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Controls From Above and Below: Snow, Soil, and Steepness Drive Diverging Trends of Subsurface Water and Streamflow Dynamics

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ABSTRACT

The importance of subsurface water dynamics, such as water storage and flow partitioning, is well recognised. Yet, our understanding of their drivers and links to streamflow generation has remained elusive, especially in small headwater streams that are often data-limited but crucial for downstream water quantity and quality. Large-scale analyses have focused on streamflow characteristics across rivers with varying drainage areas, often overlooking the subsurface water dynamics that shape streamflow behaviour. Here we ask the question: *What are the climate and landscape characteristics that regulate subsurface dynamic storage, flow path partitioning, and dynamics of streamflow generation in headwater streams?* To answer this question, we used streamflow data and a widely-used hydrological model (HBV) for 15 headwater catchments across the contiguous United States. Results show that climate characteristics such as aridity and precipitation phase (snow or rain) and land attributes such as topography and soil texture are key drivers of streamflow generation dynamics. In particular, steeper slopes generally promoted more streamflow, regardless of aridity. Streams in flat, rainy sites (< 30% precipitation as snow) with finer soils exhibited flashier regimes than those in snowy sites (> 30% precipitation as snow) or sites with coarse soils and deeper flow paths. In snowy sites, less weathered, thinner soils promoted shallower flow paths such that discharge was more sensitive to changes in storage, but snow dampened streamflow flashiness overall. Results here indicate that land characteristics such as steepness and soil texture modify subsurface water storage and shallow and deep flow partitioning, ultimately regulating streamflow response to climate forcing. As climate change increases uncertainty in water availability, understanding the interacting climate and landscape features that regulate streamflow will be essential to predict hydrological shifts in headwater catchments and improve water resources management.

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1 | Introduction

Climate change is increasingly challenging our perception of hydrological response and water management (Milly et al. 2008; Siirila-Woodburn et al. 2021). Identifying key factors that regulate water fluxes is especially important for headwater catchments that serve as the origins of stream networks. They account for 70%–80% of stream channel length (Downing 2012) and contribute substantial water and solute fluxes to downstream waters (Alexander et al. 2007). As climate change accelerates, shifting precipitation patterns interact with landscape features to shape hydrological response in headwater streams (Gleeson et al. 2011; Haitjema and Mitchell-Bruker 2005). Understanding how these interactions regulate partitioning of water into the surface and subsurface, streamflow, and evapotranspiration fluxes is essential for predicting the future of water resources. This is particularly the case in areas such as snow-dominated headwater catchments that generate high runoff to downstream waters but are exceedingly vulnerable to shifting climate (Ford et al. 2020; Immerzeel et al. 2020). Maintaining water resources and ecological health under increasing pressures will require a greater process-based understanding of water partitioning into these fluxes critical for not only water quantity but also quality (Land and Peters 2023; Li et al. 2022, 2024; Scanlon et al. 2023; Siirila-Woodburn et al. 2021; Sonne et al. 2018).

Efforts to understand water partitioning and streamflow dynamics often use classification-based methods, which group catchments by hydrological signatures reflecting how they receive, store, and release water based on climate and landscape characteristics (Chen et al. 2024; Gnann et al. 2019; Johnson et al. 2023; McMillan 2020; Wagener et al. 2007; Wlostowski et al. 2020). Climate drivers are routinely identified as important (Addor et al. 2018; Knoben et al. 2018) but cannot predict water partitioning and streamflow metrics by themselves (Addor et al. 2018; Hammond et al. 2021; Price et al. 2024; Xu et al. 2024). Landscape drivers jointly regulate water partitioning, streamflow generation, and dynamics but their roles have remained ambiguous and much debated (Chen et al. 2024; Gnann et al. 2019; Johnson et al. 2023; McMillan 2020; Wagener et al. 2007; Wlostowski et al. 2020). Subsurface water flow paths and dynamic water storage—or the storage that responds and contributes to streamflow and hereafter referred to as “water storage” (Soulsby et al. 2011)—are essential in regulating the timing and magnitude of discharge (Gorski and Zimmer 2021; Johnson et al. 2024; Li et al. 2024; Zhi et al. 2019), especially in headwater catchments (Kaule and Gilfedder 2021; Xiao et al. 2021). Illuminating subsurface water storage dynamics and flow path partitioning can help connect climate and landscape features to identify key controls of hydrological response and streamflow dynamics (Dwivedi et al. 2019; Herndon et al. 2015; Sullivan et al. 2019).

Precipitation phase (i.e., whether it falls as rain or snow) has been shown to be important for streamflow generation via subsurface flow paths (Barnhart et al. 2016). Snow is more likely to recharge to the deeper subsurface (Langston et al. 2015) while rain often preferentially partitions to evapotranspiration (Carroll et al. 2020; Sprenger et al. 2022). Compared to rain, snowmelt disproportionately contributes to streamflow, largely from deeper flow paths (Barnhart et al. 2016; Berghuijs et al. 2014),

resulting in smooth discharge regimes that are less sensitive to changes in water storage (Wlostowski et al. 2020). However, the influence of precipitation phase is not clearly separated from other characteristics (Barnhart et al. 2016; Hammond and Kampf 2020; Xu et al. 2024). For example, snow driving deeper recharge depends on factors such as antecedent conditions, seasonality of snowmelt, and melt rate, all of which are shifting under warming conditions (Hale et al. 2023; Hammond and Kampf 2020). Snow is more common in steep mountains with shallow soils—characteristics linked to shallower flow paths, flashier streamflow, and rapid discharge response to changes in dynamic storage (Bush et al. 2023; Hare et al. 2021; Jencso et al. 2010; Warix et al. 2023). Conversely, shallower flow paths are also attributed to both greater depths to bedrock (Haynes et al. 2023) and larger permeability contrasts between soils and bedrock (Hare et al. 2021; Xiao et al. 2021; Yao et al. 2021). These conflicting drivers indicate climate and landscape factors interact in complex ways to regulate streamflow generation, which is challenging to decipher (Ali et al. 2012a; Johnson et al. 2024).

Efforts to understand these interactions have been bolstered by intensively monitored sites, such as the Critical Zone and Long-Term Ecological Research Networks, which offer valuable data for comparative studies and broader generalisations about how catchment variations regulate streamflow generation dynamics (Kelleher et al. 2015; Wagener et al. 2007; Wlostowski et al. 2020). They also facilitate comparative modelling studies that can dissect the water balance and explore subsurface controls—insights often limited by inconsistent spatiotemporal and difficult-to-measure subsurface data.

Existing studies have advanced our understanding of key drivers of streamflow dynamics, although the uniqueness of place still remains a challenge (Addor et al. 2018; Beven 2000; Blöschl et al. 2019). Here we compare intensively monitored headwater catchments throughout the contiguous United States (CONUS) to answer the following questions: *What are the climate and landscape characteristics that regulate subsurface dynamic storage, flow path partitioning, and dynamics of streamflow generation in headwater streams?* A semi-distributed hydrologic model was used together with intensive hydrometeorological data to simulate hydrological processes in 15 catchments. Model results allowed us to quantify subsurface storage and groundwater flow partitioning to streams, metrics that are often challenging to measure directly. By modelling catchments across the CONUS, we aim to provide a more cohesive understanding of headwater catchment hydrology. Resolving contrasting views about these catchments that make up the majority of stream networks will be crucial for predicting how climate change and human impacts will affect water resources.

2 | Methods

2.1 | Sites

This study considered 15 minimally impacted headwater catchments located throughout the CONUS, spanning gradients of climate conditions and land characteristics (Figure 1). Selected catchments were sites with extensive data from Critical Zone Observatories (U.S. CZO network), Long Term

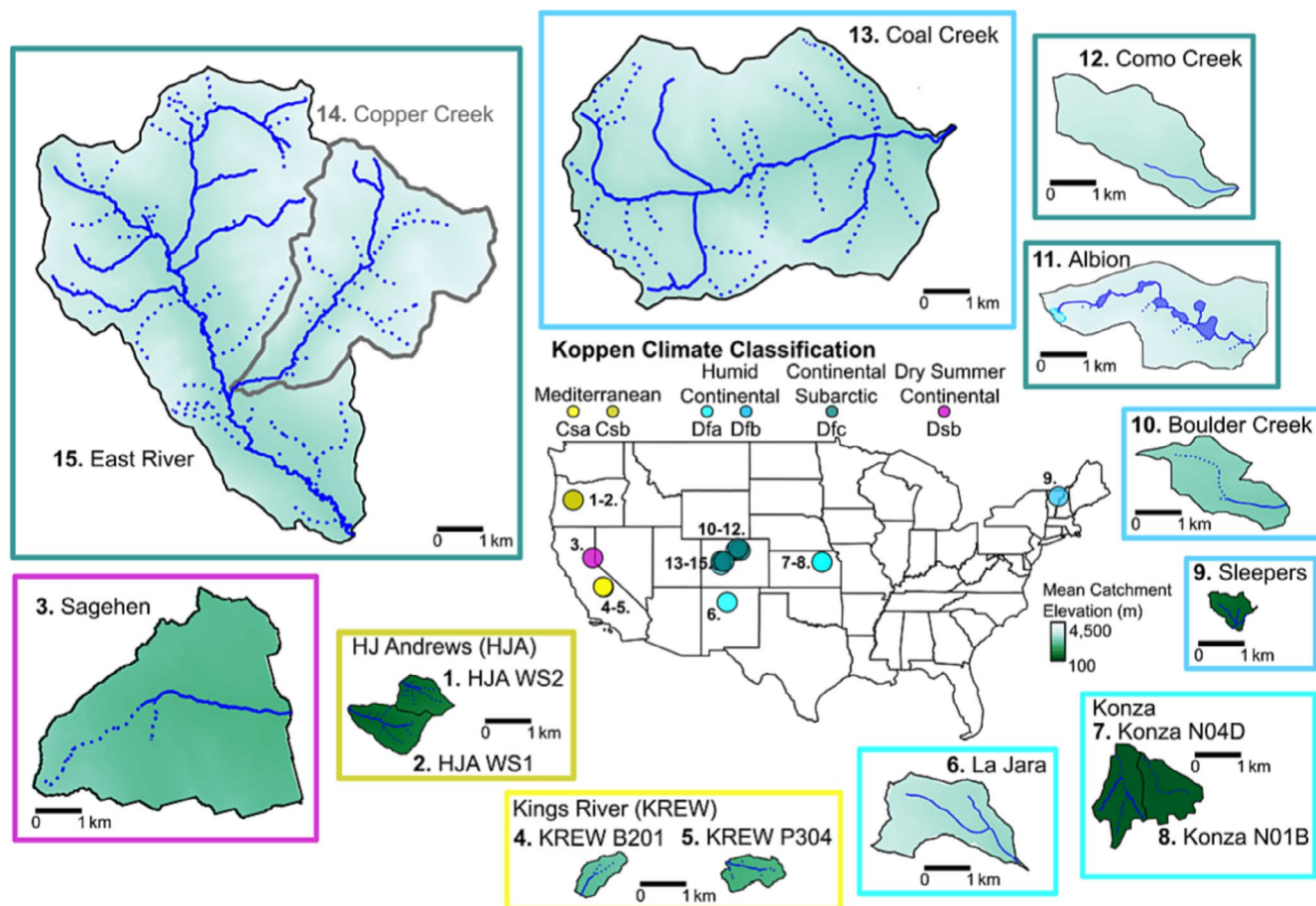


FIGURE 1 | Map of 15 site locations within the contiguous United States (filled circles) showing their respective Köppen Climate classes (circle fill colour; Csa: Hot-summer Mediterranean; Csb: Warm-summer Mediterranean; Dfa: Hot-summer humid continental; Dfb: Warm-summer humid continental; Dfc: Subarctic, and Dsb: Mediterranean-influenced hot-summer humid continental). Around the site map, catchment maps show that mean catchment elevation (green catchment fill) varies from 398 m (Konza N04D) to 3529 m (Copper Creek). Sites encompass perennial (solid blue lines) and intermittent (dashed light blue lines) streams, lakes (dark blue filled solid outlines), and glacier (light blue filled dashed outline) features.

