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Subseasonal Temperature Forecast Error Propagation to Snow Water Equivalent and Spring Runoff in Western U.S. Mountain Basins

Emily Carter¹, Michael Anderson², Sarah Bennett^{3*}

School of Earth, Energy & Environmental Sciences, Stanford University, Stanford,
CA 94305, United States

*Corresponding author: sarah.bennett@researchmail.edu

Abstract : *This study quantifies the propagation of subseasonal near-surface temperature forecast errors into snow water equivalent (SWE) and spring runoff across 21 mountainous basins in the western United States (elevation range 1,800–3,400 m; drainage area 95–2,750 km²). ERA5 reanalysis (0.25°, hourly, 1981–2023), SNODAS SWE (1 km), and 312 SNOTEL stations are integrated within a physically based SnowModel–VIC hydrologic framework. Subseasonal forecasts from European Centre for Medium-Range Weather Forecasts are perturbed using a stochastic bias generator (Gaussian + temporal autocorrelation, $\sigma = 0.8\text{--}2.5^\circ\text{C}$) and propagated through 2,400 ensemble simulations. Results show that a $+1^\circ\text{C}$ systematic bias shifts peak SWE timing earlier by 6.2–11.4 days and reduces seasonal SWE volume by 9.3–15.8%. Runoff peak discharge errors reach 18–27%, with low-elevation basins showing $1.6\times$ higher sensitivity than high-elevation basins. Variance decomposition indicates that 46% of runoff uncertainty originates from melt rate nonlinearities, while 31% arises from accumulated snowpack errors. A SHAP-based interpretability analysis identifies cumulative positive degree-days and melt threshold exceedance frequency as dominant drivers. The results reveal a nonlinear amplification chain from temperature forecast errors to water supply uncertainty at subseasonal scales.*

Keywords : *Subseasonal forecast; snow water equivalent; runoff; error propagation; hydrologic modeling*

INTRODUCTION

Mountain snowpack is a key freshwater source in the western United States. It stores winter precipitation and releases water during spring and early summer, thereby supporting streamflow, reservoir storage, irrigation, hydropower generation, and ecosystem water demand. Snow water equivalent (SWE) is widely used to quantify this stored water because it represents the amount of liquid water contained in the snowpack [1]. In recent decades, warming has changed both the amount and timing of mountain snow storage. Increased greenhouse gas forcing can also intensify the temporal clustering of heavy precipitation events, which may affect the sequence of snowfall, rain-on-snow events, and melt-season runoff generation [2]. Recent studies have further reported earlier snowmelt, shorter snow seasons, reduced low-elevation snow cover,

and more frequent snow droughts across the western United States [3,4]. These changes increase the uncertainty of spring runoff prediction, especially in transition-zone basins where small temperature errors can shift precipitation phase, accelerate melt, and strongly affect streamflow timing [5]. Subseasonal forecasts, usually covering lead times from two weeks to two months, are increasingly important for reservoir operation, drought preparedness, flood risk management, and seasonal water allocation [6]. They provide a practical bridge between short-range weather forecasts and seasonal climate outlooks. In snow-dominated basins, subseasonal temperature forecasts are particularly important because near-surface temperature controls snowfall fraction, snow accumulation, melt onset, melt rate, soil moisture recharge, and runoff generation [7]. Recent advances in ECMWF forecasts, hybrid statistical methods, and post-processing techniques have improved subseasonal prediction in many regions [8,9]. However, forecast skill remains limited in mountain terrain because steep temperature gradients, complex topography, elevation-dependent precipitation, and mixed rain–snow processes are difficult to represent accurately [10,11]. As a result, even modest temperature bias may cause large errors in SWE timing and spring runoff, especially during the melt season. Previous studies have improved SWE estimation by using SNOTEL observations, SNODAS products, ERA5 reanalysis, remote sensing data, and high-resolution snow models [12,13]. These datasets and models have helped describe snowpack distribution, evaluate long-term snow trends, and reduce uncertainty in basin-scale snow water storage. Hydrologic models such as VIC, SnowModel, and WRF-Hydro have also been widely used to simulate snow accumulation, snowmelt, soil moisture, evapotranspiration, and runoff processes in mountain watersheds [14,15]. These studies have provided important support for understanding snow hydrology in the western United States. However, many existing studies focus mainly on historical reconstruction, product comparison, model calibration, or long-term climate change assessment. Less attention has been given to how subseasonal temperature forecast errors are transferred into SWE and runoff errors across different elevation zones and basin types. This gap is important because the response of snowpack and runoff to temperature bias is not linear. A small warm bias may have little effect when temperatures remain far below freezing, but it may strongly accelerate melt when temperatures are close to the melt threshold. Similarly, a cold bias may delay melt, increase temporary snow storage, and shift runoff peaks later into the season [16,17]. These effects can accumulate over several forecast cycles and alter both SWE volume and runoff timing. The influence of temperature error may also vary with elevation, snow depth, basin aspect, and seasonal stage. Therefore, a systematic evaluation is needed to identify when and where subseasonal temperature errors are most likely to produce large hydrologic impacts. This study examines the effect of subseasonal near-surface temperature forecast errors on SWE and spring runoff in 21 mountain basins across the western United States. ERA5 meteorological fields, SNODAS SWE products, and SNOTEL observations are combined within a SnowModel–VIC modeling framework. ECMWF temperature forecasts are perturbed using a stochastic bias generator and tested through 2,400 ensemble simulations. The analysis evaluates changes in peak SWE timing, seasonal SWE volume, melt duration, runoff peak discharge, and runoff timing across different elevation zones. It further identifies the physical factors that control the transfer from temperature bias to hydrologic error, including melt-threshold sensitivity, accumulated snowpack error, elevation-dependent warming response, and nonlinear melt–runoff conversion. By linking subseasonal temperature uncertainty with snowpack and runoff response, this study provides a

