small. In a warmer climate, winter rainfall becomes more dominant than spring snowmelt, altering the spatial configuration of streamflow generation and flowing network connectivity. Note: figure is not to scale (streams and hyporheic zones are enlarged for visual clarity); overall stream network is on the order of kilometer-scale.

5 Conclusions

Our model simulations suggest a new physical hypothesis (non-equilibrium groundwater flow) to explain observed seasonal hysteresis in both stream chemistry and flowing network length. Process-based hydrological models have been criticized as overparameterized and merely representing what we already know about hydrology, and Kirchner (2006) claims that “all hydrological knowledge ultimately comes from observations, experiments, and measurements.” The present study seems to offer a counterexample, wherein a “bottom-up” approach based on grid-scale physics has yielded a novel hypothesis about catchment-scale hydrological behavior. While field surveys provide valuable insight into the first-order behavior of dynamic stream networks, the second-order hysteresis effect diagnosed here only becomes quantifiable from thousands of simulated daily stream network maps, a dataset that would require a monumental effort to collect in the field. A related groundwater hysteresis signal in measured stream geochemical timeseries supports our findings, but the connection to channel dynamics is not quantifiable from existing measurements alone. At the outset of this study, we merely sought to reproduce known stream network dynamics (i.e., expansion/contraction/disconnection) using simple physically based rules (Figs. 1–2),

but the presence of substantial scatter in the simulated scaling relationship (Fig. 4) prompted us to investigate scaling anomalies for both stream chemistry and network length, ultimately leading to our hypothesis of a groundwater hysteresis effect (Fig. 6). The emergence of unexpected complexity from the repeated application of simple mathematical rules is perhaps one of the most surprising results of computational science (Conway and Gardner, 1970; Wolfram, 1984; Cook, 2004), especially when those rules are grounded in physical constraints like the dynamic groundwater flow directions in this study (Fig. 1).

A physically based, spatially distributed surface-groundwater interaction scheme enables investigation of potential climate change effects and other disturbances. Approaches based purely on past observations (such as the L - Q power law and typical machine learning methods) are untested in out-of-sample conditions by definition, so these purely empirical approaches are problematic for investigations of nonstationarity such as climate change and land surface disturbance (Milly et al., 2008). Compared to field-based empirical scaling laws, a distributed simulation yields different predictions of the magnitude, and even the directionality, of climate-induced stream network changes (Fig. 8). While incorporating missing processes into models can be worthwhile in its own right, model experiments

with sufficient space for emergent complexity may also suggest revised conceptual models (Fig. 10) that motivate new data collection or novel interpretations of existing field data. Additional iterative model and field investigations are needed to further test and refine our understanding of surface-groundwater interactions and stream network dynamics in nonstationary environments.

Code and data availability. All processing scripts, model code, and data needed to reproduce the results and figures are archived at <https://doi.org/10.5281/zenodo.17958146> (Boardman, 2025b).

Video supplement. The video supplement, consisting of a groundwater flow and active stream network animation from the DHSVM simulations, is archived at <https://doi.org/10.5446/72156> (Boardman, 2025a).

Supplement. The supplement related to this article is available online at <https://doi.org/10.5194/hess-30-5145-2026-supplement>.

Author contributions. ENB developed the model code modifications, implemented the simulations and analysis, created the figures, and wrote the initial manuscript. MSW, NMF, JAW, and AAH each contributed to conceptualization, validation, and manuscript editing. AAH additionally contributed to supervision and funding acquisition.

Competing interests. At least one of the (co-)authors is a member of the editorial board of *Hydrology and Earth System Sciences*. The peer-review process was guided by an independent editor, and the authors also have no other competing interests to declare.

Disclaimer. Publisher's note: Copernicus Publications remains neutral with regard to jurisdictional claims made in the text, published maps, institutional affiliations, or any other geographical representation in this paper. The authors bear the ultimate responsibility for providing appropriate place names. Views expressed in the text are those of the authors and do not necessarily reflect the views of the publisher.

Acknowledgements. The authors gratefully acknowledge the reviewer and community comments, which improved the interpretation and presentation of this study.

Financial support. This research has been supported by the National Science Foundation Graduate Research Fellowship Program (grant no. 1937966) and the National Science Foundation Division of Earth Sciences (grant nos. EAR 2012310, EAR 2012188, and EAR 2308548).

Review statement. This paper was edited by Thom Bogaard and reviewed by two anonymous referees.

