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Key Points:

- Daily maximum temperatures are cooler, and minimum temperatures are warmer, on wet days relative to dry days for most of the contiguous United States
- Observed maximum temperatures have warmed more on wet than dry days, while minimum temperatures have warmed more on dry than wet days
- Climate models depict slightly enhanced warming trends on dry days compared with wet days

Supporting Information:

Supporting Information may be found in the online version of this article.

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Precipitation Dependence of Temperature Trends Across the Contiguous US

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Abstract Temperature and precipitation covary across timescales due to thermodynamic and dynamic processes. We examine spatial patterns and trends of daily precipitation dependence of maximum and minimum temperature anomalies across the contiguous United States during 1950–2020. In the warm season, maximum temperatures are anomalously cool on wet days, while in the cool season, minimum temperatures are anomalously warm on wet days. During 1950–2020, warm-season maximum temperatures increased 0.5°C more on wet days than on dry days, whereas minimum temperature on dry days warmed slightly more than on wet days in both the warm and cool season. By contrast, climate models show more subtle and consistent precipitation dependence of temperature trends with approximately 0.2°C more warming on dry days than on wet days. Improved understanding of precipitation-dependent temperature trends is critical for understanding and modeling the impacts of changing climate on snowpack, drought, and heat stress.

Plain Language Summary Are wet days warmer or cooler than dry days, and have wet or dry days warmed faster? These simple questions have answers that vary spatially, seasonally, and diurnally. Here, we explore these patterns using long-term temperature records across the contiguous United States. We find that maximum temperatures generally warmed more on wet than dry days during 1950–2020, while the opposite was seen for minimum temperatures warmed more on dry days than wet days. Global climate models show a more consistent pattern of greater warming on dry days than wet days. The extent to which wet days warm relative to dry days with continued climate change will shape impacts on critical physical, ecological, and social systems, including snowpack, agricultural and ecological drought, and heat stress.

1. Introduction

Warming trends and their patterns are well established across the globe and largely attributable to anthropogenic forcing (Bindoff et al., 2013). Trends in regional temperature on seasonal and diurnal scales can exhibit notable differences from continental and global trends due to a consortium of factors including changes in circulation patterns (Abatzoglou & Redmond, 2007), land-use change (Christidis et al., 2013), changes in aerosols (Lelieveld et al., 2019), and concurrent trends in soil moisture (Vogel et al., 2017). Complementary to standard summaries of temperature trends (e.g., annual mean temperature), insight on climate change and associated impacts may be gained by decomposing temperature trends based on precipitation occurrence and amount. The covariance structure of daily temperature and precipitation and changes thereof have several notable impacts on hydrologic and ecological systems. For example, near the climatological freezing-level, the relationship between temperature and precipitation occurrence and amount can impact flood hazards (Musselman et al., 2018), snowpack storage (Klos et al., 2014), and water supply (Berghuijs et al., 2014). Likewise, differences in temperatures during the warm season between dry days and wet days impact vegetative moisture stress through altered evaporative demand with impacts to both agriculture and ecosystems (Holden et al., 2018).

Air temperature is sensitive to local radiation budgets and the advection of air masses associated with precipitation occurrence and intensity (Berg et al., 2009; Isaac & Stuart, 1992). For example, subtropical transport of warm moist air in atmospheric rivers during winter leads to anomalously warm daily minimum temperatures across the mountains of the western United States (US; Hu & Nolin, 2019), while reduced downward shortwave radiation during wet days in the warm season suppresses daily maximum temperature. Studies have examined the covariance of temperature and precipitation on monthly and seasonal timescales using both observations and climate models (Trenberth & Shea, 2005). Observed precipitation-dependent temperature trends across the contiguous US (CONUS) have been documented for some regions and seasons. Prior work has shown greater warming trends during wet days than during dry days in the cool season over the western US (Hu & Nolin, 2020; Knowles et al., 2006; Safeeq et al., 2016). However, a comprehensive geographic, seasonal, and diurnal analysis of daily precipitation dependence of temperature trends across CONUS is lacking.

Anthropogenic climate change will likely influence the precipitation dependence of temperature trends. Resolving how these dynamic and thermodynamic factors play out regionally and seasonally can help improve simulations of projected climate impacts that may be sensitive to precipitation-dependent temperature changes. On seasonal timescales, studies have projected enhanced warming in regions with reduced latent heat flux and increased downward shortwave fluxes co-located with reduced surface moisture and precipitation (Dirmeyer et al., 2013). On daily timescales, studies have shown the role of atmospheric dynamics and differential warming of air mass source regions leading to precipitation-dependent temperature trends. For example, O'Gorman and Schneider (2009) and Rupp and Li (2017) project relatively less warming of mid-to-high latitude landmasses during extreme precipitation days compared to dry days due to the reduced warming of subtropical air mass source regions for extreme precipitation events.

This study addresses these research gaps by examining spatial and seasonal patterns of the precipitation dependence of temperature anomalies and trends across CONUS. Specifically, we examined climatological differences in both daily maximum and daily minimum temperature anomalies between dry days and wet days, as well as between very wet days and low-to-moderate wet days during the warm season and cool season. Second, we examined temperature trends during 1950–2020 decomposed by precipitation occurrence and amount. Finally, we compare results from observational records to results from global climate models (GCMs).

2. Data/Methods

2.1. Data Sets

Daily observations of maximum temperature (T_{max}), minimum temperature (T_{min}), and precipitation (P) from 1140 stations in CONUS that are part of the Historical Climate Network (USHCN) were acquired from the daily Global Historical Climatology Network (GHCN-D; Menne et al., 2012) database during 1950–2020. Data flagged as failing any GHCN quality assurance check were discarded. We examined data from USHCN stations given their long-term, higher-quality records that attempt to reduce non-climatic influences. However, since T_{max} and T_{min} data in the current GHCN-D are not corrected for non-climatic biases (e.g., observational practices, station relocations), we apply a simple correction using USHCN monthly data (v2.5) that have been corrected for biases such as time of observation using pairwise station homogenization. Corrections were applied monthly such that the average of daily GHCN temperature data within a month matches USHCN monthly data, resulting in a consistent correction for each day of the month. Months missing more than 5 days of either T_{max} or T_{min} were discarded from subsequent analyses. No corrections were made to precipitation data. Supplemental monthly latent and sensible surface heat fluxes from ERA-5 (Hersbach et al., 2020) were additionally used to assess the potential influence of land-surface energy fluxes on interannual variability and trends in precipitation-dependent temperatures.