clearer basis for improving mountain water prediction, reservoir operation, and climate risk management in snow-dominated basins of the western United States.

2. Materials and Methods

2.1 Study Area and Sample Description

This study selected 21 snow-dominated mountain basins in the western United States. The basins ranged from 1,800 to 3,400 m in elevation and from 95 to 2,750 km² in drainage area. These basins were used because snow accumulation in winter and snowmelt in spring are the main sources of runoff. A total of 312 SNOTEL stations were included to provide point-scale records of snow water equivalent (SWE), temperature, and precipitation. ERA5 reanalysis data were used as gridded meteorological forcing, and SNODAS data were used to describe spatial SWE patterns. The study period was 1981–2023, which covered wet, dry, warm, and cold snow seasons.

2.2 Experimental Design and Control Experiments

The experiment was designed to test the effect of near-surface temperature forecast errors on SWE and spring runoff. The control experiment used the original ECMWF subseasonal temperature forecasts without added errors. The experimental runs used the same forecasts after adding warm, cold, and random temperature errors. The systematic bias represented persistent warm or cold forecast errors. The random error was generated from a Gaussian distribution with temporal autocorrelation. The standard deviation ranged from 0.8 to 2.5°C. This setting was used because subseasonal temperature errors often persist for several days rather than changing independently each day. In total, 2,400 ensemble simulations were performed. The differences between the control run and the error runs were used to assess changes in peak SWE timing, seasonal SWE volume, and spring runoff peak discharge.

2.3 Measurement Methods and Quality Control

SWE, temperature, precipitation, and runoff-related variables were obtained from station data, gridded datasets, and model outputs. SNOTEL records were used as station-scale reference data. SNODAS SWE data at 1 km resolution were used to describe snowpack distribution across each basin. ERA5 hourly data at 0.25° resolution were used as meteorological input after spatial interpolation. SnowModel–VIC was used to simulate snow accumulation, snowmelt, soil water change, and runoff generation. Data quality was checked before model simulation. Missing SNOTEL values were removed or filled only when short gaps could be interpolated with confidence. Negative precipitation, abnormal SWE values, and unreasonable temperature records were screened. ERA5 and SNODAS data were checked for consistent time steps and correct spatial matching. Simulated SWE and runoff were also compared with observed patterns to confirm that the model results were reasonable.

2.4 Data Processing and Model Formulas

All data were converted to the same time scale before model input. Station records were averaged at the basin scale with elevation-based weights. ERA5 and SNODAS grids were clipped by basin boundaries and then averaged by elevation zone. Temperature errors were added to the original ECMWF forecast series before the SnowModel–VIC simulation. The perturbed temperature was calculated as:

$$T'_t = T_t + b + \varepsilon_t$$

where T'_t is the perturbed temperature at time t , T_t is the original forecast temperature, b is the systematic bias, and ε_t is the random error with temporal autocorrelation. The runoff peak discharge error was calculated as:

$$RE_Q = \frac{Q_p - Q_c}{Q_c} \times 100\%$$

where RE_Q is the runoff peak discharge error, Q_p is the peak discharge from the perturbed run, and Q_c is the peak discharge from the control run. These two equations were used to measure how temperature errors changed SWE and runoff responses.

