

Extreme early-spring polar jet shifts reduce warm-season runoff in the snow-dominated upper Colorado River Basin

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Abstract

Meridional displacements of the polar jet stream (PJS) strongly influence midlatitude surface temperature and precipitation, yet their hydrological consequences remain poorly understood. Here we show that during five extreme years from 1979 to 2025, the March PJS over western North America shifted from its climatological position south of the upper Colorado River Basin (UCRB; $31.36 \pm 8.50^\circ\text{N}$) to well north of the basin ($50.95 \pm 1.92^\circ\text{N}$). Over the UCRB, these shifts coincided with conditions that were $2.43 \pm 0.62^\circ\text{C}$ warmer and $40.5 \pm 21.4\%$ drier than average and with net snowpack loss about five times the long-term mean. Attribution experiments indicate that the shifts reduced May–August runoff by 12.6–23.3% relative to the 1981–2021 mean. Associated precipitation changes accounted for 55.7–83.2% of the reduction, compared with 11.0–43.4% for temperature changes. Relationships between March PJS position and UCRB hydroclimate are largely independent from major climate modes. An anomalously strong stratospheric polar vortex emerges as a plausible dynamical driver of the extreme jet shifts. These findings link early-spring atmospheric circulation to warm-season runoff and identify PJS position as a potentially useful indicator of water availability in the UCRB and other snow-dominated midlatitude basins.

Introduction

The polar jet stream (PJS) is a narrow, meandering band of strong westerly winds near the midlatitude tropopause¹. It arises from the pronounced north–south temperature contrast between cold polar air and warmer air at lower latitudes. By organizing extratropical storm tracks and steering individual cyclones, the PJS shapes storm trajectories and precipitation patterns^{2–6}. Its northward ridges and southward troughs also regulate the regional transport of warm and cold air^{3,7–9}. Persistent or extreme meridional displacements of the PJS can therefore generate substantial surface temperature and precipitation anomalies and have been associated with heat waves, cold spells, drought, heavy precipitation, and compound extremes^{9–14}.

These circulation-driven variations in surface temperature and precipitation are particularly consequential for river systems sustained by snow-dominated headwaters, such as the Colorado River. The Colorado River supplies water to approximately 40 million people and supports irrigated agriculture across seven U.S. states and northern Mexico^{15–17}. More than 90% of its flow originates in the snow-dominated upper Colorado River Basin (UCRB), where mountain snowmelt sustains warm-season streamflow^{17,18}. UCRB streamflow has declined substantially: naturalized annual flow decreased by 16.5% over 1916–2014¹⁷, and Colorado River flows during 2000–2014 were approximately 19% below the 1906–1999 mean¹⁶. These declines reflect the combined effects of warming and precipitation variability^{17,19}. Warming can reduce runoff by increasing evapotranspiration, decreasing the fraction of precipitation that falls as snow, and advancing snowmelt^{20–25}, while precipitation deficits can further amplify warming-driven runoff losses^{19,24}. Recent studies have identified spring precipitation and temperature as important controls on UCRB streamflow and runoff efficiency^{17,24,26}. However, the role of

large-scale atmospheric circulation—particularly the meridional position of the PJS—in shaping spring hydroclimatic conditions and the ensuing warm-season runoff remains poorly understood.

Here, we investigate how extreme northward shifts in the March PJS affect warm-season runoff in the UCRB. March marks the transition from snow accumulation to snowmelt in the UCRB and is therefore critical for the snowpack that feeds streamflow in the following warm season. We combine atmospheric reanalysis, observational datasets of surface air temperature, precipitation, and snow water equivalent (SWE), and hydrological modelling to trace the process chain linking March PJS position to surface temperature and precipitation, snowpack, and warm-season runoff. We identify five extreme northward-shift years in which the March PJS moved from its climatological position south of the UCRB to well north of the basin, coinciding with unusually warm and dry conditions and substantial net snowpack loss. Attribution experiments show that these shifts reduce May–August runoff, with precipitation changes accounting for most of the runoff reduction.

Results

Extreme northward-shift years

We define PJS latitude (PJSL) over western North America to measure the meridional position of the jet core (see Methods). Applying the 90th-percentile criterion (see Methods) to March PJSL anomalies during 1979–2025 identifies five extreme northward-shift years (Fig. 1a). Ranked in descending order of anomaly, these years are 2007 (21.89°N), 2015 (20.64°N), 2012 (19.89°N), 2004 (18.64°N), and 2017 (16.89°N). All five extreme years occur between 2004 and 2017, and their concentration late in the record contributes to a positive trend in March PJSL of 1.63 °N per decade ($p = 0.07$, $n = 47$). When these years are excluded, the trend is no longer significant ($p = 0.37$). The climatological mean March PJSL is 31.36 ± 8.50 °N (mean ± 1 standard deviation across years), south of the UCRB (Fig. 1b). By contrast, the mean March PJSL during the five extreme years is 50.95 ± 1.92 °N, well north of the UCRB (Fig. 1c).

Jet position and UCRB hydroclimate

A northward-displaced PJS is associated with warmer and drier conditions over the UCRB. March PJSL is positively correlated with March surface air temperature and negatively correlated with March precipitation across the UCRB and surrounding region (Fig. 2a–b). At the basin scale, the correlations of March PJSL with UCRB-mean March temperature and precipitation are 0.47 ($p < 0.01$, $n = 44$) and -0.31 ($p = 0.04$, $n = 44$), respectively (Fig. 2c–d). A 1° northward shift in PJSL corresponds to a 0.08°C increase in UCRB-mean temperature and a 0.50 mm decrease in precipitation. The extreme years cluster near the warm and dry ends of these relationships (red points in Fig. 2c–d). During the extreme years, UCRB-mean March temperature is 2.43 ± 0.62 °C above the 1981–2024 mean, with the strongest warming in the northern UCRB (Fig. 2e). March precipitation is lower than the 1981–2024 mean by 14.43 ± 7.61 mm, corresponding to a reduction of $40.5 \pm 21.4\%$, with the largest deficits at high elevations (Fig. 2f).