References

- Abatzoglou, J. T.: Development of gridded surface meteorological data for ecological applications and modelling, *Int. J. Climatol.*, 33, 121–131, <https://doi.org/10.1002/joc.3413>, 2013.
- Abhervé, R., Roques, C., de Dreuz, J.-R., Van Der Veen, T., Dumaine, L., Chatton, E., Brunner, P., Aquilina, L., and Servièr, L.: Projected Climate Change Impacts on Groundwater–Surface Water Connectivity in a Compartmentalized Mountain Headwater Bedrock Aquifer, *Water Resour. Res.*, 61, e2025WR040083, <https://doi.org/10.1029/2025WR040083>, 2025.
- Ahearn, D. S., Sheibley, R. W., Dahlgren, R. A., and Keller, K. E.: Temporal dynamics of stream water chemistry in the last free-flowing river draining the western Sierra Nevada, California, *J. Hydrol.*, 295, 47–63, <https://doi.org/10.1016/j.jhydrol.2004.02.016>, 2004.
- Alexander, R. B., Boyer, E. W., Smith, R. A., Schwarz, G. E., and Moore, R. B.: The Role of Headwater Streams in Downstream Water Quality, *JAWRA J. Am. Water Resour. As.*, 43, 41–59, <https://doi.org/10.1111/j.1752-1688.2007.00005.x>, 2007.
- Allan, J. D., Castillo, M. M., and Capps, K. A.: *Stream Ecology: Structure and Function of Running Waters*, Springer Nature, 494 pp., ISBN 9783030612863, 2021.
- Allen, D. M., Whitfield, P. H., and Werner, A.: Groundwater level responses in temperate mountainous terrain: regime classification, and linkages to climate and streamflow, *Hydrol. Process.*, 24, 3392–3412, <https://doi.org/10.1002/hyp.7757>, 2010.
- Andermann, C., Longuevergne, L., Bonnet, S., Crave, A., Davy, P., and Gloaguen, R.: Impact of transient groundwater storage on the discharge of Himalayan rivers, *Nat. Geosci.*, 5, 127–132, <https://doi.org/10.1038/ngeo1356>, 2012.
- Aufdenkampe, A. K., Mayorga, E., Raymond, P. A., Melack, J. M., Doney, S. C., Alin, S. R., Aalto, R. E., and Yoo, K.: Riverine coupling of biogeochemical cycles between land, oceans, and atmosphere, *Front. Ecol. Environ.*, 9, 53–60, <https://doi.org/10.1890/100014>, 2011.
- Beckers, J., Smerdon, B., Redding, T., Anderson, A., Pike, R., and Werner, A. T.: Hydrologic models for forest management applications. Part 1: Model selection, *Streamline Watershed Management Bulletin*, 13, 35–44, 2009.
- Bennett, A., Hamman, J., and Nijssen, B.: MetSim: A Python package for estimation and disaggregation of meteorological data, *The Journal of Open Source Software*, 5, 2042, <https://doi.org/10.21105/joss.02042>, 2020.
- Berghuijs, W. R., Woods, R. A., and Hrachowitz, M.: A precipitation shift from snow towards rain leads to a decrease in streamflow, *Nat. Clim. Change*, 4, 583–586, <https://doi.org/10.1038/nclimate2246>, 2014.
- Beven, K.: On subsurface stormflow: Predictions with simple kinematic theory for saturated and unsaturated flows, *Water Resour. Res.*, 18, 1627–1633, <https://doi.org/10.1029/WR018i006p01627>, 1982.
- Beven, K.: Searching for the Holy Grail of scientific hydrology: $Qt = (S, R, \Delta t)A$ as closure, *Hydrol. Earth Syst. Sci.*, 10, 609–618, <https://doi.org/10.5194/hess-10-609-2006>, 2006.