2.5 Statistical Analysis and Uncertainty Assessment

The model results were analyzed at basin and elevation-zone scales. Changes in peak SWE timing, seasonal SWE volume, and runoff peak discharge were calculated by comparing each perturbed run with the control run. Ensemble means were used to describe the average response, and ensemble ranges were used to describe the spread of results. Variance decomposition was used to estimate the relative roles of melt-rate response, accumulated snowpack error, and other hydrologic factors in runoff uncertainty. SHAP analysis was also used to identify the main factors linked to error propagation. The variables included cumulative positive degree-days, melt threshold exceedance frequency, elevation, and seasonal SWE volume. This analysis helped explain how temperature forecast errors were transferred into snowmelt and runoff errors under different basin conditions.

3. Results and Discussion

3.1 Effects of Temperature Bias on SWE Timing and Volume

The ensemble results showed that near-surface temperature errors clearly changed snow water equivalent (SWE). A warm bias caused peak SWE to occur earlier and reduced seasonal SWE volume. Under a $+1^\circ\text{C}$ bias, peak SWE occurred 6.2–11.4 days earlier than in the control run, and seasonal SWE volume decreased by 9.3–15.8% across the 21 basins. The response was stronger in low-elevation basins because more winter days were close to 0°C . In these basins, a small warm error could change snowfall into rainfall or start early snowmelt. This result agrees with previous studies showing that low- and mid-elevation snowpack is more sensitive to warming than high-elevation snowpack [18,19]. As shown in Fig. 1, earlier peak SWE was closely related to greater seasonal SWE loss.

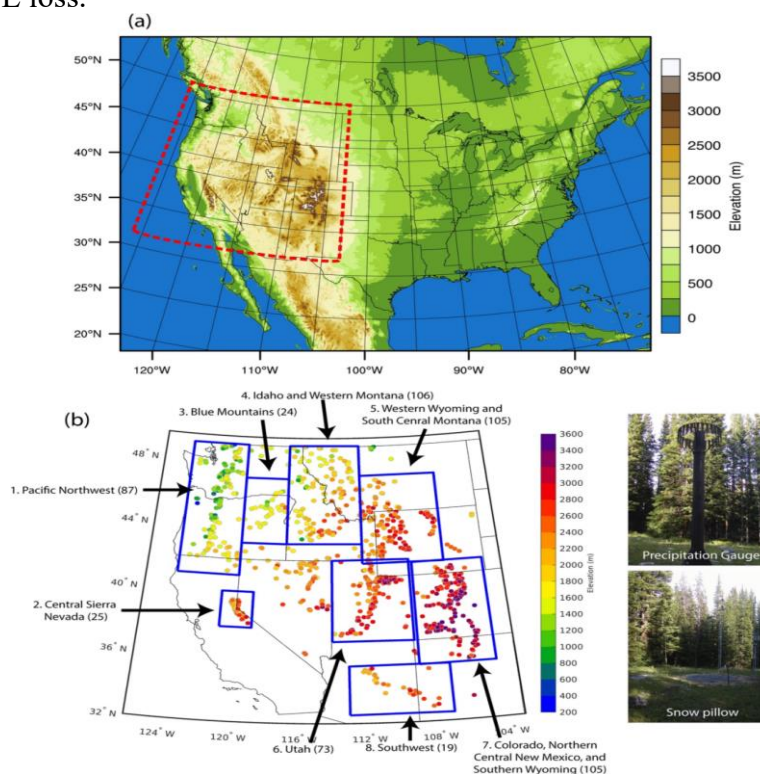


Fig. 1. Changes in peak SWE timing and seasonal SWE volume under near-surface temperature bias.

