Atmospheric Rivers are Responsible for Cyclicity in Sierra Nevada Precipitation

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ABSTRACT: Cool-season (November–March) precipitation contributes critically to California’s water resources and flood risk. In the Sierra Nevada, approximately half of cool-season precipitation is derived from a small proportion of storms classified as atmospheric rivers (ARs). The frequency and intensity of ARs are highly variable from year to year and unreliable climate teleconnections limit forecasting. However, previous research provides intriguing evidence of cycles with biennial (2.2 years) and decadal (10–20 years) periodicities in Sierra Nevada cool-season precipitation, suggesting it is not purely stochastic. To identify the source of this cyclicity, we decompose daily precipitation records (1949–2022) into contributions from ARs versus non-ARs, as well as into variations in frequency and intensity. We find that the biennial and decadal spectral peaks in Sierra Nevada precipitation totals are entirely due to precipitation delivered by ARs, and primarily due to variations in the frequency of days with AR precipitation. While total non-AR precipitation correlates with sea surface temperature (SST) and atmospheric pressure patterns associated with the El Niño–Southern Oscillation, AR precipitation shows no consistent remote teleconnections at any periodicity. Supporting this finding, atmospheric simulations forced by observed SSTs do not reproduce the biennial or decadal precipitation variations identified in observations. These results, combined with the lack of long-term stable cycles in previously published tree-ring reconstructions, suggest that the observed biennial and decadal quasi-cyclicity in Sierra Nevada precipitation is unreliable as a forecasting tool.

SIGNIFICANCE STATEMENT: In California’s Sierra Nevada, where most of the state’s above-ground water resources originate, cool-season precipitation totals exhibited year-to-year and decadal cyclicity over the past century. Long-range forecasts are notoriously unskillful in this region, so nonrandom cycles would be intriguing to water managers challenged to simultaneously minimize flood and drought risk. Over 1949–2022, precipitation cycles were driven by variations in the number of atmospheric river (AR) storms per year even though ARs account for just half of total precipitation. These findings bring us a step closer to understanding the causes of precipitation cyclicity, but we find no evidence that the cycles were underpinned by larger-scale ocean–atmosphere circulations so we caution against relying on continued cycles into the future.

KEYWORDS: Atmosphere–ocean interaction; Atmospheric circulation; Atmospheric river; Cool season; Oscillations; Precipitation

1. Introduction

The vast majority of California’s surface water resources originate as mountain precipitation during the cool season between November and March. Up to half of this precipitation can be delivered by a relatively small number of intense precipitation events classified as atmospheric rivers (ARs) (Dettinger et al. 2011; Rutz et al. 2014; Gershunov et al. 2017). ARs are narrow bands of highly concentrated and rapidly moving water vapor that commonly achieve horizontal flux rates on par with that of the Amazon River (Zhu and Newell 1998). ARs are regular features of the cool-season climatology of the North Pacific, but the location and frequency of landfalling ARs on the North American west coast are highly variable. In California, where interannual variability in precipitation total is particularly volatile, the majority of this variability is driven by ARs even though ARs are much less frequent than non-AR storms (Dettinger et al. 2011; Dettinger 2016). Thus, relatively small shifts in the number and location of cool-season AR landfalls in a given year can dictate whether California is in a state of heightened flood risk or drought (Ralph et al. 2006; Dettinger 2013; White et al. 2019).

Geographically, the Sierra Nevada range constitutes California’s primary watershed (Dettinger et al. 2018). In addition to the challenges posed by the high sensitivity of annual precipitation totals to the occurrence and intensity of a relatively small number of AR storms, forecasting of California’s
surface water resources is further limited by the lack of straightforward teleconnections between Sierra Nevada cool-season precipitation and sea surface temperatures (SSTs) (Seager and Hoerling 2014; Jones et al. 2015; Huang et al. 2019). Across much of western North America, most forecast skill at the seasonal time scale originates from a teleconnection to the El Niño–Southern Oscillation (ENSO). The warm ENSO phase promotes a north–south moisture gradient from wet anomalies in the Pacific Northwest to dry anomalies in the Southwest and the cool ENSO phase promotes a moisture pattern that is more or less the opposite (Cayan et al. 1999; Dettinger et al. 1998; Mason and Goddard 2001; Wise 2010; Cook et al. 2018; Huang et al. 2019). The Sierra Nevada, however, sits astride the ENSO teleconnection dipole and as a result cool-season precipitation totals in this transition zone are not well correlated with SSTs in the tropical Pacific or elsewhere (Dettinger et al. 1998; Higgins et al. 2000a; Dettinger et al. 2011; Cook et al. 2018; Williams et al. 2021). Some of the poor correlation between Sierra Nevada cool-season precipitation and tropical Pacific SSTs may be due to nonlinearity (e.g., El Niños are wetter than La Niñas are dry), interactions between multiple large-scale teleconnection modes of ocean–atmosphere variability (Guirguis et al. 2018; Henderson and Maloney 2018; Castellano et al. 2023), subseasonal variability in teleconnections (Castellano et al. 2023), and sensitivity to the exact location of deep tropical convection (Chiodi and Harrison 2015; Seager et al. 2015; Chen et al. 2017; Williams and Patricola 2018). Whatever the cause, atmospheric model simulations forced by observed SSTs have particularly poor skill in terms of replicating observed hydroclimatic variations within the transition zone of the western U.S. ENSO dipole (Huang et al. 2019). The interpretation is therefore that cool-season precipitation in this region, including that from ARs, is dominated by internal atmospheric variability (Baek et al. 2021).