- Beven, K. J. and Kirkby, M. J.: A physically based, variable contributing area model of basin hydrology [Un modèle à base physique de zone d'appel variable de l'hydrologie du bassin versant], *Hydrol. Sci. B.*, 24, 43–69, <https://doi.org/10.1080/02626667909491834>, 1979.
- Bieger, K., Rathjens, H., Allen, P. M., and Arnold, J. G.: Development and Evaluation of Bankfull Hydraulic Geometry Relationships for the Physiographic Regions of the United States, *JAWRA J. Am. Water Resour. As.*, 51, 842–858, <https://doi.org/10.1111/jawr.12282>, 2015.
- Blumhagen, E. D. and Clark, J. F.: Carbon sources and signals through time in an Alpine groundwater Basin, Sagehen California, *Appl. Geochem.*, 23, 2284–2291, <https://doi.org/10.1016/j.apgeochem.2008.03.010>, 2008.
- Blyth, K. and Rodda, J. C.: A stream length study, *Water Resour. Res.*, 9, 1454–1461, <https://doi.org/10.1029/WR009i005p01454>, 1973.
- Boardman, E.: Animation of Groundwater and Dynamic Stream Networks in DHSVM, TIB-AV-Portal [video], <https://doi.org/10.5446/72156>, 2025a.
- Boardman, E.: Data and Code for Stream Network Hysteresis Study Using DHSVM in Sagehen Creek Basin, Zenodo [code] and [data set], <https://doi.org/10.5281/zenodo.17958146>, 2025b.
- Boardman, E. N., Boisramé, G. F. S., Wigmosta, M. S., Shriver, R. K., and Harpold, A. A.: Improving model calibrations in a changing world: controlling for nonstationarity after mega disturbance reduces hydrological uncertainty, *Hydrol. Earth Syst. Sci.*, 29, 6333–6352, <https://doi.org/10.5194/hess-29-6333-2025>, 2025.
- Botter, G., Vingiani, F., Senatore, A., Jensen, C., Weiler, M., McGuire, K., Mendicino, G., and Durighetto, N.: Hierarchical climate-driven dynamics of the active channel length in temporary streams, *Sci. Rep.*, 11, 21503, <https://doi.org/10.1038/s41598-021-00922-2>, 2021.
- Breiman, L., Cutler, A., Liaw, A., and Wiener, M.: randomForest: Breiman and Cutlers Random Forests for Classification and Regression, CRAN [code], <https://doi.org/10.32614/CRAN.package.randomForest>, 2002.
- Brown, L. E., Milner, A. M., and Hannah, D. M.: Groundwater influence on alpine stream ecosystems, *Freshwater Biol.*, 52, 878–890, <https://doi.org/10.1111/j.1365-2427.2007.01739.x>, 2007.
- Camporese, M., Penna, D., Borga, M., and Paniconi, C.: A field and modeling study of nonlinear storage-discharge dynamics for an Alpine headwater catchment, *Water Resour. Res.*, 50, 806–822, <https://doi.org/10.1002/2013WR013604>, 2014.
- Cano-Paoli, K., Chiogna, G., and Bellin, A.: Convenient use of electrical conductivity measurements to investigate hydrological processes in Alpine headwaters, *Sci. Total Environ.*, 685, 37–49, <https://doi.org/10.1016/j.scitotenv.2019.05.166>, 2019.
- Carlston, C. W.: Drainage Density and Streamflow, U.S. Government Printing Office, 20 pp., https://www.google.com/books/edition/Drainage_Density_and_Streamflow/FLsvAAAAYAAJ (last access: 11 August 2026), 1963.
- Castro, J. M. and Thorne, C. R.: The stream evolution triangle: Integrating geology, hydrology, and biology, *River Res. Appl.*, 35, 315–326, <https://doi.org/10.1002/rra.3421>, 2019.
- Clark, M. P. and Kavetski, D.: Ancient numerical daemons of conceptual hydrological modeling: 1. Fidelity and efficiency of time stepping schemes, *Water Resour. Res.*, 46, <https://doi.org/10.1029/2009WR008894>, 2010.
- Clarke, A., Mac Nally, R., Bond, N., and Lake, P. S.: Macroinvertebrate diversity in headwater streams: a review, *Freshwater Biol.*, 53, 1707–1721, <https://doi.org/10.1111/j.1365-2427.2008.02041.x>, 2008.
- Conway, J. and Gardner, M.: Mathematical Games, *Sci. Am.*, 223, 120–123, 1970.
- Cook, M.: Universality in Elementary Cellular Automata, *Complex Systems*, 15, 1–40, <https://doi.org/10.25088/ComplexSystems.15.1.1>, 2004.
- Cristea, N. C., Lundquist, J. D., Loheide, S. P., Lowry, C. S., and Moore, C. E.: Modelling how vegetation cover affects climate change impacts on streamflow timing and magnitude in the snowmelt-dominated upper Tuolumne Basin, Sierra Nevada, *Hydrol. Process.*, 28, 3896–3918, <https://doi.org/10.1002/hyp.9909>, 2014.
- Detty, J. M. and McGuire, K. J.: Threshold changes in storm runoff generation at a till-mantled headwater catchment, *Water Resour. Res.*, 46, <https://doi.org/10.1029/2009WR008102>, 2010a.
- Detty, J. M. and McGuire, K. J.: Topographic controls on shallow groundwater dynamics: implications of hydrologic connectivity between hillslopes and riparian zones in a till mantled catchment, *Hydrol. Process.*, 24, 2222–2236, <https://doi.org/10.1002/hyp.7656>, 2010b.
- De Vries, J. J.: Seasonal expansion and contraction of stream networks in shallow groundwater systems, *J. Hydrol.*, 170, 15–26, [https://doi.org/10.1016/0022-1694\(95\)02684-H](https://doi.org/10.1016/0022-1694(95)02684-H), 1995.
- Dewitz, J. and U.S. Geological Survey: National Land Cover Database (NLCD) 2019 Products, U.S. Geological Survey, <https://doi.org/10.5066/P9JZ7AO3>, 2019.
- Dhungel, S., Tarboton, D. G., Jin, J., and Hawkins, C. P.: Potential Effects of Climate Change on Ecologically Relevant Streamflow Regimes: Climate Change and Streamflow Regimes, *River Res. Appl.*, 32, 1827–1840, <https://doi.org/10.1002/rra.3029>, 2016.
- Downing, J. A., Cole, J. J., Duarte, C. M., Middelburg, J. J., Melack, J. M., Prairie, Y. T., Kortelainen, P., Striegl, R. G., McDowell, W. H., and Tranvik, L. J.: Global abundance and size distribution of streams and rivers, *Inland Waters*, 2, 229–236, <https://doi.org/10.5268/IW-2.4.502>, 2012.
- Dralle, D. N., Lapides, D. A., Rempe, D. M., and Hahm, W. J.: Mapping Surface Water Presence and Hyporheic Flow Properties of Headwater Stream Networks With Multispectral Satellite Imagery, *Water Resour. Res.*, 59, e2022WR034169, <https://doi.org/10.1029/2022WR034169>, 2023.
- Druhan, J. L. and Benettin, P.: Isotope Ratio – Discharge Relationships of Solutes Derived From Weathering Reactions, *Am. J. Sci.*, 323, <https://doi.org/10.2475/001c.84469>, 2023.
- Dugdale, S. J., Klaus, J., and Hannah, D. M.: Looking to the Skies: Realising the Combined Potential of Drones and Thermal Infrared Imagery to Advance Hydrological Process Understanding in Headwaters, *Water Resour. Res.*, 58, e2021WR031168, <https://doi.org/10.1029/2021WR031168>, 2022.
- Durighetto, N., Vingiani, F., Bertassello, L. E., Camporese, M., and Botter, G.: Intraseasonal Drainage Network Dynamics in a Headwater Catchment of the Italian Alps, *Water Resour. Res.*, 56, e2019WR025563, <https://doi.org/10.1029/2019WR025563>, 2020.
- Durighetto, N., Britt, R., Schirmer, M., and Botter, G.: Variability in the Shape of the Active Length–Streamflow Relationship in Temporary Streams: Insights From an Em-