We complement observations with daily T_{max}, T_{min}, and P data from 20 GCMs that participated in the Coupled Model Intercomparison Project Phase 5 (CMIP5; Table S1 in Supporting Information S1). We limited our focus to historical climate experiments (1950–2005) and RCP4.5 climate experiments (2006–2020) for compatibility with the observational period. Climate model outputs were re-gridded to a common 2° spatial resolution grid.

2.2. Methods

Wet days were defined as days reporting at least 1 mm of precipitation, and very wet days as the top 10% of wet days defined separately for each station and season (Pryor et al., 2009). Dry days were defined as days reporting less than 1 mm of precipitation. To account for the influence of the seasonal cycle on temperature, temperature data were converted into anomalies relative to a centered 31-day moving average of daily 1981–2010 averages. We calculate T_{max} and T_{min} anomalies on (a) dry days, (b) wet days, (c) very wet days, and (d) low-to-moderate wet days (wet days not considered very wet). We focus on climatologies and trends over time for the cool season (November–April) and warm season (May–October). Results for traditional climatological seasons (e.g., December–February) are provided as figures in Supporting Information S1. We constrained most of our attention to these two 6-month periods due to both applied and statistical purposes. First, the covariance structure of temperature and precipitation during the cool season is important in shaping snowpack development (Hu & Nolin, 2020), while the daily covariance structure in the warm season is important for vegetation moisture stress through vapor pressure deficits (Hsiao et al., 2019). Second, our focus on the top 10% of wet days limits robust statistical analysis of trends with traditional 3-month climatological seasons at sites with infrequent wet days.

First, we examined the climatology of T_{max} and T_{min} anomalies conditioned by precipitation by pooling all data during 1981–2010. Specifically, we examined differences in temperature anomalies between wet days and dry days, as well as between very wet days and low-to-moderate wet days. We omitted stations with fewer than 10% wet days in a season. Significant differences in temperature anomalies stratified by daily precipitation category were qualified using a Student's t-test ($p < 0.05$).

Second, we examined T_{max} and T_{min} trends during dry days, very wet days, low-to-moderate wet days, and trends in the number of wet days during 1950–2020. Trends were analyzed from time series of average seasonal T_{max} and T_{min} anomalies calculated separately for dry days, wet days, and very wet days each year. This approach can lead to different sample sizes of days per year, but follows other studies using similar analytical approaches (Gonzales et al., 2019; Hu & Nolin, 2019). Complementary to our climatological analysis, we examined trends in the difference in temperature anomalies on wet days versus dry days as well as on very wet days versus low-to-moderate wet days. Years with more than 20% of days missing were omitted in station trend calculations. Trends were calculated using Sen-Theil slope estimator and were considered significant using a two-tailed Mann-Kendall trend test at $p < 0.05$. We additionally conducted tests for field significance (Livezey & Chen, 1983) to address multiple testing issues and violation of statistical independence assumptions due to spatial autocorrelation (Wilks, 2011). Trends were considered field significant when the fraction of locally significant trends of a given sign exceeds the 95th percentile of the distribution. Finally, we summarized regional trends over nine NOAA US climate regions. We report station mean trends for each region as well as the 95% confidence intervals assessed through bootstrap resampling with replacement across stations in each region.

Both the climatological and trend analyses were repeated for each GCM. While statistics were calculated separately for each GCM, we herein report results for the 20-model mean. Regional results were calculated using area-weighted trends for each NOAA US climate region.

3. Results

3.1. Climatology of Precipitation Dependence of Daily Temperature Anomalies

During the cool season (November–April), coherent patterns in differences of T_{min} and T_{max} anomalies between wet and dry days were observed across CONUS (Figure 1). Approximately 82% of stations had significantly higher T_{min} anomalies on wet days than dry days (+2.1°C warmer on wet days averaged across all stations), with the exception being in the immediate lee of the Rockies in the Great Plains (Figure 1b). The pattern for cool season T_{max} was more complex; T_{max} anomalies were significantly lower on wet days than dry days across the Great Plains and much of the southwestern US, while the opposite was found across the Ohio River Valley and Northeast (Figure 1a). Approximately 72% of stations had significantly higher T_{min} anomalies on very wet days than low-to-moderate wet days during the cool season (Figure 1d). Significantly higher T_{max} anomalies were observed on very wet days compared with low-to-moderate wet days during the cool season across windward portions of the Pacific Northwest and a broad section of the Midwest, Ohio River Valley, and Northeastern US (Figure 1c).

During the warm season (May–October), wet days had lower T_{max} anomalies and higher T_{min} anomalies compared with dry days across most of CONUS. Wet day T_{max} anomalies during the warm season were significantly lower than dry days for 99.5% of CONUS stations (station average −2.3°C; Figure 1e). By contrast, wet day T_{min} anomalies were significantly higher than dry day T_{min} anomalies for approximately 80% of stations, most notably across the Midwest and Ohio River Valley and portions of western Oregon and Washington, and Rocky Mountains (Figure 1f). Differences in temperature anomalies between very wet days and low-to-moderate wet days exhibited similar spatial patterns to those seen between wet days and dry days but were reduced in magnitude (Figures 1g and 1h). Overall, similar patterns for the warm season and the cool season were also found using

