# Relative Roles of Fall Soil Moisture and Spring Weather on the Relationship between Snow and Streamflow in the Colorado River Basin

#### Swastik Ghimire

School of Sustainable Engineering and the Built Environment, Arizona State University, Tempe, AZ 85281, United States

#### **Abstract**

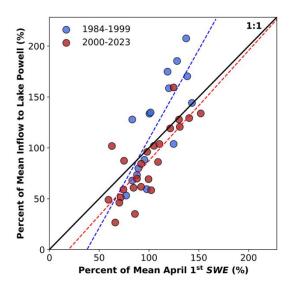
The Colorado River Basin (CRB) has experienced prolonged drought since 2000, with recent years showing a weakened relationship between snowpack and streamflow. This research investigates why near-average snowpack often fails to produce expected streamflow volumes by examining the roles of fall soil moisture and spring weather. Using the Variable Infiltration Capacity (VIC) model, controlled numerical experiments were conducted to isolate the effects of October soil moisture conditions and April-May-June climate anomalies while maintaining consistent snowpack. Results indicate that antecedent soil moisture accounts for approximately 74% of streamflow variability in the Upper Colorado River Basin (UCRB), while spring precipitation contributes about 24%. Under a constant snowpack condition, initial soil moisture alone can cause a difference of 8.45 km<sup>3</sup> in annual streamflow, with deep soil layers particularly influential. Similarly, spring weather variations under similar winter and near-peak snowpack alone produce a variation of 8.31 km<sup>3</sup> in annual streamflow in the UCRB. This research explains the "missing snowmelt" phenomenon, where water from snowmelt, especially in average snowpack years like 2020 and 2021, replenishes soil moisture deficits or is lost to evapotranspiration rather than contributing to streamflow. These findings highlight the need for water management strategies that incorporate soil moisture monitoring and spring climate forecasts, potentially improving water supply predictions during drought conditions.

#### 1. Introduction

The Colorado River Basin (CRB) serves as a critical water source for over 40 million people across seven U.S. states and parts of Mexico (Christensen et al., 2004; Wheeler et al., 2022). However, since 2000, the basin has experienced an unprecedented, prolonged drought with cascading effects on soil conditions and streamflow volumes (Udall & Overpeck, 2017). The long-term relationship between snowpack and streamflow, once a reliable predictor for water management decisions, has shown significant deviations in recent years (Hogan & Lundquist, 2024; Udall & Overpeck, 2017), raising the fundamental question: Where does all the snowmelt go?

This question gained urgency after the water years 2020 and 2021, when near-average snowpack (104% and 84% of normal, respectively) produced significantly lower streamflow volumes (71% and 51% of normal) in the Upper Colorado River Basin (UCRB), resulting in

lower than expected inflows into Lake Powell (58% and 35% of normal, respectively) (CBRFC, 2024). This divergence between expected and actual streamflow led to declarations of water shortages on the CRB. Arizona faced substantial cuts of 512,000 acre-feet (18%) in 2022, increasing to 21% in subsequent years (ADWR, 2022). Water cuts during periods of adequate snowpack have driven water managers to reevaluate their hydrologic understanding of the CRB and to seek improved datasets, modeling, and tools for improved decision-making.



**Figure 1**. Annual relation of reservoir inflow (Q) and snow water equivalent (SWE) in the UCRB. SWE is shown as April 1st amount from all SNOTEL stations in the UCRB as a percentage relative to the mean conditions over the full period (1984-2023). Q are inflows to Lake Powell (%) as a percentage relative to the mean conditions over the full period. The Millennium Drought, beginning in 2000, divides the dataset into two periods. Dashed lines represent linear regressions with slopes of 1.75 for 1984-1999 and 1.08 for 2000-2023.

The relationship between relative April 1 Snow Water Equivalent (SWE) and Lake Powell inflows has shown a distinct shift during the post-2000 drought period (Figure 1). While pre-2000 data points frequently plot above the 1:1 line, post-2000 measurements predominantly fall below it, demonstrating that equivalent snowpack percentages now generate reduced streamflow volumes. This quantifiable decrease in runoff efficiency indicates a significant alteration in the basin's hydrological processes, undermining traditional forecasting methods based primarily on snowpack measurements.

Several factors may explain this changing relationship. Spring conditions, particularly those occurring from April through June, play an expanding role as soil moisture, evaporation rates, and vegetation water demand can significantly alter runoff efficiency (Miller et al., 2014; Woodhouse et al., 2016). For example, in 2015, despite very low SWE, inflows were higher than expected due to a late-season surge in precipitation. Additionally, persistent precipitation deficits can propagate drought conditions over multiple seasons and years, with low soil moisture further reducing the portion of snowmelt that translates into streamflow.

Prior studies have sought to identify the most critical factors influencing streamflow generation during droughts in and around the CRB, yielding varying conclusions. CBRFC (2020)

conducted a sensitivity analysis to find that precipitation had the strongest influence on seasonal and annual flows, followed by soil moisture (dominant during Oct-Dec) and evapotranspiration (ET), while temperature effects were minimal (<1%). Recently, a study by Goble & Schumacher (2023) found that, on average, antecedent soil moisture and groundwater storage data show limited utility in seasonal water supply forecasts for western Colorado, though precipitation and temperature measurements after peak snowpack significantly enhanced forecast accuracy. In contrast, Alam et al. (2024) demonstrated that incorporating antecedent winter soil moisture significantly improved spring runoff forecasts. Lapides et al. (2022) used observations to specifically analyze the 'missing snowmelt' after the drought in 2021 and concluded that incorporating antecedent root-zone soil moisture deficits into prediction models could significantly decrease the overprediction of snowmelt runoff. Supporting this, Koster et al. (2023) used satellite-based soil moisture observations from SMAP to show that late-fall soil moisture conditions positively correlate with subsequent spring streamflow.