Intriguingly, there are signs of quasi-cyclicity in the time series of cool-season precipitation totals in the midlatitudes of the U.S. West Coast, including the Sierra Nevada, which would suggest that precipitation variability in this region is not purely random (Ault and St. George 2010; Johnstone 2011; Dettinger and Cayan 2014; Dettinger 2016). Precipitation oscillations are interesting from a water- and hazard-management perspective because if they can be reliably extrapolated into the near future, they may aid forecasting in a region that is otherwise lacking for predictive skill. The dominant periodicities of the oscillations are biennial (~2.2 years) and decadal (10–20 years), and they have been noted in the literature for decades (Granger 1977; Dettinger et al. 1998; Florsheim and Dettinger 2007; Ault and St. George 2010; Johnstone 2011; Williams et al. 2021). Tree-ring reconstructions, however, indicate that the observed biennial and decadal cycles of the past century were likely not stable features of cool-season precipitation in the preceding centuries, serving to caution against relying on the continuation of these cycles into the future (St. George and Ault 2011; Meko et al. 2014; Williams et al. 2021). Nonetheless, the biennial and decadal cycles of the past century appear to have remained active through the first two decades of the early twenty-first century (Williams et al. 2021), suggesting that extrapolating these cycles into the near-term future could serve as a useful guide for expectations into the near-future despite their ephemeral nature.

Here, we use daily meteorological data to develop a better understanding of the subseasonal components of the Sierra Nevada cool-seasonal precipitation record that are responsible for the observed biennial and decadal cycles. We decompose the time series of Sierra Nevada cool-season precipitation totals from 1949 to 2022 into contributions from ARs versus non-ARs, and further into contributions from anomalies in the frequency versus the intensity of daily precipitation delivered by ARs versus non-ARs. We then evaluate and test the associations between the time series of the various components of the Sierra Nevada precipitation budget and global climate variables and also assess atmospheric model simulations forced by observed SSTs, in order to identify large-scale teleconnections to precipitation cyclicity. We specifically address the following questions: Are the observed biennial and decadal cycles in Sierra Nevada cool-season precipitation due to precipitation from ARs or non-ARs and/or variations in the frequency versus intensity of days with precipitation? Do global climate analyses highlight unique correlation patterns associated with the specific periodicities of interest that may help elucidate causes of the observed cycles? Do SST-forced simulations of an atmospheric model reproduce the observed cycles?

2. Methods

a. Study region and season

We focus on the Sierra Nevada region of California as defined by the Environmental Protection Agency level-3 ecoregions for California. In calculating regional averages from gridded datasets, we applied area weighting based on the area of overlap between each grid cell and the ecoregion. Our study season is the cool season of November–March, which is when approximately three-quarters of the total precipitation falls in the Sierra Nevada region (Fig. 1). Each cool season is assigned to the calendar year containing the January–March of the cool season (e.g., cool-season 2000 refers to November 1999–March 2000).

b. Daily gridded precipitation totals for 1948–2022

We used daily precipitation totals from 2018 long-term Global Historical Climatology Network (GHCN; Menne et al. 2012) weather stations to produce daily fields of gridded precipitation totals across the western continental United States (areas west of 100°W) at 0.25° geographic resolution for 1948–2022. Detailed methods for the creation of this dataset are described in the appendix. For comparison, we also produced daily 0.25° grids of precipitation totals from the 1/24° daily products from nClimGrid (Vose et al. 2014; Durre et al. 2022) and the PRISM group at Oregon State University (Daly et al. 2008) over 1951–2022 and 1981–2022, respectively. We also considered the daily continental U.S. precipitation product from NOAA’s Climate Prediction Center (CPC) but did not use it because that dataset indicates a negative trend in Sierra
Nevada cool-season precipitation that is not indicated by any of the other products (Fig. S1 in the online supplemental material).