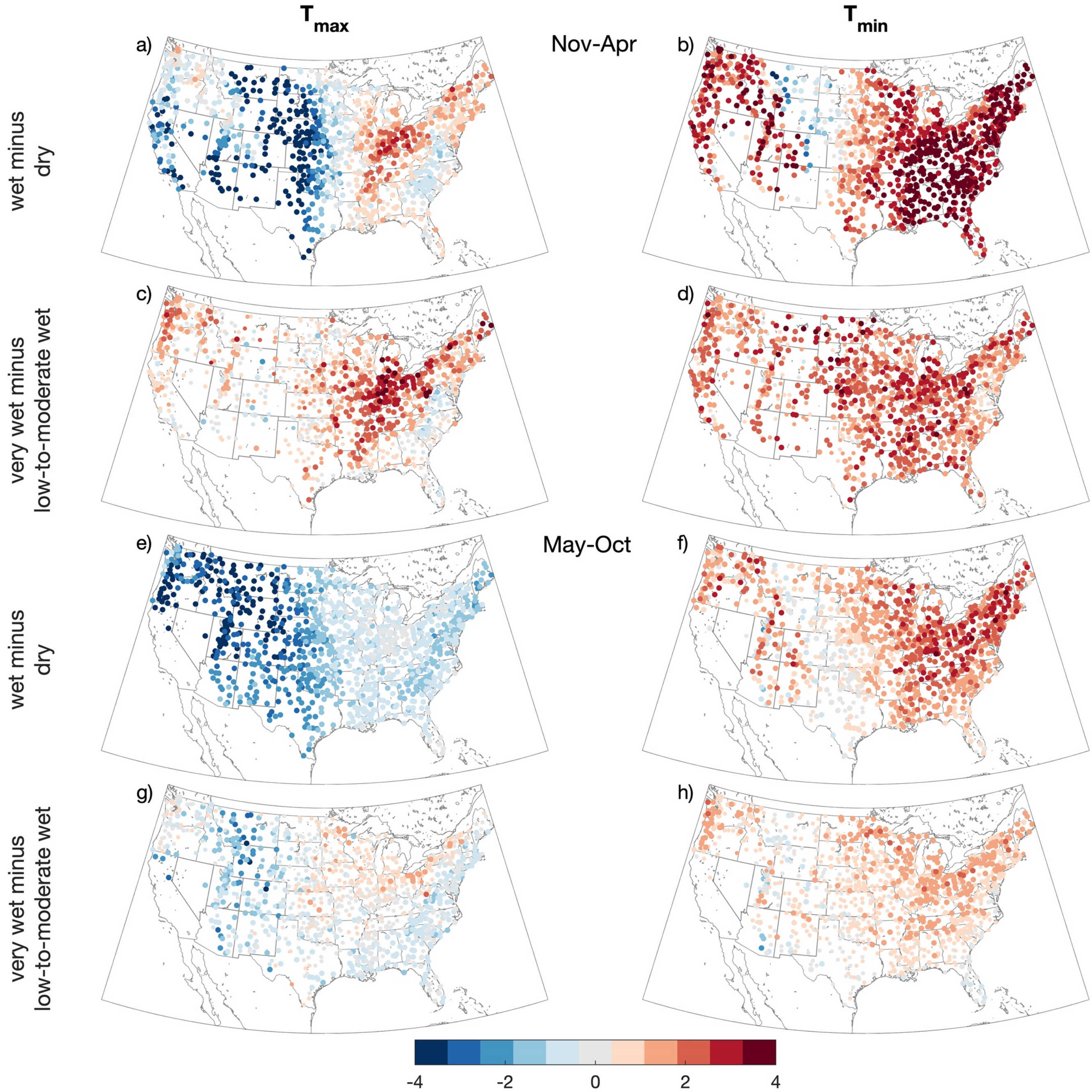

Figure 1. Differences in temperature anomalies for wet days minus dry days for (a) November–April T_{max}, (b) November–April T_{min}, (e) May–October T_{max}, and (f) May–October T_{min}. Composite differences in temperature anomalies for very wet days minus low-to-moderate wet days for (c) November–April T_{max}, (d) November–April T_{min}, (g) May–October T_{max}, and (h) May–October T_{min}. Large symbols denote statistical significance at $p < 0.05$ assessed using *t*-test. Stations with fewer than 10% wet days per season are omitted.

standard climatological seasons (Figure S1 in Supporting Information S1). Finally, we show that climate models reflect comparable precipitation-dependent differences in T_{max} and T_{min} anomalies to those observed (Figure S2 in Supporting Information S1).