March snowpack dynamics in the UCRB reflect the combined effects of temperature and precipitation. We quantified net March snowpack change as March SWE accumulation (SWEA), calculated as April 1 SWE minus March 1 SWE; negative SWEA therefore indicates net ablation. March PJSL is negatively correlated with March SWEA across most of the UCRB (Fig. 3a), consistent with reduced snowfall and accelerated snowmelt under warmer, drier conditions. During 1982–2023, the correlation between March PJSL and UCRB-mean March SWEA is -0.53 ($p < 0.01$, $n = 42$; Fig. 3b). A 1° northward shift in PJSL corresponds to a 1.04 mm decrease in UCRB-mean SWEA. Mean March SWEA is -6.7 ± 17.5 mm for 1982–2023 and -35.4 ± 11.8 mm for the extreme PJS-shift years, indicating that mean net snowpack loss during the extreme years is approximately five times the long-term mean. Similarly, the fraction of the basin experiencing a net SWE gain ($SWEA > 0$) averages $21.0 \pm 11.7\%$ during 1982–2023 (Fig. 3c) but only $5.3 \pm 2.5\%$ during the extreme years (Fig. 3d). The largest decreases in SWEA occur at elevations of 2,500–3,250 m (Fig. 3e).

Runoff response to extreme jet shifts

Attribution experiments (see Methods) indicate that extreme northward shifts of the March PJS reduce May–August runoff by 2.32 ± 0.44 km³, equivalent to $16.9 \pm 3.2\%$ of the 1981–2021 baseline mean (13.69 ± 5.52 km³; Fig. 4 and Table 1). The four subbasins with the largest reductions—1401, 1404, 1402, and 1405, in descending order—account for a combined reduction of 1.86 ± 0.33 km³, or $80.4 \pm 7.4\%$ of the basin-wide reduction (Fig. 4). This spatial concentration is consistent with the patterns of March warming, precipitation deficits, and net snowpack loss described above.

Table 1
Simulated changes in the warm-season water budget of the UCRB due to extreme PJS shifts (units: km³). Percentage changes relative to the 1981–2021 mean are shown in parentheses. The neutral year is 2014. Because forcing is replaced only in March, warm-season precipitation changes are zero.

Variable	1981–2021 mean	All forcing changes	Temperature changes only	Precipitation changes only
Precipitation	32.46 ± 9.80	0	0	0
Runoff	13.69 ± 5.52	-2.32 ± 0.44 ($-16.9 \pm 3.2\%$)	-0.58 ± 0.19	-1.64 ± 0.47
ET	50.72 ± 7.38	-1.06 ± 0.93 ($-2.1 \pm 1.8\%$)	-0.30 ± 0.14	-0.55 ± 0.74
May 1 SWE	12.49 ± 6.50	-3.17 ± 0.99 ($-25.4 \pm 7.9\%$)	-1.05 ± 0.47	-2.02 ± 0.75

The runoff reduction is primarily associated with snowpack depletion at the start of the warm season. May 1 and April 1 SWE decrease by 3.17 ± 0.99 km³ ($25.4 \pm 7.9\%$) and 5.27 ± 1.40 km³ ($29.5 \pm 7.8\%$),

respectively. The larger April 1 reduction indicates that much of the May 1 deficit results from reduced snowfall and enhanced snowmelt under warmer and drier March conditions. Reduced snowmelt also limits soil-moisture replenishment and decreases May–August ET by $1.06 \pm 0.93 \text{ km}^3$ ($2.1 \pm 1.8\%$), partially offsetting the runoff loss. Together, PJS-shift-related changes in precipitation and temperature account for $95.4 \pm 5.4\%$ of the basin-wide runoff reduction. Precipitation changes account for $1.64 \pm 0.47 \text{ km}^3$ ($70.0 \pm 9.1\%$), whereas temperature changes account for $0.58 \pm 0.19 \text{ km}^3$ ($25.4 \pm 7.6\%$). Earlier snowmelt increases March–April runoff by $0.93 \pm 0.31 \text{ km}^3$; nevertheless, total March–August runoff decreases by $1.39 \pm 0.26 \text{ km}^3$, an $8.5 \pm 1.6\%$ reduction relative to the 1981–2021 mean.

Sensitivity to neutral-year selection

Because the attribution experiments use forcing from a neutral year as the counterfactual for extreme PJS-shift years (see Methods), the estimated responses may depend on the neutral year selected. To assess this sensitivity, we repeated the full set of experiments using 1993 and 2021 as alternative neutral years (Supplementary Tables 1–2), in addition to 2014, which was used in the main analysis. Across the three neutral-year choices, extreme PJS shifts reduce May–August runoff by 12.6–23.3%, May 1 SWE by 19.2–33.3%, and April 1 SWE by 28.7–38.0%. Although the magnitude of the response varies with the selected neutral year, all water-budget components response in the same direction, and the relative changes are comparable. Associated precipitation changes dominate the May–August runoff reduction in each case, accounting for 55.7–83.2% of the total response, whereas temperature changes make a smaller contribution (11.0–43.4%). Together, precipitation and temperature changes explain 94.2–99.1% of the reduction. The four northwestern subbasins—1401, 1404, 1402, and 1405—contribute 64.8–80.4% of the UCRB-wide decrease in May–August runoff. These results indicate that the inferred water-budget response to extreme PJS shifts is robust to the choice of neutral year.

Independence from large-scale climate modes

Large-scale climate modes may influence both jet position and UCRB hydroclimate, potentially confounding the observed PJSL–hydroclimate relationships. We therefore calculated partial correlations controlling for three modes: El Niño–Southern Oscillation (ENSO) and Pacific Decadal Oscillation (PDO), which characterize large-scale sea surface temperature variability, and Arctic Oscillation (AO), which characterizes annular atmospheric variability (Supplementary Table 3). During 1979–2025, March PJSL shows weak, nonsignificant correlations with ENSO and PDO but a significant positive correlation with AO ($r = 0.36$, $p = 0.01$, $n = 47$), consistent with the relationship between AO and the hemispheric annular jet structure^{27,28}.

