

1 **Illuminating snow droughts: The future of Western**
2 **United States snowpack in the SPEAR large ensemble**

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9 **Key Points:**

- 10 • Severe snow droughts in the Western U.S. have increased in frequency by 26-70%
11 across all major watersheds over the last 60 years.
12 • The SPEAR climate model accurately simulates the increase of Western U.S. se-
13 vere snow drought that began in the early 2000s.
14 • SPEAR projects that increasing temperatures will cause much of the West to tran-
15 sition to a no-snow environment by 2100.

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Abstract

Seasonal snowpack in the Western United States (WUS) is vital for meeting summer hydrological demands, reducing the intensity and frequency of wildfires, and supporting snow-tourism economies. While the frequency and severity of snow droughts (SD) are expected to increase under continued global warming, the uncertainty from internal climate variability remains challenging to quantify. Using a 30-member large ensemble from a state-of-the-art global climate model, the Seamless System for Prediction and Earth System Research (SPEAR), and an observations-based dataset, we find WUS SD changes are already significant. By 2100, SPEAR projects SDs to be nearly 9 times more frequent under shared socioeconomic pathway 5-8.5 (SSP5-8.5) and 5 times more frequent under SSP2-4.5. By investigating the influence of the two primary drivers of SD, temperature and precipitation amount, we find the average WUS SD will become warmer and wetter. To assess how these changes affect future summer water availability, we track April 15th snowpack across WUS watersheds, finding differences in the onset time of a “no-snow” threshold between regions and large internal variability within the ensemble that are both on the order of decades. For example, under SSP5-8.5, SPEAR projects California could experience no-snow anywhere between 2058 and 2096, while in the Pacific Northwest, the earliest transition happens in 2091. We attribute the inter-regional uncertainty to differences in the regions’ mean winter temperature and the intra-regional uncertainty to irreducible internal climate variability. This analysis indicates that internal climate variability will remain a significant source of uncertainty for WUS hydrology through 2100.

Plain Language Summary

Snow drought occurs when there is significantly less snow on the ground than normal. Snow droughts can intensify water shortages, accelerate wildfires, and harm snow-based tourism economies. For the Western United States, whose water supply is already limited, a recent increase in snow drought frequency is particularly concerning. Here, we use observational data and a new climate model to examine snow drought changes across the region between 1921 and 2100. We find snow droughts are already more common and could increase almost nine times under a business-as-usual scenario or five times under moderate emissions cuts by 2100. To better understand the increase, we tracked the evolution of the two main snow drought drivers: warmer temperatures and decreased precipitation. We find the average snow drought will become warmer and wetter, indicating warming temperatures are driving the increase. As the model consists of multiple simulations of future climate, or ensemble members, that differ only in the realization of chaotic climate variability, we can determine when Western regions are expected to lose most of their spring snowpack. We find that loss timing varies dramatically between regions and ensemble members, suggesting chaotic climate variability will shape the West’s future water availability.

1 Introduction

Mountains play an indispensable role in Western United States (WUS) water supply, as their low temperatures and high precipitation capture significant water reserves in the form of snowpack. Often referred to as the “water towers” of the West, mountains store enormous amounts of winter precipitation which is measured as snow-water equivalent (SWE), or the depth of water if all snow melted instantaneously. During the dry spring and summer, the SWE is released as meltwater and supplies human populations whose water needs continue to rise (Bonsal et al., 2020). A reliable snowpack provides security to human populations across the WUS by providing water for increasing agricultural demands (Barnett et al., 2005), reducing the severity and intensity of wildfires (Trujillo et al., 2012; Gergel et al., 2017), and improving snow tourism economics (Wobus

66 et al., 2017). According to Wobus et al. (2017), ski resorts are expected to lose 50% of
67 ski season length by 2050 and 80% by 2090. Despite large seasonal variability, climate
68 change has already been found to have significantly decreased SWE globally and across
69 the WUS, particularly in late winter (Barnett et al., 2005; Kapnick & Hall, 2012; Fontrodona Bach
70 et al., 2018; Huning & AghaKouchak, 2020). When SWE is abnormally low, the region
71 is said to experience a snow drought (SD). SDs are driven by either warming, as a phase
72 change from frozen to liquid, or reduced precipitation amounts. They affect the WUS’s
73 economy and human activity, even in areas far from mountain snowpack that rely on spring
74 and summer melt waters for crop production and human consumption.

75 The adverse effects of SDs on a region’s hydrology vary depending on the type of
76 SD. Dry SDs, characterized by low precipitation and near- or below-normal temperatures,
77 result in low streamflow throughout the melt season. In contrast, warm SDs occur un-
78 der near- or above-normal precipitation and warm temperatures and often lead to early
79 season snowmelt, increased spring flood risk, and summer hydrological drought (Harpold
80 et al., 2017). While deviations from normal temperature and precipitation dictate SD
81 occurrence, their absolute conditions impact how SDs are expected to respond to climate
82 change. Shrestha et al. (2021) demonstrate that additional warming above a critical aver-
83 age winter temperature threshold of -6 to -5°C decreases snowpack. As all WUS large
84 hydrologic unit code (HUC2) regions have historical average winter temperatures at or
85 above -5°C, we expect their snowpack to be vulnerable to any level of warming.

86 To study SD across the WUS, we focus on comparing changes in SWE. Large ob-
87 servational uncertainty in WUS SWE measurements implies high biases are likely be-
88 tween any two datasets or models (Wrzesien et al., 2019). Observational model bias is
89 driven by low sampling rates and terrain complexity, present in mountain regions, and
90 is further magnified by assumptions in models used to generate SWE estimates (Wrzesien
91 et al., 2019). Coupled global climate models (GCMs) are expected to produce snowpack
92 estimates that are biased compared to observations because they have a lower spatial
93 resolution and have temperature and precipitation biases (McCrary et al., 2017; Wrze-
94 sien et al., 2019; Kim et al., 2021; McCrary et al., 2022). Despite these biases, Matiu and
95 Hanzer (2022) show that many models exhibit uniformity in simulating robust decreases
96 in WUS SWE. Huning and AghaKouchak (2020), for example, have shown that SD to-
97 tal duration, average duration, and intensity in the WUS have increased by 28% between
98 1980 and 2018, and Shrestha et al. (2021) adds that these conditions are expected to con-
99 tinue to worsen because of the WUS’s low latitude. These previous results imply that
100 although GCMs are typically biased in their SWE base state, changes relative to their
101 base states are still informative. As a result, we will primarily focus on comparing changes
102 in SWE across data sets.

103 To investigate historical and future changes in SD frequency and intensity we use
104 30-member initial condition large ensembles from a state-of-the-art coupled global cli-
105 mate model, called the Seamless System for Prediction and EArth System Research (here-
106 after SPEAR) (Delworth et al., 2020). To assess SD intensity relative to the historical
107 period, we focus on SPEAR’s simulation of severe to exceptional snow droughts (D2+
108 SD) and follow the classification framework used by the US Drought Monitor (Svoboda
109 et al., 2002). We first show that SPEAR accurately simulates changes in WUS SD by
110 comparing it to an observationally based dataset and with previous studies across the
111 historical period (1921-2011) (Livneh et al., 2013; Huning & AghaKouchak, 2020). The
112 classifications in SPEAR show both an increase in D2+ SD occurrence across the his-
113 torical period and a continued increase under future warming scenarios. To understand
114 the conditions driving these SDs, we examine the average temperature and precipitation
115 conditions for the study period, finding that temperature and not lack of precipitation
116 is the main driver of the D2+ SD increase at monthly time resolution. We then provide
117 a region-level assessment of the transition to a “no-snow” environment by the end of the
118 21st Century that accounts for scenario uncertainty and internal climate variability.