3.2 Runoff Response to Snowpack Errors

Temperature errors also changed spring runoff timing and magnitude. Runoff peak discharge errors reached 18–27% in the perturbed simulations. Low-elevation basins were about 1.6 times more sensitive than high-elevation basins. This result indicates that runoff error was not caused only by temperature bias. It also came from changes in snow storage and melt timing before runoff generation. Warm errors caused earlier melt and reduced late-season snow storage. Cold errors delayed melt and shifted runoff to a later period. These findings are consistent with studies showing that western U.S. runoff is strongly controlled by snowmelt timing and snow volume [20,21]. This study further shows that subseasonal temperature errors can pass through SWE changes and then affect spring peak discharge.

3.3 Sources of Runoff Uncertainty

The variance decomposition showed that melt-rate response and accumulated snowpack error were the main sources of runoff uncertainty. Melt-rate response explained 46% of runoff uncertainty, while accumulated snowpack error explained 31%. This means that runoff error increased strongly when temperature crossed the melt threshold. The response was not linear. A small temperature change had little effect when the basin stayed below freezing. The same temperature change caused a much larger response when the basin was near or above the melt threshold. Fig. 2 shows this process. Larger runoff errors occurred when cumulative positive degree-days and melt-threshold exceedance frequency increased together. This finding agrees with recent studies that highlight the roles of snowpack condition, elevation, and melt timing in mountain water prediction [22,23].

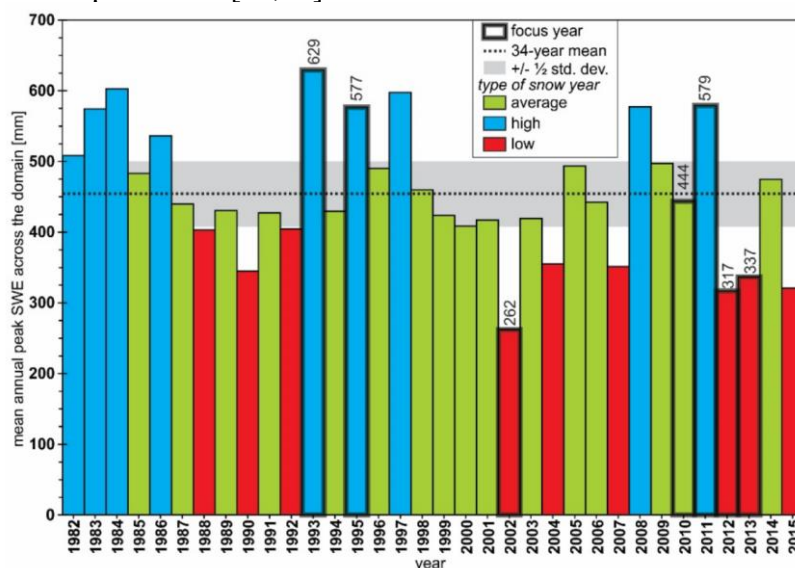


Fig. 2. Effects of positive degree-days and melt-threshold days on peak runoff error.

3.4 Comparison with Previous Studies and Hydrologic Implications

Compared with previous studies, this study focuses on the full error pathway from subseasonal temperature bias to SWE change and runoff uncertainty. Many earlier studies mainly examined SWE reconstruction, snow product evaluation, or long-term climate response. These studies improved the understanding of snowpack distribution, but they did not fully test how subseasonal forecast errors affect spring runoff. The present results show that temperature forecast errors can be enlarged through snowmelt processes, especially in low-elevation basins. This finding is useful for water-supply forecasting. Reservoir managers should treat warm subseasonal temperature bias as a warning signal for earlier snowmelt and greater runoff timing error. Future work should

also include precipitation-phase errors and rain-on-snow events because they may further increase runoff uncertainty during warm spring periods.

4. Conclusion

This study assessed the effects of subseasonal near-surface temperature forecast errors on SWE and spring runoff in snow-dominated mountain basins of the western United States. The results showed that warm temperature bias advanced peak SWE timing, reduced seasonal SWE volume, and increased errors in peak runoff. Low-elevation basins were more sensitive than high-elevation basins because their temperatures were closer to the melt threshold. The uncertainty analysis showed that melt response and accumulated snowpack error were the main sources of runoff uncertainty. This result indicates that small temperature errors can become larger after they pass through snowmelt and runoff processes. The main value of this study is that it links temperature forecast error, SWE change, and runoff response in one SnowModel–VIC framework. The findings can support snowmelt forecasting, reservoir operation, and water-supply planning. However, this study mainly considered temperature errors. Future studies should include precipitation-phase errors, rain-on-snow events, and human water regulation to improve subseasonal hydrologic prediction.

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