- pirical Analysis, *Water Resour. Res.*, 61, e2024WR038732, <https://doi.org/10.1029/2024WR038732>, 2025.
- Essaid, H. I. and Hill, B. R.: Watershed-scale modeling of stream-flow change in incised montane meadows, *Water Resour. Res.*, 50, 2657–2678, <https://doi.org/10.1002/2013WR014420>, 2014.
- Foster, L. M., Bearup, L. A., Molotch, N. P., Brooks, P. B., and Maxwell, R. M.: Energy budget increases reduce mean stream-flow more than snow–rain transitions: using integrated modeling to isolate climate change impacts on Rocky Mountain hydrology, *Environ. Res. Lett.*, 11, 044015, <https://doi.org/10.1088/1748-9326/11/4/044015>, 2016.
- Freeman, M. C., Pringle, C. M., and Jackson, C. R.: Hydrologic Connectivity and the Contribution of Stream Headwaters to Ecological Integrity at Regional Scales, *JAWRA J. Am. Water Resour. As.*, 43, 5–14, <https://doi.org/10.1111/j.1752-1688.2007.00002.x>, 2007.
- Freeze, R. A. and Cherry, J. A.: *Groundwater*, Prentice-Hall, Englewood Cliffs, N.J., 604 pp., ISBN 9780133653120, 1979.
- Fritz, K. M., Hagenbuch, E., D'Amico, E., Reif, M., Wigington, P. J., Leibowitz, S. G., Comeleo, R. L., Ebersole, J. L., and Nadeau, T.: Comparing the Extent and Permanence of Headwater Streams From Two Field Surveys to Values From Hydrographic Databases and Maps, *J. Am. Water Resour. As.*, 49, 867–882, <https://doi.org/10.1111/jawr.12040>, 2013.
- Gao, S., Chen, M., Li, Z., Cook, S., Allen, D., Neeson, T., Yang, T., Yami, T., and Hong, Y.: Mapping dynamic non-perennial stream networks using high-resolution distributed hydrologic simulation: A case study in the upper blue river basin, *J. Hydrol.*, 600, 126522, <https://doi.org/10.1016/j.jhydrol.2021.126522>, 2021.
- Godsey, S. E. and Kirchner, J. W.: Dynamic, discontinuous stream networks: hydrologically driven variations in active drainage density, flowing channels and stream order, *Hydrol. Process.*, 28, 5791–5803, <https://doi.org/10.1002/hyp.10310>, 2014.
- Gordon, B. L., Brooks, P. D., Krogh, S. A., Boisrame, G. F. S., Carroll, R. W. H., McNamara, J. P., and Harpold, A. A.: Why does snowmelt-driven streamflow response to warming vary? A data-driven review and predictive framework, *Environ. Res. Lett.*, 17, 053004, <https://doi.org/10.1088/1748-9326/ac64b4>, 2022.
- Graup, L. J., Tague, C. L., Harpold, A. A., and Krogh, S. A.: Subsurface Lateral Flows Buffer Riparian Water Stress Against Snow Drought, *J. Geophys. Res.-Bioge.*, 127, e2022JG006980, <https://doi.org/10.1029/2022JG006980>, 2022.
- Gregory, K. J. and Walling, D. E.: The variation of drainage density within a catchment, *International Association of Scientific Hydrology. Bulletin*, 13, 61–68, <https://doi.org/10.1080/02626666809493583>, 1968.
- Gu, H., Xu, Y.-P., Liu, L., Xie, J., Wang, L., Pan, S., and Guo, Y.: Seasonal catchment memory of high mountain rivers in the Tibetan Plateau, *Nat. Commun.*, 14, 3173, <https://doi.org/10.1038/s41467-023-38966-9>, 2023.
- Gupta, S., Papritz, A., Lehmann, P., Hengl, T., Bonetti, S., and Or, D.: Global Mapping of Soil Water Characteristics Parameters – Fusing Curated Data with Machine Learning and Environmental Covariates, *Remote Sensing*, 14, 1947, <https://doi.org/10.3390/rs14081947>, 2022.
- Harpold, A. A. and Molotch, N. P.: Sensitivity of soil water availability to changing snowmelt timing in the western U.S., *Geophys. Res. Lett.*, 42, 8011–8020, <https://doi.org/10.1002/2015GL065855>, 2015.