119 By separating the uncertainty into the portion attributable to internal climate vari-
 120 ability and emissions uncertainty, we can determine the distribution of D2+ SD changes
 121 until 2100, the variability in the conditions that generate drought/non-drought condi-
 122 tions, and the probability distribution of the transition timing to a no-snow regime. We
 123 assess these changes under two scenarios in the SPEAR projections (2014-2100): a middle-
 124 of-the-road scenario (Shared Socioeconomic Pathway 2-4.5, hereafter SSP2-4.5), and a
 125 high-emissions scenario (SSP5-8.5) (Delworth et al., 2020). While the two emissions sce-
 126 narios allow us to explore the effects of emissions uncertainty, the 30-member ensembles
 127 enable the estimation of internal climate variability.

128 2 Data and Methods

129 2.1 SPEAR Large Ensemble Global Climate Model

130 To assess changes in the probable distribution of historical and future SD, we an-
 131 alyzed WUS SWE in multiple 30-member SPEAR large ensembles (Delworth et al., 2020).
 132 SPEAR is a coupled global climate model recently developed at the NOAA Geophys-
 133 ical Fluid Dynamics Laboratory (GFDL) that is designed for improved prediction and
 134 projection on seasonal-to-multidecadal timescales. SPEAR is composed of GFDL’s AM4
 135 atmosphere, LM4 land, MOM6 ocean, and SIS2 sea-ice models. These component mod-
 136 els are the same as GFDL’s Global Climate Model version 4 (CM4) (Held et al., 2019),
 137 which is a contributor to the Coupled Model Intercomparison Project phase 6 (CMIP6).
 138 SPEAR’s configuration differs from CM4 as its physical parameterization choices are op-
 139 timized for climate prediction on seasonal to centennial timescales. SPEAR has a mod-
 140 erately high atmospheric and land-surface resolution (approximately 50 km) and a coarser
 141 ocean and sea-ice horizontal resolution of about 1°, which has meridional refinement to
 142 0.33° at the equator. For this study, we use SPEAR’s monthly SWE, temperature, and
 143 precipitation across the historical period and projections from 2014-2100 under both SSP2-
 144 4.5 and SSP5-8.5 emissions scenarios.

145 2.2 Observational Data

146 To evaluate SPEAR’s historical simulation of SWE, temperature, and precipita-
 147 tion, we use an observations-based dataset (Livneh et al., 2013), available from 1915 to
 148 2011, hereafter the Livneh dataset. Livneh uses statistically gridded in situ daily pre-
 149 cipitation and temperature observations on a 1/16° grid to generate SWE estimates (among
 150 other land surface variables) using the Variable Infiltration Capacity (VIC) land model
 151 (Liang et al., 1994). To compare the Livneh dataset with the SPEAR ensemble mem-
 152 bers, we re-gridded Livneh to SPEAR’s 1/2° grid and re-sampled it to SPEAR’s monthly
 153 timescale. Despite incorporating observational data, gridded datasets, like Livneh, re-
 154 tain large uncertainties across variables including temperature, precipitation and SWE
 155 (Walton & Hall, 2018; Wrzesien et al., 2019). Many recent papers have found SWE es-
 156 timates to vary widely, by upwards of a factor of 3 in some cases (Wrzesien et al., 2019),
 157 leading us to expect significant absolute biases between SWE estimates (McCrary et al.,
 158 2017, 2022). To overcome this issue, we focus our analysis on proportional changes, com-
 159 paring SWE values to their own historical distributions within each dataset, and then
 160 comparing these relative changes across datasets.

161 We chose 1921-2011 as our historical period as it is the overlapping period of the
 162 Livneh and historical SPEAR datasets. We use the 90 complete winters to validate SPEAR
 163 and develop a baseline against which to compare the modeled future climatology. We
 164 chose to consider data at monthly resolution intervals for the following three reasons: (1)
 165 data availability, as SPEAR only recorded SWE at monthly intervals; (2) consistency
 166 with previous studies (Huning & AghaKouchak, 2020); and (3) because the monthly res-
 167 olution is an appropriate timescale for monitoring snow drought.

2.3 Comparison of a Climate Large Ensemble to Observations

Delworth et al. (2020) and Maher et al. (2022) demonstrate that SPEAR accurately reproduces temperature and precipitation patterns across the US and outperforms many other state-of-the-art large ensemble climate models. Delworth et al. (2020) finds that SPEAR has negligible temperature bias and a slight positive precipitation bias across the WUS. As temperature and precipitation inform snowfall, Delworth et al. (2020) lends confidence that the underlying conditions at SPEAR’s approximately 50 km resolution are well-simulated. Delworth et al. (2020), Johnson et al. (2022), and Maher et al. (2022) assess SPEAR’s accuracy in representing teleconnections of the El Niño-Southern Oscillation (ENSO) and the Pacific Decadal Oscillation (PDO) to North American climate. As ENSO and PDO drive inter-annual variability across the region, assessing SPEAR’s representation of these teleconnections is important for understanding how accurately the model may reproduce other extremes across the region, like SDs. Delworth et al. (2020) shows SPEAR accurately captures the relationship between PDO and North American precipitation, while Maher et al. (2022) finds that when PDO and ENSO are in phase, temperature and precipitation anomalies are amplified and vice versa. When comparing SPEAR’s performance against other GCMs, Johnson et al. (2022) reports that SPEAR improves on CMIP5-generation models with a better representation of global ENSO-related temperature and precipitation patterns and Maher et al. (2022) reports SPEAR has higher accuracy and resolution than five other large ensemble models after comparing correlations of ENSO and PDO with North American winter temperature and precipitation anomalies between observations and models. Together, these studies affirm SPEAR as one of the best models to investigate changes and variability in the WUS’ SWE because of its accurate representation of the response of temperature and winter hydroclimate to large-scale climate drivers.

However, as both studies focus on SPEAR’s performance in reconstructing large-scale temperature and precipitation patterns, we still need to validate SWE patterns against Livneh before exploring future behavior. Livneh differs from SPEAR in that it contains only a single realization of the historical period, i.e. what actually happened, while the SPEAR ensemble captures 30 possible climates in each of its runs. The range of conditions that SPEAR’s ensemble members experience is called the ensemble spread and it arises entirely from internal climate variability. Internal climate variability contributes significantly to inter-model spread in CMIP multi-model ensembles (Deser et al., 2020) and is essential for modeling extremes. When evaluating model bias, however, it means that, short of a taking a long-term average as shown in Figure 1, we do not expect biases between observations and either a single SPEAR ensemble member or the SPEAR ensemble mean to be reflective of SPEAR’s accuracy in simulating the climate. While we do not expect a single SPEAR ensemble member or the ensemble mean to reproduce Livneh exactly, we do expect SPEAR to simulate a realization of the climate at least as extreme as the observed historical climate over most regions. However, with only 30 ensemble members it is still reasonable to expect an occasional observation to fall outside of the SPEAR spread. Thus, if the change in SD frequency observed in Livneh falls within the SPEAR ensemble spread, we can assume SPEAR produces a realistic historical climate. Our analysis reveals that the majority of the Livneh SWE statistics fall near clusters of SPEAR ensemble members, further strengthening the conclusion that SPEAR accurately represents the WUS climate as demonstrated in Figures 2 and S3.

2.4 Drought Classification

Before we can assess changes in SD, we first introduce our SD classification method. To ensure that only regions which typically have snow are eligible for classification, we restrict our region of study to the “historically snowy” region, areas that historically have average seasonal SWE maxima above 20 mm, based on the SPEAR ensemble mean. We

219 then assign a classification based on how extreme each month is compared to the his-
 220 torical distribution of SWE across all grid cells and months.