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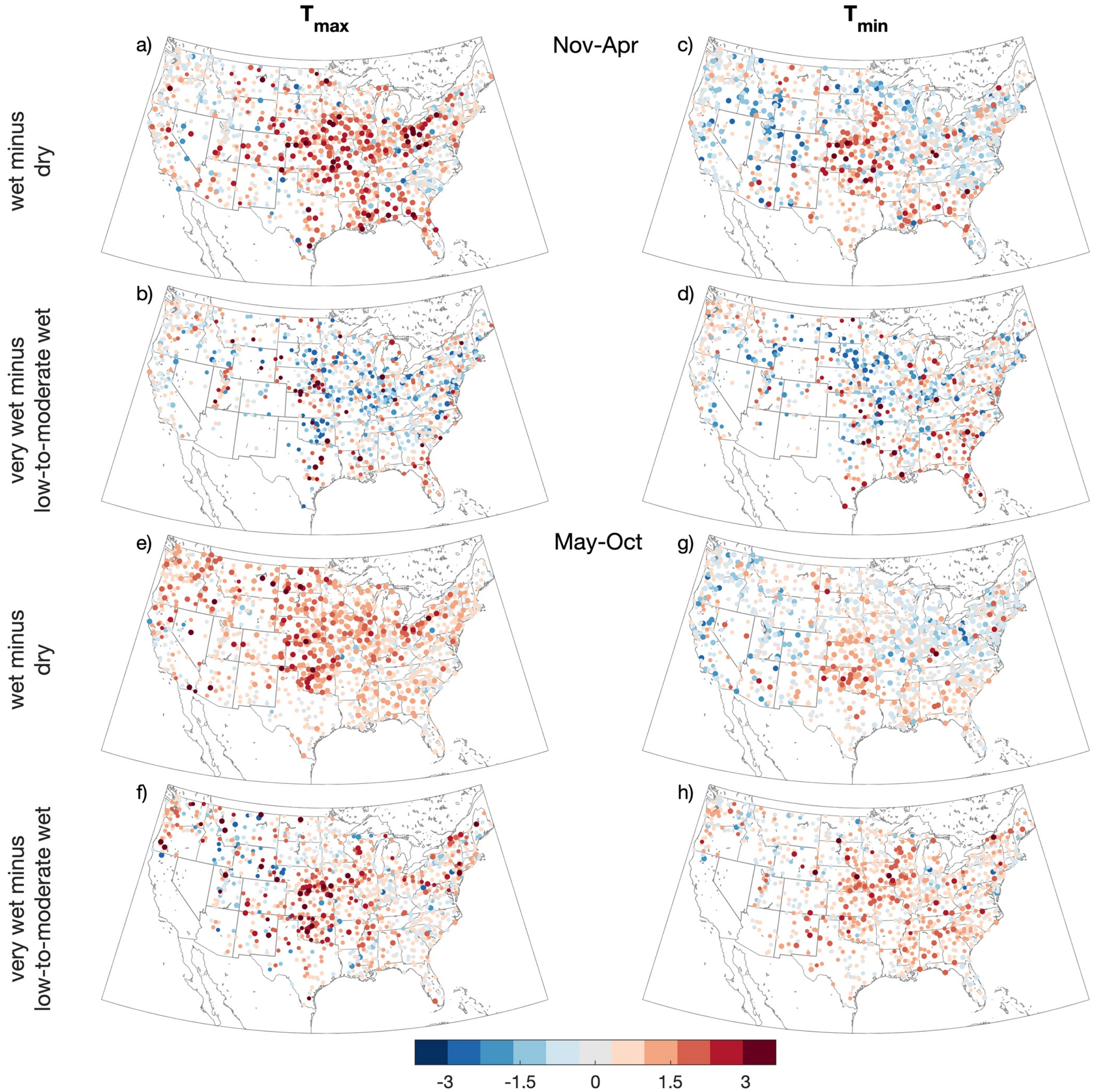

Figure 2. Trends during 1950–2020 (°C over the 71-year record) in temperature anomalies for wet days minus dry days for (a) November–April T_{max}, (b) November–April T_{min}, (e) May–October T_{max}, and (f) May–October T_{min}. Linear trends during 1950–2020 in temperature anomalies for very wet days minus low-to-moderate wet days for (c) November–April T_{max}, (d) November–April T_{min}, (g) May–October T_{max}, and (h) May–October T_{min}. Large symbols denote statistically significant ($p < 0.05$) trends. Trends in temperature for very wet days minus low-to-moderate wet days are omitted for stations with fewer than 10% wet days per season.

3.2. Precipitation Dependence of Temperature Trends

Regionally distinct precipitation-dependent trends in T_{min} and T_{max} anomalies were observed over CONUS during 1950–2020 (Figure 2; Figure S3 in Supporting Information S1 for climatological seasons). In the cool season, T_{max} anomalies on wet days warmed an average of +0.39°C relative to dry days over the 71-year period, including widespread significant relative warming across the central and southeastern US (Figure 2a, Tables S2 and S3 in Supporting Information S1). In the warm season, T_{max} anomalies on wet days warmed +0.53°C relative to dry days, with the most significant widespread relative differences in precipitation-dependent T_{max} trends observed

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across the Great Plains and Midwest (Figure 2e). Differences in T_{min} trends on wet days versus T_{min} trends on dry days were weaker and more spatially heterogeneous than for T_{max} with relative cooling of wet days versus dry days in both seasons (Tables S2 and S3 in Supporting Information S1).

Patterns in temperature trends on very wet days versus low-to-moderate wet days exhibited more subtle and heterogeneous differences, especially during the cool season. Very wet days in the cool season cooled relative to low-to-moderate wet days for both T_{max} and T_{min} anomalies by −0.46°C and −0.39°C, respectively (station average). By contrast, very wet days warmed +0.29°C and +0.26°C relative to low-to-moderate wet days in the warm season for both T_{max} and T_{min}, respectively. However, unlike widespread significant differences in temperature anomaly trends shown between wet days and dry days, differential temperature trends between very wet and low-to-moderate wet days were not field significant (Table S3 in Supporting Information S1).

3.3. Regional Summaries of Observations and Models

Most of the nine NOAA US climate regions showed positive trends in T_{max} and T_{min} anomalies during 1950–2020 in both the cool season and warm season (Figure 3; Table S2 in Supporting Information S1) with overall larger trends seen for T_{min} as reported by previous studies (Easterling et al., 1997). However, distinct differences in regional temperature trends were found when disaggregating by precipitation and season. In the cool season, dry days had greater T_{min} warming than wet days, and low-to-moderate wet days had greater warming than very wet days for most regions except the South and Southeast. In contrast, trends in T_{max} were higher on wet days relative to dry days in the warm season. Substantial asymmetry in dry day temperature trends for T_{max} versus T_{min} during the warm season were seen for most regions in the central and eastern US (Figure 3). Notably, several regions showed negligible warm season trends in dry day T_{max} in contrast to warming seen both in dry day T_{min} and both T_{max} and T_{min} on wet days during the warm season.