- Hasan, M. M., Strong, C., Brooks, P. D., Burian, S. J., and Barber, M. E.: Quantifying climate change impacts on low flows of small high mountain watersheds: A nonstationary approach, *J. Hydrol.: Regional Studies*, 48, 101463, <https://doi.org/10.1016/j.ejrh.2023.101463>, 2023.
- Hewlett, J. D. and Hibbert, A. R.: Factors affecting the response of small watersheds to precipitation in humid areas, *Forest Hydrology*, 11, 275–290, 1967.
- Holloway, J. M. and Dahlgren, R. A.: Seasonal and event-scale variations in solute chemistry for four Sierra Nevada catchments, *J. Hydrol.*, 250, 106–121, [https://doi.org/10.1016/S0022-1694\(01\)00424-3](https://doi.org/10.1016/S0022-1694(01)00424-3), 2001.
- Hrachowitz, M. and Clark, M. P.: HESS Opinions: The complementary merits of competing modelling philosophies in hydrology, *Hydrol. Earth Syst. Sci.*, 21, 3953–3973, <https://doi.org/10.5194/hess-21-3953-2017>, 2017.
- Huang, X., Hall, A. D., and Berg, N.: Anthropogenic Warming Impacts on Today's Sierra Nevada Snowpack and Flood Risk, *Geophys. Res. Lett.*, 45, 6215–6222, <https://doi.org/10.1029/2018GL077432>, 2018.
- Jaeger, K. L., Olden, J. D., and Pelland, N. A.: Climate change poised to threaten hydrologic connectivity and endemic fishes in dryland streams, *P. Natl. Acad. Sci. UA*, 111, 13894–13899, <https://doi.org/10.1073/pnas.1320890111>, 2014.
- Jensen, C. K., McGuire, K. J., and Prince, P. S.: Headwater stream length dynamics across four physiographic provinces of the Appalachian Highlands, *Hydrol. Process.*, 31, 3350–3363, <https://doi.org/10.1002/hyp.11259>, 2017.
- Jensen, C. K., McGuire, K. J., McLaughlin, D. L., and Scott, D. T.: Quantifying spatiotemporal variation in headwater stream length using flow intermittency sensors, *Environ. Monit. Assess.*, 191, 226, <https://doi.org/10.1007/s10661-019-7373-8>, 2019.
- Jones, D. R., Schonlau, M., and Welch, W. J.: Efficient Global Optimization of Expensive Black-Box Functions, *J. Global Optim.*, 13, 455–492, <https://doi.org/10.1023/A:1008306431147>, 1998.
- Kampf, S. K. and Lefsky, M. A.: Transition of dominant peak flow source from snowmelt to rainfall along the Colorado Front Range: Historical patterns, trends, and lessons from the 2013 Colorado Front Range floods, *Water Resour. Res.*, 52, 407–422, <https://doi.org/10.1002/2015WR017784>, 2016.
- Kampf, S. K., Faulconer, J., Shaw, J. R., Sutfin, N. A., and Cooper, D. J.: Rain and channel flow supplements to subsurface water beneath hyper-arid ephemeral stream channels, *J. Hydrol.*, 536, 524–533, <https://doi.org/10.1016/j.jhydrol.2016.03.016>, 2016.
- Kendall, M. G.: *Rank Correlation Methods*, 4th Edn., Charles Griffin, London, ISBN 9780852641996, 1975.
- Kendall, K. A., Shanley, J. B., and McDonnell, J. J.: A hydrometric and geochemical approach to test the transmissivity feedback hypothesis during snowmelt, *J. Hydrol.*, 219, 188–205, [https://doi.org/10.1016/S0022-1694\(99\)00059-1](https://doi.org/10.1016/S0022-1694(99)00059-1), 1999.
- Kirchner, J. W.: Getting the right answers for the right reasons: Linking measurements, analyses, and models to advance the science of hydrology, *Water Resour. Res.*, 42, <https://doi.org/10.1029/2005WR004362>, 2006.
- Kirchner, J. W., Godsey, S. E., Solomon, M., Osterhuber, R., McConnell, J. R., and Penna, D.: The pulse of a montane ecosystem: coupling between daily cycles in solar flux, snowmelt, transpiration, groundwater, and streamflow at Sagehen Creek and Independence Creek, Sierra Nevada, USA, *Hydrol. Earth Syst.*