221 Our methodology assigns standardized indices to each location by month and uses
 222 the US Drought Monitor’s (USDM) drought classification method for hydrological drought
 223 to categorize observations into six descriptive bins: near normal (NN), abnormally dry
 224 (D0), and moderate (D1), severe (D2), extreme (D3), and exceptional (D4) drought. Wet
 225 conditions are classified analogously, with labels W0-W4 for increasingly wet months;
 226 see Figure S2 (Svoboda et al., 2002; Huning & AghaKouchak, 2020). We use a non-parametric
 227 empirical model to classify SWE, temperature, and precipitation values for each month.
 228 Without assuming the underlying distributions, a non-parametric model allows us to ef-
 229 ficiently capture the variability without imposing subjective constraints on the data.

We begin by assigning each extended winter month of the year (Oct-April) a score based on the historical conditions at that location. Our time indices are by year (y) and month (m), e.g. $t_{1931,1}$ for January 1931, and spatial indices are in degrees latitude (i) and longitude (j). For example, $s_{40.5,250}^{t_{1931,1}}$ corresponds to a SWE value at latitude-longitude pair (40.5, 250) during January 1931. We now compute an empirical distribution over $\mathbf{S}_{i,j}^m = (s_{i,j}^{t_{1921,m}}, s_{i,j}^{t_{1922,m}}, \dots, s_{i,j}^{t_{2011,m}})$, representing the historical SWE values during month m at location (i, j) . We then assign a value in $(0, 1)$ to each SWE measurement using the empirical cumulative distribution function, $\hat{F}_{i,j}^m$, based on the proportion of the observed data in $\mathbf{S}_{i,j}^m$ that fall below it. In equation 1, $\mathbb{I}(\cdot)$ takes the value 1 if SWE measurement x is larger than the historical SWE measurement, $\mathbf{S}_{i,j}^{t_{y,m}}$, and 0 otherwise. We sum over the historical period which ranges from 1921 to 2011, which is 91 complete years.

$$\hat{F}_{i,j}^m(x) = \frac{\text{no. of SWE values less than } x}{91} = \frac{1}{91} \sum_{y=1921}^{2011} \mathbb{I}(\mathbf{S}_{i,j}^{t_{y,m}} < x) \quad (1)$$

For each observed or simulated SWE value, $s_{i,j}^{t_{y,m}}$, we can then compute the z-score by plugging the SWE value into the corresponding \hat{F} and then into the inverse normal distribution, Φ . We refer to these z-scores as ZSWE, which are indexed by location, month, and year. We can now classify snow droughts from the SWE value, $s_{i,j}^{t_{y,m}}$, using

$$ZSWE_{i,j}^{y,m} = \Phi\left(\hat{F}_{i,j}^m(s_{i,j}^{y,m})\right) \quad (2)$$

230 Each month is then assigned a classification (W4-W0, NN, D0-D4) which can now be
 231 compared across regions. While we primarily use this framework to classify SDs, we ex-
 232 tend the classification scheme to temperature and precipitation as needed.

233 A similar empirical methodology is used by Huning and AghaKouchak (2020) to
 234 classify snow droughts across the Alps, Himalayas, and WUS. Their framework is inspired
 235 by the USDM which uses the same D0-D4 classification. However, the USDM approach
 236 is not purely statistical, relying on experts to incorporate regional sensitivity into the
 237 published drought classification. Without experts, our model attempts to match the fre-
 238 quency of meteorological droughts in the US Drought Monitor (USDM) with snow drought
 239 frequency because the USDM is the widely accepted standard, despite its subjectivity
 240 (Svoboda et al., 2002). While our method may result in a mismatch of SWE values and
 241 impact in some locations, it provides a statistically-rigorous way to quickly capture ex-
 242 tremes without gathering detailed human and environmental data for each pixel.

243 2.5 Computing Changes in Snow Drought

244 We can now apply our drought classification scheme to evaluate how well SPEAR
 245 reconstructs historical changes. We define two 41-year windows containing 40 complete
 246 winters to assess change, and after applying our drought classification scheme to snow-
 247 pack data aggregated to the HUC2-level, we count the number of D2+ SD occurrences

248 across the early and late historical periods, given by a ZSWE of less than -1.3 , e.g. $\mathbb{I}(Z_R^t <$
 249 $-1.3)$ for HUC2 region R at time t . The percent change for a given region, Δ_R , is de-
 250 rived via

$$\Delta_R = \frac{\sum_{t'} \mathbb{I}(Z_R^{t'} < -1.3)}{\sum_t \mathbb{I}(Z_R^t < -1.3)} \cdot 100\% \text{ for } t \in (1930, 1970), t' \in (1971, 2011) \quad (3)$$

251 For example, in the Upper Colorado region, 27 months of Livneh-derived D2+ SD
 252 occur in the early historical period and 28 in the late historical period, translating to an
 253 increase of 3.7%. Next, we leverage the SPEAR ensemble spread to determine whether
 254 the overall trend is significant.

255 2.6 Snow Transition Threshold

256 In addition to evaluating drought climatology, we are also motivated to determine
 257 how a changing SWE will affect water resources. We seek to discern when a shifting cli-
 258 mate will begin to severely and persistently impact snow as a water resource. Long-term
 259 droughts are particularly damaging, as one or two years of low snow-pack can be buffered
 260 by groundwater, above-ground reservoirs, or stored in live biomass, but these buffers dwindle
 261 with extended exposure to drought conditions. Thus, we are particularly interested
 262 in determining when no-snow conditions are expected to become systemic (Siirila-Woodburn
 263 et al., 2021; Harpold et al., 2017).

To determine this transition, we focus on April SWE because April typically cor-
 responds to peak SWE. By first calculating the fraction of April 15th SWE remaining
 in the historically snowy portion across each of the 5 HUC2 regions: Upper Colorado,
 Lower Colorado, Great Basin, Pacific Northwest, and California (abbreviated UC, LC,
 GB, PNW, and CA), we can classify an April ($m = 4$) grid cell $s_{i,j}^{t,4}$ as no-snow for that
 year if there is *at most* 10% of the historical snowfall average remaining at the location
 (Siirila-Woodburn et al., 2021). We then calculate the regional no-snow area proportion
 as the fraction of the historically snowy region which experiences those conditions. For-
 mally, we let \mathcal{N}_R^Y denote this no-snow area proportion, where R represents the region,
 for our application a WUS HUC2, and Y the year. As before, $\mathbf{S}_{i,j}^{ty,4}$ is the average his-
 torical SWE value for the grid cell and $s_{i,j}^{ty,4}$ the SWE value for the specific year. Us-
 ing 10% as our no-snow threshold, $\mathbb{T} = 0.1$, then \mathcal{N}_R^Y can be written as:

$$\mathcal{N}_R^Y = \frac{\sum_{(i,j) \in R} \mathbb{I}(s_{i,j}^{tY,4} < \mathbb{T} \cdot \bar{\mathbf{S}}_{i,j}^4)}{|(i,j) \in R|} \quad (4)$$

Thus we have a fraction of the historically snowy region that is snow free in a given year
 in April. To assess when no-snow conditions become endemic, we apply a 10-year moving-
 window mean and then define the no-snow transition time as the year when the moving-
 window mean *last* crosses the area threshold, \mathcal{A} , before 2100. Applying this procedure
 to all ensemble members, we compute a distribution for when these conditions are likely
 to become endemic. Formally, the no-snow transition time for an ensemble member, \mathcal{T} ,
 is given by:

$$\mathcal{T} := \left[\min t : \tilde{\mathcal{N}}_R^{t'} \geq \mathcal{A} \forall t < t' \leq 2100 \right] \quad (5)$$

264 where $\tilde{\mathcal{N}}_R^{t'}$ gives the moving-window mean fraction of region R that experiences no-snow
 265 conditions at time t' . By requiring the moving-window average to be above \mathcal{A} for all sub-
 266 sequent years (until 2100), \mathcal{T} is uniquely determined. For a graphical explanation of this
 267 method, please refer to Figure S5.