This study employs the Variable Infiltration Capacity (VIC) hydrological model to determine the major streamflow drivers in the CRB through controlled numerical experiments. Unlike earlier work, which often combines statistical methods with observational data, this research uses a physical process-based framework to isolate specific effects of spring climate anomalies and multi-year soil moisture deficits on streamflow while maintaining consistent snowpack conditions. The central goal of this study is to quantify the relative importance of fall soil moisture conditions and spring climate anomalies in driving the snowmelt-streamflow relationship in the CRB. By understanding these mechanisms, water managers can develop more accurate forecasting approaches and adaptive strategies in the face of ongoing drought and climate uncertainty.

#### 2. Colorado River Basin

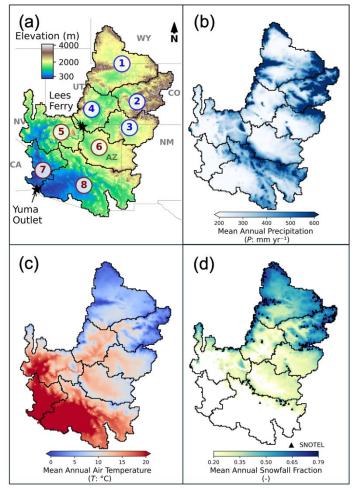
#### 2.1 Site Characteristics

The CRB encompasses approximately 640,000 km², extending from the Rocky Mountains to the Gulf of California. The basin spans seven U.S. states (Wyoming, Colorado, Utah, New Mexico, Arizona, Nevada, and California) and two Mexican states (Sonora and Baja California). It is conventionally divided into the Upper Colorado River Basin (UCRB) and the Lower Colorado River Basin (LCRB), with Lees Ferry, Arizona, serving as the division point (The Colorado River Compact, 1922) (Figure 2a).

The basin exhibits significant topographic variation, with elevations ranging from sea level at the Gulf of California to over 4,000 m in the Rocky Mountains. This elevation gradient creates distinct ecological and hydroclimatic zones. The UCRB is characterized by mountainous terrain with high-elevation snowpack zones above 2,500 m, while the LCRB features canyon-dominated landscapes in the northern portion and lower-elevation desert plains in the south.

The CRB experiences considerable spatial and temporal precipitation variability. Mountain headwaters receive over 800 mm of precipitation annually (Figure 2b), with mean

annual temperatures well below 0°C (Figure 2c), whereas desert valleys receive approximately 100 mm of precipitation per year, with maximum daily temperatures exceeding 49°C (Lukas & Payton, 2020). While the UCRB receives most precipitation as winter snowfall (November through April), both regions experience significant summer rainfall from the North American Monsoon (July through September).



**Figure 2.** (a) Elevation distribution (m) in the CRB with sub-basin boundaries labeled with numbers and colors (Blue numbers for UCRB: 1: Green, 2: Upper Colorado, 3: San Juan, and 4: Glen Canyon; Brown numbers for LCRB: 5: Grand Canyon, 6: Little Colorado, 7: Lower Colorado, and 8: Gila) and key outlet locations. Mean annual (a) precipitation (mm yr<sup>-1</sup>) and (b) air temperature (°C) derived from PRISM (1984-2023). (d) Mean annual snowfall fraction of the total precipitation from VIC simulations (1984-2023), along with SNOTEL stations.

The Colorado River naturally provides approximately 18.2 km³ of annual flow measured at Lees Ferry (1906-2017 mean). The UCRB contributes approximately 85% of the total runoff (Christensen et al., 2004), while the LCRB tributaries provide minimal flow due to arid conditions. The natural flow regime has been substantially altered by water infrastructure development, including major storage facilities like Glen Canyon Dam (forming Lake Powell) and Hoover Dam (forming Lake Mead), which can hold 21.97 km³ of water—approximately 80% of the basin's reservoir storage capacity.

The basin is predominantly characterized by shrub/scrub ecosystems, followed by evergreen and deciduous forests (Bohn & Vivoni, (2019). Herbaceous vegetation appears in scattered patches, while wetland ecosystems and open water bodies constitute a very small portion of the total area, reflecting the arid to semi-arid climate conditions that dominate the region.

# 2.2 Meteorological Forcing

For this study, meteorological forcing data from the Parameter-elevation Relationships on Independent Slopes Model (PRISM) (Daly et al., 2008) was used to drive the hydrological model. The PRISM dataset leverages a knowledge-based interpolation approach that accounts for factors such as elevation and coastal proximity to produce high-resolution (4 km) precipitation and temperature grids.

The use of PRISM data addresses several limitations identified in previous studies. For instance, most studies in the CRB depended on the Livneh et al. (2015) dataset. However, it employs a fixed lapse rate of 6.5 °C/km for temperature interpolation, introducing systematic elevation-dependent biases (Shulgina et al. (2023)). These biases significantly affect minimum daily temperature estimates, resulting in substantial cold biases at high elevations, which can lead to overestimation of snow accumulation. In contrast, PRISM implements a variable lapse rate approach that better captures the complex temperature patterns across diverse topography in the CRB.

The improved representation of temperature gradients is crucial for accurately simulating snowpack dynamics and subsequent snowmelt processes, which are central to understanding streamflow generation in the basin. Additionally, PRISM provides more timely updates (daily releases for operational purposes), enabling simulations with the most current meteorological conditions, an essential requirement for this study focusing on recent drought periods.

## 3. Methods

# 3.1 Hydrologic Model Framework

The VIC model was employed to simulate hydrological processes across the CRB. VIC is a semi-distributed, large-scale hydrological model that simulates water and energy balances at the land surface. It uses a grid-based approach (6 km resolution in this study), dividing the land surface into cells while representing sub-grid variability in vegetation and soil characteristics. The model operates without lateral water movement between grid cells, treating precipitation as the primary input to each individual cell.