c. Identification of atmospheric rivers and atmospheric river precipitation

We used 6-hourly atmospheric data from the 2.5° geographic resolution reanalysis from the National Center for Environmental Protection and the National Center for Atmospheric Research (NCEP–NCAR; Kalnay et al. 1996) to identify ARs for 1948–2022 following the methods of Gershunov et al. (2017). Briefly, we calculated 6-hourly gridded integrated vapor transports (IVT) and integrated water vapor (IWV) from the surface to 300 hPa in the geographic domain 20°–60°N, 160°–100°W using zonal wind velocity $u$, meridional wind velocity $v$, and specific humidity $q$ at the near-surface and each available pressure level from 1000 to 300 hPa (available pressure levels: 1000, 925, 850, 700, 600, 500, 400, 300 hPa), excluding unrealistic data from levels where atmospheric pressure is higher than at the surface. We then linearly interpolated each grid cell’s data to a vertical resolution of 1 hPa for calculation of IVT and IWV. We then identified spatially contiguous regions where IVT $>$ 250 kg m$^{-1}$ s$^{-1}$ and IWV $>$ 15 kg m$^{-2}$ and classified them as ARs if they were at least 1500 km in length for each of $\geq$3 consecutive 6-hourly time steps. We measured AR length as the shortest path connecting the centers of the two farthest-displaced grid cells in the AR without exiting the AR domain. We identified ARs that persisted from one time step to the next as those that had at least three overlapping grid cells. We attributed daily precipitation for a given 0.25° grid cell to an AR if the AR overlapped the grid cell on the day of or day after the precipitation, consistent with the approach of Gershunov et al. (2017) and Dettinger et al. (2011). Notably, there are large ranges of AR intensities, durations, and shapes, and differences among the reanalysis datasets used to calculate these, which inevitably cause uncertainty in AR-detection algorithms, particularly for events with lower humidity (Rutz et al. 2019; Ralph et al. 2019).

d. Global climate data

In analyses of global surface temperature, monthly mean SSTs came from the NOAA Extended Reconstruction, version 5 (ERSSTv5; Huang et al. 2017), and monthly mean continental surface temperature came from the NCEP–NCAR reanalysis (skin temperature). All gridded geopotential height and pressure data came from the NCEP–NCAR reanalysis.

e. Atmospheric model analysis

To evaluate the potential role of SST as a driver of observed variability in Sierra Nevada cool-season precipitation, we analyzed precipitation produced by a 10-member ensemble of atmospheric simulations from NCAR’s Community Atmosphere Model, version 6 (CAM6; Bogenschutz et al. 2018). The CAM6 is the atmospheric component of version 2.1.2 of NCAR’s Community Earth System Model. The SST-forced CAM6 simulations were performed with a nominal geographic resolution of 1° from January 1880 through December 2020 with prescribed SSTs from the ERSSTv5 and sea ice.
from the Hadley Center (Hurrell et al. 2008). Observed natural and external forcings were prescribed consistent with the Historical and Shared Socioeconomic Pathways 3–7.0 scenarios from the sixth Coupled Model Intercomparison Project (Eyring et al. 2016; O’Neill et al. 2016) for 1880–2014 and 2015–20, respectively. We also considered an alternate set of CAM6 simulations in which observed SSTs were only prescribed for the tropics (20°S–20°N), the mean seasonal SST cycle was prescribed poleward of 30° in each hemisphere, and SSTs were linearly interpolated between. The purpose of these tropics-only SST-forced simulations, which covered 1880–2014, is to isolate the influence of observed tropical SSTs on climate. We further disaggregated simulated cool-season precipitation totals into contributions from heavy precipitation days when simulated precipitation in a given grid cell exceeded the 95th percentile of all nonzero daily precipitation totals for that grid cell, as this method was shown by Dettlinger (2016) to approximate the contribution from ARs in California. We evaluated each ensemble of CAM6 outputs during its period of overlap with the observational GHCN precipitation dataset. When comparing observations with the CAM6-simulated record of Sierra Nevada precipitation, we upcaled the GHCN grid to the CAM6 spatial resolution prior to calculating the observed record for the Sierra Nevada.

f. Time series analysis

We decomposed records of cool-season precipitation into contributions from anomalies in precipitation frequency versus intensity. We defined cool-season precipitation frequency as the number of days per cool season with precipitation (≥0.1 mm) and intensity as the average precipitation total among these precipitation days. The contribution of frequency (intensity) anomalies to the cool-season precipitation total in a given year is that year’s cool-season frequency (intensity) anomaly multiplied by the long-term average cool-season intensity (frequency). For calculations of anomalies long-term averages, the baseline period was the cool seasons from 1949 to 2022.

To evaluate cyclicity in precipitation time series, we estimated time series spectra using the Blackman–Tukey smoothed periodogram (Chatfield 1975; Bloomfield 2000) with a window length of $M = 25$. This is $1/3$ of the length of the 74-yr time series used in our study and at the upper end of the range recommended by Chatfield (1975) due to the relatively short time series length. To extract time series of cycles associated with the dominant periodicities in a time series, we used the single-channel singular-spectrum analysis (SSA), which decomposes a single time series into discrete components with dominant periodicities (Vautard and Ghil 1989; Vautard et al. 1992; Allen and Smith 1996).

Correlation between time series were assessed as the Pearson’s correlation coefficient. Correlation significance was adjusted accounting for the effect of first-order temporal autocorrelation on effective sample size (Dawdy and Matalas 1964).

3. Results and discussion

Figure 1 shows the water-year (October–September) and cool-season (November–March) precipitation totals in the Sierra Nevada region for 1949–2022 as well as the spectra associated with each time series. Cool-season precipitation accounted for 77% of total precipitation in this region during water years 1949–2022 (Figs. 1a,c). The spectral peaks associated with biennial (~2.2 years) and decadal (~12–16 years) quasi-cyclicity were powerful enough in the cool season (Fig. 1d) to also be the dominant spectral peaks for total water-year precipitation (Fig. 1b). These results were corroborated across all three precipitation datasets considered here.