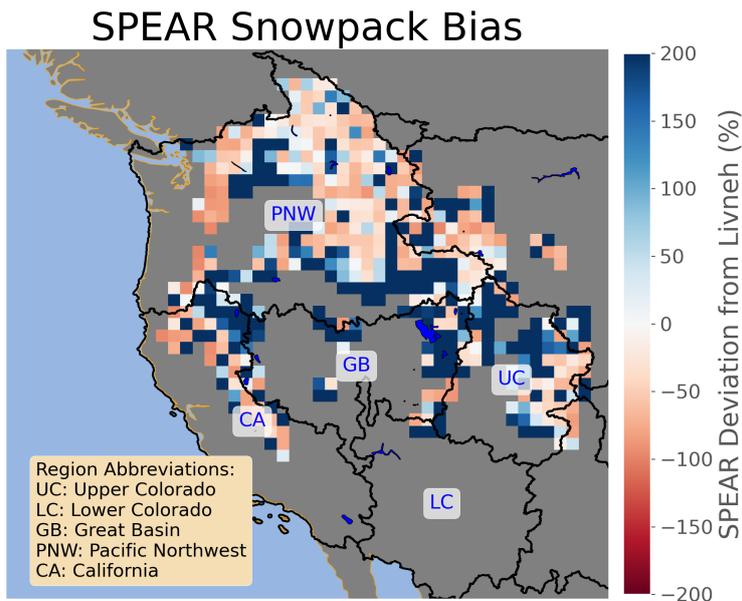


Figure 1. Winter average SPEAR SWE deviation from Livneh (%). Red indicates regions where SPEAR has a negative SWE bias while blue indicates regions with a positive bias. The five HUC2 regions are outlined in black.

3 Results

3.1 SPEAR Model Evaluation

3.1.1 *SPEAR Ensemble Mean Bias*

Before assessing how accurately SPEAR reconstructs historical change, we compute WUS SWE bias to assess absolute error. By taking the difference of monthly SWE averaged over the winter season (Oct–April) and the entire historical period for both datasets, we find that SPEAR has a negative snow bias across much of the Mountain West. Figure 1 reveals that in regions characterized by high elevation, SPEAR often has average SWE values less than 50% of Livneh values, while in regions adjacent to mountains, SPEAR overestimates SWE by a factor of two or more. While these are significant absolute biases, the difference is not particularly surprising because by resampling the $1/16^\circ$ Livneh grid to match SPEAR’s $1/2^\circ$, bias is introduced because higher elevations have disproportionately more snow than low elevations and are not accurately captured by SPEAR’s $1/2^\circ$ resolution due to topological smoothing (McCrary et al., 2022). We also compare historical temperature and precipitation biases in Figure S1, finding that, consistent with Delworth et al. (2020), SPEAR has a slight positive precipitation bias across the WUS.

3.1.2 *Evaluating Snow Drought Changes across the Historical Period*

Despite large absolute biases in SWE, SPEAR can still provide insights for future SDs if it reproduces trends and relative variability in SWE, temperature, and precipitation. Figure 2 reveals that across SPEAR, the ensemble means of all five WUS HUC2 regions experience increases in D2+ SD, ranging from an average of 26% (LC) to over 70% (UC). When we compare Livneh to the SPEAR distribution, we find that the same Livneh D2+ SD statistic always falls within the ensemble spread and is between the first and third quartiles in three of the five regions. The increases in D2+ SD occurrence are consistent with findings in Huning and AghaKouchak (2020), who use 1980–2018 as their

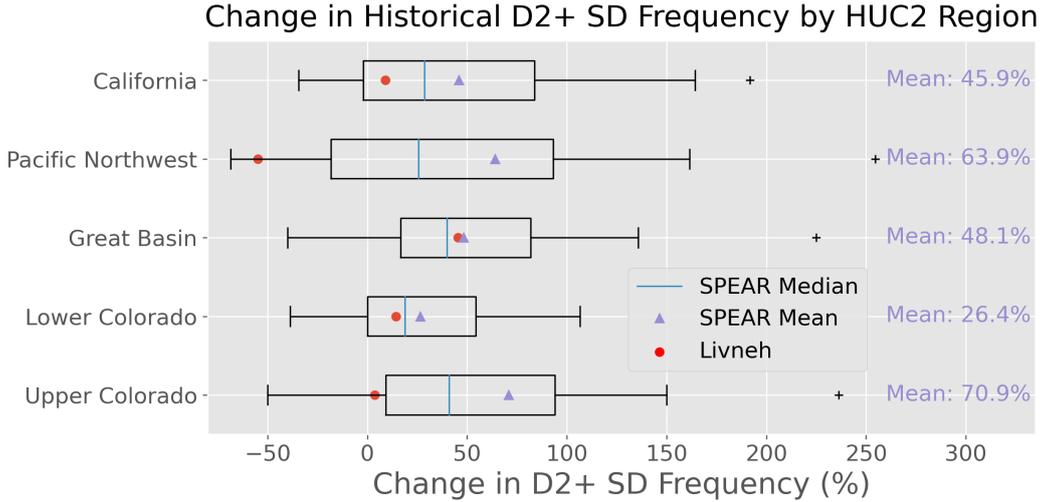


Figure 2. Comparison of SPEAR-estimated D2+ SD increases across the 1921-2011 historical period to Livneh observed increases. The SPEAR distribution is given by the box and whisker plot. The lower and upper bounds of the box correspond to the 25th and 75th percentiles, respectively, and points more than 1 interquartile range away from the box are denoted with a “+”. The observed change in D2+ SD frequency in the Livneh dataset is marked with a red circle.

293 historical period — in fact, a 95% confidence interval for the SPEAR ensemble mean across
 294 four of the five regions contains the 28% benchmark for drought intensity increases found
 295 in Huning and AghaKouchak (2020), with only the UC interval exceeding the benchmark
 296 with a 30% lower bound on historical D2+ SD increases. While we could not use the same
 297 historical period due to data constraints, the agreement helps to further validate the SPEAR
 298 ensemble. See supplemental Text S1 and Figure S3 for an analysis of changes in precip-
 299 itation and temperature across the historical period.

300 3.2 Analyzing SWE into the 21st Century: Accelerating Loss

301 We next shift our attention to projected changes in 21st century D2+ SD, focus-
 302 ing first on changes in droughts classified with our ZSWE metric. We construct our em-
 303 pirical CDF $\hat{F}_{i,j}^m$ distributions from the historical period (1921-2011) and calculate cor-
 304 responding ZSWE scores for each winter month across the historically snowy west (2014-
 305 2100) for all 30 ensemble members. Projected changes in SWE are dramatic, with rapid
 306 increases in D2+ SD occurring at mid-century (Figure 3). Under SSP5-8.5, we find that
 307 towards the end of the century, all regions are projected to experience severe, extreme,
 308 or exceptional SD during most months. Under SSP2-4.5, SD increases are less severe,
 309 with conditions by the end of the century resembling conditions under SSP5-8.5 by mid-
 310 century. As expected, the higher forcing scenario corresponds with an accelerated time-
 311 line for increases in snow drought frequency. SD frequencies for all 18 study decades are
 312 shown in Figure S4.