Controlling for these climate modes has little effect on the relationships of March PJSL with SWEA and temperature. The PJSL–SWEA correlation remains largely unchanged after controlling separately for ENSO, PDO, or AO (unadjusted $r = -0.53$, $n = 42$; partial $r = -0.53$, -0.55 , and -0.49 , respectively; all $p < 0.01$). The PJSL–temperature relationship is similarly robust (unadjusted $r = 0.47$, $n = 44$; partial $r = 0.48$,

0.51, and 0.40, respectively; all $p < 0.01$), despite a positive correlation between March temperature and AO ($r = 0.35$, $p = 0.02$). March precipitation is positively correlated with ENSO ($r = 0.34$, $p = 0.02$, $n = 44$). Controlling for ENSO weakens the PJSL–precipitation correlation from -0.31 ($p = 0.04$) to -0.26 , although the relationship remains significant at the $p < 0.10$ threshold. The PJSL–precipitation relationship also remains significant after controlling separately for PDO or AO (partial $r = -0.30$ and -0.32 , respectively; $p < 0.10$ for both). Overall, the PJSL–hydroclimate relationships are largely independent from the three climate modes.

Potential causes of the extreme jet shifts

A strong stratospheric polar vortex tends to confine cold polar air, strengthen the meridional temperature gradient along its equatorward flank, and favor a poleward displacement of the PJS^{29,30}. The five extreme northward shifts of the March PJS coincide with these conditions. During the extreme years, mean polar-cap (70° – 90° N) zonal wind at 10 hPa (U10) is 9.4 m s^{-1} stronger than the 1979–2025 climatological mean (Fig. 5a), and positive U10 anomalies are statistically significant ($p < 0.10$) over most of the polar cap. This relationship is also evident beyond the composite analysis: March PJSL covaries significantly with March polar-cap U10 during 1979–2025 ($r = 0.42$, $p < 0.01$, $n = 47$). Together, these results support an anomalously strong stratospheric polar vortex as a plausible dynamical driver of the extreme jet shifts.

The poleward displacement of the PJS is evident as a meridional dipole in the composite U250 anomaly, characterized by strengthened westerlies on the poleward flank (45° – 65° N) and weakened westerlies on the equatorward flank (20° – 40° N; Fig. 5b). The dipole is relatively weak over 150° E– 180° ($+2.66 \text{ m s}^{-1}$) but intensifies sharply eastward, reaching $+13.62 \text{ m s}^{-1}$ over western North America (120° – 90° W). It remains pronounced across eastern North America ($+7.83 \text{ m s}^{-1}$ over 90° – 60° W) before weakening over the Atlantic. Thus, the extreme northward shifts in the March PJS extend from the northeastern Pacific across North America rather than being confined to western North America. This spatial pattern places the storm track anomalously far poleward and well upstream of the UCRB, likely contributing to the dry conditions over the basin.

Projected March jet shifts

To assess whether continued warming is associated with a northward shift of the March PJS, we analyzed 13 CMIP6 model runs spanning 1979–2100 under SSP585 and SSP370 (Supplementary Tables 4–5). Under SSP585, five of 13 runs project northward trends, but only one trend is statistically significant (EC-Earth3_r1i1p1f1: 0.20° N per decade, $p = 0.07$). When the end-of-century period (2061–2100) is compared with the historical baseline (1981–2020), three runs project a higher mean March PJSL, and the change is statistically significant in only one run (EC-Earth3_r1i1p1f1: 1.81° N, $p = 0.05$). Only two runs project a greater number of extreme northward-shift years during 2061–2100 than during

1981–2020. Collectively, the SSP585 simulations provide no robust evidence of a northward shift in the March PJS through 2100. The SSP370 simulations yield the same overall conclusion.

Discussion

Extreme northward shifts in the March PJS connect early-spring atmospheric circulation to warm-season water availability in the UCRB through a physically consistent sequence of warmer and drier conditions, greater net snowpack loss, and reduced runoff. These findings complement previous evidence that spring precipitation and temperature exert strong controls on UCRB runoff^{17,24,26}. The attribution experiments further show that associated precipitation changes account for most of the runoff reduction, while temperature changes make a smaller but material contribution.

The circulation composites suggest that an unusually strong stratospheric polar vortex is a plausible dynamical precursor of the extreme jet shifts. This interpretation is consistent with established stratosphere–troposphere coupling mechanisms in which a strong polar vortex favors a poleward displacement of the tropospheric jet^{28, 29}. Jet position reflects a closely balanced “tug-of-war” between multiple factors, including lower-level Arctic warming, upper-level tropical warming, and polar-vortex strength^{6, 30, 31}. Among these candidate factors, however, only the polar-vortex anomaly is apparent during the extreme jet-shift years.

Several limitations constrain the interpretation. The 47-year observational record contains only five extreme years, and linear partial correlations cannot exclude low-frequency or nonlinear modulation. The hydrological model reproduces basin-scale snowpack and runoff variability but performs less well in low-SWE vegetation classes and several low-runoff subbasins (see Methods). These factors favor a basin-scale, process-based interpretation over precise subbasin estimates.

The CMIP6 model runs do not provide robust evidence of a northward shift in March PJS over western North America through 2100 under SSP370 or SSP585. However, climate models have difficulties in representing both natural jet-stream variability and the response to anthropogenic forcing^{32–34}, limiting confidence in the projected changes. Irrespective of whether a long-term northward shift emerges, the observed and modelled process chain identifies March PJS position as a potentially useful source of information for diagnosing and predicting warm-season water availability in the UCRB and other snow-dominated midlatitude basins.

Methods

Definition of PJS latitude

PJS latitude (PJSL) is defined as the latitude of maximum upper-tropospheric zonal wind^{3,31}. We calculated monthly PJSL over western North America (125–90°W, 20–70°N) using monthly mean 250-hPa zonal wind (U250) in the ERA5 reanalysis³² for 1979–2025 and from 13 Coupled Model

Intercomparison Project Phase 6 (CMIP6) model runs for 1979–2100, with projections under SSP370 and SSP585 (Supplementary Table 6). The CMIP6 runs were selected based on their ability to simulate key processes governing the climate of western North America³³. Following a percentile-based approach commonly used to define temperature extremes³⁴, we define extreme northward-shift years as years in which the March PJSJ anomaly exceeds the 90th percentile of anomalies during 1979–2025.