Ecological Research (LTER) sites, Science Focus Areas (SFA), and experimental/research watersheds run by the U.S. Government (United States Department of Agriculture (USDA) and United States Geological Survey (USGS)). The catchments span three orders of magnitude in drainage area, about 3200 m in mean elevation, and cover two of the five main Köppen climate classes (i.e., Mediterranean & Continental) (Beck et al. 2016; Köppen 2011). The basin reliefs range from 69 m to 1350 m and mean slopes from 8% to 59%. Catchments are either forested, grassland, or majority barren while soils and lithology vary from catchment to catchment. The most dominant catchment characteristics are shown in Table 1 (additional characteristics in SI Table S2). Additionally, one catchment (La Jara) had pre-fire and post-fire states that were considered as separate catchments for analysis.

2.2 | Data

2.2.1 | Climate and Discharge Data

Hydrometeorological and land-characteristic data for the 15 catchments were sourced from various open-access repositories (Table S1). Daily-scale time-series data included precipitation

[mm/d], air temperature [$^{\circ}\text{C}$], potential evapotranspiration (PET) [mm/d], snow water equivalent (SWE) [mm], and area-normalised stream discharge (Q) [mm/d]. SWE data for Coal Creek, East River, Copper Creek, KREW P304, KREW B201, and Sagehen were obtained from the SNOW TELmetry (SNOTEL) network. PET data were downloaded from catchment-respective repositories (PET in these repositories is typically calculated via Penman-Monteith (1965)). If PET data were unavailable, the Hargreaves/Hargreaves-Samani equation was used (Hargreaves and Samani 1985) due to its limited data requirements compared to other methods. When available, precipitation and air temperature were sourced from project-monitored meteorological stations closest to the catchment or, if not available, from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) (PRISM Climate Group 2021). All time-series data sources are outlined in Table S1.

2.2.2 | Land Characteristic Data

Catchment drainage areas were delineated from digital elevation data from the USGS 3D Elevation Program (3DEP) using USGS StreamStats (U.S. Geological Survey 2019). The dominant lithology of each catchment was obtained from the

TABLE 1 | Site information and selected land characteristics including area, mean elevation, mean slope, soil texture and depth, lithology, vegetation, Köppen climate classification.

Catchment	Landscape	Lat, long [stream gage]	Area [km ²]	Mean elevation [m]	Mean slope [%]	Soil texture	Soil depth [m]	Dominant lithology	Dominant vegetation [%]	Köppen climate	P as snow [%]
Albion	Niwot Ridge LTER Rocky Mountains	40.0426, −105.5923	7.1	3579	42	Sandy loam	0.82	Crystalline igneous bedrock	Barren/ Ice (34%)	Dfc	76
Boulder Creek	Gordon Gulch CZO Rocky Mountains	40.0166, −105.4743	3.60	2624	23	Sandy loam	1.17	Crystalline igneous bedrock	Evergreen forest (95%)	Dfb	25
Coal Creek	East River SFA Rocky Mountains	38.8710, −106.9850	53.08	3168	30	Loam	1.66	Mesaverde sandstone	Evergreen forest (63%)	Dfb	66
Como Creek	Niwot Ridge LTER Rocky Mountains	40.0349, −105.5440	4.90	3300	19	Sandy loam	1.75	Gneiss, granite	Evergreen forest (61%)	Dfc	47
Copper Creek	East River SFA Rocky Mountains	38.9571, −106.9883	24.00	3529	54	Sandy loam	0.21	Mancos shale	Barren/ Alpine (50%);	Dfc	75
East River	East River SFA Rocky Mountains	38.9220, −106.9510	84.13	3349	45	Sandy loam	0.65	Mancos shale	Shrub/ Scrub (38%)	Dfc	73
HJ Andrews WS1	Andrews Forest LTER Cascade Mountains	44.2068, −122.2595	0.96	733	59	Loam	2.2	Little butte formation (massive tuffs and breccias)	Evergreen forest (88%)	Csb	1
HJ Andrews WS2	Andrews Forest LTER Cascade Mountains	44.2096, −122.2567	0.60	812	53	Loam	1.80	Little butte formation (massive tuffs and breccias)	Evergreen forest (91%)	Csb	2
Kings River B201	Experimental Watershed (USDA) Sierra Mountains	36.9800, −119.0792	0.53	2257	18	Sandy loam	0.92	Granite	Evergreen forest (92%)	Csa	51
Kings River P304	Experimental Watershed (USDA) Sierra Mountains	37.0525, −119.1953	0.49	1899	22	Sandy loam	1.50	Granite	Evergreen forest (99%)	Csa	46
Konza N01B	Konza Prairie LTER Great Plains	39.0867, −96.5770	1.20	409	11	Silty clay	1.03	Repeating layers of mudstone (2–4 m) and limestone (1–2 m)	Grassland/ Herbaceous (97%)	Dfa	3

(Continues)

TABLE 1 | (Continued)

Catchment	Landscape	Lat, long [stream gage]	Area [km ²]	Mean elevation [m]	Mean slope [%]	Soil texture	Soil depth [m]	Dominant lithology	Dominant vegetation [%]	Koppen climate	P as snow [%]
Konza N04D	Konza Prairie LTER	39.0874, −96.5770	1.20	398	13	Silty clay	1.02	Repeating layers of mudstone (2–4 m) and limestone (1–2 m)	Grassland/ Herbaceous (97%)	Dfa	6
La Jara Post-Fire	Rocky Mountains	35.7550, −106.3661	3.76	3100	27	Sandy loam	2.20	Rhyolite tuff	Grassland/ Herbaceous (51%)	Dfa	46
La Jara Pre-Fire	Rocky Mountains	35.7550, −106.3661	3.76	3100	27	Sandy loam	2.20	Rhyolite tuff	Evergreen forest (75%)	Dfa	45
Sagehen	Sierra Mountains	39.4317, −120.2408	27.60	2157	16	Sandy clay loam	1.09	Triassic/Jurassic metamorphic rock overlain by Tertiary volcanics (andesite) overlain by glacial till/ alluvium	Evergreen forest (93%)	Dsb	51
Sleepers	Research Watershed (USGS)	44.4906, −72.1618	0.41	601.5	13	Sandy loam	1.16	Quartz–mica phyllite, calcareous granulite	Deciduous forest (85%)	Dfb	20

Abbreviations: Csa: Hot-summer Mediterranean; Csb: Warm-summer Mediterranean; Dfa: Hot-summer humid continental; Dfb: Warm-summer humid continental; Dfc: Subarctic; and Dsb: Mediterranean-influenced hot-summer humid continental), and percent (%) precipitation (P) as snow.

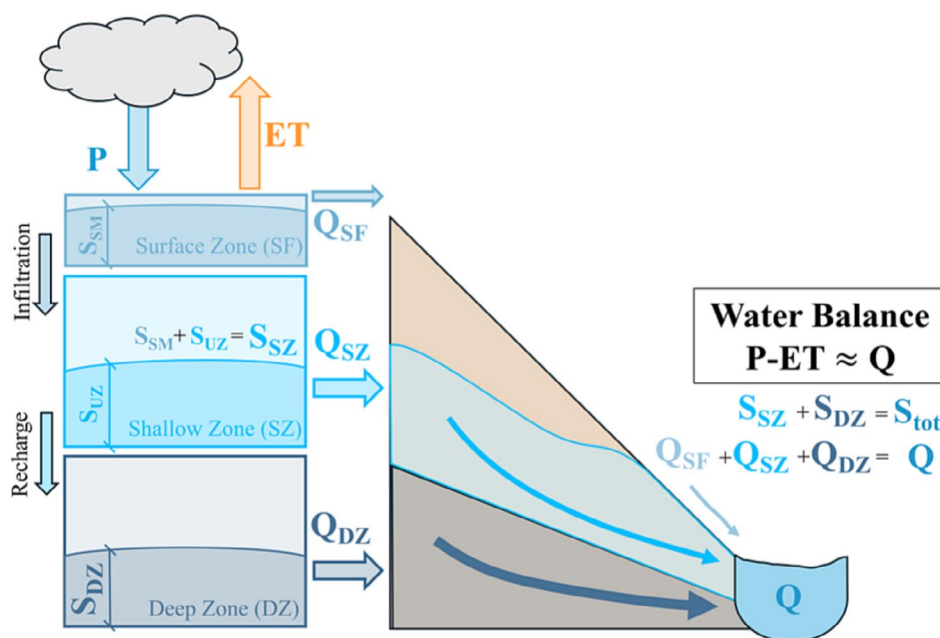


FIGURE 2 | HBV model structure. Three flow paths originate from the conceptual bucket-type model, a near-surface flow (Q_{SF}), an intermediate flow path from a shallow (upper) zone (Q_{SZ}), and a slow flow path from a deep (lower) zone (Q_{DZ}). Total stream discharge (Q) is the summation of Q_{SF} , Q_{SZ} , and Q_{DZ} . Each zone has water storage, represented by S_{SM} for the very shallow soils near the surface, S_{UZ} for the upper subsurface storage box of HBV, and S_{DZ} for the lower subsurface storage box of HBV. The sum of S_{SM} and S_{UZ} is total shallow dynamic storage (S_{SZ}), which is added to total deep dynamic storage (S_{DZ}) to estimate total catchment dynamic storage (S_{tot}).