A core feature of VIC is the 'variable infiltration curve,' which allows infiltration capacity to vary with soil moisture, improving runoff and baseflow simulations. The model employs a multi-layer soil structure that tracks moisture storage and fluxes across different soil depths. VIC's energy balance component captures evapotranspiration dynamics, providing a detailed picture of soil moisture evolution under different scenarios.

In this study, a three-layer soil configuration was implemented, with an upper surface layer (approximately 10 cm deep), a middle root zone layer (100-150 cm), and a lower deep soil layer (3-4.5 m). Each layer plays a distinct role in hydrological processes: the surface layer responds quickly to precipitation inputs and generates surface runoff when infiltration capacity is exceeded; the root zone supports plant transpiration and contributes to both runoff and percolation; and the deep soil layer primarily controls baseflow generation through the ARNO baseflow formulation.

The VIC model represents snowpack with a two-layer approach: a thin surface layer interacting with the atmosphere and a thicker pack layer. The model tracks both mass and energy balance components, calculating processes like accumulation, melt, refreezing, and changes in snow albedo. At elevations above 1,500 m, the model uses elevation bands to better represent orographic effects on precipitation and temperature within each grid cell.

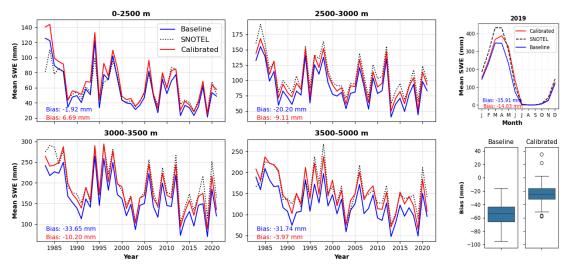
This study implemented the latest VIC-5 framework with significant enhancements, including updated snow parameterization, improved precipitation phase partitioning using wetbulb temperature, and calibrated vegetation parameters based on MODIS observations. These improvements provide a more robust and novel representation of hydrological processes in the CRB.

## 3.2 Model Calibration and Validation

A comprehensive calibration approach was implemented to ensure accurate representation of hydrological processes in the CRB. The calibration was conducted in two phases: first, the snow module was calibrated against ground SNOTEL observations, followed by soil parameter adjustments to improve streamflow simulations.

For snow calibration, 163 SNOTEL stations across the basin were selected based on elevation correspondence with model grid cells (absolute difference <250 m). The calibration focused on modifying snow albedo parameters to improve both the magnitude and timing of SWE. Three key parameters were adjusted: (1) snow albedo accumulation parameter A was increased from 0.94 to 0.98, (2) snow albedo thawing parameter A was increased from 0.80 to 0.92, and (3) snow albedo thawing parameter B was increased from 0.46 to 0.85. These adjustments resulted in higher albedo values during both snow accumulation and ablation phases, reducing the rate of simulated snowmelt to better match observed conditions.

The calibration substantially reduced negative bias in SWE simulation compared to SNOTEL measurements. As seen in Figure 3, in the critical snow elevation band of 3,000-3,500 m, bias decreased from -33.65 mm to -10.20 mm (69% reduction), while at the highest elevations (3,500-5,000 m), bias improved from -31.74 mm to -5.57 mm (82% reduction). For the overall peak SWE across water years (example shown for 2019 in Figure 3), the mean bias was substantially reduced from around -60 mm to around -25 mm, confirming better performance across all water years post-calibration.

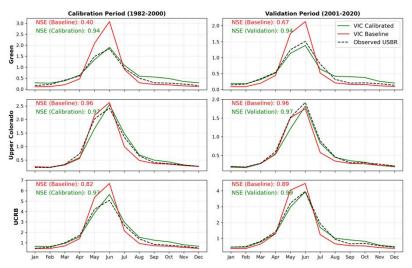


**Figure 3.** (left) Comparison of mean SWE between observations (SNOTEL), baseline, and calibrated conditions across elevation bands (1984-2020). (right) Comparison of mean SWE across SNOTEL, VIC baseline and calibrated versions for WY 2019; Box plot summarizing peak SWE bias reduction for all years (1984-2020).

Following snow calibration, soil parameters were adjusted to improve streamflow representation. Five key parameters were modified: (1) soil depth ( $D_2$ ) was increased across all basins to provide greater water storage capacity, (2) maximum baseflow rate ( $Ds_{max}$ ) values were adjusted to better represent baseflow contributions, (3) the fraction of  $Ds_{max}$  where non-linear baseflow begins (Ds) was increased to allow higher baseflow generation at lower soil moisture levels, (4) the infiltration shape parameter ( $B_{inf}$ ) was increased moderately to improve the partitioning between surface runoff and infiltration, and (5) snow roughness parameters were adjusted to account for basin-specific snow process differences. The parameter values are summarized in Table 1.

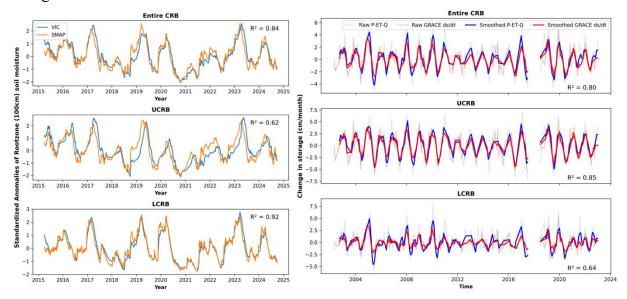
**Table 1**. Soil parameters in the major sub-basins after calibration.

