Record Low North American Monsoon Rainfall in 2020 Reignites Drought over the American Southwest

Andrew Hoell, Xiao-Wei Quan, Martin Hoerling, Rong Fu, Justin Mankin, Isla Simpson, Richard Seager, Cenlin He, Flavio Lehner, Joel Lisonbee, Ben Livneh, Amanda Sheffield

Model experiments suggest climate change increased the risk for record low American Southwest precipitation in June–September 2020, but confidence is low due to model biases and no significant observed trends.

AFFILIATIONS: Hoell and Hoerling—NOAA Physical Sciences Laboratory, Boulder, Colorado; **Quan**—NOAA Physical Sciences Laboratory, and Cooperative Institute for Research in the Environmental Sciences, University of Colorado, Boulder, Colorado; **Fu**—University of California, Los Angeles, Los Angeles, California; **Mankin**—Dartmouth College, Hanover, New Hampshire, and Lamont Doherty Earth Observatory of Columbia University, Palisades, New York; **Simpson**—Climate and Global Dynamics Laboratory, National Center for Atmospheric Research, Boulder, Colorado; **Seager**—Lamont Doherty Earth Observatory of Columbia University, Palisades, New York; **He**—Research Applications Laboratory, National Center for Atmospheric Research, Boulder, Colorado; **Lehner**—Department of Earth and Atmospheric Sciences, Cornell University, Ithaca, New York, and Climate and Global Dynamics Laboratory, National Center for Atmospheric Research, Boulder, Colorado; **Lisonbee and Sheffield**—NOAA National Integrated Drought Information System, and Cooperative Institute for Research in the Environmental Sciences, University of Colorado, Boulder, Colorado; **Livneh**—Cooperative Institute for Research in the Environmental Sciences, and Department of Civil, Environmental, and Architectural Engineering, University of Colorado, Boulder, Colorado

CORRESPONDING AUTHOR: Andrew Hoell, andrew.hoell@noaa.gov

DOI: 10.1175/BAMS-D-21-0129.1

Drought has plagued the American Southwest since 2000, leading to the second lowest estimated 19-yr average soil moisture in approximately 1200 years (Williams et al. 2020), fueling destructive wildfires (Fu et al. 2021) and inducing low flows in major rivers (Udall and Overpeck 2017; Hoerling et al. 2019). In 2020/21, drought deepened against the backdrop of two decades of accumulated drought damages that exceed $131.4 billion (NCEI 2021) and caused alarm about potential water delivery shortages in the Colorado River basin (U.S. Bureau of Reclamation 2021). The proximate causes for persistent regional droughts include low precipitation (Lehner et al. 2018) and increased evaporative demand in concert with warming temperatures (Crockett and Westerling 2018; Williams et al. 2020). While there is strong evidence for anthropogenic forcing of the warming trend (e.g., USGCRP 2018), recent work has also pointed to a potential human effect on Southwest precipitation (Pascale et al. 2017; Hoerling et al. 2019; He et al. 2020).

Precipitation deficits during the 2020 monsoon season were especially severe over Arizona, New Mexico, Colorado, and Utah (the Four Corners states) and were crucial in re-establishing the regional drought