State Geologic Map Compilation (SGMC) geodatabase published by the U.S. Geological Survey (Horton et al. 2017). Other data repositories used for catchment characteristic information include the National Land Cover Database (NLCD), which provides data on land use (Dewitz and U.S. Geological Survey 2021), and the Soil Survey Geographic Database (SSURGO) (Soil Survey Staff 2023). From SSURGO, average soil parameters for each catchment were calculated as weighted averages based on the proportion of land area covered by each soil type.

2.3 | Hydrologic Modelling

Each catchment was modelled using the bucket-type catchment runoff model, *Hydrologiska Byråns Vattenbalansavdelning* (HBV; Figure 2), a widely applied catchment runoff model (Bergström 1976; Seibert and Bergström 2021; Seibert and Vis 2012). HBV takes time series inputs of measured precipitation [mm], air temperature [°C], and PET [mm]. HBV determines the precipitation phase based on a calibrated temperature threshold parameter above which all precipitation is considered to fall as rain. Below this temperature threshold precipitation is considered to fall as snow and multiplied by a parameter called the “snowfall correction factor”. This factor considers the effects of systematic measurement errors (e.g., wind losses) and interception losses and is usually lower for forested areas than for open areas. After precipitation, HBV simulates the major water fluxes, snow melt, evapotranspiration (ET), surface and subsurface groundwater flow to generate discharge. Simulated discharge output is calibrated against discharge data measured at the catchment outlet. In addition to discharge, the time series of modelled outputs includes daily values of evapotranspiration

(ET), subsurface water storage, and runoff (water flowing from land to streams), which is composed of flow from three subsurface water stores.

Conceptual subsurface storage is present in HBV as soil moisture (S_{SM}), upper subsurface storage (S_{UZ}), and lower subsurface storage (S_{DZ}) (Seibert and Bergström 2021; Seibert and Vis 2012). The sum of these quantities represents total “dynamic water storage”—defined as the water storage that responds and contributes to streamflow (Soulsby et al. 2011). Our definition encompasses the storage that approaches zero when all fluxes, including runoff and ET cease as this water storage is particularly relevant for describing intermittent streams and their active drainage network (Godsey and Kirchner 2014; Staudinger et al. 2017).

The standard HBV structure with three outflow paths (Q_{SF} , Q_{SZ} , and Q_{DZ}) was used. This structure represents catchments as a soil moisture zone atop two stacked buckets. The subsurface is not parameterized based on directly measurable physical characteristics, such as soil properties. Instead, calibrated parameters in the groundwater (also called response) routine are used to determine how water is partitioned between fluxes and subsurface storage components (Table S4). The model uses a traditional degree-day approach to calculate snowmelt rates and partitions snowmelt and precipitation input between ET and discharge based on water and energy balance. Discharge is separated into surface and subsurface flow based on soil moisture accounting, and subsurface flow is partitioned between the middle and lower buckets. HBV has multiple structures, but the standard structure tends to hit the balance of generating good fits across many catchment types (Karimi et al. 2022) without being too simplistic to isolate different runoff generation processes (Fenicia et al. 2013).

This lumped representation is used to estimate the temporal dynamics of catchment-scale streamflow generation without requiring spatial details, a difficult task when examining over a dozen catchments.

The middle and lower buckets can be conceptualised as the shallow soil zone (SZ) and the deep groundwater zone (DZ), respectively. Although the model does not explicitly delineate a vadose and saturated zone, the SZ is mostly unsaturated, except during times of high flow, and can be considered mostly vadose zone, whereas the deep zone is mostly saturated. HBV calculates infiltration from the SF to SZ via a soil moisture routing routine and recharge from the SZ to the DZ via a calibrated percolation rate. The water apportioned to the stream consists of intermediate (Q_{SZ}) and slow flows (Q_{DZ}) from the stacked SZ and DZ buckets, as well as a quick-flow component that approximates fast-flow paths such as near-surface runoff (Q_{SF}). Annual streamflow fractions from the near-surface ($f(Q_{SF})$), the shallow zone ($f(Q_{SZ})$), and the deep zone ($f(Q_{DZ})$) are represented as annual flow path flux over total annual discharge.

2.4 | Model Calibration

HBV was calibrated for each catchment against measured stream discharge and, when available, SWE. Each catchment was calibrated across three continuous years of data that were constrained to water years (WY) 2016–2018, when those data were available. Adequate data for this time period did not exist for Como Creek, Kings River B201, Kings River P304, or La Jara. These catchments were instead calibrated against the closest periods that did have adequate data. The time periods simulated in HBV for each catchment are included in Table S3.

Model performance was assessed using four efficiency metrics to assess multiple facets of a catchment's hydrograph. The (Equation 1) Nash-Sutcliffe Efficiency (NSE) (Nash and Sutcliffe 1970) was used to assess fit on peak flows,

$$NSE = 1 - \frac{\sum_{i=1}^n (Q_{obs,i} - Q_{sim,i})^2}{\sum_{i=1}^n (Q_{obs,i} - \bar{Q}_{obs})^2} \quad (1)$$

The (Equation 2) *NSElog*, or the NSE of natural log(Q), was used to assess fit on low flows,

$$NSElog = 1 - \frac{\sum_{i=1}^n (\ln(Q_{sim,i}) - \ln(Q_{obs,i}))^2}{\sum_{i=1}^n (\ln(Q_{obs,i}) - \ln(\bar{Q}_{obs}))^2} \quad (2)$$

To calculate these metrics, n is the number of time steps, $Q_{obs,i}$ is the observed discharge data at time i , and $Q_{sim,i}$ is the simulated discharge at time i . The (Equation 3) Kling-Gupta Efficiency (*KGE*) (Gupta et al. 2009) was an additional measure to simultaneously evaluate correlation, bias, and variability.

$$KGE = 1 - \sqrt{(r-1)^2 + \left(\frac{\sigma_{sim}}{\sigma_{obs}} - 1\right)^2 + \left(\frac{\mu_{sim}}{\mu_{obs}} - 1\right)^2} \quad (3)$$

where r is the linear correlation between observed and simulated discharge values, σ_{obs} and σ_{sim} are the standard deviations of the observed and simulated discharge values, respectively, and μ_{obs} and μ_{sim} are the means of the observed and simulated discharge values, respectively. The fourth and final metric, (Equation 4) volume error (*VE*) was used to evaluate how well the model represents annual discharge volumes,

$$VE = 1 - \frac{\left| \sum_{i=1}^n (Q_{obs,i} - Q_{sim,i}) \right|}{\sum_{i=1}^n (Q_{obs,i})} \quad (4)$$

with 1 indicating perfect performance. The model is a better estimate of discharge than mean discharge when $NSE > 0$ and $KGE > -0.4$ (Knoben et al. 2019). Here, satisfactory model performance is defined when NSE , $NSElog$, KGE , and VE values are > 0.5 and excellent performance when all values > 0.75 .

A year of data was used as a warm-up period to allow HBV state variables to reach equilibrium with meteorological conditions. The Genetic Algorithm and Powell (GAP) optimization tool (Seibert 2000; Seibert and Vis 2012) was then used for automatic calibration of 200 calibration trials. For each calibration trial, the GAP tool generates optimised parameter sets by an evolutionary mechanism of selection and recombination of a set of initial, randomly selected parameters from boundaries taken from Beck et al. (2016). Subsequently, the parameter sets are fine-tuned using Powell's quadratically convergent method (Press et al. 2002). Parameters were optimised against a weighted mean objective function which combines NSE (weight = 0.4), $NSElog$ (weight = 0.4), and VE (weight = 0.2). The fitted model was then assessed against the 4 efficiency metrics above to ensure satisfactory performance. Due to the random elements inherent to GAP, each of the 200 trials produced distinct model parameter sets (SI Figure S1). The mean of the 200 calibration trials was used in an effort to address parameter uncertainty and equifinality (Karimi et al. 2022). If the model did not produce a good fit and multiple parameters were calibrated to the maximum or minimum of their initial bounds, these parameter boundaries were expanded and the GAP trials were run again. This process was repeated until no further improvement in model performance was achieved.

2.5 | Calculation of Hydrological Signatures

2.5.1 | Water Balance and Budyko Equation

Hydrologic systems often function within the bounds of either water or energy limitations when groundwater inputs, losses, or storage changes are negligible. In arid environments, atmospheric demand exceeds water input ($P \ll PET$) and ET converges towards P , implying that ET is limited by water supply. In humid environments, precipitation exceeds atmospheric demand ($P \gg PET$), and ET is limited by atmospheric demand and collapses towards PET . These concepts are encapsulated in the empirical Budyko equation (Budyko 1974), which suggests that long-term mean evapotranspiration (ET) is determined by water availability (precipitation, P) and atmospheric evaporative demand (potential evapotranspiration, PET) by

relating the long-term evaporative index (ET/P) to the aridity index (PET/P):

$$\frac{ET}{P} = \frac{1}{\left[1 + \left(\frac{P}{PET}\right)^{-\beta}\right]^{\frac{1}{\beta}}} \quad (5)$$

In this form of the Budyko equation (Turc-Pike (Pike 1964; Turc 1954)), the dimensionless β , which typically varies between 1 and 3, describes the curvature of the association between evaporative and aridity indices (Chen and Sivapalan 2020; Choudhury 1999; Yang et al. 2008). P and PET were input data while ET was output from HBV. HBV does not account for groundwater losses of water that flows deeper in the subsurface and does not contribute to runoff or streamflow. These unaccounted losses can cause HBV to overestimate ET to maintain water balance.

2.5.2 | Storage-Discharge Sensitivity Function

A simple power law describes the response of streamflow discharge to changes in dynamic storage:

$$Q = aS_{tot}^b \quad (6)$$

Here Q is discharge [mm/d] model output, S_{tot} is area-normalised dynamic storage [mm] model output, a is the y-intercept of the curve [mm^{1-b}/d], and b is the power law exponent, which represents the sensitivity of discharge to changes in storage [unitless]. This simple power law formula has been widely used to characterise outflow of lumped storage models (Ali et al. 2012b; Chapman 1999; Harman and Sivapalan 2009; Wittenberg and Sivapalan 1999), with b -values observed to range from 1.1 to 9.1 (Chapman 1999; Wittenberg 1993; Wittenberg and Sivapalan 1999).