We next split cool-season precipitation into the contributions from ARs (Figs. 2a,b) versus non-ARs (Figs. 2c,d). We found that 51% of cool-season precipitation in the Sierra Nevada was associated with ARs during 1949–2022. This proportion was corroborated when the analysis was repeated with the daily nClimGrid dataset during 1952–2022 (52%) and the daily PRISM dataset during 1982–2022 (48%). A 50% contribution from ARs is on the upper end of the ~30%–50% range that may be inferred from Rutz et al. (2014), but this is largely reconciled by differences in definition of cool season, the study period, and the precipitation dataset. When we consider the Rutz et al. definition of cool season (November–April) and their compressed study period of 1989–2011, the AR contribution drops to 44%. When we also use the CPC dataset used by Rutz et al. the AR contribution is 41%. These results are also consistent with a recent estimate that ARs contributed to 43% of Sierra Nevada snowpack of 1949–2018 (Shulgina et al. 2023).

Although precipitation associated with ARs and non-ARs contributed equally to cool-season precipitation total, AR precipitation dominated the interannual variability. The total variance of AR precipitation (Fig. 2a) was more than 3 times the non-AR variance (Fig. 2c). As a result, the total cool-season precipitation was more strongly correlated with AR precipitation ($r = 0.90; p < 10^{-3}$) than with non-AR precipitation ($r = 0.61; p < 10^{-3}$). These results are consistent with the finding by Dettlinger (2016) that interannual variability in total annual precipitation in northern California is dominated by the wettest 5% of daily precipitation totals. In addition, Figs. 2b and 2d confirm that the biennial and decadal spectral peaks in the cool-season and water-year precipitation time series (Figs. 1b,d) are entirely driven by AR precipitation. Importantly, however, Fig. 2 also indicates that some of the region’s most severe drought events, in particular 1976–77 and 2012–15, resulted from large negative anomalies in both AR and non-AR precipitation.

We next decomposed the time series of total cool-season AR precipitation into variations driven by AR frequency (anomalies in the number of days with AR precipitation) versus AR intensity (anomalies in the precipitation total on AR days) (Fig. 3). Although precipitation anomalies driven by AR frequency versus intensity were significantly correlated ($r = 0.57; p < 10^{-3}$), the variance in anomalies driven by AR frequency was nearly 4 times that of anomalies driven by AR intensity (Figs. 3a,c). As such, total cool-season AR precipitation...
was more strongly correlated with AR frequency than AR intensity ($r = 0.95$ vs $0.77$). While the biennial and decadal spectral peaks were evident in both time series, they were much more prominent in the time series of AR frequency than AR intensity (Figs. 3b,d). This finding builds on prior results from Lamjiri et al. (2017, 2018), who found that storm totals in California tend to be driven more by storm duration than mean storm intensity. Thus, the biennial and decadal spectral peaks in total water-year Sierra Nevada precipitation can be attributed primarily to the frequency of cool-season AR days.

![Fig. 2](image-url)  
**Fig. 2.** (top) Time series and (bottom) spectra of cool-season (November–March) $P$ totals in the Sierra Nevada delivered by (a),(b) atmospheric rivers (ARs) and (c),(d) non-ARs. Datasets used for the time series in (a) and (c) are our daily Global Historical Climatology Network (GHCN) dataset (purple) for 1949–2022, the daily PRISM dataset (orange) for 1982–2022, and the daily NOAA nClimGrid dataset (green) for 1952–2022. The spectra plots in (b) and (d) are based on GHCN and NOAA (PRISM is excluded since its daily product is much shorter than the GHCN and NOAA daily products). Circles in (b) and (d) indicate significant (95%) difference from white noise, and gray areas (and year ranges next to the gray areas) bound the periods with significant or marginally significant (90%) spectral peaks in the GHCN time series.

![Fig. 3](image-url)  
**Fig. 3.** As in Fig. 2, but for $P$ anomalies in the Sierra Nevada that were driven by interannual variations in (a),(b) AR frequency vs (c),(d) AR intensity.
Even though non-AR precipitation totals showed no distinctive tendency toward biennial or decadal variance (Fig. 2d), the intensity of non-AR precipitation nonetheless exhibited a significant decadal spectral peak (Fig. S2 in the online supplemental material). Similar to AR precipitation, however, variability in non-AR precipitation was dominated by variability in non-AR frequency and less so non-AR intensity. This observation combined with the dominance of ARs in determining interannual variability in cool-season precipitation (Figs. 2a,c) caused the decadal component of non-AR intensity to be a relatively small contributor to the overall cool-season precipitation record in the Sierra Nevada during our study period.

We next used global correlation analyses of cool-season surface temperatures and 500-hPa geopotential heights to investigate potential large-scale climate drivers of the various components of the Sierra Nevada cool-season precipitation record discussed above (Fig. 4). Maps in Fig. 4a show correlation with the full cool-season precipitation total as well as the frequency and intensity components. Maps in Figs. 4b and 4c show correlations with the contributions from AR and non-AR precipitation, respectively, as well as their frequency and intensity components. Given our earlier finding that interannual variability in precipitation totals are driven more by variations in the frequency rather than mean intensity of precipitation days, it is unsurprising that the correlation fields associated with total precipitation (top row) are generally more similar to those for precipitation frequency (middle row) than with precipitation intensity (bottom row).