Changes in precipitation frequency as well as land-surface energy fluxes are hypothesized to have contributed to some of the observed precipitation-dependent temperature trends. For example, limited change in warm-season dry day T_{max} anomalies across portions of the central US during 1950–2020 may be imparted by increased latent heat fluxes (e.g., Jasinski et al., 2019) given that such land-surface fluxes have a larger impact on the surface energy budget on dry days than wet days (Adegoke et al., 2003). Notably, a significant increase in warm season latent heat flux was found only for the Rockies/Plains region during 1950–2020 in ERA-5 data (Figure S4 in Supporting Information S1). Additionally, we observed a significant increase in warm season wet days for 22% of stations (Figure S5 in Supporting Information S1), with widespread increases in the Rockies/Plains, Midwest and Northeast, consistent with previous studies (Bartels et al., 2020; Karl & Knight, 1998). Increased wet day frequency during the warm season and overall increased precipitation across much of the eastern two-thirds of CONUS during the last 71-year has increased surface soil moisture (Dai et al., 2004), in contrast to decreased warm season soil moisture across the western US (Williams et al., 2020). Across much of the central US, we posit that increased precipitation and latent heat fluxes have suppressed warm season dry day T_{max}. In support of these hypotheses, we find weak ($r = 0.3$–0.4), albeit statistically significant ($p < 0.05$), positive interannual correlations between the difference between wet day and dry day T_{max} in the warm season and both the number of wet days (from in situ observations) and latent heat flux (from ERA-5) for several regions (Figure S4 in Supporting Information S1).

Climate models depict more homogeneous changes in precipitation-dependent temperature trends (Figure 3; Figure S6 in Supporting Information S1). During the cool season, models depict attenuated warming for wet days relative to dry days, with the most notable differences in the Northwest and West regions where dry days warm 30%–40% more than very wet days for both maximum and minimum temperatures. During the warm season, models depict slightly less warming on wet days than dry days for most regions. While climate models showed relatively weak differences in precipitation-dependent temperature trends, there was general agreement in the sign of the differences across models (Table S4 in Supporting Information S1).

Formal attribution of the drivers of differences between GCM and observed asymmetric precipitation-dependent temperature trends is beyond the scope of the current analysis, though we briefly discuss potential mechanisms here. Observed precipitation-dependent T_{min} trends are similar to climate model trends with slightly enhanced warming on dry days compared with wet days. In contrast, differences between observations and climate models of the precipitation dependence of T_{max} trends are evident, particularly in the warm season. This suggests that

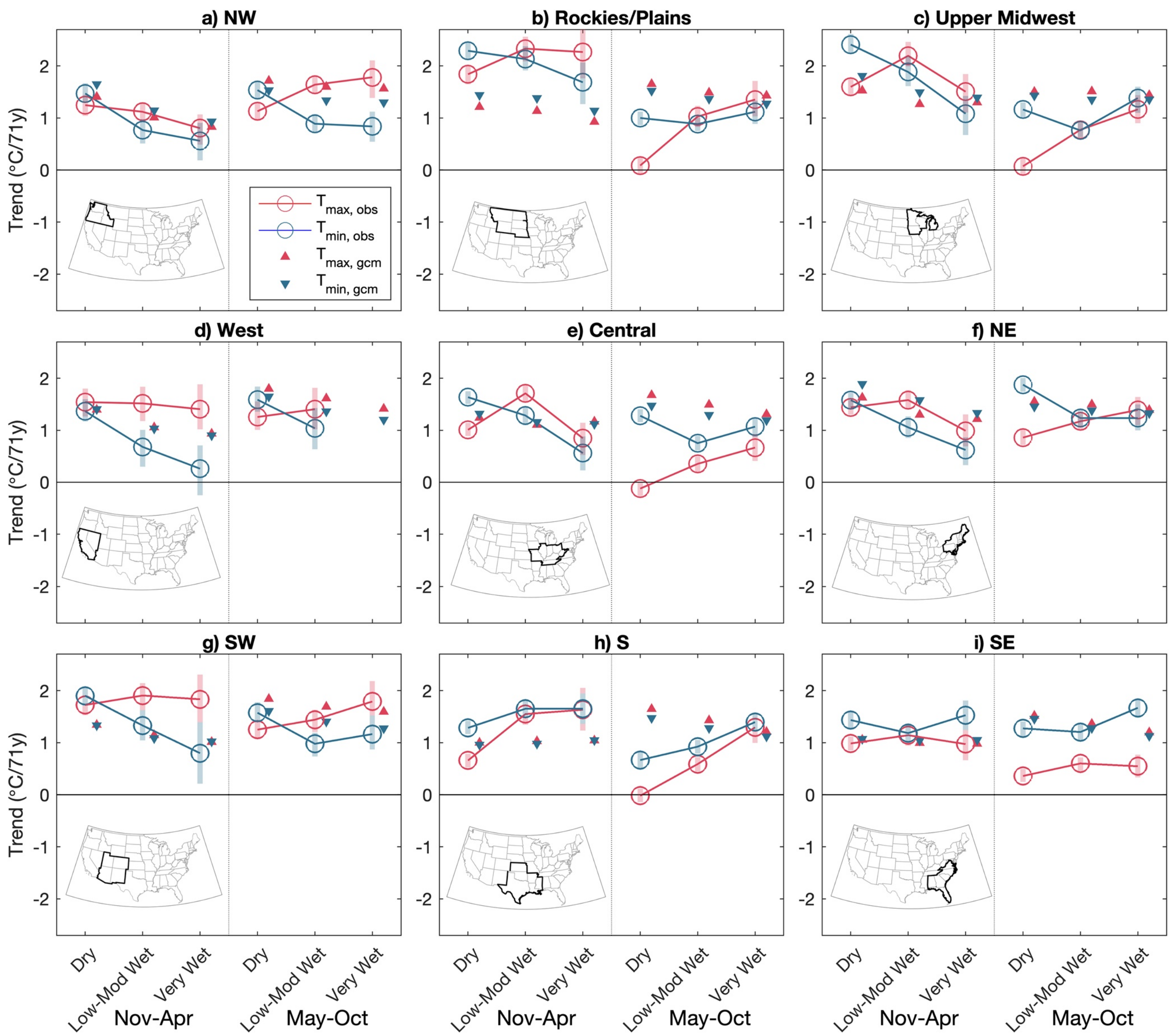

Figure 3. Regional trend in daily maximum temperature (T_{max}) and daily minimum temperature (T_{min}) for dry days, low-to-moderate wet days, and very wet days during 1950–2020 for November–April (left) and May–October (right). The regional trend is provided for station mean trends bracketed by the 95% confidence interval for each region obtained by bootstrap resampling of station trends. Regions with more than one-third of stations not having sufficient data for trend calculation are omitted. Triangles depict the mean trend computed from 20 individual climate models. The coverage of each National Oceanic and Atmospheric Administration climate regions is shown in the lower-left corner of each subplot.