313 Examining the spatial distribution of D2+ SDs in Figure 3, a pattern of regional
 314 “hot spots” emerges through time. D2+ SD frequency is consistently higher in certain
 315 regions beginning in 2030 in SSP5-8.5 and SSP2-4.5. For example, the Washington Cas-
 316 cades and Colorado Rockies are projected to experience more frequent D2+ SD across
 317 all decades than regions in south-central Idaho and the California Sierra Nevada. We ex-
 318 pected to see more dramatic D2+ SD increases in the southern basins, including the Cal-

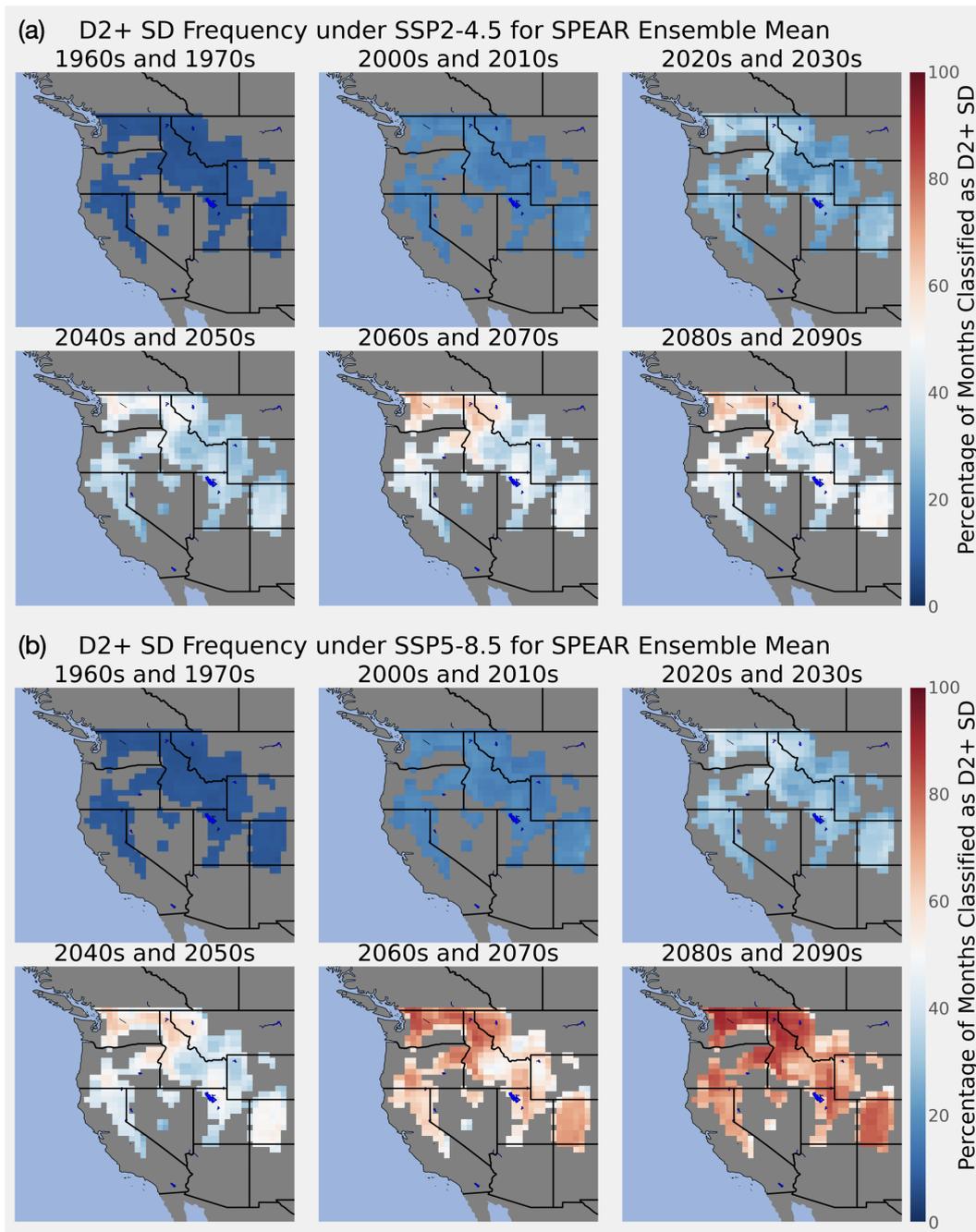


Figure 3. SPEAR D2+ SD frequencies between 1960-2100 under (a) low (SSP2-4.5) and (b) high (SSP5-8.5) emissions scenarios. The plots are masked to historically snowy regions and shaded by the percentage of winter months that the grid-cell experiences D2+ SD across a two decade period. Historically snowy regions are characterized by having an average peak SWE of at least 20mm. All 18 study decades are shown individually in Figure S4.

319 ifornia and Lower Colorado regions, as Shrestha et al. (2021) found that even low amounts
 320 of warming at southern latitudes result in strong SWE loss signals. We assume the hot
 321 spot pattern emerges because we are looking over a narrow enough range of latitudes that
 322 the latitude signal is overshadowed by regional variation, perhaps coming from elevation
 323 variability. Shrestha et al. (2021) examined basins ranging from the Yukon to Columbia
 324 River basins that have average winter temperatures of -8°C to $+4^{\circ}\text{C}$, finding that below
 325 -5°C to -6°C warming temperatures did not reduce SWE. Our HUC2 regions had mean
 326 winter temperatures in historically snowy regions ranging from -5.1°C (UC) to 0.3°C (Cal-
 327 ifornia). Therefore, we expect any amount of warming will decrease SWE and correspond-
 328 ingly increase D2+ SD.

329 While Figure 3 reveals the expected changes in D2+ SD frequency under different
 330 emissions scenarios, it does not show the impact of internal climate variability. The anal-
 331 ysis of a large ensemble allows us to examine this effect by looking at the distribution
 332 of SD frequency across the ensemble. To study internal climate variability at the level
 333 of the entire WUS, we consider D2+ SD across the WUS in each ensemble member sep-
 334 arately. The individual trajectories, shown in Figure 4, reveal large tail probabilities that
 335 emphasize the region may experience worse drought conditions much earlier than the en-
 336 semble mean. For example, under both future warming scenarios, the ensemble mean
 337 D2+ SD frequency is reached in some ensemble members a decade or two earlier. This
 338 emphasizes that the WUS must be prepared for D2+ SD conditions well before the en-
 339 semble mean expects them.

340 Figure 4 also reveals just how dramatic the increases in D2+ SD frequency may
 341 be. SPEAR ensemble members experience an average of 5-12% D2+ SD frequency dur-
 342 ing the historical period and an average of 6.5% before 2000. However, the probability
 343 of D2+ SD is projected to be over 35% by 2050 under SSP5-8.5, while under SSP2-4.5,
 344 the 35% D2+ SD probability is projected for 2070. Examining the shape of the two curves,
 345 we see an inflection point in 2000. Before 2000, both curves do not show a noticeable in-
 346 crease in D2+ SD frequency while after 2000 the increase is dramatic and sustained. Un-
 347 der SSP2-4.5, the increase in D2+ SD has a second inflection point in 2070, where the
 348 increase in snow droughts flattens. We assume the slowdown parallels the changes in the
 349 underlying climatology discussed in 3.3. Contrary to the simulations, Livneh does not
 350 show the same uptick in drought frequency in 2000. When examining the observed changes
 351 in Figure 2, we find a 53% decrease in D2+ SD frequency in the PNW. While within the
 352 SPEAR ensemble range, this decrease is far from the SPEAR ensemble mean and per-
 353 haps explains the deviation.

354 3.3 Temperature and Precipitation Controls on SWE

355 As changes in SWE are primarily driven by changes in temperature and precipi-
 356 tation climatology (McCrary et al., 2017; Harpold et al., 2017), we next examine changes
 357 in SWE in the phase space spanned by temperature and precipitation. By aggregating
 358 over the entire historically snowy WUS, we can determine how temperature and precipi-
 359 tation anomalies are driving the dramatic increase in SD. In Figure 5, each dot repre-
 360 sents the average temperature and precipitation anomaly by decade and is colored ac-
 361 cording to the average ZSWE score. By definition, the average all-month historical (1921-
 362 2011) temperature and precipitation mean is $(0, 0)$. However, by breaking the century
 363 down by decade we can see variation within the 20th century.