Data and evaluation metrics

Monthly surface air temperature and precipitation data for 1981–2024 were obtained from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) dataset³⁵. Snow water equivalent (SWE) data for 1982–2023 was obtained from the University of Arizona Daily 4-km Gridded SWE and Snow Depth from Assimilation of In-Situ and Modeled Data over the Conterminous United States, Version 1 (hereafter UA SWE)³⁶. We used runoff observations from the USGS at the Hydrologic Unit Code (HUC) subbasin scale to evaluate the simulated runoff. We evaluated model performance against the reference datasets using three metrics: the Kling–Gupta efficiency (KGE)³⁷; the Pearson correlation coefficient (r); and the relative mean bias.

Model configuration and experimental design

We used Noah-MP, a one-dimensional land surface model that simulates vertical water and energy exchanges within each grid cell^{38,39}, to simulate hydrological processes across the Colorado River Basin (Supplementary Fig. 1a) at 9-km spatial resolution during 1981–2021. Hourly precipitation forcing was obtained from the Analysis of Record for Calibration⁴⁰; all other meteorological forcing variables were obtained from CONUS404, a high-resolution hydroclimatic reanalysis for the conterminous United States⁴¹. Vegetation types (Supplementary Fig. 1b) were prescribed using the 1-km USGS 24-category vegetation dataset, and soil types (Supplementary Fig. 1d) were derived from the hybrid State Soil Geographic Database⁴².

To quantify the effects of extreme northward shifts in the March PJS on UCRB runoff, we conducted four experiments. The baseline (BSLN) experiment comprised a continuous 1981–2021 simulation driven by the original forcing data. In the neutral-all (NA) experiment, we replaced all March forcing variables in extreme PJS-shift years with values from a neutral year. In the neutral-temperature (NT) and neutral-precipitation (NP) experiments, we replaced only March temperature and precipitation, respectively. The BSLN–NA comparison quantifies the combined effects of all PJS-shift-related forcing changes on UCRB runoff, whereas the BSLN–NT and BSLN–NP comparisons isolate the effects of temperature and precipitation, respectively. We focused the attribution experiments on temperature and precipitation because these variables exert primary controls on the UCRB water balance^{17,19}.

We define the neutral year as the candidate year in which March PJSL and UCRB-mean March temperature and precipitation are jointly closest to their climatological values. We ranked candidate years according to their three-dimensional Euclidean distance in standardized space:

$$dist = \sqrt{Z_{PJSL}^2 + Z_T^2 + Z_P^2}$$

1

where *dist* is the Euclidean distance, and Z_{PJSL} , Z_T , and Z_P are the z scores of March PJSL, UCRB-mean March temperature, and UCRB-mean March precipitation, respectively. Based on this metric, we selected 2014 as the primary neutral year: its March PJSL is nearly identical to the climatological mean ($Z_{PJSL} = 0.04$; Supplementary Table 7), and its UCRB-mean March temperature and precipitation are each within 0.5 standard deviations of their respective climatological means. We conducted experiments with 1993 (ranked second) and 2021 (ranked third) to assess sensitivity to the choice of neutral year.

We used atmospheric forcing from an observed neutral year rather than climatological-mean forcing because independently averaged forcing variables may form physically inconsistent combinations. For example, stormy conditions are often associated with lower temperatures, but independently averaging each forcing variable across years disrupts this covariance and can yield combinations that do not occur in the atmosphere. Climatological averaging also suppresses synoptic variability, yielding unrealistically smooth March forcing and potentially biased model responses. In contrast, forcing from an observed neutral year preserves the temporal and physical coherence—including intervariable covariance, storm sequences, weather transitions, and diurnal cycles—while representing near-climatological March conditions.

Model evaluation

Noah-MP reproduces the temporal evolution and mean annual cycle of SWE across the UCRB (Supplementary Figs. 2–3). Relative to UA SWE, the UCRB-mean monthly SWE time series yields KGE = 0.91, $r = 0.96$, and a relative mean bias of 8.2%; the mean annual cycle yields KGE = 0.89 and $r = 0.98$. Time-series performance is similarly strong in forest and savanna areas (KGE = 0.83–0.90; $r = 0.97$ for both). Performance is weaker in grassland and shrubland areas (KGE = 0.47–0.61), where Noah-MP underestimates SWE by 28.7% and 34.2%, respectively, although temporal correlations remain high ($r = 0.88$ –0.93).

Noah-MP also reproduces observed runoff dynamics at the UCRB scale (Supplementary Figs. 4–6). Relative to USGS observations, the UCRB-mean monthly runoff time series has KGE = 0.83, $r = 0.91$, and a relative mean bias of – 13.8%; the mean annual cycle yields KGE = 0.84 and $r = 0.98$. Performance is generally strong in subbasins 1401–1404, where time-series KGE values range from 0.74 to 0.84, correlations from 0.79 to 0.93, and biases from – 8.1% to 2.1%. Model skill is lower in subbasins 1405 and 1406 and is lowest in subbasins 1407 and 1408, where the model substantially underestimates

runoff by 46.9% and 44.4%, respectively. Evaluation of the mean annual cycles shows a similar spatial pattern in model skill (Supplementary Fig. 6).

Overall, the strong agreement between simulated and observed SWE and runoff at the UCRB scale supports the use of Noah-MP in the basin-scale attribution experiments. However, the model's lower skill in low-SWE grassland and shrubland areas and in several low-runoff subbasins indicates that subbasin-scale results, particularly those for subbasins 1407 and 1408, should be interpreted with caution.

Trend regression and correlation analyses

We estimated the long-term trend in March PJSL using ordinary least squares (OLS) regression and evaluated its significance using a two-sided Student's t test. At each grid cell, we calculated the Pearson correlation coefficient (r) between March PJSL and the corresponding March hydroclimate variable over their common period of record and evaluated its significance using the same test. At the basin scale, we averaged each hydroclimate variable over the UCRB and fitted an OLS regression between the basin-mean series and March PJSL.