factors not directly tied to anthropogenic forcing, such as the observed trends in precipitation and precipitation frequency, and possible local changes in land-use (Mishra et al., 2015), have contributed to observed precipitation dependence of T_{max}. We hypothesize that such differences are partially tied to internal variability. First, given the significant interannual correlations between wet day frequency and precipitation-dependent T_{max} (Figure S4 in Supporting Information S1), we note that observed increases in the number of wet days in the warm season in portions of the central and eastern US deviate from climate model simulations and are outside the range of trends simulated across the 20 climate models in some regions (Table S5 in Supporting Information S1). Increased precipitation and precipitation-frequency across the eastern two-thirds of CONUS may be potentially linked to pan-Pacific teleconnections (Strong et al., 2020). Second, changes in surface energy budgets imposed by the documented agricultural intensification and irrigation in the Midwest (e.g., Mueller et al., 2016; Nikiel & Eltahir, 2019) would tend to reduce dry day $T_{max;}$; these factors may not be adequately represented in GCMs. Lastly, while we used identical definitions of wet days for in situ observations and GCM output, differences in spatial scales–particularly for convective precipitation in the warm season–likely confound direct comparisons.

4. Discussion and Conclusions

Building on previous studies that examine monthly and seasonal covariance between temperature and precipitation (Madden & Williams, 1978; Trenberth & Shea, 2005), we demonstrate widespread significant differences in daily temperature anomalies conditioned by precipitation in both observations and climate models across CONUS. These results are largely consistent with first principles that dictate thermodynamic and advective processes, with distinct diurnal and seasonal differences. Increased downward longwave radiation associated with elevated atmospheric moisture and cloud cover as well as stronger warm air advection, including that from atmospheric rivers (Neiman et al., 2011), on very wet days favors anomalously high $T_{\min}$, particularly during the cool season for most of the region. By contrast, increased cloud cover during wet days inhibits downward shortwave radiation at the surface and daytime warming leading to generally anomalously low $T_{\max}$, particularly during the warm season. Notably, these advective and thermodynamic controls vary seasonally, geographically, and diurnally. For example, we show that $T_{\min}$ and $T_{\max}$ wet days are cooler than dry days during the cool season in the lee of the US Rockies, similar to results in the lee of the Canadian Rockies (Isaac & Stuart, 1992). The high frequency of downslope winds in the lee of the Rockies in the cool season (Abatzoglou et al., 2020) may contribute to compressional warming on dry days for part of the region.

Warming temperature trends were broadly observed across $T_{\min}$ and $T_{\max}$, seasonally, and across precipitation classes. The overall direction and magnitude of reported trends follow previous studies (Portmann et al., 2009), though trends shown here exhibit a few key differences when disaggregated by precipitation. Significant asymmetry in precipitation-dependent temperature trends was noted including widespread relative warming of $T_{\max}$ on wet days compared to dry days, particularly during the warm season. By contrast, observations showed a weak tendency for reduced warming of $T_{\min}$ on wet days compared to dry days. Whereas previous studies have shown relative warming of wet days compared to dry days regionally during the cool season (Safeeq et al., 2016), we show this response to be much more widespread and evident for $T_{\max}$ but not for $T_{\min}$. By contrast, climate models show consistent, albeit weak, precipitation-dependent temperature trends, predominantly with greater warming of both $T_{\min}$ and $T_{\max}$ on dry relative to wet days.

Observed and future changes in temperature have a constellation of impacts for society and the environment. Very wet days in regions where water resources are snow dependent such as the western US showed reduced rates of warming in the cool season relative to other days. Recognizing that heavy snowfall events account for 20%–38% of annual snowfall totals (Lute & Abatzoglou, 2014), reduced warming on very wet days in climate model simulations may buffer snowpack declines relative to assumed changes that are agnostic with respect to precipitation dependent temperature changes. Some climate projections project such asymmetric precipitation-dependent temperature changes under continued climate change (Rupp & Li, 2017). Changing temperature-precipitation covariance structures may also represent a source of error for the many studies of climate change impacts that use historical temperature sensitivity of a social or ecological outcome to anticipate future conditions (Marshall et al., 2020). Statistical downscaling approaches should incorporate such differential rates of warming conditioned on precipitation (e.g., Cannon, 2018) in contrast to simple approaches that apply uniform warming. Finally, climate projections suggest a decrease in wet day occurrence across parts of the western US by the end of the century with limited changes in the eastern US (Polade et al., 2014). Given the distinct differences in $T_{\max}$ and $T_{\min}$ trends between wet and dry days, such changes in wet day occurrence would likely be reflected in overall temperature changes.

Data Availability Statement

Data sets used herein were acquired from the following public repositories: (a) GHCN-Daily (https://www.ncdc.noaa.gov/ghcn-daily-description/), (b) USHCN v2.5 data (https://www.ncei.noaa.gov/data/us-historical-climatology-network/2.5/), (c) Daily CMIP5 output (https://esgf-node.llnl.gov/search/cmip5/).