Basin/Parameters	D <sub>2</sub> (m)	Dsmax	Ds	Binf	Snow rough (m)	
Green	2	1.5	0.4	0.14	0.003	
Upper Colorado	1.3	-	0.05	0.1	0.001	
San Juan	1	0.5	0.4	0.1	0.014	
Glen Canyon	1	-	-	-	-	
LCRB	1.5	1.5	0.005	-	-	



**Figure 4.** Assessment of baseline and calibrated VIC monthly mean streamflow in the major sub-basins in the CRB for calibration (1982-2000) and validation (2001-2020) periods.

The calibrated model showed excellent performance in reproducing observed streamflow across all major sub-basins. For the UCRB, Nash-Sutcliffe Efficiency (NSE) values improved from 0.82 to 0.97 during calibration (1982-2000) and from 0.89 to 0.99 during validation (2001-2020) (Figure 4). The model also effectively captured both the timing and magnitude of peak flows, typically during the late spring and early summer months, as well as the recession curves during late summer and fall.



**Figure 5.** (left) Comparison of standardized anomalies of VIC Layer 1+2 (rootzone) SM outputs with SMAP rootzone SM. Values are shown as weekly rolling means. (right) Comparison of GRACE change in storage with water balance from VIC. Data is smoothed to quarterly means to reduce noise.

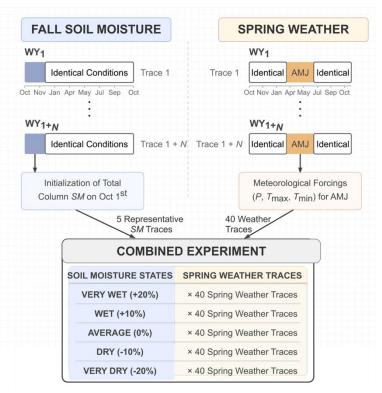
To further validate model performance, outputs were compared against independent satellite-derived soil moisture from SMAP (2015-2024) and terrestrial water storage observations

from GRACE (2002-2024) (Figure 5). Strong agreement was observed between VIC and SMAP for both surface (R<sup>2</sup>=0.71) and root zone (R<sup>2</sup>=0.84) soil moisture dynamics. Similarly, the GRACE water storage change comparison yielded high correlation (R<sup>2</sup>=0.80), confirming the model's ability to represent water balance components beyond the calibration targets. This comprehensive calibration and novel validation approach establishes a robust foundation for hydrological modeling in the Colorado River Basin. Due to the high-quality forcing data, advanced model structure, and rigorous calibration procedures employed, this dataset represents one of the most reliable hydrological products available for the CRB. Publication of these datasets is planned for future work, which will enable expanded research capabilities in the lower basin and support informed decision-making in the face of post-2026 renegotiations in the basin.

# 3.3 Numerical Experiments

Following model calibration and validation, a series of numerical experiments were designed to systematically quantify the effects of fall soil moisture and spring weather on streamflow generation. These controlled experiments (see framework in Figure 6) isolated individual factors while holding others constant, enabling attribution of hydrological responses to specific mechanisms. Three main experiments were conducted:

- 1. Effects of Initial Soil Moisture: This experiment isolated the impact of antecedent (October 1) soil moisture conditions on annual streamflow while maintaining consistent meteorological forcing throughout the water year. Water year 2020 was selected as the baseline due to its near-average snowpack conditions (104% of 1991-2020 mean). In each of the 40 simulations, the initial soil moisture conditions from October 1, 2020, were replaced with conditions from another year in the historical record (1984-2023), modifying all three soil layers simultaneously. All other forcings remained identical to 2020, ensuring that differences in hydrological responses could be attributed solely to initial soil moisture variations.
- 2. Effects of Spring Weather: This experiment quantified the influence of April-May-June (AMJ) climate anomalies on streamflow generation while maintaining consistent initial soil moisture and snowpack conditions. Again, using WY 2020 as the baseline, 40 simulations were conducted where only the AMJ precipitation, maximum temperature, and minimum temperature were varied according to historical conditions from 1984-2023. This controlled framework allowed for systematic evaluation of how spring climate impacts snowmelt efficiency and subsequent streamflow under identical antecedent and peak snowpack conditions.



**Figure 6.** Schematic representation of the numerical experiments to evaluate the relative controls of fall soil moisture and spring weather on streamflow in the UCRB. For each individual experiment, forty traces were constructed using WY 2020 conditions (labeled 'Identical Conditions') where either the initial October 1st SM was obtained from other WYs (left) or the meteorological conditions during AMJ were obtained from the other WYs (right). For the combined experiment, five representative fall soil moisture traces (Very Wet, Wet, Average, Dry, and Very Dry) were combined with the forty spring weather traces.

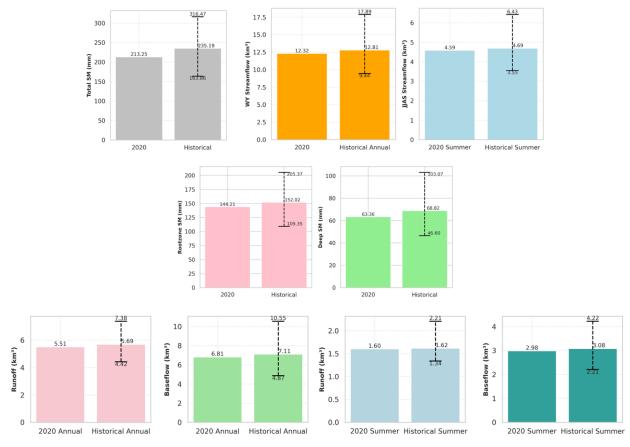
3. <u>Combined Effects Experiment</u>: This experiment investigated the interactive effects of both factors simultaneously. To maintain computational feasibility, five representative initial soil moisture conditions were selected ranging from very wet (+23.80% relative to mean) to very dry (-22.39%), and combined with all 40 AMJ climate scenarios, resulting in 200 unique simulations. This design enabled quantification of the relative importance and potential interaction effects between soil moisture and spring climate in determining streamflow outcomes.