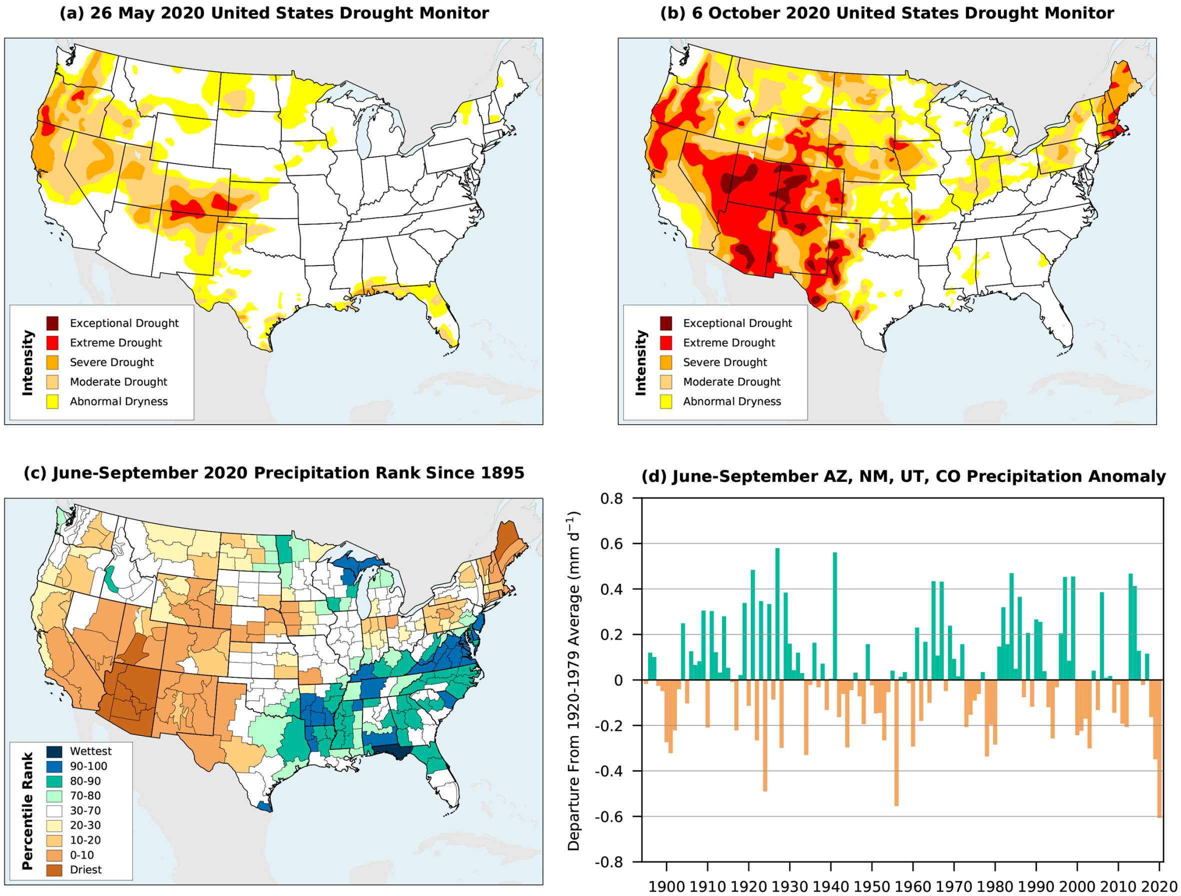

Fig. 1. USDM issued on (a) 26 May 2020 and (b) 6 Oct 2020. (c) June–September 2020 precipitation percentile rank since 1895. (d) For the Four Corners states, June–September area average precipitation anomaly time series relative to the past (1920–79) climate average.

(Fig. 1). On 26 May 2020, the United States Drought Monitor (USDM; Svoboda et al. 2002) indicated that less than half of the Four Corners states area was in at least moderate drought (Fig. 1a). By 6 October 2020, 75% of the area was covered by extreme drought (Fig. 1b). June–September precipitation averaged over the Four Corners states was the lowest since at least 1895 (Figs. 1c,d).

Here we examine whether anthropogenic climate change influenced an unprecedented failure of 2020 summer monsoon rains that reignited drought conditions. We focus on the Four Corners states during June–September 2020 using observed analyses, historical coupled climate models, atmospheric models, and event-attribution experiments.

Tools and methods.

Observed analyses. Drought assessments are from the USDM (Svoboda et al. 2002).[1] Observed precipitation analyses for June–September 1895–2020 are based on United States climate divisions (Vose et al. 2014).[2] Precipitation for the Four Corners states is an area-weighted average for all climate divisions in Utah, Arizona, Colorado, and New Mexico.