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References

Abatzoglou, J. T, Hatchett, B. J., Fox-Hughes, P., Gershunov, A., & Nauslar, N. J. (2020). Global climatology of synoptically-forced downslope winds. *International Journal of Climatology*, *41*(1), 31–50. https://doi.org/10.1002/joc.6607

Abatzoglou, J. T., & Redmond, K. T. (2007). Asymmetry between trends in spring and autumn temperature and circulation regimes over western North America. *Geophysical Research Letters*, *34*(18), L18808. https://doi.org/10.1029/2007GL030891

Adegoke, J. O., Pielke Sr, R. A., Eastman, J., Mahmood, R., & Hubbard, K. G. (2003). Impact of irrigation on midsummer surface fluxes and temperature under dry synoptic conditions: A regional atmospheric model study of the US High Plains. *Monthly Weather Review*, *131*(3), 556–564. https://doi.org/10.1175/1520-0493(2003)131<0556:ioioms>2.0.co;2

Bartels, R. J., Black, A. W., & Keim, B. D. (2020). Trends in precipitation days in the United States. *International Journal of Climatology*, *40*(2), 1038–1048. https://doi.org/10.1002/joc.6254

Berg, P., Haerter, J. O., Thejll, P., Piani, C., Hagemann, S., & Christensen, J. H. (2009). Seasonal characteristics of the relationship between daily precipitation intensity and surface temperature. *Journal of Geophysical Research*, *114*, D18102. https://doi.org/10.1029/2009JD012008

Berghuijs, W. R., Woods, R. A., & Hrachowitz, M. (2014). A precipitation shift from snow towards rain leads to a decrease in streamflow. *Nature Climate Change*, *4*(7), 583–586. https://doi.org/10.1038/nclimate2246

Bindoff, N. L., Stott, P. A., AchutaRao, K. M., Allen, M. R., Gillett, N., Gutzler, D., et al. (2013). Chapter 10 - Detection and attribution of climate change: From global to regional. *In Climate change 2013: The physical science basis. IPCC Working Group I Contribution to AR5*. Cambridge: Cambridge University Press.

Cannon, A. J. (2018). Multivariate quantile mapping bias correction: An N-dimensional probability density function transform for climate model simulations of multiple variables. *Climate Dynamics*, *50*(1–2), 31–49. https://doi.org/10.1007/s00382-017-3580-6

Christidis, N., Stott, P. A., Hegerl, G. C., & Betts, R. A. (2013). The role of land use change in the recent warming of daily extreme temperatures. *Geophysical Research Letters*, *40*(3), 589–594. https://doi.org/10.1002/grl.50159

Dai, A., Trenberth, K. E., & Qian, T. (2004). A global dataset of Palmer Drought Severity Index for 1870–2002: Relationship with soil moisture and effects of surface warming. *Journal of Hydrometeorology*, *5*(6), 1117–1130. https://doi.org/10.1175/JHM-386.1

Dirmeyer, P. A., Jin, Y., Singh, B., & Yan, X. (2013). Trends in land–atmosphere interactions from CMIP5 simulations. *Journal of Hydrometeorology*, *14*(3), 829–849. https://doi.org/10.1175/JHM-D-12-0107.1

Easterling, D. R., Horton, B., Jones, P. D., Peterson, T. C., Karl, T. R., Parker, D. E., et al. (1997). Maximum and minimum temperature trends for the globe. *Science*, *277*(5324), 364–367. https://doi.org/10.1126/science.277.5324.364

Gonzales, K. R., Swain, D. L., Nardi, K. M., Barnes, E. A., & Diffenbaugh, N. S. (2019). Recent warming of landfalling atmospheric rivers along the west Coast of the United States. *Journal of Geophysical Research: Atmospheres*, *124*(13), 6810–6826. https://doi.org/10.1029/2018JD029860

Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., et al. (2020). The ERA5 global reanalysis. *Quarterly Journal of the Royal Meteorological Society*, *146*(730), 1999–2049. https://doi.org/10.1002/qj.3803

Holden, Z. A., Swanson, A., Luce, C. H., Jolly, W. M., Maneta, M., Oyler, J. W., et al. (2018). Decreasing fire season precipitation increased recent western US forest wildfire activity. *Proceedings of the National Academy of Sciences*, *115*(36), E8349–E8357. https://doi.org/10.1073/pnas.1802316115

Hsiao, J., Swann, A. L. S., & Kim, S.-H. (2019). Maize yield under a changing climate: The hidden role of vapor pressure deficit. *Agricultural and Forest Meteorology*, *279*, 107692. https://doi.org/10.1016/j.agrformet.2019.107692

Hu, J. M., & Nolin, A. W. (2019). Snowpack contributions and temperature characterization of landfalling atmospheric rivers in the western Cordillera of the United States. *Geophysical Research Letters*, *46*(12), 6663–6672. https://doi.org/10.1029/2019GL083564

Hu, J. M., & Nolin, A. W. (2020). Widespread warming trends in storm temperatures and snowpack fate across the Western United States. *Environmental Research Letters*, *15*(3), 34059. https://doi.org/10.1088/1748-9326/ab763f

Isaac, G. A., & Stuart, R. A. (1992). Temperature–Precipitation relationships for Canadian stations. *Journal of Climate*, *5*(8), 822–830. https://doi.org/10.1175/1520-0442(1992)005<0822:TRFCS>2.0.CO;2

Jasinski, M. F., Borak, J. S., Kumar, S. V., Mocko, D. M., Peters-Lidard, C. D., Rodell, M., et al. (2019). NCA-LDAS: Overview and analysis of hydrologic trends for the national climate assessment. *Journal of Hydrometeorology*, *20*(8), 1595–1617. https://doi.org/10.1175/jhm-d-17-0234.1

Karl, T. R., & Knight, R. W. (1998). Secular trends of precipitation amount, frequency, and intensity in the United States. *Bulletin of the American Meteorological Society*, *79*, 231–242. https://doi.org/10.1175/1520-0477(1998)079<0231:stopaf>2.0.co;2

Klos, P. Z., Link, T. E., & Abatzoglou, J. T. (2014). Extent of the rain-snow transition zone in the western US under historic and projected climate. *Geophysical Research Letters*, *41*(13), 4560–4568. https://doi.org/10.1002/2014GL060500

Knowles, N., Dettinger, M. D., & Cayan, D. R. (2006). Trends in snowfall versus rainfall in the western United States. *Journal of Climate*, *19*(18), 4545–4559. https://doi.org/10.1175/jcli3850.1