For each experiment, outputs were analyzed to determine how variations in the tested parameters affected annual streamflow volumes, seasonal flow patterns, and different streamflow components (surface runoff vs. baseflow). The experiments specifically focused on the Upper Colorado River Basin (UCRB), which generates approximately 85% of the total flow in the CRB. Results were expressed as both absolute values and anomalies relative to long-term means to facilitate interpretation in the context of water management applications.

## 4. Results

#### 4.1 Effects of Fall Soil Moisture

The soil moisture experiment revealed that antecedent conditions alone can drive substantial variability in annual UCRB streamflow outcomes. While maintaining identical meteorological conditions across all simulations, annual streamflow volumes ranged from 9.44 to 17.89 km³, representing a 1.9-fold difference or 8.45 km³ variation due solely to initial soil moisture differences (Figure 7; top panel). Water year 2020, the baseline for this experiment, exhibited below-average initial soil moisture (213.25 mm compared to the historical mean of 235.19 mm), corresponding with below-average streamflow (12.32 km³ versus the historical mean of 12.81 km³).

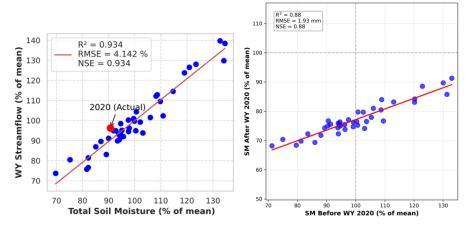


**Figure 7.** (top panel) Range of variability of initial SM, WY and summer streamflow in the ensemble members compared to actual conditions in WY 2020. (middle and bottom panel) Range of variability of rootzone and deep SM, runoff, and baseflow in the ensemble members compared to actual conditions in WY and Summer 2020.

Component analysis (middle and bottom panel) revealed distinct mechanisms through which soil moisture affects streamflow generation. Despite considerable variation in rootzone soil moisture, its impact on surface runoff was relatively modest with comparison to historical mean conditions. In contrast, deep soil moisture variations had a proportionally larger impact on

streamflow outcomes through baseflow generation. Approximately 67% of the total streamflow variation was attributable to changes in baseflow rather than surface runoff.

The seasonal analysis revealed that summer (June-September or JJAS) streamflow exhibited less sensitivity to initial soil moisture conditions compared to annual totals, with values ranging from 3.55 to 6.43 km³ across the simulations (compared to the actual 2020 value of 4.59 km³ and the historical mean of 4.69 km³). This seasonal difference suggests that initial soil moisture effects persist throughout the water year but have proportionally greater influence during pre-summer months through baseflow generation.



**Figure 8.** (left) Scatter plot showing relationship between initial SM conditions (October 1) with WY streamflow. (right) Scatter plot of the relationship between SM before the start of WY and its effect on the SM at the end of the WY.

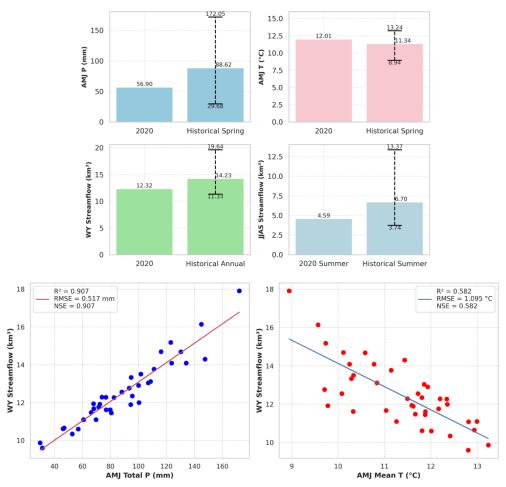
Correlation analysis demonstrated strong positive relationships between initial soil moisture conditions and subsequent water year streamflow production ( $R^2 > 0.9$ ) (Figure 8). Even scenarios starting with above-average initial soil moisture experienced significant drying throughout the water year under 2020's meteorological conditions, ending at 80-90% of the long-term mean (Figure 8). This pattern suggests a potential feedback mechanism where available soil moisture supports increased evapotranspiration, further contributing to soil water depletion throughout the water year.

The observed sensitivity to soil moisture has important implications for drought propagation and recovery. Soil layers, especially deep, retain memory of previous conditions over longer timescales than surface or root zone layers, potentially explaining why streamflow remains suppressed even after meteorological drought conditions appear to have improved or when winter snowpack returns to near-normal levels.

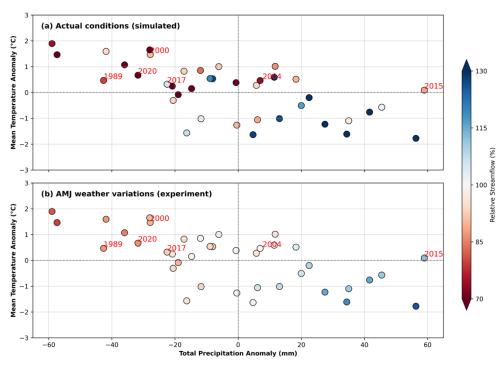
## 4.2 Effects of Spring Weather

The spring weather experiment demonstrated that AMJ weather conditions substantially influence annual streamflow outcomes even when winter and peak snowpack conditions remain constant. Across the 40 simulations, annual streamflow volumes ranged from 11.33 to 19.64 km<sup>3</sup>, a difference of 8.31 km<sup>3</sup> attributable solely to variations in spring weather patterns (Figure 9).

Precipitation during the AMJ period strongly influenced annual streamflow generation (R<sup>2</sup>=0.91) more than temperature (R<sup>2</sup>=0.58) (Figure 9; bottom), though both factors were identified as significant contributors to the overall water balance. The seasonal analysis revealed that summer (JJAS) streamflow showed greater sensitivity to AMJ climate variations than water year totals, with values ranging from 3.74 to 13.37 km<sup>3</sup>. This amplified summer sensitivity demonstrates the direct and immediate impact of spring weather on the primary snowmelt season due to temporal proximity.