364 As expected, all-month decadal averages in the historical period cluster around a
 365 zero temperature and precipitation deviation. We observe small changes in anomalies
 366 before 2000, a finding consistent with our understanding of changing D2+ SD frequency.
 367 Beginning in the 2000s, the all-month decadal-average rapidly shifts towards warmer and
 368 wetter conditions. By 2050 under SSP5-8.5, the average temperature and precipitation
 369 are 1.50 and 0.25 standard deviations higher than the 20th century average, respectively.

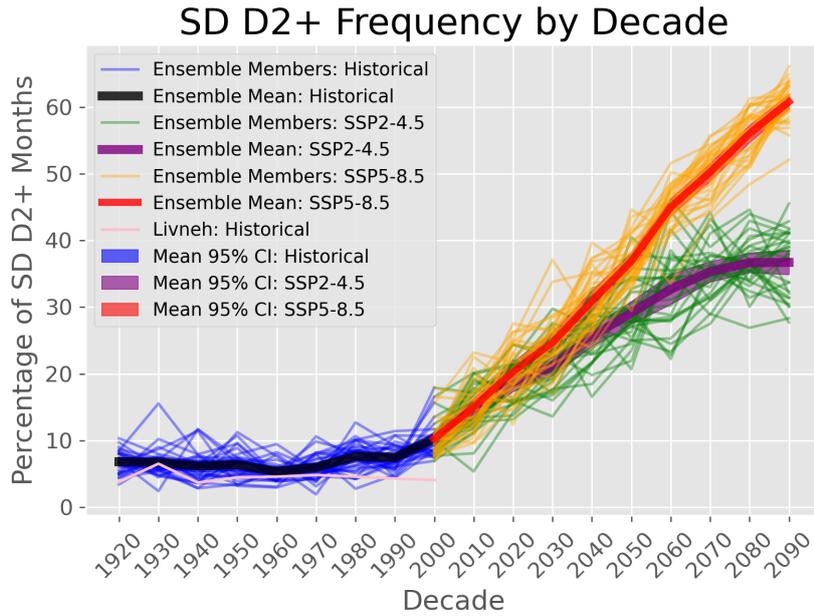


Figure 4. Each thin curve represents the percentage of historically snowy months classified as D2+ SDs and averaged by decade in Livneh (pink) and for each member of the three SPEAR ensembles; historical (blue), SSP2-4.5 (green), and SSP5-8.5 (yellow). The dark curves and surrounding shaded regions represent the ensemble mean and 95% confidence interval for the historical (blue), SSP2-4.5 (purple), and SSP5-8.5 (red) scenarios.

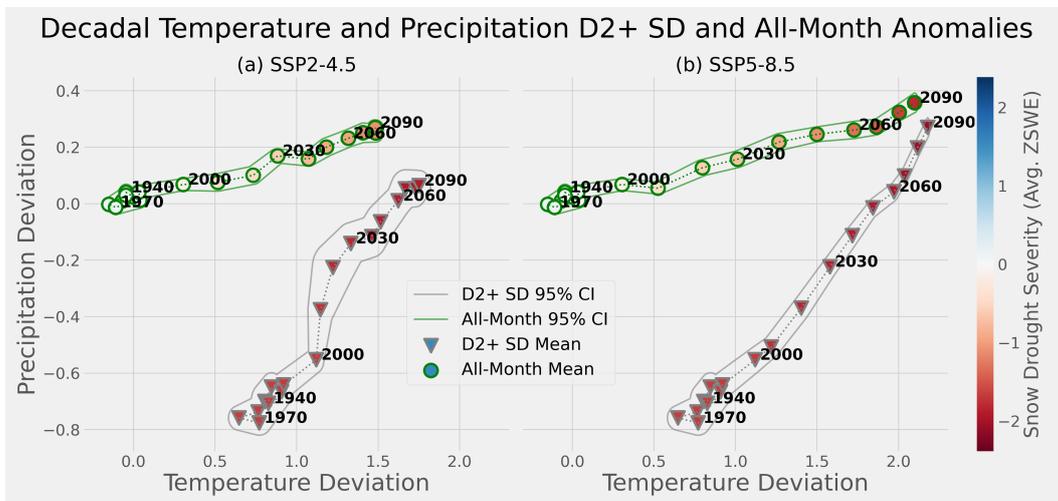


Figure 5. Temporal evolution of average temperature and precipitation anomalies with respect to the historical conditions (1921-2011). Each dot represents the average temperature and precipitation condition for historically snowy locations during winter (Oct-April) for a given decade either for all months and locations (outlined in green) or only for months classified as D2+ (outlined in gray). Each point is shaded by its average ZSWE score; thus because D2+ SD months are restricted to have a ZSWE of less than -1.3 , these points average snow drought conditions are less than -1.3 . Both all-month and D2+ SD-month points are surrounded by a contour which captures 95% of ensemble members. Panel (a) depicts these changes under SSP2-4.5 while (b) depicts changes under SSP5-8.5.

370 This corresponds to a dramatic warming and slight wetting across the WUS and indi-
 371 cates the average month in 2050 to be warmer than 93% of months in the historical pe-
 372 riod for a given location. For SSP2-4.5, the values are 1.18 and 0.20, respectively, reflect-
 373 ing a moderate increase in temperature and precipitation by mid-century, with the av-
 374 erage month in 2050 being warmer than 88% of historical months.

375 To understand changes in SDs, we also track the underlying climatology of months
 376 that experience D2+ SD. Outlined in grey in Figure 5, we find historical D2+ SD av-
 377 erages are both dry and warm with an average temperature and precipitation anomaly
 378 of 0.6 to 0.8 and -0.6 to -0.8, respectively, indicating historical snow droughts are pri-
 379 marily driven by a near equal combination of both warm and dry conditions. These con-
 380 ditions suggest that an average historical D2+ SD month is both warmer and drier than
 381 75% of months. However, when examining SPEAR’s future climate, we find the aver-
 382 age drought is both warmer and *wetter*. By 2050 under SSP5-8.5, the temperature de-
 383 viation is 1.84 while the precipitation deviation is -0.015, indicating that future D2+ SDs
 384 are significantly warmer than the historical ones and that dry conditions are no longer
 385 needed to produce a SD. We conclude future D2+ SD conditions are driven by the in-
 386 creasingly high-temperature average, which is warmer than 97% of historical conditions.
 387 By 2090, the average drought month has a temperature deviation of 2.18 and a precip-
 388 itation deviation of 0.27, close to the all-month anomalies of 2.10 and 0.36 for temper-
 389 ature and precipitation, respectively. Average monthly temperature for both D2+ and
 390 all-month averages are in the 98th percentile of historical conditions, indicating that fu-
 391 ture winter conditions will, on average, be extremely warm and that the difference be-
 392 tween average conditions for all months and SD months has decreased. Examining the
 393 ZSWE scores for 2090 under SSP5-8.5 confirms that the convergence is also reflected in
 394 SWE changes, with the average all-month ZSWE being -1.79 and the average D2+ month
 395 having a ZSWE of -2.10. Thus, the 2090 all-month average is expected to be a D3 SD,
 396 while the average month classified as a SD is D4. Under SSP2-4.5, conditions do not reach
 397 such an extreme, with average all-month conditions by 2090 reaching 1.48 for temper-
 398 ature, 0.27 for precipitation, and -1.10 ZSWE. The temperature, precipitation, and ZSWE
 399 deviations for the months that experience D2+ SD are 1.75, 0.064, and -1.91, respectively.
 400 Although the gap between drought months and all-months shrinks, the difference is far
 401 less extreme than under SSP5-8.5; the average month under SSP2-4.5 is only given a D1
 402 snow drought classification. The convergence of the all-month and drought-month tem-
 403 perature and precipitation anomalies, particularly under SSP5-8.5 emphasize that D2+
 404 SDs will require increasingly smaller deviations from normal conditions to produce. This
 405 underscores that SDs will become a “new normal” for the WUS by the end of the 21st
 406 century.