As expected (Cayan and Roads 1984), the most prominent and consistent correlation patterns in Fig. 4 are those representing the local connection between Sierra Nevada cool-season precipitation and eastward storm tracks from the northeast Pacific Ocean to the midlatitude U.S. West Coast. These strong negative correlations with geopotential heights immediately adjacent to the U.S. West Coast are expected because Sierra Nevada cool-season precipitation is generally caused by the passage of westerly low pressure systems from the North Pacific. Thus, the presence of strong negative correlations with geopotential heights locally does not provide novel information toward identifying large-scale climate processes that systematically promote or suppress the frequency or intensity of Sierra Nevada storms.

On the other hand, in comparing the Fig. 4 correlation maps for precipitation totals from ARs versus non-ARs (top row of Figs. 4b and 4c, respectively), the shapes and locations of the local negative correlations with geopotential heights over the U.S. West Coast are distinct. While non-AR precipitation totals correlate negatively with geopotential heights over the whole region of the western United States and
coastal North Pacific Ocean, the correlation fields associated with AR precipitation are more complex. For AR precipitation, the negative geopotential height correlations are centered off the coast of the Pacific Northwest and lie to the north of a zonal band of positive correlations over the subtropical northeast Pacific and Baja California (Fig. 4b). This local correlation is similar to that reported previously by Guirguis et al. (2018, 2020) and suggests that AR precipitation is promoted by a steepened meridional gradient of geopotential heights off the California coast that channels southwesterly ARs from the subtropics to the Sierra Nevada. This is corroborated by the correlation maps in Fig. 5 showing that AR precipitation in the Sierra Nevada is strongly associated with high rates of southwesterly IVT directed out of the subtropics directly toward central California (Fig. 5b). In contrast, non-AR precipitation correlates with a cyclonic IVT...
circulation feature centered over the central Californian coast and enhanced IVT into southern California (Fig. 5c).

Precipitation from ARs also correlates significantly and positively with SSTs in the subtropical northeast Pacific and with surface temperature over the western United States (Fig. 4b). This is at least partly due to the top-down positive effect of southwesterly ARs on surface temperatures but could also represent the positive effect of warm subtropical SSTs and near-surface air on the moisture content of ARs. In contrast, non-AR precipitation is not positively correlated with subtropical SSTs and is negatively correlated with surface temperatures across much of the North American west coast (Fig. 4c).

Looking to the tropics, the top panel in Fig. 4a suggests a weak positive association between total Sierra Nevada precipitation and El Niño–like spatial patterns of SSTs and geopotential height anomalies, and this weak ENSO signal is associated with precipitation frequency (Fig. 4a, middle) but not intensity (Fig. 4a, bottom). Further, comparing the middle panel of Fig. 4b (correlation with AR frequency) with the middle panel of Fig. 4c (correlation with non-AR frequency) clarifies that the ENSO signal in the precipitation frequency time series is due specifically to non-AR frequency. Non-AR frequency correlates positively and significantly with SSTs in the eastern and central tropical Pacific, negatively and significantly with SSTs in the western tropical Pacific, and positively with geopotential heights throughout the tropics, particularly over the eastern Pacific. Taking the difference between warm SSTs in the western tropical Pacific (5°S–5°N, 120°–160°E) and cool SSTs in the eastern tropical Pacific (5°S–5°N, 120°–80°W), we find that the strength of this gradient correlates significantly ($p < 0.01$) more negatively with non-AR precipitation frequency ($r = -0.41; p < 10^{-5}$) than with AR precipitation frequency ($r = -0.09; p = 0.44$) (Fig. S3 in the online supplemental material). Thus, AR precipitation events may be responsible for masking an otherwise detectable and useful relationship between tropical Pacific SSTs and Sierra Nevada precipitation. On the other hand, the geographic boxes we chose to represent the western and eastern tropical Pacific were specifically chosen to optimize correlation with non-AR precipitation frequency and, although the correlation is highly significant, it is not especially strong. Further, the significant correlation is heavily affected by the most El Niño–like years (Fig. S3). Excluding the two years with the weakest SST gradients, 1998 and 1983, reduces the correlation to $r = -0.31$ ($p < 0.01$) and excluding the next two weakest SST-gradient years as well (2016 and 1973) causes the correlation to be only marginally significant ($r = -0.22; p = 0.07$). Thus, more work is needed before we can conclude with confidence that non-AR precipitation is more sensitive to ENSO than AR precipitation.

Last, despite the general lack of correlation between Sierra Nevada AR precipitation and tropical SSTs, the positive correlation with geopotential heights and anticyclonic atmospheric circulation over the subtropical northeast Pacific (Figs. 4b and 5b) is mirrored over the subtropical southern Pacific (Fig. 4b). These hemispherically symmetric correlation features are suggestive of a tropical forcing on AR precipitation in the Sierra Nevada via an influence on midlatitude circulation despite the lack of a coherent signal in tropical SSTs (Seager et al. 2005). Notably, Guirguis et al. (2019) found that although ENSO does not appear to have a consistent effect on interannual precipitation totals in the greater Sierra Nevada region, it does appear to modulate other AR characteristics such as the storm track orientation at landfall.