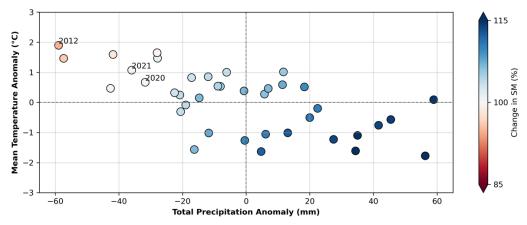


**Figure 9.** (top) Range of variability of Spring (AMJ) P, T and UCRB WY and Summer (JJAS) streamflow in the historical record compared to actual conditions in WY 2020. Vertical lines in the right bars show maximum, mean and minimum values on record (1984-2023). (bottom) Scatter plots showing relationships between AMJ P with WY streamflow (left) along with AMJ T with WY streamflow (right) for the UCRB



**Figure 10.** Relative WY streamflow compared to AMJ climate anomalies (Baseline: 1984-2023) for (a) Actual conditions (b) Constant snowpack experiments.

A clear pattern emerged when examining the joint effects of spring precipitation and temperature (Figure 10). Years with cool-wet spring conditions consistently produced higher streamflow (often exceeding 125% of average), while warm-dry springs led to significantly reduced streamflow (often below 75% of average) (Figure 10b). This pattern highlights how dramatically spring weather can alter the amount of streamflow produced even when starting with identical snowpack conditions. For example, a year with average snowpack but a warm, dry spring (like 2020) can produce streamflow similar to a below-average snowpack year, while cool, wet spring conditions can boost streamflow well above what would be expected from snowpack alone.



**Figure 11.** Change in SM (% of value after WY 2020 with respect to value before WY 2020) caused by variations in AMJ P and T.

The spring climate conditions also influenced soil moisture carryover to the following water year. Most years showed soil moisture improvements compared to 2020 conditions, demonstrating how favorable spring climate can positively affect basin hydrology (Figure 11). However, several years with warm-dry spring conditions showed continued soil moisture deficits, reinforcing the notion that unfavorable AMJ climate can propagate drought conditions through reduced soil moisture recharge.

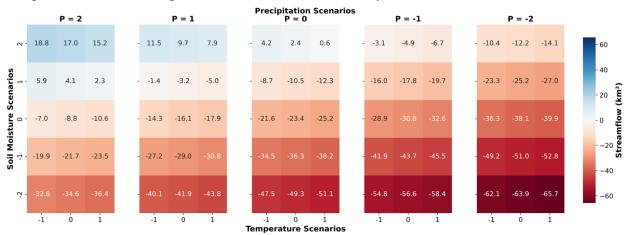
These findings highlight the importance of incorporating spring weather projections into water supply forecasts. The substantial streamflow variability observed in response to spring weather variations suggests that current operational approaches relying heavily on April 1st snowpack measurements may miss critical factors driving actual water availability, particularly during drought periods.

## 4.3 Combined Effects Across CRB Sub-basins

The 200 simulations across varying combinations of initial soil moisture and AMJ climate revealed distinct patterns in streamflow generation within the UCRB. To provide a continuous representation across the full parameter space, a multiple regression approach was developed after standardizing all variables. For the UCRB, the following relationship was identified:

$$\Delta Q = -23.44 + 12.90 \times SM + 7.31 \times P - 1.80 \times T \tag{1}$$

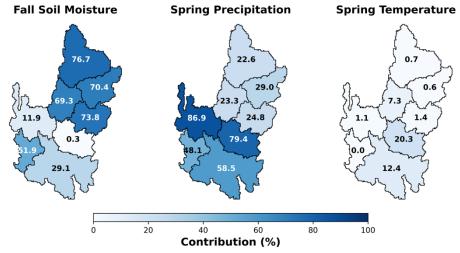
Where  $\Delta Q$  represents the relative change in UCRB streamflow, and SM, P, and T represent the standardized anomalies of October 1 soil moisture, AMJ precipitation, and AMJ temperature, respectively. This equation demonstrated high explanatory power (R<sup>2</sup>=0.89) and was used to interpolate streamflow responses for conditions not directly simulated.



**Figure 12.** Change in streamflow (%) across a range of SM, P, and T conditions from the 200 simulations. Other values were filled using equation 1.

The standardized coefficients reveal that antecedent soil moisture exerts the strongest influence on streamflow response, with a coefficient approximately 1.8 times larger than that of precipitation and about 7 times the magnitude of temperature. The negative intercept term (-

23.4%) suggests a systematic baseline reduction in streamflow relative to the historical mean, meaning that even average soil and climatic conditions in 2020 would not have produced near-average streamflow. In fact, it would have taken either very wet spring or wet initial conditions before 2020 to produce near-normal streamflow (Figure 12).



**Figure 13.** Relative contribution of each of the variables (SM, P, T) to change in streamflow across major sub-basins of the CRB.

**Table 2.** Multilinear regression model coefficients ( $c_1$ ,  $c_P$ ,  $c_T$ , and  $c_{SM}$ ), along with performance metrics (coefficient of determination,  $R^2$ , and condition number, CN) to predict the relative changes in streamflow at the outlets of each sub-basin in the CRB.