2.5.3 | Seasonality Index

The seasonality index describes the relative timing and magnitude of terrestrial water supply to evaporative demand (Woods 2009):

$$Seasonality = A_{Supply} \operatorname{sgn}(A_{Demand}) \cos(2\pi(\theta_{Supply} - \theta_{Demand}) / 365) \quad (7)$$

Here A and Θ represent the amplitude and time offset of sinusoidal functions (Equations S2 and S3) fit to the time series of mean water supply and demand. Water supply was the sum of daily rain and snowmelt simulated by HBV, representing the water that could potentially infiltrate into the subsurface. PET input data was used as the evaporative water demand, and water input was the sum of simulated rainfall and snowmelt. GAP runs were averaged across every day of the water year to give one set of daily time series for analysis. A negative seasonality index occurs when water supply and demand are out of phase, while a positive index occurs when supply and demand are in phase. The magnitude of seasonality is sensitive to the amplitude of water supply (A_{supply}); when there is little variation in water supply, its amplitude and calculated seasonality will be

zero. For example, the Mediterranean (dry summer) climate of the HJA watersheds both has a seasonality index around -1 , indicating out-of-phase seasonality of their rain-dominated input and demand. On the other hand, the Konza catchments, which have a humid continental climate, have a seasonality of ~ 0.6 , indicating in-phase seasonality, where rainfall tends to occur in warmer times with higher atmospheric demand. The highest seasonality values (> 1) are found in catchments that are dominated by snow, as snow melt recharge occurs during warmer times with higher atmospheric demand.

2.5.4 | Richards-Baker Flashiness Index

The Richards-Baker Flashiness Index (RBI) is a commonly used metric for quantifying stream flashiness, or how quickly streamflow rises and falls relative to total streamflow (Baker et al. 2004; McMillan 2020).

$$RBI = \frac{\sum_{i=1}^n |Q_i - Q_{i-1}|}{\sum_{i=1}^n Q_i} \quad (8)$$

Here i refers to the daily time steps and Q refers to modelled mean daily streamflow. RBI values were calculated for each GAP run, then averaged for each catchment. RBI values were also calculated for observed stream discharge (Q_{obs}).

2.6 | Identifying Significant Correlations and Influential Drivers

2.6.1 | Correlations

To compare stationary catchment attributes to varying climate and hydrological data, mean annual averages of climate and hydrological data were calculated for each catchment. Across the 15 catchments, the distributions of catchment features and mean annual climate and hydrological data often strayed from normality. This is a common occurrence for natural systems as data can often be skewed and irregular. Additionally, correlations between variables are frequently non-linear, and strong correlations may not arise when using linear tests such as Pearson's correlation. As such, correlations between land and hydrological variables were estimated using the non-parametric Spearman rank correlation (ρ) (Spearman 1904). A significance level of 5% was used as the cutoff to define statistical significance (p value ≤ 0.05). Positive ρ values indicate monotonically increasing correlations, and negative ρ values indicate monotonically decreasing correlations between variables. Many significant correlations are noted in the SI Text S5, Tables S5–S9, and Figures S3–S8 and were narrowed down to the most important based on linear modelling as discussed below.

2.6.2 | General Linear and General Linear Mixed Effects Models for Parameter Analysis

Spearman correlations were often similarly strong and significant between multiple variables. Therefore, general linear and mixed effects models (via the “lme4” package in R (Bates

et al. 2015)) were used to evaluate and identify dominant connections between storage-discharge b-values, streamflow flashiness (RBI), flow path partitioning, and land and discharge metrics. Random effects were added based on significant correlations. Some variables were used as fixed effects if they could be converted to categorical information. For example, the seasonality of catchments ranged from about -1 to 2 , and we could parse seasonality into a two-category fixed effect with one category representing in-phase seasonality (>0) and the other category representing out-of-phase seasonality (<0). Fixed effects were used and compared to the random effects-only linear models to assess the possibility of discrete groups with alternate intercepts. Models with catchments as a fixed effect were tested but did not perform as well as those using catchment or climate properties. Model performance was evaluated using correlation coefficients, the Akaike Information Criterion (AIC) (Akaike 1974; Burnham and Anderson 2002), and the Shapiro–Wilk test for residual normality (Shapiro and Wilk 1965). The best models had high correlation coefficients, low AIC values, and normally distributed residuals. Multiple models of all parameter combinations were assessed to identify dominant relationships among autocorrelated variables (Text S8 and Tables S10–S18).

3 | Results

3.1 | HBV Predicts Daily Discharge Better in Snowy and Wet Sites

Mean model efficiency metrics assessing how well HBV reproduced daily discharge dynamics showed nearly all models behaved better than using mean discharge as predicted daily discharge ($NSE > 0$ & $KGE > -0.4$; Figure 3a–c). All models showed high performance in predicting the annual water balance ($VE > 0.75$; Figure 3d). Mean daily model output of the 200 GAP runs satisfactorily reproduced daily dynamics of stream discharge data for all but the four lowest discharge catchments (La Jara, Boulder Creek, and both Konza catchments) (Figure 4).

Sites with more precipitation as snow exhibited one peak discharge event later in the water year (spring/early summer

snowmelt) and were generally well predicted by HBV. Streamflow was predicted notably well in high discharge sites where most streamflow was sourced from snowmelt, which is common in the Rocky Mountains (East River, Copper Creek, Coal Creek). Model performance declined as high discharge sites became more rain dominated, especially in sites that may receive mixed snow and rain precipitation and experience rain on snow events—more common to the northeast and Sierra Nevada and Cascade Mountain ranges (Sagehen, Sleepers, HJA WS 1 & 2).

3.2 | Higher Deep-Water Fractions ($f(Q_{DZ})$) in Arid and Flat Sites

Annual discharge Q varied from 1328 mm/year in the most humid catchment, HJ Andrews WS2 ($p = 2554$ mm/year) to 59 mm/year in the most arid catchment, Boulder Creek ($p = 501$ mm/year) (Figure S2). PET increased with the aridity index, while all other variables, including ET, P, and Q (Figure 5a) decreased with increasing aridity across sites. Annual discharge was generally lower in arid sites compared to humid sites. However, upon closer inspection, Q decreased with aridity in humid sites ($PET/p < 1$) but increased with aridity in arid sites ($PET/p > 1$).

Runoff ratios (RR), or the annual fraction of precipitation that is converted to Q , are significantly and negatively correlated with evaporative index values (Spearman's $\rho = -0.58$; p value = 0.02). Slope emerged as the second most significant driver (Spearman's $\rho = 0.56$; p value = 0.03); meaning steeper sites, particularly in high-elevation arid climates, have higher runoff ratios (Figure 5c,d) and comparatively higher Q . Mean annual PET varied from a minimum of 755 mm/yr in Sleepers River to a maximum of 1946 mm/year in HJ Andrews WS1 and was generally consistent across years in each catchment. HJ Andrews WS1 also showed the highest ET (1289 mm/year) while the high elevation catchment Albion showed the lowest (215 mm/year), likely due to its glaciers and large amount of barren land.

The Budyko curve (Figure 5b) reflected the integrated effects of climate and vegetation on the water balance. Sleepers River

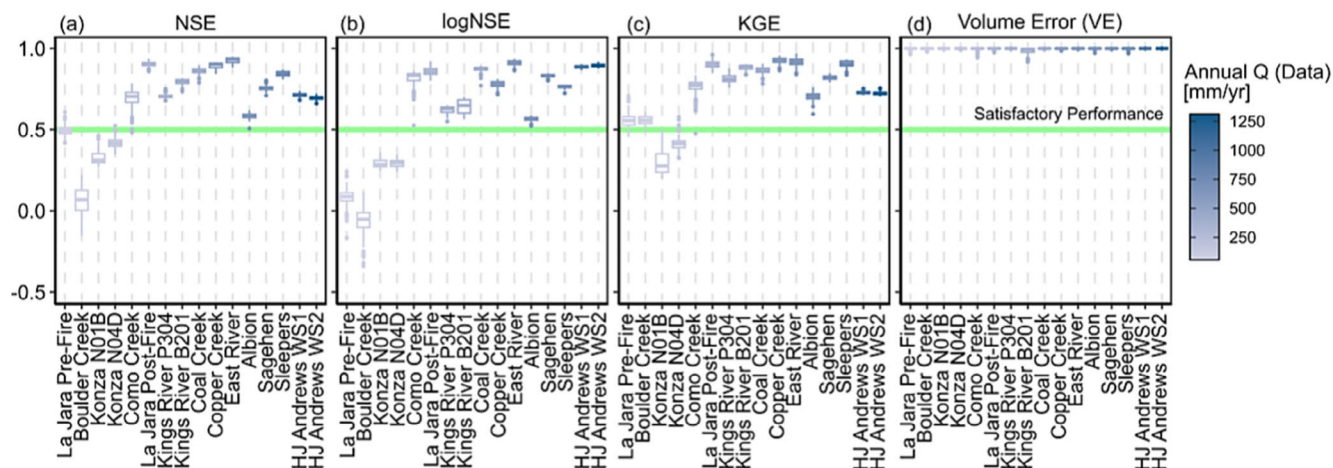


FIGURE 3 | Box plots of mean model fit metrics used to assess fit to daily discharge for the 200 GAP calibration trials for each catchment. All but the four lowest discharge catchments (Boulder Creek, Konza N01B, Konza N04D, and La Jara) showed satisfactory model fits based on (a) Nash–Sutcliffe Efficiency (NSE), (b) log NSE, (c) King–Gupta Efficiency (KGE), and (d) Volume Error (VE).