[1] https://droughtmonitor.unl.edu/Data/GISData.aspx

[2] www.ncei.noaa.gov/pub/data/cirs/climdiv/

Model simulations. Coupled climate simulations for 1920–2019 are diagnosed. One is the 40-member Community Earth System Model version 1 large ensemble (CESM1; Kay et al. 2015) and the second is the 30-member Seamless System for Prediction and Earth System Research (SPEAR; Delworth et al. 2020). A 10-member ensemble of Community Atmosphere Model version 6 simulations (CAM6; Danabasoglu et al. 2020) are also diagnosed. In all three, time-evolving greenhouse gases and anthropogenic aerosols are specified: CESM1 following a CMIP5 protocol (Taylor et al. 2012) and SPEAR and CAM6 following a CMIP6 protocol (Eyring et al. 2016). CAM6 is further constrained by specified monthly observed sea surface temperature (SST; Huang et al. 2017) and sea ice variations (Rayner et al. 2003), and are employed since surface boundary conditions have been shown to play a role in shaping American Southwest precipitation (Schubert et al. 2016).

Event-attribution experiments are diagnosed using parallel 50-member ECHAM5 (Roeckner et al. 2006) atmospheric model ensembles for 1979–2020. The first ensemble (*factual*) is conducted like the CAM6 simulations in which the observed SSTs, sea ice, and chemical composition are specified based on monthly historical analyses. The second ensemble [*counterfactual* (cf)] sets the atmospheric chemical composition to circa 1900 values and removes observed 1900–2019 linear SST trends from their interannual variations [see Sun et al. (2018) and Hoerling et al. (2019) for details]. Two assumptions on long-term SST change are made: one in which observed zonally averaged SST trends are removed (cfv1) and the second in which the observed two-dimensional SST trend pattern is removed from time-evolving SSTs (cfv2). Simulated Four Corners states precipitation is obtained by calculating the average of all grid points in that four-state region. Model data may be obtained from the Facility for Weather and Climate Assessments (Murray et al. 2020).[3]

[3] https://psl.noaa.gov/repository/facts/

Methods. Past (1920–79) and recent (1990–2019) climates are compared to estimate the effects of historical change in June–September precipitation. Such a comparison in the historical simulations isolates the effect of the prescribed forcing, which is mostly anthropogenic (Bindoff et al. 2013). For event-attribution experiments, the recent climate is given by factual ensembles for 1990–2019 and the past climate is given by the cfv1 and cfv2 ensembles.

Our principal metric for assessing climate change effects is the relative risk ratio (e.g., Otto et al. 2018) of low precipitation, where values larger than one indicate more frequent low precipitation in the recent climate relative to the past. Histograms are evaluated to calculate relative risk of change in seasonal precipitation falling below the 50% (median), 10% (decile), 5% (ventile), and 1% (percentile) thresholds of June–September precipitation. Confidence intervals of relative risk ratios are derived using a bootstrapping approach, given negligible temporal autocorrelation of June–September precipitation in the observed analysis ($r = -0.02$) and in the models (not shown). The bootstrapping approach is described in the online supplemental material.

Two approaches, both based on bootstrapping, provide a brief appraisal of model performance. The first compares the first three moments (mean, variance, skewness) of precipitation in the model's past and recent climates to the observed analysis. The second compares the mean precipitation difference between past and recent climates in the models to the observed analysis. The bootstrapping approach is described in the supplement. In terms of regional precipitation characteristics, the mean, variance, and skewness of the models differ from each other and the observed analysis to varying degrees (Table 1). Some models simulate more realistic mean precipitation (e.g., SPEAR) while others simulate more realistic variability (e.g., ECHAM5), although no models simulate both well. In terms of average precipitation difference from past to recent climates, some models are able to simulate the small observed precipitation increase as a possible outcome within a 95% confidence interval of its bootstrapped simulated distribution (e.g., SPEAR, CESM1, ECHAM5 cfv1 in Fig. S1).

Results.

Whereas record low precipitation in June–September 2020 over the Four Corners states capped off a 3-yr stretch of below average rainfall (Fig. 1d), no significant trend since 1895 is

Table 1. Mean, variance, and skewness of past (1920–79) and recent (1990–2019) climate precipitation in the observed analysis and bootstrapped model ensembles. Three values are provided for the model ensembles, the 2.5th (blue) and 97.5th (orange) percentiles to estimate the 95% confidence interval, and the median (gray).