To further investigate potential drivers of biennial and decadal variability in Sierra Nevada AR precipitation we used SSA to decompose the time series of cool-season AR precipitation anomalies, as well the contributions from AR frequency and intensity anomalies, into the oscillatory components that represent their biennial- and decadal-scale variations (Fig. 6, top row). Specifically, each time series in the top panel of Fig. 6a represents the sum of the pair of SSA components with periodicities closest to 2.2 years and each time series in the top panel of Fig. 6b represents the sum of the pair of SSA components with periodicities closest to 15 years. The spectra of the SSA-derived time series in the top row are shown in the second row, confirming that they have the expected biennial and decadal periodicities.

The SSA-derived time series shown in Fig. 6a establish that the biennial oscillations in AR frequency, intensity, and total were synchronous throughout the study period, with a common periodicity of ~2.16 years. However, the amplitude of the biennial variability of AR totals reduced substantially over the study period, largely due to a near loss of amplitude in the biennial mode of AR intensity (Fig. 6a). On the other hand, the waveform of biennial amplitude in AR frequency was more stable throughout the study period, which would have contributed to the dominant role of AR frequency in driving variability in AR precipitation totals overall.

Unlike the biennial variations, the decadal variations of AR frequency and intensity are less coherent, with the oscillations in AR intensity having a somewhat longer period than those for AR frequency (Fig. 6b). Given our earlier finding that variations in AR precipitation totals are dominated more by AR frequency than AR intensity (Fig. 3), it is unsurprising that the decadal mode of total AR precipitation is more aligned with the decadal frequency component than with the intensity component. Despite the decadal components of AR frequency and intensity being out of phase over most of the study period, both experienced a loss of amplitude from the early 2000s through the early 2010s. In the most recent decade, the AR frequency component resumed oscillating, positive in the late 2010s and subsequently negative, and the AR intensity component remained more neutral.

Overall, the time series representing the biennial mode of AR frequency accounts for 25% of interannual variability in cool-season precipitation totals, the decadal mode accounts for 23% of variability, and the sum of the two modes accounts for 45% (Fig. S4 in the online supplemental material). The three years when the sums of these two AR frequency modes were most negative were 1977, 1990, and 1992, which were all severe drought years (the combined modes account for 55% of the total precipitation deficit in these years). The biennial and decadal AR frequency modes also figured prominently in the extended pluvial conditions of the early 1980s and the extended drought conditions of the early 1990s.
The maps in **Fig. 6** show how the biennial and decadal time series of AR frequency correlated with cool-season surface temperatures and 500-hPa geopotential heights (see Fig. S5 in the online supplemental material for correlation maps for surface pressure and 200-hPa heights). We focus on AR frequency here because of the prior finding that AR frequency was the dominant driver of overall AR precipitation variability as well as the associated biennial and decadal spectral peaks. Beyond the local correlation patterns associated with storm tracks directed into the Sierra Nevada, the large-scale correlation patterns associated with biennial and decadal variability once again indicate relatively weak correlations with tropical SSTs. However, both maps include the same hemispherically symmetric positive correlations with geopotential heights that were seen in **Fig. 4** over the subtropical North and South Pacific centered near 120°W, which may hint at a common tropical forcing (Evans et al. 2001; Seager et al. 2003, 2005; Shakun and Shaman 2009), but correlations between tropical Pacific SSTs are weak and of opposite signs for the biennial versus decadal modes.

In addition to the correlation analyses presented in **Fig. 6** we performed additional comparisons of the biennial and decadal components of the AR frequency record with common Pacific climate indices as well as SSTs and atmospheric pressure records in specific regions of interest. The Pacific climate indices included SSTs in the Niño-3, -3.4, and -4 regions; the Pacific decadal oscillation (Mantua et al. 1997); the interdecadal Pacific oscillation (Henley et al. 2015); the Southern Oscillation index (Ropelewski and Jones 1987); the El Niño longitudinal index (Williams and Patricola 2018); and the Pacific–North American index (Wallace and Gutzler 1981). None of the climate indices correlated well with the biennial components of AR frequency plotted in **Fig. 5a**. Nor did they contain leading biennial modes of variability, as determined from SSA, that corresponded strongly to those observed for AR frequency. In addition, while **Fig. 6a** indicates a significant...
correlation between biennial variability of AR frequency and SSTs in the tropical Indian Ocean, biennial variability was not a dominant feature of that region’s SST record according to spectral analysis and SSA.