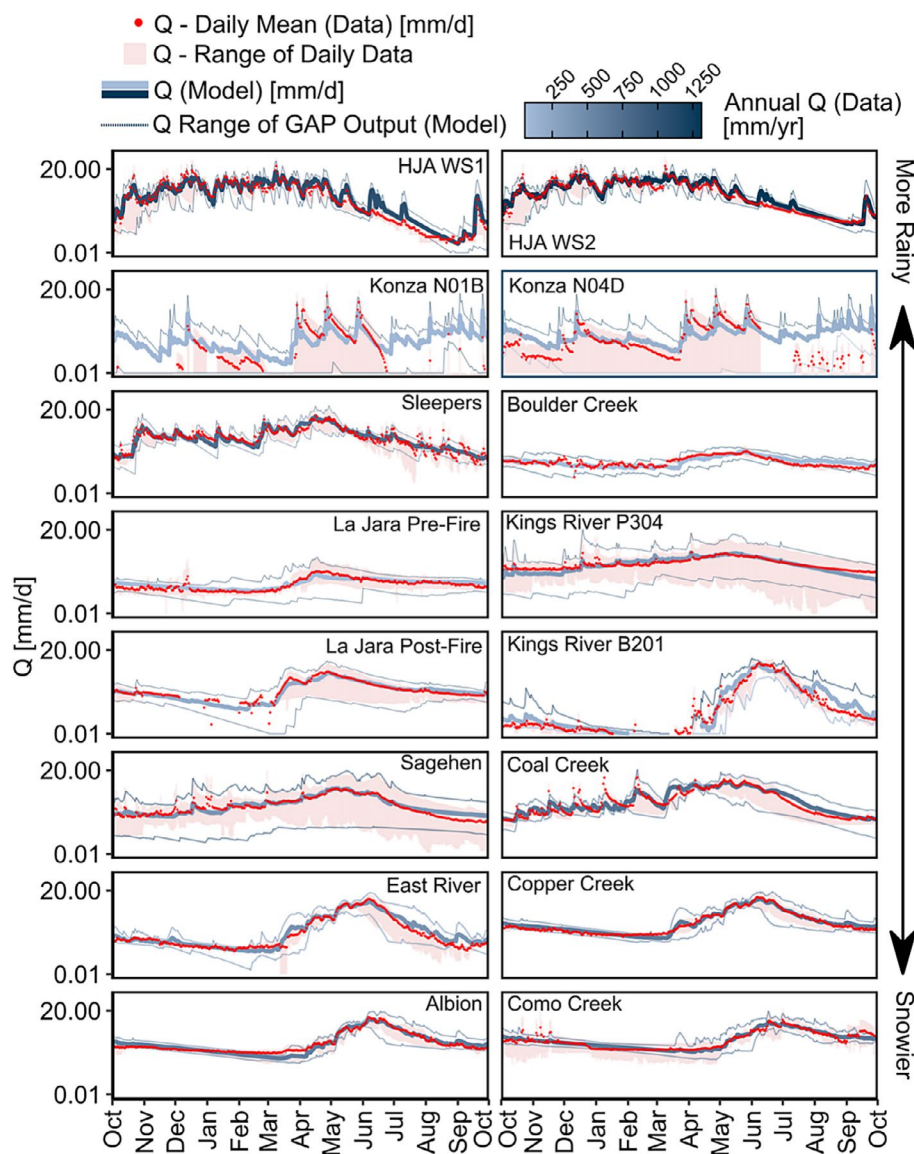


FIGURE 4 | Multi-year mean modelled daily discharge (solid line), range of multi-year mean output of 200 GAP calibration trials (thin blue lines), multi-year mean measured discharge (red dots), and the range of discharge measured each day over the averaged years (red shade). Catchments are ordered from the least (top) to most snowy (bottom).

was the most humid catchment, followed by those along the Cascade and Sierra Nevada mountains. Catchments in the U.S. interior (Rockies and Kansas) were more arid. Most catchments fell close to a Budyko curve except for Albion and East River, which fell below all theoretical Budyko curves, indicating an overestimation of discharge. Conversely, Boulder Creek fell above the water limit line, indicating an overestimation of ET. Sites departing from the Budyko curves may have other controls (in addition to aridity) on water partitioning between ET and Q.

Annual flow path partitioning showed unimodal distributions for the 200 GAP calibration trials (Figure 6a), meaning calibration trials often resulted in consistent values for $f(Q_{SF})$, $f(Q_{SZ})$, and $f(Q_{DZ})$. Kings River B201, La Jara Post-Fire, and Albion, however, showed large spreads of $f(Q_{SZ})$ and $f(Q_{DZ})$. While surface flow, $f(Q_{SF})$, consistently made up the smallest fraction of annual streamflow in all catchments, deep zone contributions,

$f(Q_{DZ})$, were more often the dominant component in flatter catchments with lower runoff ratios. Conversely, shallow zone contributions, $f(Q_{SZ})$, often dominate in steeper catchments with higher runoff ratios and discharge.

While trends are visible, neither shallow nor deep zone contributions significantly correlated with slope. They, however, did correlate with runoff ratios and Q (Figure 6b,c). Specifically, $f(Q_{DZ})$ was negatively correlated with $f(Q_{SZ})$ (Spearman's $\rho = -0.99$, p value < 0.01 ; Figure S5), Q (Spearman's $\rho = -0.61$, p value $= 0.01$; Figure S5), and runoff ratios (Spearman's $\rho = -0.52$, p value $= 0.03$; Figure S5). This is not surprising as the model assumes streamflow originates from the three flow components, and the summation of their fractions is one. Arid catchments with lower discharge tend to have greater deep zone contributions ($f(Q_{DZ})$) while catchments with higher runoff ratios—often steeper catchments—tend to exhibit greater shallow zone contributions ($f(Q_{SZ})$).

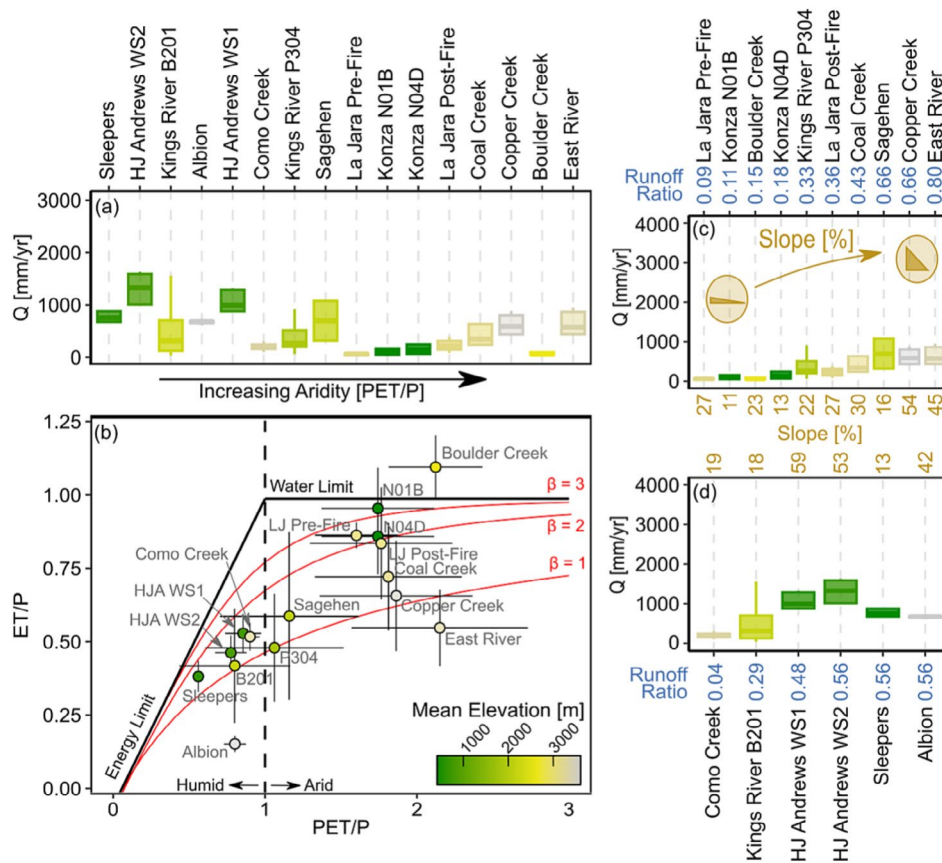


FIGURE 5 | (a) Boxplot of mean annual discharge (Q [mm/year]) from 200 GAP trials ordered by lowest (left) to highest (right) aridity, where Q generally decreased with aridity in humid sites but increased with aridity in arid sites. Based on the (b) Budyko plot, higher-elevation sites have more arid climates (higher aridity index; PET/P) and a higher evaporative index (ET/P). Most sites fall along a Budyko curve. Runoff ratios ($RR = Q/P$, blue values), plotted from lowest (left) to highest (right) in (c) arid and (d) humid sites were often larger in catchments with steeper slopes (brown values), though not all catchments fall within this trend.

3.3 | Less Sensitive Storage-Discharge Relationships (Low b -Values) in Catchments With Sandy Soils, Greater $f(Q_{DZ})$, and Out-of-Phase Seasonality

Subsurface water storage (S_{tot}) was highest in Copper Creek, while S_{tot} in Sleepers River was the lowest. Maximum storage was observed in catchments with steeper slopes (Spearman's $\rho = 0.51$, p value = 0.04; Figure 7a), higher PET (Spearman's $\rho = 0.70$, p value = 0.03; Figure 7b), and less sandy soils (Spearman's $\rho = -0.55$, p value = < 0.01; Figure 7c).

A simple power-law storage-discharge relationship ($Q = aS_{tot}^b$; Figure 8a) was used to describe how Q responded to changes in S_{tot} . High b -values indicate that Q is highly sensitive to changes in water storage. Calculated b -values ranged from 1.2 in Kings River B201 to a peak of 7.4 in Como Creek and were generally greater in high-relief catchments (Spearman's $\rho = 0.50$, p value = 0.05; SI Figures S7). Spearman correlations were strong between b -values and variables such as catchment area (Spearman's $\rho = 0.66$, p value < 0.01; SI Figures S7) and perennial snow and ice cover [%] (Spearman's $\rho = 0.62$, p value = 0.01; SI Figures S7). However, general linear modelling (SI Text S8) identified $f(Q_{DZ})$, seasonality, and sand as the most influential variables, with their interaction effects yielding the best model. More sensitive storage-discharge relationships (higher b -values)

occurred in catchments with greater S_{tot} (Spearman's $\rho = 0.29$, p value = 0.02; Figure 8b), lower $f(Q_{DZ})$ (Spearman's $\rho = -0.53$, p value = 0.04; Figure 8c), less sand sized soils (Spearman's $\rho = -0.52$, p value = 0.04; Figure 8d), and more in-phase seasonality (Spearman's $\rho = 0.63$, p value < 0.01; Figure 8e)—where water input and demand (PET) occur simultaneously—which was common for high-elevation catchments. Mean catchment elevation and seasonality were strongly related to many similar variables such as precipitation as snow [%] (P as snow [%] v. Elevation: Spearman's $\rho = 0.83$, p values < 0.01; P as snow [%] v. Seasonality: Spearman's $\rho = 0.62$, p value = 0.01) and rock outcrop or barren land [%] (rock [%] v. Elevation: Spearman's $\rho = 0.79$, p value < 0.01; rock [%] v. Seasonality: Spearman's $\rho = 0.59$, p value = 0.02), which are all characteristics of snowy and steep high-elevation mountains.

3.4 | Rainy, Silty Sites Have the Flashiest Streamflow

Streamflow flashiness (RBI) was positively correlated with b -values and was substantially greater in lower elevation rainy catchments (Figure 9a) with more silt (Spearman's $\rho = 0.76$, p value < 0.01; Figure 9a) and clay (Spearman's $\rho = 0.54$, p value = 0.03; Figure S8) sized soils. RBI was quantified for both observed discharge (Q_{obs}) and simulated discharge (Q).