- Sci., 24, 5095–5123, <https://doi.org/10.5194/hess-24-5095-2020>, 2020.
- Klos, P. Z., Link, T. E., and Abatzoglou, J. T.: Extent of the rain-snow transition zone in the western U.S. under historic and projected climate, *Geophys. Res. Lett.*, 41, 4560–4568, <https://doi.org/10.1002/2014GL060500>, 2014.
- La Barbera, P. and Rosso, R.: On the fractal dimension of stream networks, *Water Resour. Res.*, 25, 735–741, <https://doi.org/10.1029/WR025i004p00735>, 1989.
- LANDFIRE: LANDFIRE 2022 Existing Vegetation Type (EVT), U.S. Department of the Interior, Geological Survey, and U.S. Department of Agriculture, <https://landfire.gov/data> (last access: 11 August 2026), 2022.
- Lane, C. R., D'Amico, E., Christensen, J. R., Golden, H. E., Cheng, F. Y., Hammond, J. C., Husic, A., Jaeger, K. L., Jones, C. N., Kelleher, C. A., Li, L., Mahoney, D. T., McMillan, H. K., Price, A. N., Sando, R., Segura, C., Seybold, E. C., Ward, A. S., and Zimmer, M.: Identifying Headwater Streams across the Conterminous United States, *Ecosystems*, 29, 22, <https://doi.org/10.1007/s10021-025-01041-z>, 2026.
- Lapides, D. A., Leclerc, C. D., Moidu, H., Dralle, D. N., and Hahm, W. J.: Variability of stream extents controlled by flow regime and network hydraulic scaling, *Hydrol. Process.*, 35, e14079, <https://doi.org/10.1002/hyp.14079>, 2021.
- Lee, S.-Y., Fullerton, A. H., Sun, N., and Torgersen, C. E.: Projecting spatiotemporally explicit effects of climate change on stream temperature: A model comparison and implications for coldwater fishes, *J. Hydrol.*, 588, 125066, <https://doi.org/10.1016/j.jhydrol.2020.125066>, 2020.
- Limerinos, J. T.: Determination of the manning coefficient from measured bed roughness in natural channels, U.S. Geological Survey, <https://doi.org/10.3133/wsp1898B>, 1970.
- Liu, S., Kuhn, C., Amatulli, G., Aho, K., Butman, D. E., Allen, G. H., Lin, P., Pan, M., Yamazaki, D., Brinkerhoff, C., Gleason, C., Xia, X., and Raymond, P. A.: The importance of hydrology in routing terrestrial carbon to the atmosphere via global streams and rivers, *P. Natl. Acad. Sci. USA*, 119, e2106322119, <https://doi.org/10.1073/pnas.2106322119>, 2022.
- Lundquist, J. D. and Cayan, D. R.: Surface temperature patterns in complex terrain: Daily variations and long-term change in the central Sierra Nevada, California, *J. Geophys. Res.-Atmos.*, 112, <https://doi.org/10.1029/2006JD007561>, 2007.
- Mahoney, D. T., Christensen, J. R., Golden, H. E., Lane, C. R., Evenson, G. R., White, E., Fritz, K. M., D'Amico, E., Barton, C. D., Williamson, T. N., Sena, K. L., and Agouridis, C. T.: Dynamics of streamflow permanence in a headwater network: Insights from catchment-scale model simulations, *J. Hydrol.*, 620, 129422, <https://doi.org/10.1016/j.jhydrol.2023.129422>, 2023.
- Mandelbrot, B. B.: *The fractal geometry of nature*, W. H. Freeman, New York, 468 pp., ISBN 9780716711865, 1982.
- Mann, H. B.: Non-parametric tests against trend, *Econometrica*, 13, 163–171, 1945.
- Manning, A. H., Clark, J. F., Diaz, S. H., Rademacher, L. K., Earman, S., and Niel Plummer, L.: Evolution of groundwater age in a mountain watershed over a period of thirteen years, *J. Hydrol.*, 460–461, 13–28, <https://doi.org/10.1016/j.jhydrol.2012.06.030>, 2012.
- Marçais, J., Gauvain, A., Labasque, T., Abbott, B. W., Pinay, G., Aquilina, L., Chabaux, F., Viville, D., and De Dreuz, J.-R.: Dating groundwater with dissolved silica and CFC concentrations in crystalline aquifers, *Sci. Total Environ.*, 636, 260–272, <https://doi.org/10.1016/j.scitotenv.2018.04.196>, 2018.
- Marx, A., Dusek, J., Jankovec, J., Sanda, M., Vogel, T., van Geldern, R., Hartmann, J., and Barth, J. A. C.: A review of CO₂ and associated carbon dynamics in headwater streams: A global perspective, *Rev. Geophys.*, 55, 560–585, <https://doi.org/10.1002/2016RG000547>, 2017.
- McCleskey, R. B., Clor, L. E., Lowenstern, J. B., Evans, W. C., Nordstrom, D. K., Heasler, H., and Huebner, M. A.: Solute and geothermal flux monitoring using electrical conductivity in the Madison, Firehole, and Gibbon Rivers, Yellowstone National Park, *Appl. Geochem.*, 27, 2370–2381, <https://doi.org/10.1016/j.apgeochem.2012.07.019>, 2012.
- McGlynn, B. L. and McDonnell, J. J.: Quantifying the relative contributions of riparian and hillslope zones to catchment runoff, *Water Resour. Res.*, 39, <https://doi.org/10.1029/2003WR002091>, 2003.
- McGlynn, B. L., McDonnell, J. J., Seibert, J., and Kendall, C.: Scale effects on headwater catchment runoff timing, flow sources, and groundwater-streamflow relations, *Water Resour. Res.*, 40, <https://doi.org/10.1029/2003WR002494>, 2004.
- Meyer, J. L., Strayer, D. L., Wallace, J. B., Eggert, S. L., Helfman, G. S., and Leonard, N. E.: The Contribution of Headwater Streams to Biodiversity in River Networks, *J. Am. Water Resour. As.*, 43, 86–103, <https://doi.org/10.1111/j.1752-1688.2007.00008.x>, 2007.
- Meyers, Z. P., Rademacher, L. K., Frisbee, M. D., and Warix, S. R.: Extending classical geochemical weathering studies through the mountain block: The effect of increasing scale on geochemical evolution in the Sierra Nevada (CA), *Chem. Geol.*, 598, 120831, <https://doi.org/10.1016/j.chemgeo.2022.120831>, 2022.
- Milly, P. C. D., Betancourt, J., Falkenmark, M., Hirsch, R. M., Kundzewicz, Z. W., Lettenmaier, D. P., and Stouffer, R. J.: Stationarity Is Dead: Whither Water Management?, *Science*, 319, 573–574, <https://doi.org/10.1126/science.1151915>, 2008.
- Milly, P. C. D., Betancourt, J., Falkenmark, M., Hirsch, R. M., Kundzewicz, Z. W., Lettenmaier, D. P., Stouffer, R. J., Dettinger, M. D., and Krysanova, V.: On Critiques of “Stationarity Is Dead: Whither Water Management?”, *Water Resour. Res.*, 51, 7785–7789, <https://doi.org/10.1002/2015WR017408>, 2015.
- Null, S. E., Viers, J. H., and Mount, J. F.: Hydrologic Response and Watershed Sensitivity to Climate Warming in California's Sierra Nevada, *PLOS ONE*, 5, e9932, <https://doi.org/10.1371/journal.pone.0009932>, 2010.
- Patterson, N. K., Lane, B. A., Sandoval-Solis, S., Persad, G. G., and Ortiz-Partida, J. P.: Projected Effects of Temperature and Precipitation Variability Change on Streamflow Patterns Using a Functional Flows Approach, *Earth's Future*, 10, e2021EF002631, <https://doi.org/10.1029/2021EF002631>, 2022.
- Patton, N. R., Lohse, K. A., Godsey, S. E., Crosby, B. T., and Seyfried, M. S.: Predicting soil thickness on soil mantled hillslopes, *Nat. Commun.*, 9, 3329, <https://doi.org/10.1038/s41467-018-05743-y>, 2018.
- Payton Gardner, W., Susong, D. D., Kip Solomon, D., and Heasler, H.: Snowmelt hydrograph interpretation: Revealing watershed scale hydrologic characteristics of the Yellowstone volcanic plateau, *J. Hydrol.*, 383, 209–222, <https://doi.org/10.1016/j.jhydrol.2009.12.037>, 2010.