407 3.4 Timeline for Snow-Free Conditions

408 In addition to changes in D2+ SD frequency, we also examine how total SWE avail-
 409 ability is expected to change, by assessing the timing of Western regions’ transition to
 410 a no-snow regime. A no-snow regime, characterized by a 10-year moving average of April
 411 SWE consistently below 10% of the historical April average, indicates severely limited
 412 summer water supply from SWE. To understand when a no-snow regime is likely to af-
 413 fect a HUC2 region, we examine the distribution of transition times to no-snow across
 414 SPEAR’s ensemble members. By varying the area threshold, \mathcal{A} , we can assess how quickly
 415 conditions are expected to deteriorate. Figure 6 shows the distribution of the transition
 416 to no-snow regimes for 3 different area thresholds, \mathcal{A} : 50%, 75%, and 90%, for the his-
 417 torically snowy HUC2 regions. Note that by construction, an individual ensemble mem-
 418 ber’s transition year always occurs later for higher \mathcal{A} . However, the ensemble distribu-
 419 tions can overlap, which indicates large variability in the severity of conditions, especially
 420 later this century.

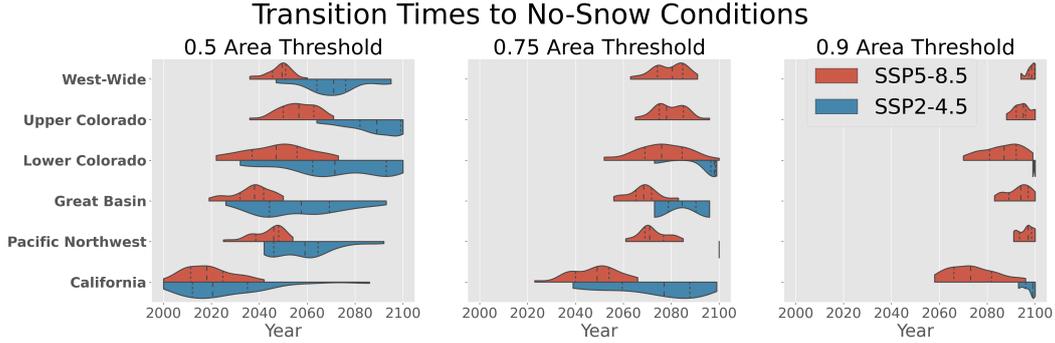


Figure 6. Distribution of SPEAR-simulated transition times to no-snow regimes, or \mathcal{T} , by Western HUC2 region, split between SSP5-8.5 and SSP2-4.5 scenarios. The 3 subplots represent the different thresholds $\mathcal{A} = 50\%$, 75% and 90% . Meeting a higher threshold corresponds with an increased proportion of the region experiencing perennial no-snow conditions, and implies more severe conditions. The vertical lines in the distributions represent the quantiles of the ensemble members that transition. We also include a transition time for the entire historically snowy WUS, labeling it “West-Wide”.

421 When aggregated to the entire historically snowy WUS (“West-Wide”), the average
 422 transition time for $\mathcal{A} = 50\%$ is 2071 for SSP2-4.5 and 2048 for SSP5-8.5. However,
 423 when considered as separate regions, transition times for $\mathcal{A} = 50\%$ varied from as early
 424 as 2025 (CA) to 2088 (UC) under SSP2-4.5 and 2018 (CA) to 2056 (UC) for SSP5-8.5.
 425 The snow-free transition distribution center occurs later for all regions under SSP2-4.5
 426 scenario than SSP5-8.5. However, the difference is less pronounced in regions that ex-
 427 perience a no-snow transition earlier, such as California. We conclude that while follow-
 428 ing a lower emissions trajectory improves the probability that transitioning to a no-snow
 429 regime will occur later, large irreducible internal climate variability could result in a tran-
 430 sition to no-snow much sooner than the ensemble mean projects.

431 Another notable feature of Figure 6 is the large range of transition times within
 432 each region of the 30-ensemble member transition times. We find that in some ensem-
 433 ble members, the earliest transition occurs over 15 years earlier than the mean transi-
 434 tion for many regions. For example, under the SSP5-8.5 and 90% area threshold, the first
 435 ensemble member in the Lower Colorado region transitions to no-snow in 2069 while the
 436 mean transition time of the ensemble members is not until 2086. The shape of the tran-
 437 sition time distribution under SSP2-4.5 is also more spread out than the high emissions
 438 scenario indicating larger uncertainty in the onset of no-snow conditions. The compressed
 439 timeline is a byproduct of the rapid warming accelerating the transition to no-snow be-
 440 cause the forcing of temperature and precipitation changes happens more quickly. Thus,
 441 internal climate variability is particularly influential in SSP2-4.5 when determining no-
 442 snow transition times, while in SSP5-8.5, the accelerated radiative forcing is the dom-
 443 inant effect. Furthermore, while emissions reductions improve the probability that the
 444 no-snow transition will occur later in the 21st century, they do not guarantee a later ar-
 445 rival. For example, in the PNW, a quarter of the SSP2-4.5 SPEAR members transition
 446 to no-snow before the median ensemble member under SSP5-8.5. This is particularly true
 447 for regions where the transition is projected to occur earlier in the 21st century, likely
 448 because scenario forcing is much more similar.

449 To assess the probability that a region becomes snow free over the next century,
 450 we examine the fraction of ensemble members that transition to no-snow before 2100.
 451 We model the likelihood of the transition by the maximum likelihood estimator (MLE),

452 or fraction of ensemble members that hit the transition threshold by 2100, and display
 453 these values in Table 1. By further splitting across the low and high emissions scenar-
 454 ios, we can model how the likelihood also changes as a function of the radiative forcing
 455 scenario. In Table 1, we see that under SSP5-8.5, $\mathcal{A} = 75\%$ is guaranteed by 2100 across
 456 all regions. The highest threshold ($\mathcal{A} = 90\%$) is guaranteed only for California, while
 457 uncertainty remains for the other 4 HUC2s. Conditions by 2100 are much less severe un-
 458 der SSP2-4.5, with only $\mathcal{A} = 50\%$ likely or certain for all regions, while for $\mathcal{A} = 75\%$,
 459 only California is very likely to transition to a low-snow regime; the other regions have
 460 low probability of doing so. For $\mathcal{A} = 90\%$ it is unlikely that any region will have tran-
 461 sitioned by 2100 under SSP2-4.5.

462 Furthermore, when we compare the likelihood of transition to no-snow conditions
 463 with the historical regionally averaged winter temperature, we find the coldest regions
 464 are least likely to transition while the warmest are most likely. For example, under SSP5-
 465 8.5 with $\mathcal{A} = 90\%$, the order of regions by cold to warm average winter temperature
 466 and lowest to highest transition probability is the same: UC (-5.1°C , 30%), PNW (-3.9°C ,
 467 53%), GB (-2.4°C , 70%), LC (-0.7°C , 83%), and CA (0.3°C , 100%). Like Shrestha et al.
 468 (2021), we find that warming any region with a winter average temperature to greater
 469 than -5°C negatively impacts SWE. We also find that warmer regions are expected to
 470 experience a greater increase in no-snow conditions, emphasizing the role historical tem-
 471 perature has in determining not only whether a region will see decreased SWE but also
 472 the magnitude of the change.