Overall, the results of our correlation analyses do not support the hypothesis that the observed biennial and decadal quasi-cyclicity in Sierra Nevada cool-season AR precipitation is driven by consistent large-scale ocean–atmosphere teleconnections. However, it is well known that nonlinearities and interactions among teleconnection processes play important roles in the climate of the North Pacific, which standard correlation analyses may not detect (Higgins et al. 2000b; Henderson and Maloney 2018; Williams and Patricola 2018; Tseng et al. 2019; Toms et al. 2020). We therefore also evaluated simulated cool-season precipitation from the 10-member CAM6 forced by observed SSTs (Figs. 7a,b). Despite a significant correlation between the observed and ensemble-mean simulated time series during their 1949–2020 period of overlap (Fig. 7a; $r = 0.30$, $p < 0.01$), the SST-forced ensemble members exhibited no tendency for periodicities in the biennial or decadal bands where spectral peaks were observed (Fig. 7b). This result was somewhat different when we considered the CAM6 simulations with tropical-only SST forcing (Figs. 7c,d). In that case, there was a tendency for higher-frequency variability, with individual ensemble members exhibiting significant spectral peaks at periodicities of 2.1–3.5 years. In fact, when we decomposed the tropically forced CAM6 precipitation records into contributions from the heaviest (top 5%) precipitation days versus days with less intense precipitation, we found that the tendency among those simulations to produce significant 2–3-yr periodicities was dominated by interannual variability in less intense precipitation, in contrast to observations (Fig. S6 in the online supplemental material).

Collectively, the general lack of strong correlations with climate and SST-forced CAM6 simulations strongly suggest that although SST teleconnections do affect cool-season precipitation totals in the Sierra Nevada, they are not responsible for the biennial or decadal periodicities in cool-season AR activity that has been observed.

![Fig. 7. (a),(c) Time series and (b),(d) spectra of observed and CAM6 atmospheric simulations of records of Sierra Nevada cool-season precipitation when forced by observed sea surface temperatures (SSTs). Precipitation totals were converted to standardized anomalies (std devs). In (a) and (b), the CAM6 model was forced by observed SSTs and sea ice globally and the period of overlap with observations was cool seasons 1949–2020. In (c) and (d), the CAM6 model was forced by observed SSTs only in the tropics and the period of overlap was 1949–2014. In all plots, thin colored lines represent the 10-member ensemble, the thick black line is the ensemble mean, and the thick purple line represents observations over the same time period as the CAM6 data [no ensemble mean in (b) and (d)]. Correlation values in (a) and (c) represent correlation between the observed and ensemble-mean time series. Circles in the spectral plots indicate significant (95%) difference from white noise.](image)
4. Conclusions

Observed biennial (~2.2 years) and decadal (10–20 years) cycles in Sierra Nevada cool-season (November–March) precipitation over the past century provide evidence that annual precipitation totals in this region may not be entirely random, and thus serve as a source of hope for forecast skill on time scales of seasonal and beyond. To better understand the origins of these cycles we decomposed the Sierra Nevada cool-season precipitation record into contributions from atmospheric rivers (ARs) versus non-ARs and into contributions from anomalies in the frequency versus intensity of precipitation from these storm types. We found that although both storm types contributed equally to the total amount of cool-season precipitation over the study period of 1949–2022, ARs are entirely responsible for the biennial and decadal cycles. We further found that the interannual variability of AR precipitation totals as well as the biennial and decadal cycles are primarily driven by variations in the frequency of days with AR precipitation, though the intensity of AR precipitation days were secondarily important.

Our global correlation analyses did not reveal any clear remote teleconnections driving the interannual variability or biennial and decadal oscillations in Sierra Nevada precipitation from ARs. On the other hand, non-AR precipitation exhibited a significant positive correlation with an El Niño–like weakened east–west sea surface temperature (SST) gradient across the tropical Pacific Ocean, and this correlation was entirely driven by variations in non-AR precipitation frequency as opposed to intensity. This result adds nuance to the common narrative that Sierra Nevada precipitation is not consistently associated with the El Niño–Southern Oscillation (Jones et al. 2015). For precipitation from ARs, it is possible that teleconnections with the tropics may be complex rather than nonexistent, which should motivate continued work to understand the factors that modulate teleconnections between tropical climate and Sierra Nevada AR activity over time. If the biennial and decadal oscillations in AR activity did arise from temporally varying teleconnections to tropical climate, however, this process was not captured in the SST-forced atmospheric model simulations that we evaluated. In those simulations in which the observed SST record was prescribed, there was no tendency for the model to reproduce the observed biennial or decadal cycles in cool-season Sierra Nevada precipitation. Thus, we find no clear driver of the observed biennial and decadal cycles of cool-season AR activity in the Sierra Nevada, which builds on our prior finding that cycles in Sierra Nevada precipitation appear to be transient (Williams et al. 2021). We therefore suggest that it would be unwise at this time to allow expectations of continued biennial and/or decadal cyclicity, or any belief that climate models that do not reproduce the observed cyclicity are—as a consequence—flawed, to guide long-range forecasts or water management decisions in California.

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APPENDIX

Gridded Daily Precipitation from Station Data

Considering all daily weather-station records available from the Global Historical Climatology Network (Menne et al. 2012), we compiled a master database of daily precipitation totals for the 5988 stations within a 2° buffer of the western United States (areas of western continental United States west of 100°F) that had valid data for ≥50% of days in each of ≥20 years during 1948–2022. We then performed an initial zero-filling procedure in which missing values were replaced with zero on days when all other stations (≥2) with valid data within 50 km reported no precipitation. When there were fewer than two stations within 50 km with valid data, but at least two stations within 100 km with valid data, the zero filling was repeated when all available stations within 100 km reported zero precipitation.