To assess the robustness of the PJSL–hydroclimate relationships to large-scale climate variability, we calculated partial correlations controlling separately for three major climate modes affecting western North America: El Niño–Southern Oscillation (ENSO), Pacific Decadal Oscillation (PDO), and Arctic Oscillation (AO). ENSO was represented by the Niño 3.4 index, calculated as the area-averaged sea surface temperature (SST) anomaly over 5°S–5°N and 170°W–120°W using the NOAA Extended Reconstructed Sea Surface Temperature version 6 (ERSSTv6; <https://psl.noaa.gov/data/correlation/nina34.anom.data>). We obtained the ERSSTv5-based PDO index from NOAA's Physical Sciences Laboratory (<https://psl.noaa.gov/pdo/>). This index is the principal component time series associated with the leading empirical orthogonal function (EOF) of monthly SST anomalies over the North Pacific (20–70°N), after removal of the monthly climatology and global-mean SST anomaly. The AO index, obtained from the NOAA Climate Prediction Center (https://www.cpc.ncep.noaa.gov/products/precip/CWlink/daily_ao_index/), is constructed by projecting monthly mean 1000-hPa geopotential-height anomalies poleward of 20°N onto the leading EOF. For each index, we used the March value for each year to maintain consistency with the jet and hydroclimate analyses. For PJSL (x), a hydroclimate variable (y), and a climate-mode index (z), the partial correlation is

$$r_{xy \cdot z} = \frac{r_{xy} - r_{xz}r_{yz}}{\sqrt{(1 - r_{xz}^2)(1 - r_{yz}^2)}}$$

2

where r_{xy} , r_{xz} , and r_{yz} are the corresponding pairwise Pearson correlation coefficients. We assessed the significance of each partial correlation using a two-sided Student's t test with $n - 3$ degrees of

freedom. We controlled for each mode separately and considered $p < 0.10$ statistically significant; we applied the same criterion to the Pearson correlation analyses.

Declarations

Competing interests

The authors declare no competing interests.

Author contributions

Y.Q.: Conceptualization, Data curation, Methodology, Software, Formal analysis, Visualization, Writing – original draft. J.F.: Writing – review & editing, Supervision, Funding acquisition, Project administration. G.N.: Writing – review & editing, Software. A.B.: Writing – review & editing.

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Data availability

All data used in this study are available in the Zenodo repository at [10.5281/zenodo.21898672](https://doi.org/10.5281/zenodo.21898672).

Code availability

All analysis scripts used in this study are available in the Zenodo repository at [10.5281/zenodo.21898672](https://doi.org/10.5281/zenodo.21898672). The Noah-MP source code is available from the GitHub repository [mfarmani95/NoahMP_Dual](https://github.com/mfarmani95/NoahMP_Dual).