- Penna, D., Tromp-van Meerveld, H. J., Gobbi, A., Borga, M., and Dalla Fontana, G.: The influence of soil moisture on threshold runoff generation processes in an alpine headwater catchment, *Hydrol. Earth Syst. Sci.*, 15, 689–702, <https://doi.org/10.5194/hess-15-689-2011>, 2011.
- Prancevic, J. P. and Kirchner, J. W.: Topographic Controls on the Extension and Retraction of Flowing Streams, *Geophys. Res. Lett.*, 46, 2084–2092, <https://doi.org/10.1029/2018GL081799>, 2019.
- Prancevic, J. P., Seybold, H., and Kirchner, J. W.: Variability of flowing stream network length across the US, *Science*, 387, 782–786, <https://doi.org/10.1126/science.ado2860>, 2025.
- Price, A. N. and Kaiser, K. E.: Process-Based Hydrologic Model Representations of Non-Perennial Streamflow in the Pacific Northwest, USA, *Water Resour. Res.*, 62, e2025WR040626, <https://doi.org/10.1029/2025WR040626>, 2026.
- Rademacher, L. K., Clark, J. F., Hudson, G. B., Erman, D. C., and Erman, N. A.: Chemical evolution of shallow groundwater as recorded by springs, Sagehen basin; Nevada County, California, *Chem. Geol.*, 179, 37–51, [https://doi.org/10.1016/S0009-2541\(01\)00314-X](https://doi.org/10.1016/S0009-2541(01)00314-X), 2001.
- Rademacher, L. K., Clark, J. F., Clow, D. W., and Hudson, G. B.: Old groundwater influence on stream hydrochemistry and catchment response times in a small Sierra Nevada catchment: Sagehen Creek, California, *Water Resour. Res.*, 41, <https://doi.org/10.1029/2003WR002805>, 2005.
- Ridgeway, J. B. and Surfleet, C. G.: Effects of Stream-side Buffers on Stream Temperatures Associated With Forest Management and Harvesting Using DHSVM-RBM; South Fork Caspar Creek, California, *Front. For. Glob. Change*, 4, <https://doi.org/10.3389/ffgc.2021.611380>, 2021.
- Rigge, M. B., Bunde, B., Shi, H., and Postma, K.: Rangeland Condition Monitoring Assessment and Projection (RCMAP) Fractional Component Time-Series Across the Western U.S. 1985–2020 (2.0, October 2021), U.S. Geological Survey, <https://doi.org/10.5066/P95IQ4BT>, 2021.
- Roberts, M. C. and Archibold, O. W.: VARIATION OF DRAINAGE DENSITY IN A SMALL BRITISH COLUMBIA WATERSHED, *J. Am. Water Resour. As.*, 14, 470–476, <https://doi.org/10.1111/j.1752-1688.1978.tb02183.x>, 1978.
- Rodhe, A. and Seibert, J.: Groundwater dynamics in a till hillslope: flow directions, gradients and delay, *Hydrol. Process.*, 25, 1899–1909, <https://doi.org/10.1002/hyp.7946>, 2011.
- Sen, P. K.: Estimates of the Regression Coefficient Based on Kendall's Tau, *J. Am. Stat. Assoc.*, 63, 1379–1389, <https://doi.org/10.1080/01621459.1968.10480934>, 1968.
- Senatore, A., Miceli, M., Liotti, A., Durigetto, N., Mendingo, G., and Botter, G.: Monitoring and Modeling Drainage Network Contraction and Dry Down in Mediterranean Headwater Catchments, *Water Resour. Res.*, 57, e2020WR028741, <https://doi.org/10.1029/2020WR028741>, 2021.
- Shaw, S. B.: Investigating the linkage between streamflow recession rates and channel network contraction in a mesoscale catchment in New York state, *Hydrol. Process.*, 30, 479–492, <https://doi.org/10.1002/hyp.10626>, 2016.
- Soil Survey Staff: Soil Survey Geographic (SSURGO) Database, <https://sdmdataaccess.sc.egov.usda.gov> (last access: 11 August 2026) 2022.
- Spence, C.: A Paradigm Shift in Hydrology: Storage Thresholds Across Scales Influence Catchment Runoff Generation, *Geography Compass*, 4, 819–833, <https://doi.org/10.1111/j.1749-8198.2010.00341.x>, 2010.
- Sproles, E. A., Leibowitz, S. G., Reager, J. T., Wigington Jr, P. J., Famiglietti, J. S., and Patil, S. D.: GRACE storage-runoff hystereses reveal the dynamics of regional watersheds, *Hydrol. Earth Syst. Sci.*, 19, 3253–3272, <https://doi.org/10.5194/hess-19-3253-2015>, 2015.
- Stieglitz, M., Shaman, J., McNamara, J., Engel, V., Shanley, J., and Kling, G. W.: An approach to understanding hydrologic connectivity on the hillslope and the implications for nutrient transport, *Global Biogeochem. Cy.*, 17, <https://doi.org/10.1029/2003GB002041>, 2003.
- Strahler, A. N.: Quantitative analysis of watershed geomorphology, *Eos Trans. AGU*, 38, 913–920, <https://doi.org/10.1029/TR038i006p00913>, 1957.
- Sun, F., Berg, N., Hall, A., Schwartz, M., and Walton, D.: Understanding End-of-Century Snowpack Changes Over California's Sierra Nevada, *Geophys. Res. Lett.*, 46, 933–943, <https://doi.org/10.1029/2018GL080362>, 2019.
- Sun, R., Hernández, F., Liang, X., and Yuan, H.: A Calibration Framework for High-Resolution Hydrological Models Using a Multiresolution and Heterogeneous Strategy, *Water Resour. Res.*, 56, e2019WR026541, <https://doi.org/10.1029/2019WR026541>, 2020.
- Tague, C. and Peng, H.: The sensitivity of forest water use to the timing of precipitation and snowmelt recharge in the California Sierra: Implications for a warming climate, *J. Geophys. Res.-Biogeo.*, 118, 875–887, <https://doi.org/10.1002/jgrg.20073>, 2013.
- Thackeray, C. W., Derksen, C., Fletcher, C. G., and Hall, A.: Snow and Climate: Feedbacks, Drivers, and Indices of Change, *Curr. Clim. Change Rep.*, 5, 322–333, <https://doi.org/10.1007/s40641-019-00143-w>, 2019.
- U.S. Geological Survey: USGS TNM Hydrography (NHD), U.S. Geological Survey, <https://www.usgs.gov/national-hydrography/national-hydrography-dataset> (last access: 11 August 2026), 2019.
- van Meerveld, H. J., Seibert, J., and Peters, N. E.: Hillslope–riparian-stream connectivity and flow directions at the Panola Mountain Research Watershed, *Hydrol. Process.*, 29, 3556–3574, <https://doi.org/10.1002/hyp.10508>, 2015.
- Venables, W. N. and Ripley, B. D.: Modern Applied Statistics with S, Springer New York, New York, NY, <https://doi.org/10.1007/978-0-387-21706-2>, 2002.
- von Freyberg, J., Radny, D., Gall, H. E., and Schirmer, M.: Implications of hydrologic connectivity between hillslopes and riparian zones on streamflow composition, *J. Contam. Hydrol.*, 169, 62–74, <https://doi.org/10.1016/j.jconhyd.2014.07.005>, 2014.
- Von Schiller, D., Bernal, S., Dahm, C. N., and Martí, E.: Nutrient and Organic Matter Dynamics in Intermittent Rivers and Ephemeral Streams, in: Intermittent Rivers and Ephemeral Streams, Elsevier, 135–160, <https://doi.org/10.1016/B978-0-12-803835-2.00006-1>, 2017.
- Ward, A. S., Schmadel, N. M., and Wondzell, S. M.: Simulation of dynamic expansion, contraction, and connectivity in a mountain stream network, *Adv. Water Resour.*, 114, 64–82, <https://doi.org/10.1016/j.advwatres.2018.01.018>, 2018.