Sub-basin	<i>c</i> <sub>1</sub>	СР	$c_T$	CSM	$\mathbb{R}^2$	CN
CDD	24.11	5.22	2.10	0.50	0.04	1.05
CRB	-24.11	5.33	-3.10	9.59	0.84	1.95
UCRB	-23.44	7.31	-1.80	12.90	0.89	2.33
LCRB	-28.48	4.72	-1.44	2.52	0.35	1.85
Green	-17.07	7.74	-1.36	14.26	0.86	2.48
Upper Colorado	-26.04	8.28	-1.18	12.90	0.92	2.57
San Juan	-34.00	8.37	-2.00	14.45	0.88	1.58
Glen Canyon	-20.82	8.85	-4.96	15.27	0.85	1.86
Little Colorado	-32.30	4.01	-2.03	0.25	0.30	1.49
Grand Canyon	-33.75	7.07	-0.80	2.62	0.28	1.89
Lower Colorado	5.33	6.32	-0.02	6.56	0.86	1.39
Gila	-30.78	3.97	-1.83	2.80	0.33	1.63

When extended to individual sub-basins, a notable spatial pattern emerged. Soil moisture states exerted dominant influence in the UCRB sub-basins, while climate factors played a more significant role in the LCRB sub-basins (Figure 13). The Green River basin showed the strongest soil moisture influence, while the Little Colorado basin demonstrated minimal soil moisture effect (coefficient: 0.25) but greater sensitivity to spring precipitation and temperature.

Particularly interesting was the enhanced importance of temperature in the Little Colorado and Gila Basins compared to other regions, possibly due to their lower elevations and warmer mid-latitude mountain climate, which increases their sensitivity to temperature-driven evapotranspiration. These regional differences highlight the need for location-specific approaches to water management and forecasting across the diverse CRB.

The relative contribution analysis quantified the importance of each factor across subbasins. For the UCRB, soil moisture accounted for approximately 74.6% of explained streamflow variance, followed by precipitation (23.9%) and temperature (1.46%). In contrast, the LCRB showed a different pattern, with precipitation as the dominant factor (about 72% of variance) and soil moisture playing a secondary role. The results from the regression analysis for each sub-basin is summarized in Table 2.

These findings suggest that water management in the CRB should account for the dominant role of soil moisture in the UCRB, where most of the basin's water originates. This oversight may explain why water managers have consistently overestimated expected runoff despite average snowpack conditions in recent years.

## 5. Discussion

# 5.1 Importance of Fall Soil Moisture

The results demonstrate that fall soil moisture conditions exert a dominant influence on annual streamflow in the UCRB, accounting for approximately 74% of streamflow variability when compared with spring climate factors. This finding challenges traditional water management approaches that rely heavily on winter snowpack measurements to predict seasonal water availability. The strong influence of initial soil moisture conditions, particularly in deeper soil layers, provides a mechanistic explanation for the observed weakening of snowpack-streamflow relationships during the ongoing drought.

Deep soil moisture emerges as a critical control on baseflow generation. While surface soil layers respond quickly to meteorological conditions, deep soil moisture can maintain deficits over multiple years, creating a persistent "memory" effect that influences hydrological responses long after meteorological drought conditions have improved. This memory effect explains why even years with average snowpack, such as 2020 and 2021, can produce below-average streamflow when soil moisture reservoirs remain depleted from previous drought years.

The experimental results indicate that a significant portion of snowmelt during drought periods goes toward replenishing soil moisture deficits rather than contributing to streamflow. This moisture replenishment creates a diversion pathway where potential streamflow is

redirected toward soil storage and subsequently to evapotranspiration, effectively creating the "missing snowmelt" phenomenon observed in recent years. The spatial analysis reveals important regional variations in soil moisture influence. The dominance of soil moisture controls is strongest in the headwater regions of the UCRB, particularly the Green and Upper Colorado sub-basins, where the majority of the basin's water originates. These areas exhibit the largest deep soil moisture coefficients in the regression analysis, indicating greater sensitivity to antecedent conditions. In contrast, lower elevation basins in the LCRB show reduced soil moisture influence, suggesting that different mechanisms govern hydrological responses in these regions.

These findings highlight the need for expanded soil moisture monitoring in the CRB, particularly at depths beyond the surface layer. Remote sensing products like SMAP provide valuable information about surface and root zone conditions, but their limited penetration depth (approximately 5 cm for direct measurements) misses the critical deep soil moisture dynamics identified in this study. Integration of satellite observations with calibrated hydrological models and ground-based monitoring networks could provide a more comprehensive assessment of basin-wide soil moisture conditions, potentially improving seasonal water supply forecasts.

## 5.2 Importance of Spring Weather Conditions

While soil moisture dominates the annual water balance in the UCRB, spring weather conditions emerged as a critical factor influencing the efficiency of snowmelt conversion to streamflow. The finding that AMJ climate variations alone can cause an 8.31 km³ difference in annual streamflow volumes highlights the importance of this transition period for water supply outcomes. Spring precipitation showed particularly strong influence (R²=0.91), with temperature playing a secondary but still significant role (R²=0.58).

The temporal analysis revealed distinct seasonal sensitivities, with summer (JJAS) streamflow showing amplified response to spring climate variations compared to annual totals. This heightened sensitivity can be attributed to the temporal proximity between spring conditions and the primary snowmelt season. Favorable spring conditions not only enhance direct runoff but can also partially offset antecedent soil moisture deficits, improving overall snowmelt efficiency. Conversely, unfavorable spring conditions (warm and dry) can exacerbate existing moisture limitations, further reducing the streamflow contribution from snowmelt.

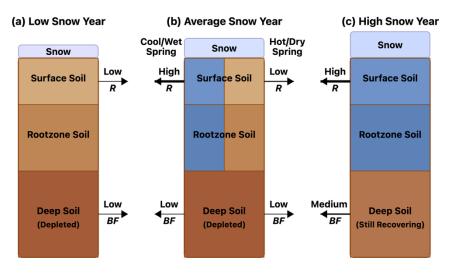
The interaction between spring climate and snow processes extends beyond simple temperature-driven melt dynamics. While warmer spring temperatures increase melt rates, they also enhance evaporative demand, potentially reducing the proportion of snowmelt that reaches streams. Similarly, spring precipitation can supplement snowmelt inputs, but its effectiveness depends on rainfall intensity and antecedent soil conditions. High-intensity rainfall may generate immediate runoff on saturated soils but could have limited benefit on dry soils where infiltration capacity remains high.