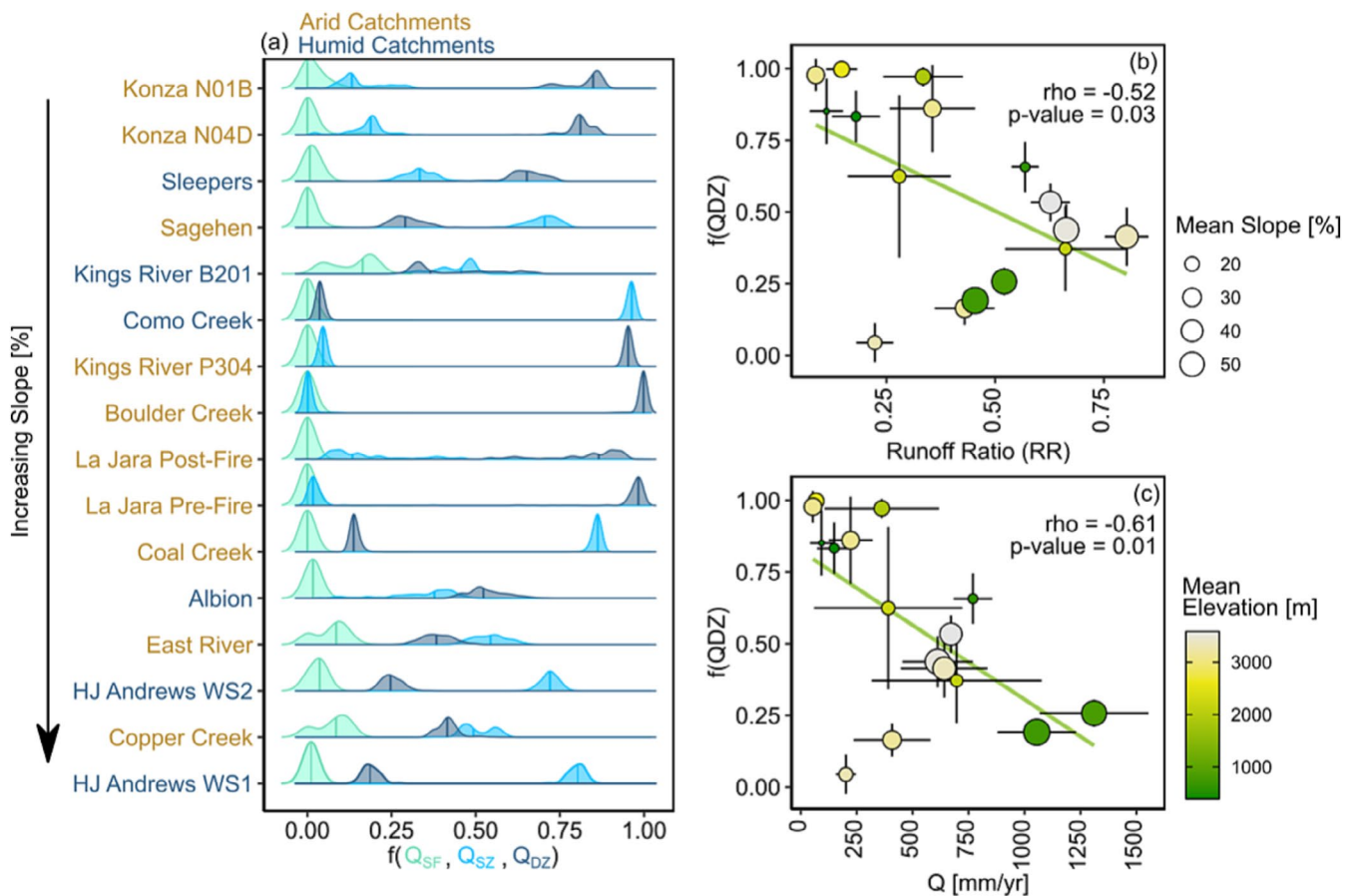


FIGURE 6 | (a) Distribution of flow path partitioning in 200 GAP calibration trials; catchments are ordered from flattest (top) to steepest (bottom) mean slope are mostly monomodal with respect to each flow path. In general, flatter catchments had more flow from the deep zone ($f(Q_{DZ})$). $f(Q_{DZ})$ did not correlate with slope but significantly correlated with the water balance variables (b) Runoff Ratio (RR; Spearman's $\rho = -0.52$; $p\text{-value} = 0.03$) and (c) mean annual discharge (Q [mm/year]; Spearman's $\rho = -0.61$; $p\text{-value} = 0.01$) which are determined, in part, by slope.

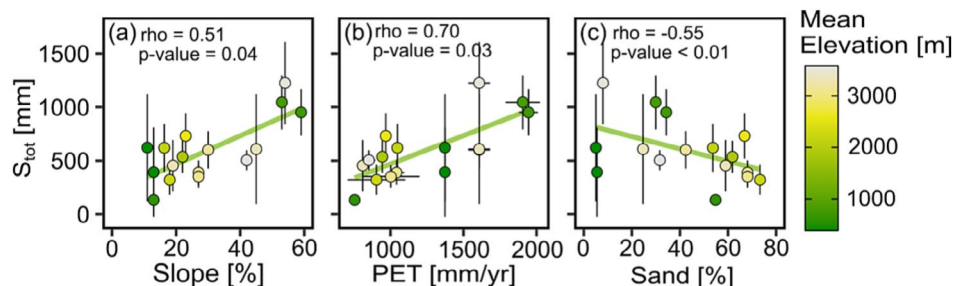


FIGURE 7 | Total dynamic storage (S_{tot}) is significantly correlated with (a) mean catchment slope (Slope [%] (Spearman's $\rho = 0.51$, $p\text{-value} = 0.04$), (b) mean annual potential evapotranspiration (PET [mm/yr]; Spearman's $\rho = 0.70$, value = 0.03), and (c) sandy sized soils (Sand [%], Spearman's $\rho = -0.55$, $p\text{-value} < 0.01$).

Flashiness values calculated with Q_{obs} were often higher than Q ; however, they showed nearly similar trends. RBI reached minima in sites with more sandy sized soils (Spearman's $\rho = -0.58$, $p\text{-value} = 0.02$; Figure S8). RBI showed a strong positive relationship with rock outcrop/barren land (Spearman's $\rho = 0.56$, $p\text{-value} = 0.02$), despite rock outcrop/barren land being absent in the flashiest sites. Rather, in snow-dominated sites, a slight trend of greater streamflow flashiness emerged with more rock outcrop/barren land and less soil, as evidenced by the lower amounts of clay, silt, and sand-sized particles in high-elevation sites where rock outcrop/barren land is present

(Figure S9). Water capacity [mm] (Spearman's $\rho = 0.79$, $p\text{-value} < 0.01$, Figure S8) showed the strongest correlation with RBI. However, water capacity was autocorrelated with soils. Instead, soil silt [%] was identified as the most significant control on discharge flashiness when comparing general-linear and linear-mixed-effects models (SI Text S8), with flashier streamflow in sites with siltier soils.

There was a clear separation in streamflow flashiness between low-elevation and mid- to high-elevation sites, with the latter exhibiting distinctly decreased flashiness (Figure S8).

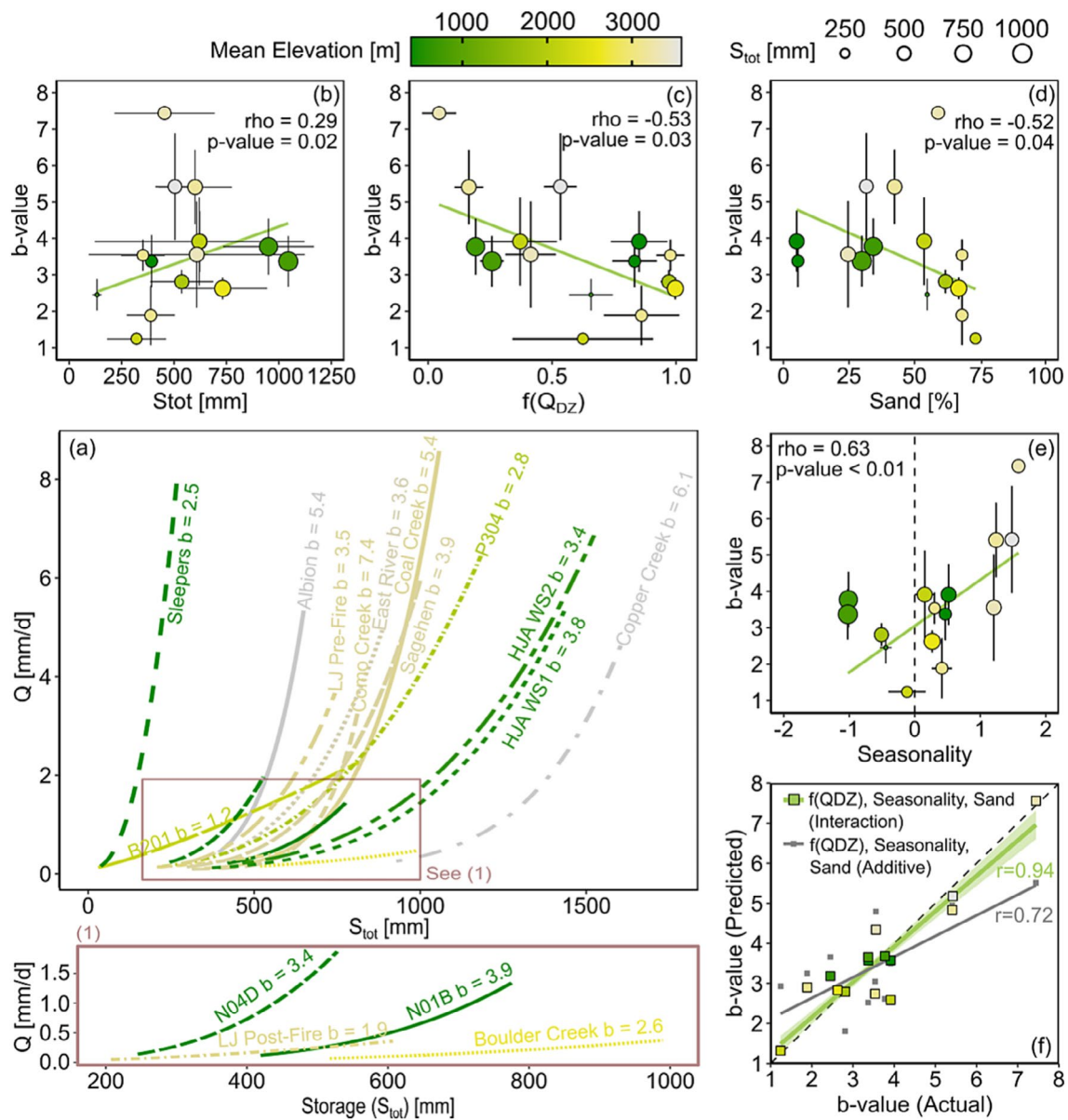


FIGURE 8 | (a) Storage-discharge relationship ($Q = aS_{tot}^b$), with the b -value indicating discharge (Q) sensitivity to changes in dynamic storage (S_{tot}). The inset highlights the four low- Q catchments: La Jara (LJ) Pre-Fire, Konza N04D, Konza N01B, and Boulder Creek. Higher b -values correlate with (b) greater total dynamic storage (Stot; Spearman's $\rho = 0.29$, p value = 0.02), (c) lower deep zone contributions ($f(Q_{DZ})$; Spearman's $\rho = -0.53$, p value = 0.04), (d) less sandy soils (Sand [%]; Spearman's $\rho = -0.52$, p value = 0.04), and (e) greater in-phase seasonality (Spearman's $\rho = 0.63$, p value < 0.01), typical of snow-dominated climates. (f) General linear models show that the interaction of $f(Q_{DZ})$, seasonality, and sand [%] (light green line) predicted b -values best.