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Figures

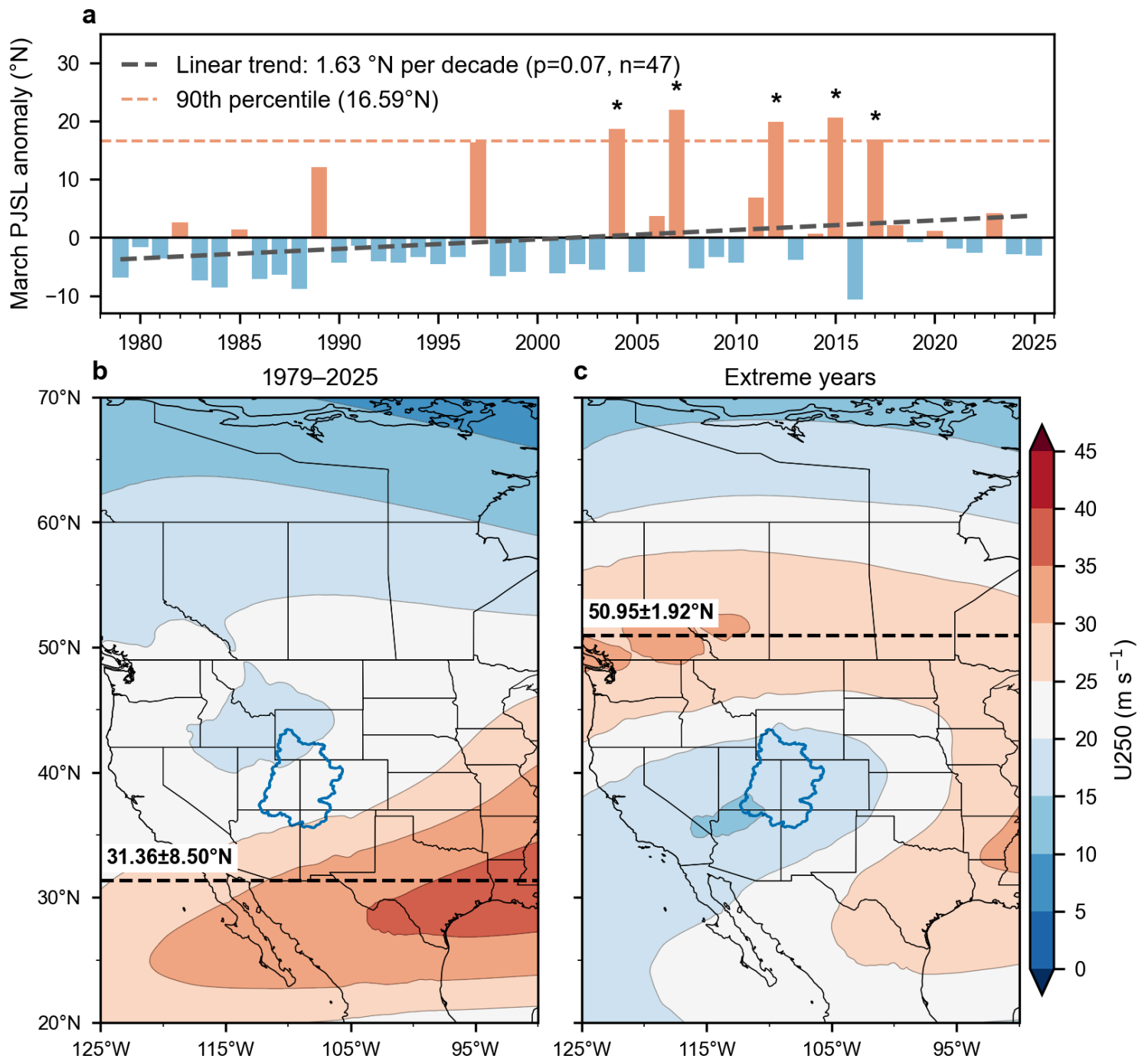


Figure 1

Extreme northward-shift years of March PJSL. (a) Time series of March PJSL anomalies relative to the 1979–2025 mean. Northward and southward anomalies are shown in red and blue, respectively. Extreme years exceeding the 90th-percentile threshold (16.59°N ; dashed red line) are marked with asterisks. The dashed gray line shows the linear trend. Spatial distributions of mean March 250-hPa zonal wind (U250) over western North America for (b) 1979–2025 and (c) the extreme years. The dashed black line in each panel indicates the corresponding mean PJSL, and the blue outline delineates the UCRB.

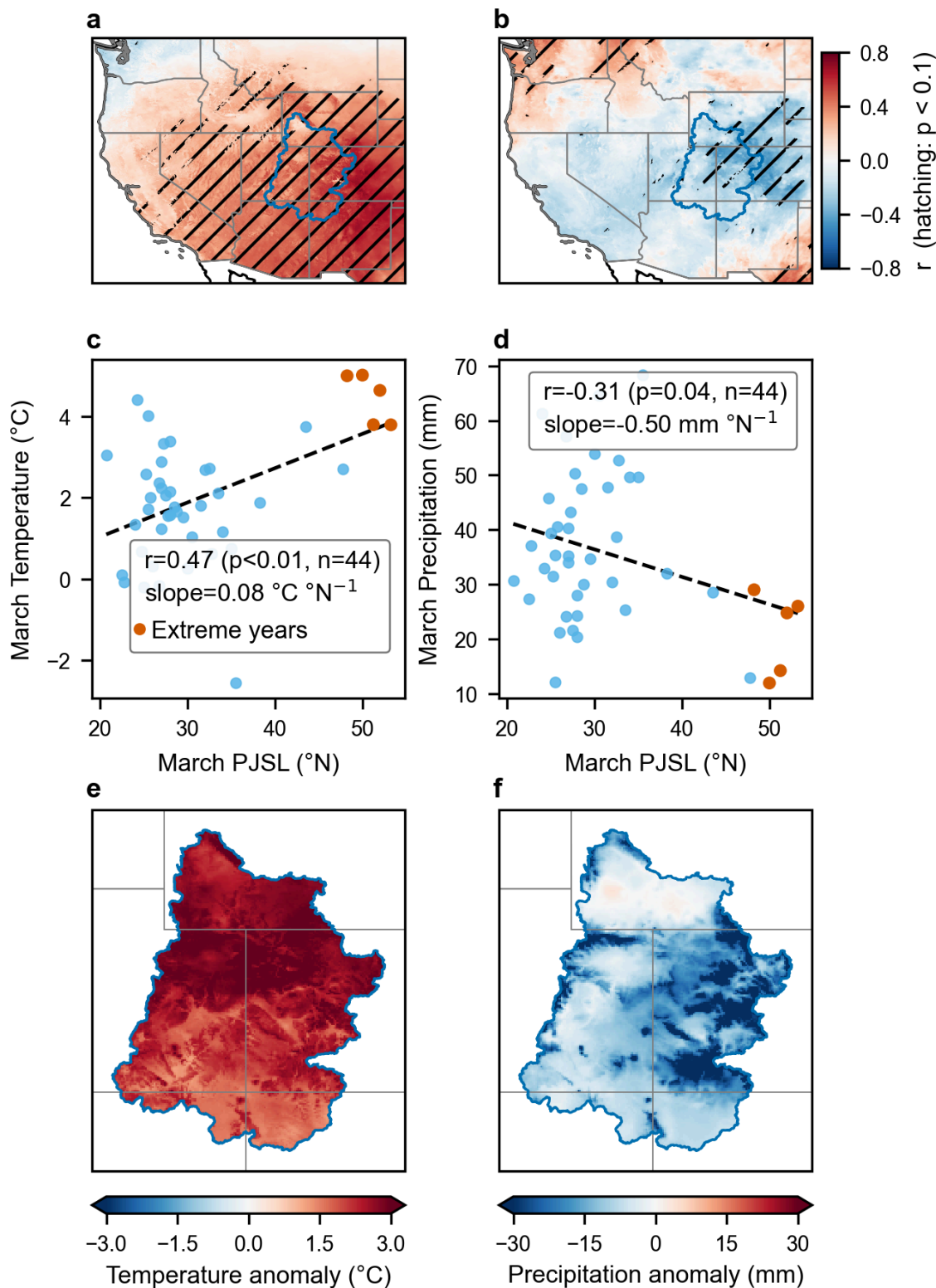


Figure 2

A northward-displaced March PJS is associated with warmer and drier conditions over the UCRB. Spatial distributions of the correlation coefficient (r) between March PJS and (a) March surface air temperature and (b) March precipitation over the region surrounding the UCRB during 1981–2024. Hatched areas indicate $p < 0.1$, and the blue outline delineates the UCRB. Scatterplots of UCRB-mean March (c) temperature and (d) precipitation versus PJS. The correlation coefficient (r), p value, and regression

slope are shown. The dashed black line indicates the regression fit, and the red points denote the extreme PJS-shift years. Composite March anomalies in (e) temperature and (f) precipitation during the extreme PJS-shift years relative to the 1981–2024 mean.