473 Table 1 indicates that under either SSP2-4.5 or SSP5-8.5 we expect at least half
 474 of the historically snowy WUS to have less than 10% of its historical April SWE by 2100.
 475 Both columns where $\mathcal{A} = 50\%$ show greater than 80% probability for all regions, with
 476 the threshold guaranteed under SSP5-8.5. We also find that under SSP5-8.5, 4 of the 5
 477 Western watersheds are more likely than not to cross the $\mathcal{A} = 90\%$ no-snow threshold
 478 by 2100. Upper Colorado is the exception with only a 30% chance, likely driven by lower
 479 average winter temperatures. While severe, it is important to consider how snow-covered
 480 area and total snow volume differ. As SWE declines are dominated by losses at lower
 481 elevations that are closer to the freezing point (Mote et al., 2005; Minder, 2010), we ex-
 482 pect the topological smoothing of SPEAR may result in an overestimate of the total amount
 483 of SWE storage lost. Therefore we expect the area-based no-snow transition to over-predict
 484 the hydrological impact of warming.

485 4 Summary

486 In this study, we analyze large ensembles from a coupled global climate model, SPEAR,
 487 to understand changes in SWE across the 20th and 21st centuries. According to SPEAR,
 488 the frequency of D2+ SD has already increased dramatically across the historical period,
 489 with an average increase across all regions of 51%. While higher than the estimate of 28%
 490 in observational data found by Huning and AghaKouchak (2020), the large amount of
 491 internal climate variability of WUS SWE within the SPEAR large ensemble indicates
 492 that chaotic climate variability could account for some of the difference. SPEAR projects
 493 even more dramatic changes to come by 2100, classifying over 35% of winter months as
 494 snow droughts under RCP2-4.5 and 60% under RCP5-8.5 compared with a normalized
 495 9.6% across the historical period. End-of-the-century projections suggest the average monthly
 496 temperature will exceed the 93rd and 97th percentiles of historical conditions under RCP2-
 497 4.5 and RCP5-8.5, respectively, and were found to be the primary driver of increased D2+
 498 SD. To understand when future conditions will deviate significantly from ‘normal,’ we
 499 applied the no-snow classification defined in Siirila-Woodburn et al. (2021) to each grid
 500 cell and across years for all SPEAR ensemble members, and aggregated on the HUC2
 501 level. We found that for the most severe threshold, $\mathcal{A} = 90\%$, a no-snow transition was
 502 more likely than not in four out of the five WUS HUC2s, the UC region being the ex-
 503 ception. Under RCP2-4.5, only $\mathcal{A} = 50\%$ was likely for all regions. Furthermore, our

Probability of No-Snow Transition by 2100						
HUC2 Region	SSP2-4.5: Area Threshold			SSP5-8.5: Area Threshold		
	50%	75%	90%	50%	75%	90%
Upper Colorado	83	0	0	100	97	30
Lower Colorado	87	23	7	100	100	83
Great Basin	100	7	0	100	100	70
Pacific Northwest	100	3	0	100	100	53
California	100	93	17	100	100	100
West-Wide	100	0	0	100	100	20

Table 1. Probability of a snow free transition occurring before 2100 at the 3 thresholds \mathcal{A} based on the fraction of ensemble members who transition to a no-snow regime by 2100. We show the probabilities by area threshold, 50%, 75%, and 90%, across SSP2-4.5 and SSP5-8.5 for the historically snowy portions of each of the 5 Western HUC2 regions.

504 finding that California is expected to transition to no snow earlier than most regions,
 505 and Upper Colorado later, is consistent with Siirila-Woodburn et al. (2021) who use dif-
 506 ferent climate models in their analysis. These conclusions emphasizes the role of future
 507 emissions in determining the no-snow transition timing.

508 We found regions with higher average winter temperatures were more likely to ex-
 509 perience a transition to no-snow. The Lower Colorado and California regions, which have
 510 the highest average winter temperatures, also had the highest probability of reaching no-
 511 snow conditions across both emissions scenarios and all area thresholds. The Pacific North-
 512 west and Upper Colorado, the regions with the coldest average temperatures, had the
 513 smallest transition probabilities. This finding parallels Shrestha et al. (2021), who found
 514 a strong correlation between average basin temperatures and the sensitivity of the re-
 515 gion’s snow to warming.

516 **5 Remarks**

517 By using initial condition large ensembles from a state-of-the-art GCM to study
 518 SD, we can conduct a region-wide study that accounts for both radiatively forced changes
 519 and the uncertainty attributable to internal climate variability. However, while SPEAR
 520 has higher atmospheric and land resolution than most current GCMs, its $1/2^\circ$ horizon-
 521 tal resolution is low when compared with many mountain snowpack models (Minder, 2010),
 522 which makes it unable to resolve complex mountain topography. This limitation can re-
 523 sult in significant warm biases and less snow (Matiu & Hanzer, 2022). We expect this
 524 may make SPEAR snowpack estimates particularly sensitive to warming, and therefore
 525 likely to overestimate increases in SD. Furthermore, Hoylman et al. (2022) asserts that
 526 using timescales longer than 30 years for drought baseline climatology, as has been done
 527 here and in the vast majority of previous literature (Svoboda et al., 2002), can result in

528 over-estimating the drought threat in a climate that is shifting towards (in this case) a
 529 less snowy state – although they argue that the reference period should take into con-
 530 sideration the adaptive capability of the system in question. Further work should inves-
 531 tigate both the sensitivity of SD estimates to GCM resolution and the effect of reference
 532 climatology choice on drought severity estimation.

533 Here, we have assessed changes in SD across the WUS in a GCM, focusing on val-
 534 idating historical changes, assessing changes to the underlying climatology, and deter-
 535 mining when WUS regions may essentially become snow-free. For this latter objective,
 536 we developed a metric, the no-snow transition time, to track both how soon a region is
 537 expected to change and the uncertainty of this timing attributable to internal climate
 538 variability. One promising avenue for future research is to examine SD changes over smaller
 539 regions, such as HUC4s, to determine the most vulnerable locations on a sub-region scale.
 540 This would also allow further exploration of SWE’s sensitivity to latitude and elevation,
 541 although at smaller watershed scales the GCM’s horizontal resolution will become more
 542 problematic. Also, estimating total SWE losses and melt timing across each region would
 543 allow us to better estimate the impacts of snow droughts on the West’s hydrological sys-
 544 tem. The impacts of future SDs will be felt across the entire country, both directly from
 545 the hydrological and tourism resources that consistent snowpack provides and indirectly
 546 through loss of agricultural output from summer water shortages or drifting wildfire smoke.
 547 Understanding the probable severity and timing of when these conditions are projected
 548 to become most damaging, alongside uncertainty from emissions and internal climate vari-
 549 ability, will allow policymakers and infrastructure planners to best prepare the West for
 550 a future with less snow.

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557 **Data availability statement:** The Livneh daily CONUS near-surface gridded
 558 meteorological and derived hydrometeorological data used in the historical analysis are
 559 available from the NCEI at doi:10.7289/V5X34VF6 (Livneh et al., 2013). The SPEAR
 560 ensemble simulation data used to assess historical and future snow drought in this study
 561 are kept at 10.5281/zenodo.7121527, with the full publicly-available dataset available
 562 at https://www.gfdl.noaa.gov/spear_large_ensembles/ (Delworth et al., 2020). The
 563 HUC2 shapefiles used to aggregate the climate data are kept at 10.5281/zenodo.7121527,
 564 which are originally from the USGS watershed boundary dataset ([https://www.usgs](https://www.usgs.gov/national-hydrography/watershed-boundary-dataset)
 565 [.gov/national-hydrography/watershed-boundary-dataset](https://www.usgs.gov/national-hydrography/watershed-boundary-dataset)). The scripts used for data
 566 processing and statistical analysis are preserved at 10.5281/zenodo.7130302 and de-
 567 veloped openly on GitHub at <https://github.com/Julians42/SnowDroughts>.

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