RBI was negatively correlated with elevation (Spearman's $\rho = -0.6$, p value = 0.01) but elevation did not arise as a significant variable by general linear models. However, comparison of general linear models suggested that this was due to a variable autocorrelated with elevation that was not initially significantly correlated with RBI (SI Text S8). Further comparison of models with elevation-correlated variables revealed RBI was influenced by the percentage of precipitation as snow (P as snow [%]). While the initial Spearman correlation was not statistically significant there was a trend of lower streamflow flashiness with greater P as snow [%] (Spearman's $\rho = -0.5$, p value = 0.06), where sites with > 30% of P as snow [%] exhibited notably lower RBI values (Figure 9c). This suggests that the difference in RBI values between low-elevation

and mid- to high-elevation sites stemmed from P as snow [%], resulting in P as snow [%] and soil silt [%] as the most influential variables on RBI (Figure 9d).

Highest RBI values occurred in rainy sites with a high proportion of silt and clay-sized soils, while sandy soils exhibited lower RBI values, regardless of P as snow. Notably, sites with significant P as snow [%] did not show a corresponding increase in RBI with higher clay and silt content and consistently exhibited low RBI values (SI Text S7, Figure S10). Sites with the highest b -values were the same high-elevation sites that showed a positive relationship between RBI and rock outcrop, even though RBI values remained low overall for snow-dominated sites (Figure 9a).

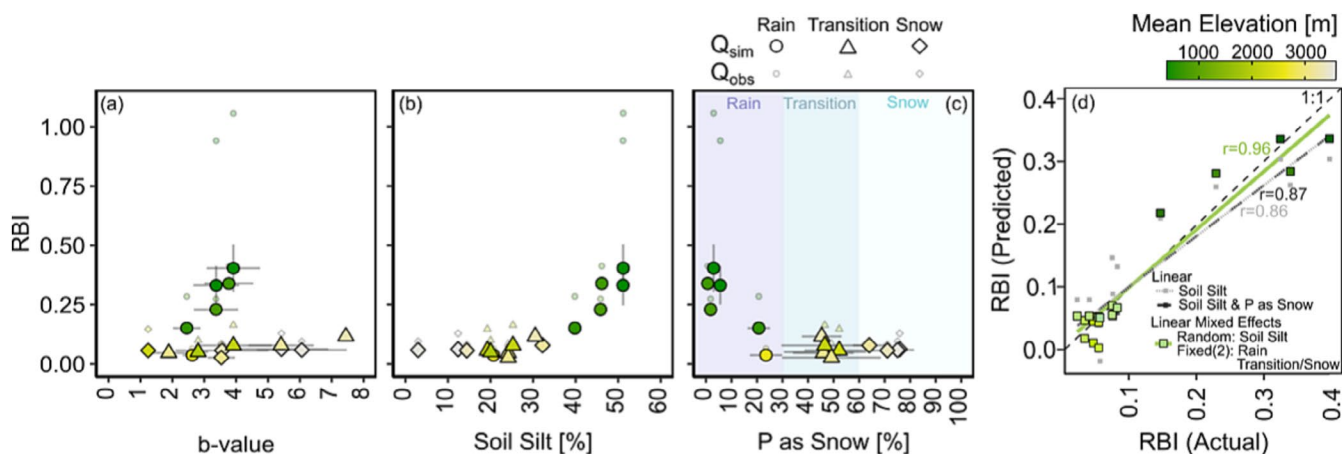


FIGURE 9 | Streamflow flashiness was quantified by the Richards-Baker Flashiness Index (RBI) for Q_{obs} (data; small transparent points) and Q (model; large opaque points). (a) High b-values only correlated to high RBI values in rainy sites. RBI values were lower in catchments with (b) coarser soil textures with less silt (Spearman's $\rho = 0.76$, p value < 0.01) and (c) higher P as snow. (d) Comparing linear and mixed-effects models showed RBI is best explained (highest r and AIC) when soil texture is treated as a fixed effect within the context of rain-dominated and snow/snow-transition (random effect) catchments.

4 | Discussion

Many large-sample catchment data-sets have been compiled (Chagas et al. 2020; Coxon et al. 2020; Delaigue et al. 2024; Fowler et al. 2021, 2024; Hao et al. 2021; Höge et al. 2023; Klingler et al. 2021; Liu et al. 2024; Mangukiyana et al. 2025; Teutschbein 2024), offering opportunities for catchment comparison across gradients of climates and land uses. Our analysis of 15 headwater catchments underscores the value of quantifying subsurface water storage and groundwater flow path partitioning. Results here identified aridity, precipitation phase, topography, and soil texture as the key climate and landscape controls regulating streamflow generation and dynamics. Flat, rainy sites exhibit flashier stream discharge compared to steep, snowy sites, whereas discharge in both environments can be sensitive to changes in dynamic storage depending on soil texture (Figure 10). We show that more sensitive storage-discharge relationships do not always equate to the flashiest discharge regimes. This work further emphasises that soil texture regulates hydrological behaviour by modulating climatic inputs along an elevational gradient—a pattern reflecting soil weathering processes from high to low elevations and the co-evolution of climate and critical zone structure. While climate factors such as aridity and precipitation phase are often considered the primary controls on streamflow, this study underscores the significant role of soil, which is often overlooked (Trancoso et al. 2017; Xu et al. 2024). Here we show how soil texture influences subsurface storage and flow path partitioning and shapes streamflow behaviour. Ultimately, this study improves our understanding of catchment hydrological behaviour, providing a baseline understanding of minimally human impacted catchments to better compare and forecast the impacts of continuing perturbations on water-resources.

The results here are subject to data and model limitations. In general, 15 sites remain limited, as the available data only covered two of the five main Köppen climate classes in the United States and disproportionately represented mountainous regions. Additionally, model structure can affect the interpretation of dynamic storage and groundwater flow path partitioning (Karimi

et al. 2022; Mockler et al. 2016), which are difficult to validate due to a lack of subsurface data. HBV is a semi-distributed bucket-type model and does not explicitly represent the water table. Conversely, real-world development of the water table—and thus hydrologic head driving streamflow generation—depends on recharge, aquifer transmissivity, geometry, bedrock geological structure and topography (Gleeson et al. 2011; Haitjema and Mitchell-Bruker 2005) and is accounted for in HBV by a storage recession coefficient. HBV adjusts precipitation and temperature values using user-defined elevation zones and lapse rates. It does not, in this work, account for how snow accumulation, vegetation, and ET processes vary based on aspect or differences in hill- and toe-slope, which can influence recharge and preferential flow path development (De Cicco et al. 2018; Donaldson et al. 2024; Hinckley et al. 2012; Webb et al. 2018). Shallow and deep flow paths and ET processes vary spatially in catchments and are difficult to track without more computationally expensive approaches such as particle tracking (Dennedy-Frank et al. 2024).

This work assessed behaviour across many catchments and focused on common data which limited more detailed spatially explicit analysis. Streamflow data reflect integration across the entire catchment, so we considered the catchment-scale average that we could reasonably validate. We also focused more on annual ET values rather than daily, as we do not have measured daily ET but reasonably captured the annual water balance based on model volume error and the Budyko framework (Reaver et al. 2022). Model simulations generally produced consistent distributions of dynamic storage volumes and shallow and deep groundwater contributions, and this consistency can provide valuable insights into catchment behaviour (Singh et al. 2021).

4.1 | Soils Modulate Hydrological Behaviour in Snowy–Rainy Catchments

Our results show that snowy catchments exhibit distinct streamflow regimes from rainy catchments, indicating the strong control from above of climate on discharge behaviour. Once the

Steep and Snowy

Flat and Rainy

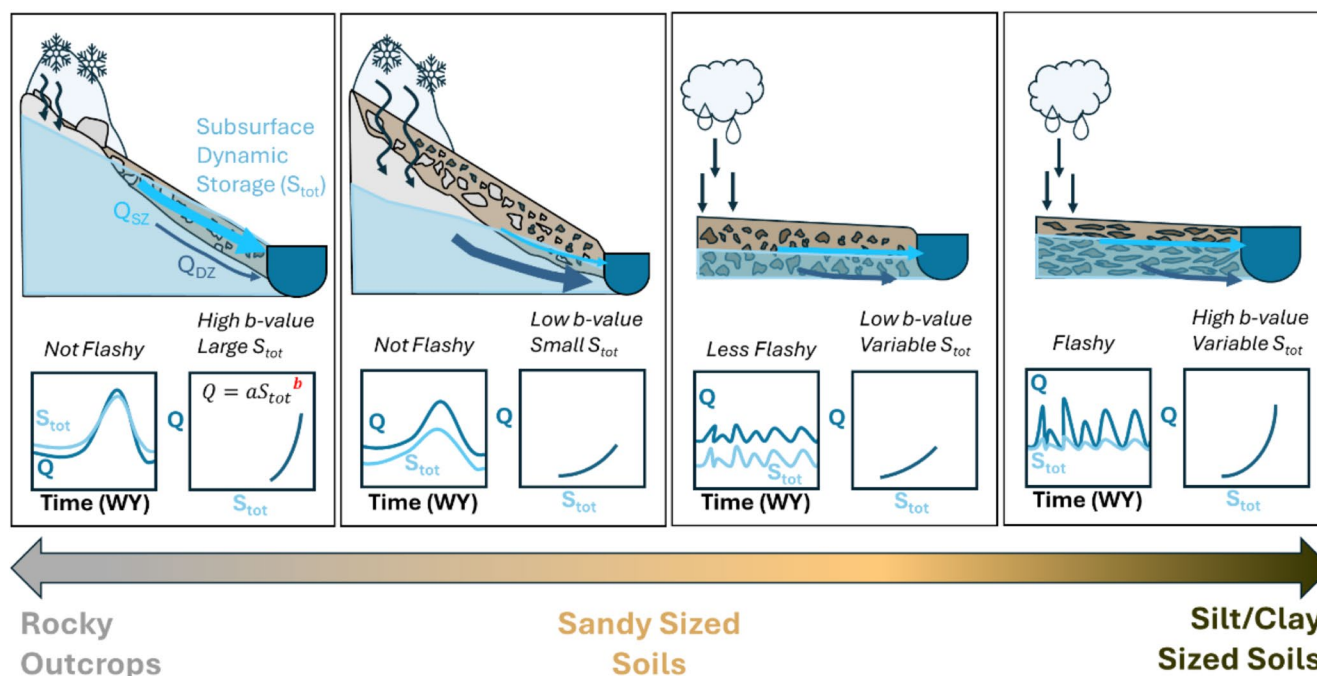


FIGURE 10 | A conceptual model of streamflow generation dynamics across varying climate and landscape conditions. Flat, rainy sites (right) often have more silty/clayey soils, suggesting greater weathering to finer sized particles. These sites exhibit flashier streamflow (higher RBI values) and streamflow is more sensitive to changes in dynamic water storage (S_{tot}) (higher b -values) over the water year (WY). In contrast, snowy sites with coarse, sandy soils exhibit less flashy discharge, lower dynamic storage, discharge that is less sensitive to storage changes (lower b -values), and more predominant deeper flow paths.

precipitation infiltrates, the control of soil texture becomes important to describe streamflow dynamics (McMillan et al. 2022; Trancoso et al. 2016; Xiao et al. 2019).