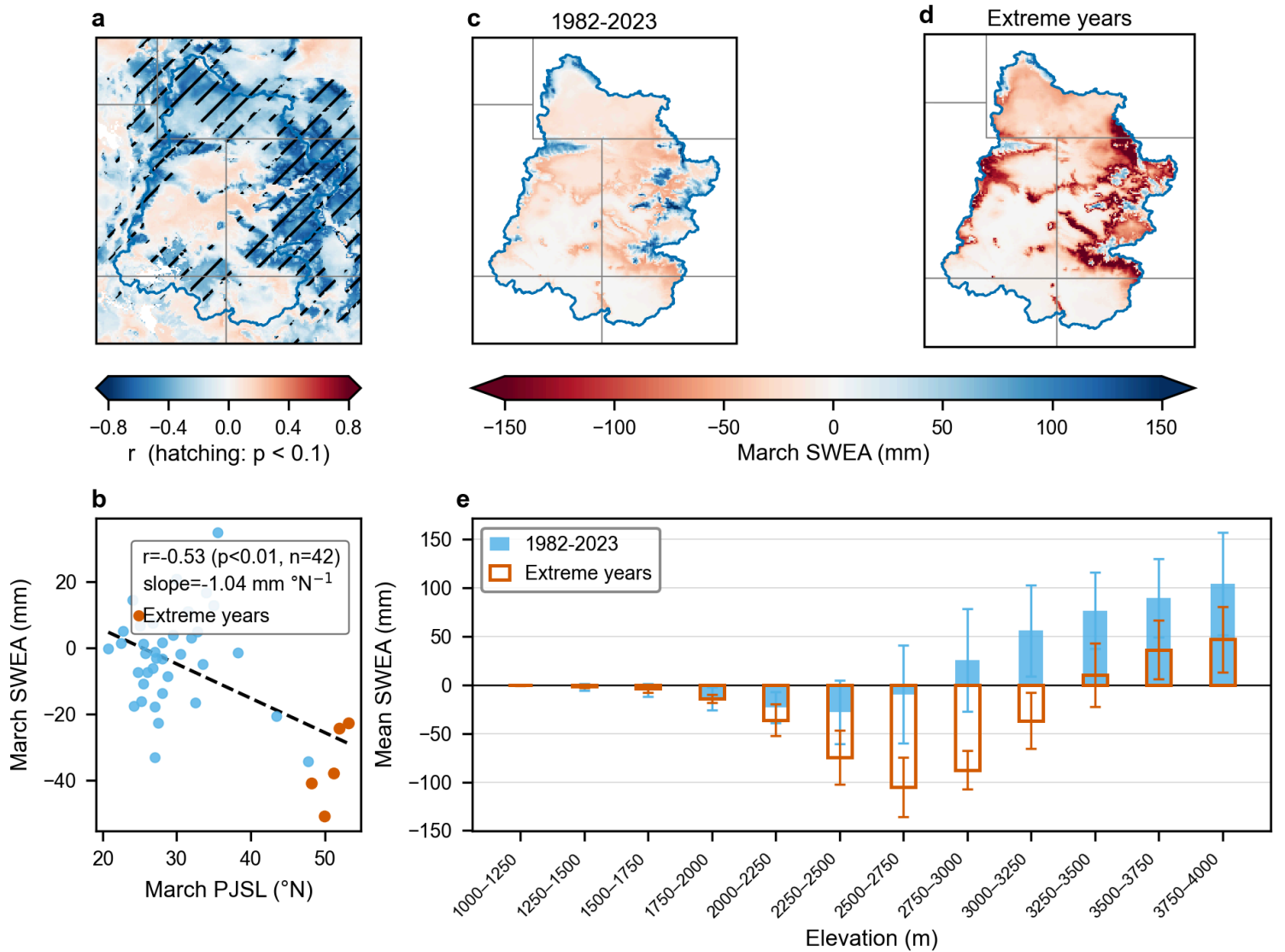


Figure 3

A northward-displaced March PJS is associated with greater net snowpack loss in the UCRB. (a) Spatial distribution of the correlation coefficient (r) between March PJS and SWEA during 1982–2023. Hatched areas indicate $p < 0.1$. The blue outline delineates the UCRB. (b) Scatterplot of UCRB-mean March SWEA versus PJS; the r , p value, and regression slope are shown. The dashed black line indicates the regression fit, and the red dots denote the extreme PJS-shift years. Spatial distributions of mean March SWEA during (c) 1982–2023 and (d) the extreme years. (e) Mean March SWEA by elevation bin during 1982–2023 and the extreme years. Error bars indicate ± 1 standard deviation across years.