	Past (1920–79)			Recent (1990–2019)		
	Mean	Variance	Skewness	Mean	Variance	Skewness
Observed analysis	1.256	0.057	0.374	1.281	0.058	0.459
CESM1	1.847	0.057	−0.431	1.851	0.052	−0.476
	1.924	0.085	0.162	1.959	0.089	0.181
	2.000	0.121	0.943	2.067	0.138	0.966
SPEAR	1.132	0.067	−0.170	1.011	0.050	−0.331
	1.212	0.099	0.355	1.120	0.092	0.374
	1.295	0.140	0.947	1.236	0.157	1.391
CAM6	1.464	0.078	−0.153	1.233	0.028	−0.415
	1.551	0.114	0.366	1.315	0.051	0.375
	1.641	0.160	0.974	1.491	0.084	1.196
ECHAM5 cfv1	0.804	0.049	−0.220	0.665	0.041	−0.378
	0.870	0.073	0.351	0.764	0.073	0.295
	0.940	0.104	0.999	0.863	0.116	1.065
ECHAM5 cfv2	0.785	0.048	−0.121	0.666	0.042	−0.380
	0.851	0.071	0.379	0.763	0.073	0.293
	0.921	0.099	0.951	0.685	0.115	1.053

found (Figs. 1d and 2a; see also Fig. S1a in the online supplemental material). Further, no statistically significant change in the frequency of low precipitation is noted from past to recent climates (Fig. 2g). Given the brevity of observations, we use multiple models and large ensembles, controlled in various ways for historical climate drivers, to test the effect of climate change on low precipitation occurrences.

Four of five models indicate statistically significant decreases in mean June–September precipitation from past to recent climates over the Four Corners states, with only CESM1 dissenting (Figs. 2b–f). SPEAR and CAM6 simulate 0.089 mm day^{-1} (7%) and 0.235 mm day^{-1} (15%) mean precipitation declines, respectively, via a dry shift in the probability distribution from past to recent climates. The same climate change sensitivity in these transient experiments is also found in the ECHAM5 event-attribution experiments. All these experiments are consistent in their widespread precipitation decreases from past to recent climates over the American Southwest, though their spatial patterns differ (Fig. S2). The CESM1, in contrast, simulates a slight increase in June–September precipitation from past to recent climates.

Statistically significant increases in the risk of extreme low seasonal precipitation in the recent climate relative to the past is found across four of five models, given that the 95% confidence intervals exceed a relative risk of unity (whiskers in Fig. 2g). As indicated by changes in risk (dots in Fig. 2g), low decile occurrences for seasonal rainfall are found to be 1.5–2.5 times more likely, while the more extreme low percentile occurrences are found to be 2.5–5.5 times more likely in SPEAR, CAM6, ECHAM5 cfv2, and ECHAM5 cfv1. The 95% confidence interval, or uncertainty, is larger for smaller ensembles (cf. CAM6 and SPEAR) and precipitation thresholds that occur less frequently.