The combined climate-soil moisture interaction creates complex feedback mechanisms during the critical transition period. For instance, years with dry fall conditions but favorable

spring weather (cool and wet) can still produce near-average streamflow by supplementing moisture deficits at a critical time. Conversely, wet fall conditions followed by unfavorable spring conditions may still result in below-average streamflow if evaporative losses during the melt season are substantial.

From a water management perspective, these findings suggest that forecasting approaches need to incorporate seasonal climate predictions for the spring melt period. Current operational practices that rely primarily on April 1st snowpack measurements may miss critical factors that determine actual water availability, particularly during drought periods when soil moisture deficits and spring climate anomalies can substantially alter the snow-to-flow relationship. Incorporating probabilistic climate forecasts for the AMJ period could significantly improve seasonal runoff predictions, potentially allowing water managers to make more informed decisions about reservoir operations and water allocations.

# 5.3 Implications for Water Resources Management



**Figure 14.** Conceptual diagram of soil moisture and streamflow dynamics in the CRB during long-term drought conditions. Each column represents a different snow condition during a WY (Low, Average, or High Snow Years).

The findings from this study have significant implications for water resources management in the Colorado River Basin, particularly during drought conditions. The demonstrated importance of soil moisture and spring climate in controlling streamflow generation challenges traditional forecasting approaches that rely primarily on snowpack measurements. Water managers should consider incorporating these additional factors into their decision-making frameworks to improve operational outcomes.

Several specific recommendations emerge from this research:

(i) <u>Enhanced Monitoring Networks</u>: Expand soil moisture monitoring capabilities beyond surface measurements to capture conditions in deeper soil layers where critical memory effects occur. This could involve installing additional soil moisture

- sensors at strategic locations and depths throughout the basin, particularly in headwater regions where soil moisture influence is strongest.
- (ii) <u>Integrated Forecast Models</u>: Develop operational forecast systems that incorporate soil moisture conditions, snowpack measurements, and seasonal climate predictions for the spring period. These systems could use physically-based hydrological models calibrated to basin conditions, potentially improving forecast skill during drought periods when traditional approaches fall short.
- (iii) <u>Drought Recovery Planning</u>: Recognize that hydrological drought recovery occurs at different timescales for different system components. While surface conditions may respond quickly to favorable meteorological conditions, deep soil moisture and baseflow may require multiple wet years to fully recover from prolonged drought. This temporal disconnect should inform long-term drought planning and response strategies.
- (iv) <u>Basin-Specific Approaches</u>: Tailor water management strategies to the specific hydrological drivers of each sub-basin. The significant regional variations in factor importance—with soil moisture dominating in the UCRB and precipitation in the LCRB—suggest that a one-size-fits-all approach across the entire CRB may not be optimal.

Recent operational experiences support these recommendations. The 2020 and 2021 water years, when near-average snowpack produced well below-average streamflow, resulted in unexpected reservoir declines and emergency management actions. In contrast, the above-average snowpack of 2023 provided significant runoff, highlighting the complex interplay between snowpack, soil moisture, and climate conditions in determining water availability. This concept is sketched in Figure 14.

# 6. Concluding Remarks

This research has provided new insights into the changing relationship between snowpack and streamflow in the CRB during drought conditions. By isolating the effects of fall soil moisture and spring weather through controlled numerical experiments, their relative roles were quantified in determining streamflow outcomes and in explaining the "missing snowmelt" phenomenon observed in recent years.

Three key conclusions emerge from this study: First, antecedent soil moisture conditions, particularly in deep soil layers, exert the dominant influence on annual streamflow in the UCRB, accounting for approximately 74% of streamflow variability. During drought periods, a significant portion of snowmelt goes toward replenishing soil moisture deficits rather than contributing to streamflow, creating a persistent "memory" effect that can influence hydrological responses for several years even after meteorological drought conditions have improved.

Second, spring (April-May-June) weather conditions substantially influence snowmelt efficiency, with variations in spring climate alone causing differences up to 8.31 km³ in annual

streamflow volumes. Cool, wet spring conditions boost streamflow generation, while warm, dry conditions suppress it, even when starting with identical snowpack. This temporal proximity effect is particularly pronounced for summer streamflow, highlighting the immediate impact of spring conditions on the primary snowmelt season.

Third, the relative importance of these factors varies significantly across sub-basins, with soil moisture showing strongest influence in headwater regions where most water originates, while precipitation dominates in lower-elevation basins with lower overall water contribution. This spatial variability suggests the need for location-specific approaches to water management and forecasting.

These findings address the fundamental question of what happens to snowmelt during drought periods. When soils are dry from prolonged drought, snowmelt first replenishes these deficits before contributing to streamflow. As soil moisture is replenished, it becomes available for plant transpiration and soil evaporation, effectively creating a diversion pathway that redirects potential streamflow toward atmospheric losses. This mechanism explains why years with average snowpack can produce below-average streamflow when antecedent soil conditions are dry.

For water managers, these results highlight the need to move beyond snowpack-based forecasting approaches to more comprehensive frameworks that incorporate soil moisture monitoring and spring climate predictions. By accounting for these additional factors, forecasters can provide more accurate assessments of water availability, potentially improving operational decisions during drought periods.

Future research should focus on developing operational products that combine ground-based observations, remote sensing data, and hydrological modeling to provide more comprehensive evaluations of basin conditions. Additionally, exploring how climate change might alter the relationships identified in this study would provide valuable insights for long-term water planning in the CRB.

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