Lelieveld, J., Klingmüller, K., Pozzer, A., Burnett, R. T., Haines, A., & Ramanathan, V. (2019). Effects of fossil fuel and total anthropogenic emission removal on public health and climate. *Proceedings of the National Academy of Sciences*, *116*(15), 7192–7197. https://doi.org/10.1073/pnas.1819989116

Livezey, R. E., & Chen, W. Y. (1983). Statistical field significance and its determination by Monte Carlo techniques. *Monthly Weather Review*, *111*(1), 46–59. https://doi.org/10.1175/1520-0493(1983)111<0046:SFSAID>2.0.CO;2

Lute, A. C., & Abatzoglou, J. T. (2014). Role of extreme snowfall events in interannual variability of snowfall accumulation in the western United States. *Water Resources Research*, *50*(4), 2874–2888. https://doi.org/10.1002/2013WR014465

Madden, R. A., & Williams, J. (1978). The correlation between temperature and precipitation in the United States and Europe. *Monthly Weather Review*, *106*(1), 142–147. https://doi.org/10.1175/1520-0493(1978)106<0142:TCBTAP>2.0.CO;2

Marshall, A. M., Foard, M., Cooper, C. M., Edwards, P., Hirsch, S. L., Russell, M., & Link, T. E. (2020). Climate change literature and information gaps in mountainous headwaters of the Columbia River Basin. *Regional Environmental Change*, *20*(4), 134. https://doi.org/10.1007/s10113-020-01721-7

Menne, M. J., Durre, I., Vose, R. S., Gleason, B. E., & Houston, T. G. (2012). An overview of the global historical climatology network-daily database. *Journal of Atmospheric and Oceanic Technology*, *29*(7), 897–910. https://doi.org/10.1175/jtech-d-11-00103.1

Mishra, V., Ganguly, A. R., Nijssen, B., & Lettenmaier, D. P. (2015). Changes in observed climate extremes in global urban areas. *Environmental Research Letters*, *10*(2), 24005. https://doi.org/10.1088/1748-9326/10/2/024005

Mueller, N. D., Butler, E. E., McKinnon, K. A., Rhines, A., Tingley, M., Holbrook, N. M., & Huybers, P. (2016). Cooling of US Midwest summer temperature extremes from cropland intensification. *Nature Climate Change*, *6*(3), 317–322. https://doi.org/10.1038/nclimate2825

Musselman, K. N., Lehner, F., Ikeda, K., Clark, M. P., Prein, A. F., Liu, C., et al. (2018). Projected increases and shifts in rain-on-snow flood risk over western North America. *Nature Climate Change*, *8*(9), 808–812. https://doi.org/10.1038/s41558-018-0236-4

Neiman, P. J., Schick, L. J., Ralph, F. M., Hughes, M., & Wick, G. A. (2011). Flooding in western Washington: The connection to atmospheric rivers. *Journal of Hydrometeorology*, *12*(6), 1337–1358. https://doi.org/10.1175/2011JHM1358.1

Nikiel, C. A., & Eltahir, E. A. B. (2019). Summer climate change in the Midwest and Great Plains due to agricultural development during the twentieth century. *Journal of Climate*, *32*(17), 5583–5599. https://doi.org/10.1175/JCLI-D-19-0096.1

O'Gorman, P. A., & Schneider, T. (2009). The physical basis for increases in precipitation extremes in simulations of 21st-century climate change. *Proceedings of the National Academy of Sciences*, *106*(35), 14773–14777. https://doi.org/10.1073/pnas.0907610106

Polade, S. D., Pierce, D. W., Cayan, D. R., Gershunov, A., & Dettinger, M. D. (2014). The key role of dry days in changing regional climate and precipitation regimes. *Scientific Reports*, *4*, 4364. https://doi.org/10.1038/srep04364

Portmann, R. W., Solomon, S., & Hegerl, G. C. (2009). Spatial and seasonal patterns in climate change, temperatures, and precipitation across the United States. *Proceedings of the National Academy of Sciences*, *106*(18), 7324–7329. https://doi.org/10.1073/pnas.0808533106

Pryor, S. C., Howe, J. A., & Kunkel, K. E. (2009). How spatially coherent and statistically robust are temporal changes in extreme precipitation in the contiguous USA? *International Journal of Climatology*, *29*(1), 31–45. https://doi.org/10.1002/joc.1696

Rupp, D. E., & Li, S. (2017). Less warming projected during heavy winter precipitation in the Cascades and Sierra Nevada. *International Journal of Climatology*, *37*(10), 3984–3990. https://doi.org/10.1002/joc.4963

Safeeq, M., Shukla, S., Arismendi, I., Grant, G. E., Lewis, S. L., & Nolin, A. (2016). Influence of winter season climate variability on snow–precipitation ratio in the western United States. *International Journal of Climatology*, *36*(9), 3175–3190. https://doi.org/10.1002/joc.4545

Strong, C., McCabe, G. J., & Weech, A. (2020). Step increase in eastern U.S. Precipitation linked to Indian Ocean warming. *Geophysical Research Letters*, *47*(17), e2020GL088911. https://doi.org/10.1029/2020GL088911

Trenberth, K. E., & Shea, D. J. (2005). Relationships between precipitation and surface temperature. *Geophysical Research Letters*, *32*, L14703. https://doi.org/10.1029/2005GL022760

Vogel, M. M., Orth, R., Cheruy, F., Hagemann, S., Lorenz, R., van den Hurk, B. J. J. M., & Seneviratne, S. I. (2017). Regional amplification of projected changes in extreme temperatures strongly controlled by soil moisture-temperature feedbacks. *Geophysical Research Letters*, *44*(3), 1511–1519. https://doi.org/10.1002/2016GL071235

Wilks, D. S. (2011). Statistical methods in the atmospheric sciences. Vol. 100. Academic press.

Williams, A. P., Cook, E. R., Smerdon, J. E., Cook, B. I., Abatzoglou, J. T., Bolles, K., et al. (2020). Large contribution from anthropogenic warming to an emerging North American megadrought. *Science*, *368*(6488), 314–318. https://doi.org/10.1126/science.aaz9600