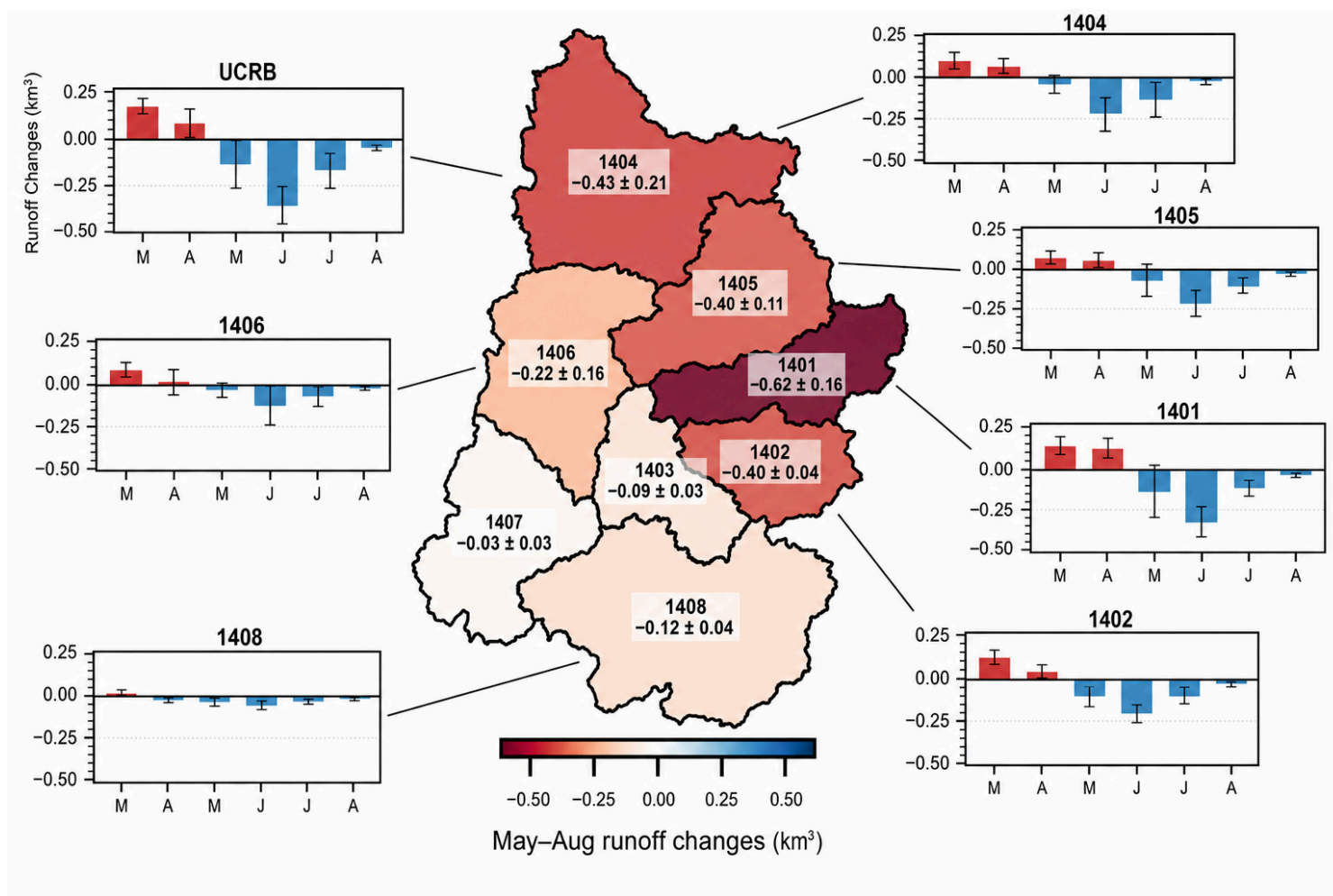


Figure 4

Simulated runoff response to extreme northward shifts of the March PJS. Map colors and lower subbasin labels show mean May–August runoff changes (km³), whereas upper labels give HUC IDs. Insets show monthly runoff changes from March through August for the UCRB and individual subbasins. Values and error bars denote means $\pm$ one standard deviation across the extreme years. Insets are omitted for subbasins 1403 and 1407 because their changes are small.

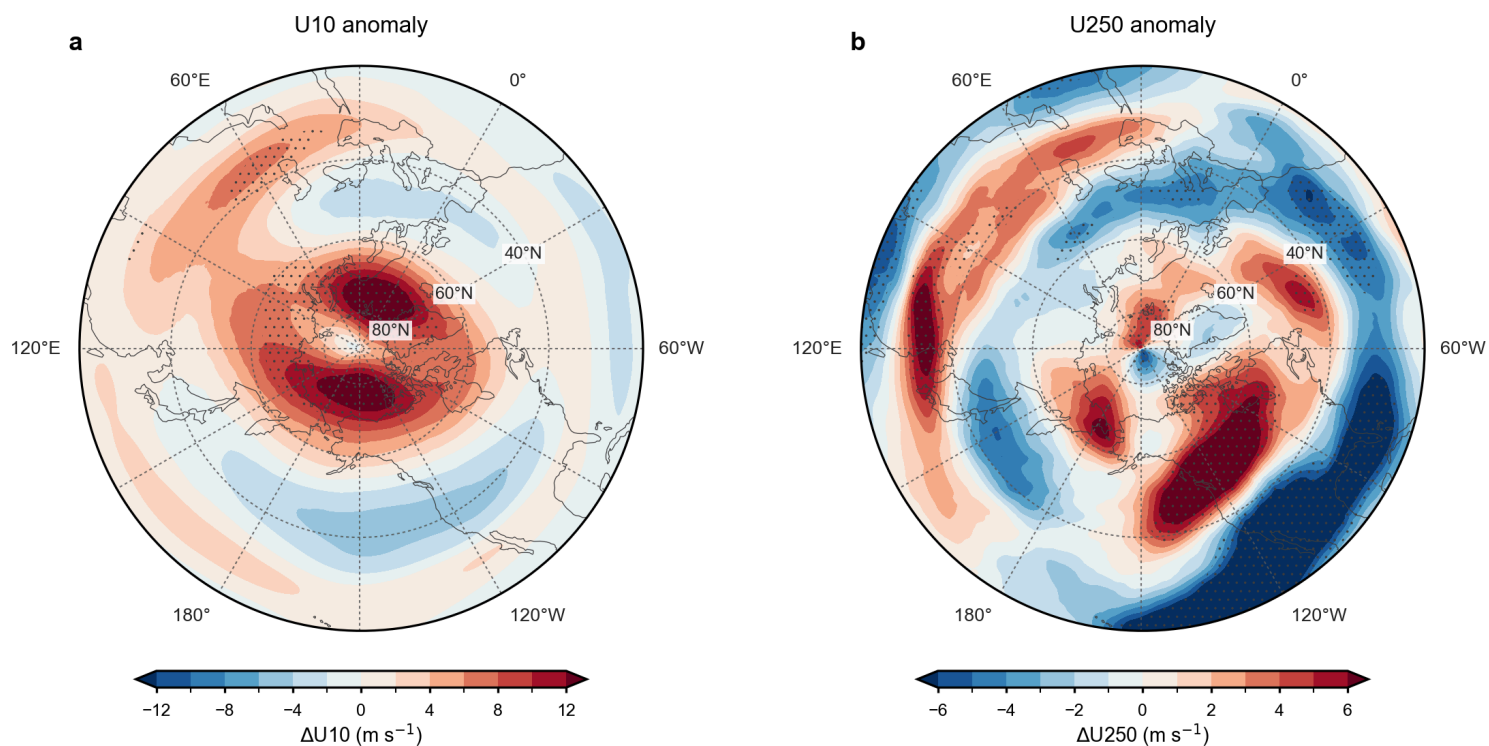


Figure 5

Extreme northward shifts in the March PJS are accompanied by a stronger stratospheric polar vortex. Composite anomalies in mean (a) 10-hPa and (b) 250-hPa zonal wind during the extreme PJS-shift years relative to the 1979–2025 mean. Dotted areas indicate $p < 0.10$.

Supplementary Files

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