From this master database, we identified 2102 “primary stations” within the boundaries of the western United States that had particularly thorough coverage over the study period. To identify these stations with thorough coverage, we split our study period (water years 1949–2022, where water year is October–September) into four approximately equal quarters (water years 1949–66, 1967–85, 1986–2003, and 2004–22) and found stations with valid values (including zero filling) on ≥70% of days in each quarter. Among these primary stations, the mean percentage of days with valid precipitation values in the study period was 94% and all stations had >78% daily coverage.

These primary stations were then subjected to gap filling in which nearby stations from the master database were used to infill missing daily precipitation totals using quantile mapping. To fill a missing value on day $i$ at primary station $j$, a master station within 50 km of station $j$ with a valid value on day $i$ was considered as a potential predictor station as
long as a number of criteria are fulfilled based on agreement between daily precipitation measurements between the two stations during a seasonally constrained calibration period. Because spatial relationships between stations may vary seasonally, the calibration period was all days from all years 1948–2022 that are within a 3-month window centered on the month day \( i \). A potential predictor station was only considered if 1) it had \( \geq 100 \) days with overlapping valid values with station \( j \), 2) \( \geq 10 \) of these days had co-occurring nonzero precipitation at both stations, and 3) there was statistically significant \( (p < 0.05) \) correlation between both stations in terms of occurrences of nonzero precipitation as well as precipitation totals on days when both stations experienced precipitation.

To test precipitation-occurrence correlation, we converted the potential predictor station’s calibration-period precipitation totals into quantiles based on the empirical distribution function, used these values as predictors of the probability of nonzero precipitation at station \( j \), and assessed significance of the Matthew’s correlation coefficient between observed and estimated occurrence of nonzero precipitation. To test precipitation intensity correlation, we evaluated the significance of the Pearson’s correlation coefficient between precipitation quantile values on co-occurring nonzero precipitation days at both stations. Only potential predictor stations that produced \( p \) values below the 0.05 significance threshold for both correlation tests were considered further and in cases when more than one potential predictor station was available to fill a given missing value, the station with the highest Pearson’s correlation for nonzero precipitation quantiles was selected. Last, quantile mapping was used to replace the missing value on day \( i \) at station \( j \) with the station \( j \) precipitation total that corresponds with the quantile value observed at the predictor station.

This quantile mapping approach risks imposing a wet bias in cases when the predictor station has more calibration-period zero-precipitation days than does the target station. For example, if zero precipitation corresponds to a quantile value of 0.7 at the predictor station but of 0.4 at the target station, then quantile mapping would cause the target precipitation to be assigned a nonzero precipitation value each time the predictor station experienced zero precipitation. We avoided this wet bias by, in such cases, gap filling with a randomly drawn target-station precipitation value (including zeros) from calibration-period days when the predictor station experienced zero precipitation. Caveats to this approach are that it can introduce precipitation totals in cases in which precipitation was not physically plausible and randomly drawing precipitation totals causes repetitions of our gap-filling exercise to yield nonidentical results. Strengths are that, for stations where missing values are clustered in time, it avoids imposing a wet bias for extended periods, which could induce artificial trends in precipitation frequency and intensity. In any case, randomly assigned nonzero precipitation values are rare, accounting for only 2.6% of all gap-filled values.

After the above-described gap filling, the average daily coverage among the 2102 primary stations during the study period was 99.8%, and 69.8% of stations had full daily coverage. To fill additional gaps, we repeated the above procedure considering predictor stations that are 50–100 km from target stations, which increased average daily coverage to \( >99.9\% \), with 91.3% of stations having 100% coverage. At this point we dismissed 69 stations that had \( <99.5\% \) of daily coverage in any of the four quarters of the study period, leaving us with 2033 primary stations.

To finish the gap-filling process and finalize the network of primary stations, we carried out two final steps. First, we repeated our gap-filling exercise, now allowing previously gap-filled values to inform additional gap fillings. To limit the influence of gap fillings from distant stations, we only considered predictor stations within 50 km. After this, we dismissed 15 stations that did not meet the criterion of \( >99.9\% \) daily coverage in each of the four quarters of our study period. Among the remaining 2018 primary stations, 2009 had 100% data coverage during water years 1949–2022 and no station had more than 5 missing days in any month.

Last, the remaining 35 days of missing data across nine stations were filled with each station’s climatological median value among all 1948–2022 days from the same month as the missing day.

Last, we gridded the primary station records of daily precipitation total to 0.25° geographic resolution across the western United States by calculating the average daily precipitation record across all stations within each 0.25° grid cell. When no stations were within the 0.25° grid cell, we iteratively expanded the gridcell boundary used to search for stations by 0.025° in all directions until at least one station fell within the grid cell. We then bias corrected the 0.25° totals by multiplying such that monthly climatologies of mean daily precipitation total matched those of the monthly version of the National Oceanic and Atmospheric Administration (NOAA) nClimGrid dataset (Vose et al. 2014; Durre et al. 2022), which we upscaled to 0.25° from its native 1/24°, during the 1948–2022 period of overlap.

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