- Ward, A. S., Wondzell, S. M., Schmadel, N. M., and Herzog, S. P.: Climate Change Causes River Network Contraction and Disconnection in the H.J. Andrews Experimental Forest, Oregon, USA, *Front. Water*, 2, <https://doi.org/10.3389/frwa.2020.00007>, 2020.
- Warix, S. R., Navarre-Sitchler, A., Manning, A. H., and Singha, K.: Local Topography and Streambed Hydraulic Conductivity Influence Riparian Groundwater Age and Groundwater-Surface Water Connection, *Water Resour. Res.*, 59, e2023WR035044, <https://doi.org/10.1029/2023WR035044>, 2023.
- Whiting, J. A. and Godsey, S. E.: Discontinuous headwater stream networks with stable flowheads, Salmon River basin, Idaho, *Hydrol. Process.*, 30, 2305–2316, <https://doi.org/10.1002/hyp.10790>, 2016.
- Wigmosta, M. S. and Perkins, W. A.: Simulating the Effects of Forest Roads on Watershed Hydrology, in: *Land Use and Watersheds: Human Influence on Hydrology and Geomorphology in Urban and Forest Areas*, American Geophysical Union (AGU), 127–143, <https://doi.org/10.1029/WS002p0127>, 2001.
- Wigmosta, M. S., Vail, L. W., and Lettenmaier, D. P.: A distributed hydrology-vegetation model for complex terrain, *Water Resour. Res.*, 30, 1665–1679, <https://doi.org/10.1029/94WR00436>, 1994.
- Winter, T. C., Harvey, J. W., Franke, O. L., and Alley, W. M.: Ground water and surface water: A single resource, U.S. Geological Survey, <https://doi.org/10.3133/cir1139>, 1999.
- Wolfram, S.: Universality and complexity in cellular automata, *Physica D*, 10, 1–35, [https://doi.org/10.1016/0167-2789\(84\)90245-8](https://doi.org/10.1016/0167-2789(84)90245-8), 1984.
- Wondzell, S. M.: The role of the hyporheic zone across stream networks, *Hydrol. Process.*, 25, 3525–3532, <https://doi.org/10.1002/hyp.8119>, 2011.
- Zanetti, F., Durighetto, N., Vingiani, F., and Botter, G.: Technical note: Analyzing river network dynamics and the active length–discharge relationship using water presence sensors, *Hydrol. Earth Syst. Sci.*, 26, 3497–3516, <https://doi.org/10.5194/hess-26-3497-2022>, 2022.
- Zanetti, F., Botter, G., and Camporese, M.: Stream Network Dynamics of Non-Perennial Rivers: Insights From Integrated Surface-Subsurface Hydrological Modeling of Two Virtual Catchments, *Water Resour. Res.*, 60, e2023WR035631, <https://doi.org/10.1029/2023WR035631>, 2024.
- Zimmer, M. A. and McGlynn, B. L.: Bidirectional stream–groundwater flow in response to ephemeral and intermittent streamflow and groundwater seasonality, *Hydrol. Process.*, 31, 3871–3880, <https://doi.org/10.1002/hyp.11301>, 2017a.
- Zimmer, M. A. and McGlynn, B. L.: Ephemeral and intermittent runoff generation processes in a low relief, highly weathered catchment, *Water Resour. Res.*, 53, 7055–7077, <https://doi.org/10.1002/2016WR019742>, 2017b.