Although substantial water storage and flow paths can occur in deeper rock layers (Cochand et al. 2019; Rempe and Dietrich 2018) and approximately half of the sites partitioned most of their annual flow to deep zone flow paths, this study found no significant correlations between hydrological variables and geologic variables such as bedrock porosity and permeability (Gleeson et al. 2014). Only data available at all sites was compared, which limited information such as specific yield or secondary porosity (e.g., bedrock fracturing and weathering) where additional storage and preferential flow paths often occur (Worthington et al. 2016). A few of these catchments likely have complex hydrogeological structures such as faulting and folding that affect flow; however, there is no data on how these features affect flow path partitioning. For example, stream water ages in Sagehen suggest streamflow dominated by groundwater with residence times of decades (Manning et al. 2012; Rademacher et al. 2005) but annual streamflow from HBV was comprised of ~75% shallow zone flow. The bulk of observations and understanding are often constrained to the shallowest parts of groundwater systems (Condon et al. 2020); thus, to fully resolve our conceptual understanding of flow path partitioning with real-world measurements, greater deep subsurface data is needed.

On the other hand, the influence of lithology on flow partitioning is often expressed more through weathering-derived soils rather than directly through bedrock properties (Tang

et al. 2020). In areas with sharp weathering fronts and sharply decreasing permeability, water may follow shallow flow paths to streams, interacting minimally with deeper flows through rock phases (Xiao et al. 2021). These preferential flow paths could extend to the interface between saprolite and bedrock (Radke et al. 2019; Worthington et al. 2016), yet still have limited interaction with intact rock layers. In these cases, the characteristics of the underlying geology may have a limited role in defining hydrological signatures while soils drive flow path partitioning to the shallow zone.

It is interesting that results here show that rainy catchments exhibited substantially flashier discharge behaviour than snowy catchments, as streamflow in smaller catchments is historically considered as more flashy (Baker et al. 2004). This analysis of small catchments emphasises that streamflow flashiness is organised more by hydroclimate and not by catchment size as hypothesised by Baker et al. (2004) (Gannon et al. 2022). Soils in rainy sites ranged from sandy loam to silty clay, with flashiness increasing as soils developed more silt and clay textures. Finer textured soils in rainy sites could suggest more chemical weathering in warmer and wetter conditions that promote clay formation (Deepthy and Balakrishnan 2005; Rasmussen et al. 2010; Velde 1995). The greatest dynamic storage in the rainy catchments observed in the mountain sites of HJ Andrews WS1 and WS2 suggests greater relief increases available storage and promote more water storage in mountain areas (Staudinger et al. 2017). Higher water storage, however, does not translate to higher storage-discharge sensitivity, which depends more on shallow vs. deep zone contributions. Taken together, finer

soils in rainy sites likely lead to more water flow via shallower flow paths and higher streamflow flashiness, as suggested in Dwivedi et al. (2019).

Existing literature suggests that flashy streamflow is associated with small drainage areas, thin soils, and steep slopes that promote rapid streamflow and shallower flow paths (Baker et al. 2004; Douinot et al. 2022; Jencso et al. 2009; McGlynn and McDonnell 2003). While this is often the case, we found that the flashiest streamflow occurs in rainy catchments, and sustained snowmelt, with subsequent gradual emptying of water storage, dampens flashiness (Meriö et al. 2019; Trancoso et al. 2017) regardless of landscape. It is possible that greater sustained snowmelt input during high atmospheric demand— or more in-phase seasonality—promotes more stable, less flashy streamflow generation (Hale et al. 2023; Hammond and Kampf 2020). Snowy catchments also have higher $f(Q_{SZ})$ and the most sensitive storage-discharge relationships. However, storage-discharge sensitivity decreased as soils became more sandy, which coincided with lower elevation mountain catchments that would have undergone more mechanical weathering (Kellerer-Pirklbauer 2017; Rasmussen et al. 2010). These physically weathered and snowy catchments tend to be sandier, which promotes infiltration (Webb et al. 2018), recharge to deeper flow paths, and reduces dynamic storage and storage-discharge sensitivity. Thus, similar to rainy catchments, more $f(Q_{DZ})$ resulted in less sensitive storage-discharge relationships, while greater $f(Q_{SZ})$ resulted in more sensitive storage-discharge relationships.

4.2 | The Control of Slope and Aridity on the Water Balance

The Budyko curve hypothesis asserts that climate (aridity) predominantly regulates the water balance at the catchment scale (Berghuijs et al. 2020; Budyko 1974). While this is the case in most sites, several deviated significantly, indicating control of drivers other than climate. Small, geologically complex catchments can experience substantial groundwater losses (Fan 2019; Wlostowski et al. 2020). In these “leaky” catchments (e.g., Boulder Creek), models like HBV can overestimate ET due to the closed water balance assumption, leading to the positioning of these catchments above the water limit line. This could explain the ET overestimation (more than double) in HJ Andrews (Waichler et al. 2005). In another example, glacier cover in Albion contributes to melt and generates more runoff than expected (Liu et al. 2022) such that this site falls below a Budyko curve. In fact, many high-elevation catchments fell below Budyko curves, potentially suggesting rapid runoff driven by steep slopes and thin soils in mountainous areas (McGlynn et al. 2002; Troch et al. 2013).

Steeper slopes correspond to higher runoff ratios across all catchments, highlighting the influence of topography on water balance. Arid sites with low runoff ratios, gentle slopes, and low mean annual discharge tend to have a greater proportion of streamflow originating from deep flow paths ($f(Q_{DZ})$). However, our findings also indicate that under comparable slope and relief conditions, higher-elevation catchments exhibited a greater proportion of runoff from deep flow paths ($f(Q_{DZ})$) compared to those at lower elevations. This suggests deeper infiltration

generally in higher-elevation regions, likely driven by increased snowmelt and steeper topographic gradients (Goderniaux et al. 2013; Jasechko et al. 2016; Jencso et al. 2010; Winograd et al. 1998). These findings emphasise the control of climate, but also how landscape characteristics such as slope play a secondary role in water balance along climate gradients (Gannon et al. 2022; Kelleher et al. 2015; McMillan 2020).

4.3 | Future Implications

HBV struggled with reproducing daily streamflow dynamics in the most arid catchments, a common challenge for hydrological models (Feng et al. 2020, 2024; Fowler et al. 2020; Li et al. 2024; McMillan 2020). For example, the models in Konza and La Jara Post-Fire showed poorer performance. Such challenges could arise from low data quality in these arid places because of the challenges in data collection (Seybold et al. 2023; Zimmer et al. 2020). This difficulty reflects the broader challenge of modelling water resources under arid climates and raises concerns about the structure of models applied to catchments experiencing rapid and anthropogenically driven disturbances, especially as intermittent streamflow and drought conditions are increasing (Hammond et al. 2022; Hammond et al. 2021; Zipper et al. 2021).

As climate change intensifies (Ikeda et al. 2021; López-Moreno et al. 2021), snowmelt-reliant catchments could become flashier in warmer conditions. This shift could pose challenges for water management, particularly in regions like the western U.S., where infrastructure is designed for sustained snowmelt rather than rapid, rain-driven runoff (Brown et al. 2019; Li et al. 2017; Milly et al. 2008; Siirila-Woodburn et al. 2021). Catchments near the current snowlines are particularly vulnerable to shifts in precipitation phase, as even modest warming could significantly alter hydrologic behaviour. For instance, in the winter months, snowlines in the Southern Cascades and Northern Sierras are at an average elevation 1750–2000 m and 2250–2500 m in the Central and Southern Sierras (Shulgina et al. 2023). The catchments in these elevation ranges in this study receive 20%–60% of precipitation as snow, near the threshold of 30% where catchments begin to show increased flashiness due to soil properties (Meriö et al. 2019). Rising snowlines will likely decrease discharge and alter watershed connectivity, as these catchments no longer receive a large, sustained snowmelt pulse during the water year. Expanding future studies to catchments vulnerable to warming and declining snow is essential for identifying and mitigating the impacts of climate change on water resources, highlighting the need for greater research on less-studied, rain-dominated mountainous regions.

5 | Conclusion

This study highlights the combined effects of aridity, precipitation phase, topography, and soil texture, emphasising the critical role of soils in modulating hydrology. Streamflow flashiness is highest in flat, rainy sites (< 30% snow) with fine, soils, which enhance rapid runoff. In contrast, snow dampens flashiness, regardless of other landscape features, by promoting more stable hydrological responses. While flashier streamflow is often

linked to more sensitive storage–discharge relationships, our results show that streamflow can be sensitive to changes in dynamic storage in both flashy (rainy) and non-flashy (snowy) catchments. The most sensitive storage–discharge relationships occur in steep, snowy, rocky catchments, where streamflow is largely driven by shallow flow paths. As elevation decreases, soil becomes sandier, allowing deeper infiltration from both snowmelt and rainfall, leading to lower dynamic storage, weaker storage–discharge sensitivity, and streamflow dominated by deep flow paths. Conversely, in rainy low-elevation sites with finer, more weathered soils, shallow flow paths dominate, driving both higher storage–discharge sensitivity and flashier discharge regimes. These findings suggest that as warming reduces snow dominance in high-elevation regions, streamflow may become flashier, increasing uncertainty for water resource management. This shift poses significant challenges, particularly in the western U.S., where snowmelt is vital for surface and groundwater supplies (Bales et al. 2006; Li et al. 2017; Markovich et al. 2019; Pfister et al. 2017). As climate change continues, integrating subsurface understanding will be essential to enhance our ability to predict hydrological responses, better inform water management strategies, and facilitate ecosystem health and sustainable water supplies in an increasingly unpredictable world.

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Data Availability Statement

The data that support the findings of this study are openly available in Zenodo at <https://zenodo.org/records/14905386>, reference number <https://doi.org/10.5281/zenodo.14905386>.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.