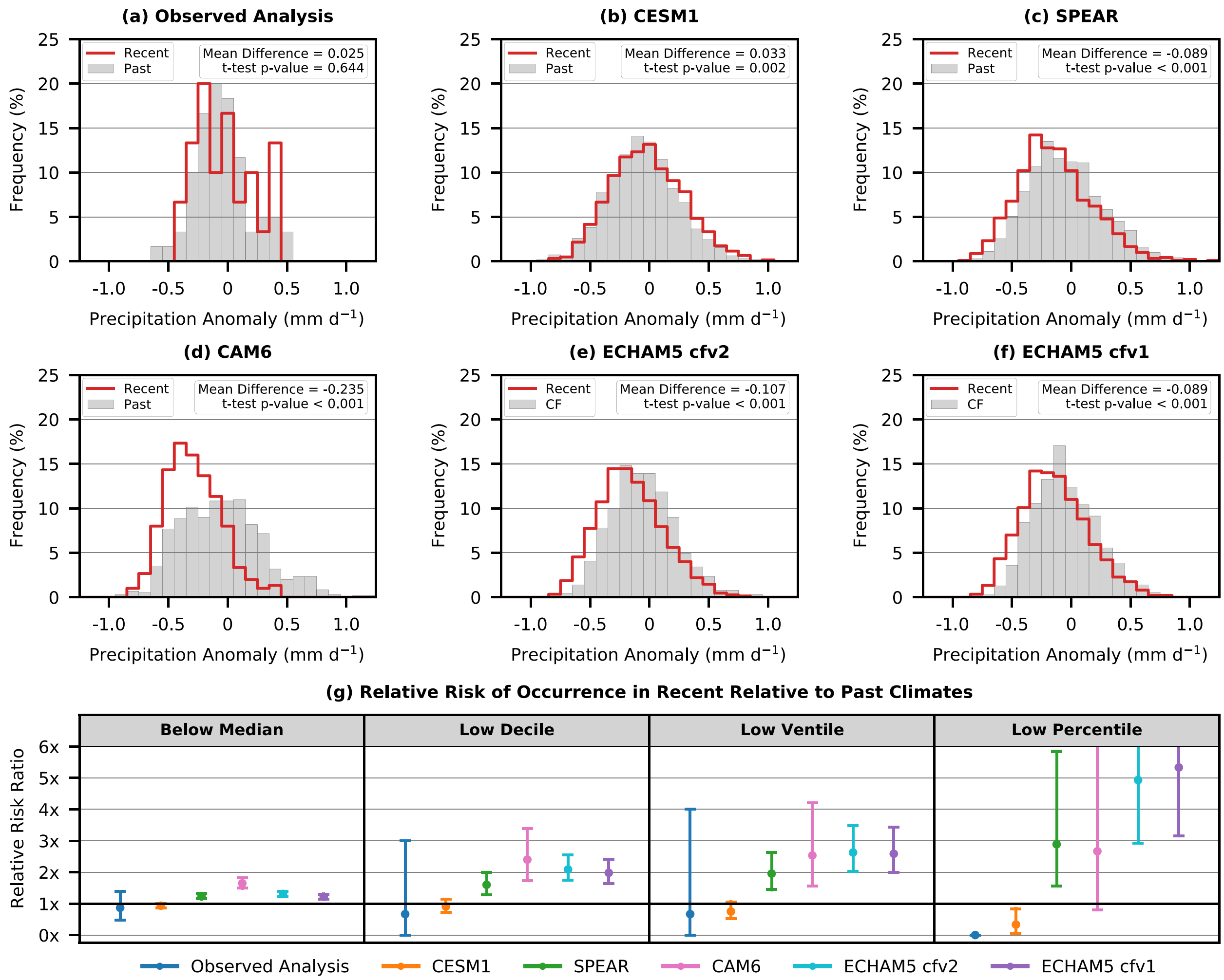

Fig. 2. (a)–(f) For June–September over the Four Corners States, area average precipitation anomaly histograms of past (1920–79) or counterfactual (gray) and recent (1990–2019) or factual (red) climates. Anomalies are calculated relative to the past or counterfactual climate average. (g) Relative risk of below median, decile, ventile, and percentile occurrence in the recent relative to the past climate (dot) and its 95% confidence interval (whisker) for the observed analysis (blue), CESM1 (orange), SPEAR (green), CAM6 (pink), ECHAM5 cfv2 (cyan), and ECHAM5 cfv1 (purple).

The decrease in precipitation from past to recent climates is consistent with the studies of He et al. (2020), which employed CMIP5 and CMIP6 models, and of Pascale et al. (2017), which employed a single model. Both studies point to an increase in atmospheric stability as a cause of precipitation decreases related to the North American monsoon, a result worth probing in future physically based attribution studies of June–September precipitation over the Four Corners states. Future physically based attribution studies would be strengthened by the use of models with higher horizontal resolution and models that permit convection. Models with higher horizontal resolution (e.g., 50 km) allow for a more accurate simulation of moisture surge events from the Gulf of California (Pascale et al. 2016) and convection-permitting models integrated at 2.5 km provide a reasonable representation of organized convection important to precipitation over the American Southwest during the monsoon season.

Discussion and concluding remarks.

Most model experiments used herein indicate record low June–September 2020 precipitation in the Four Corners states (Fig. 1) was made more likely due to climate change (Fig. 2), although our confidence in this result is low because such a change has not been observed since 1895 and the models do not perfectly reproduce precipitation statistics in the region

(Table 1). Four of the five models indicate that low decile and percentile occurrences are 1.5–2.5 and 2.5–5.5 times more likely, respectively, due to climate change. The model results are consistent across three widely used experiment types—historical simulations using coupled and atmospheric models, and event-attribution simulations—which together provide a more robust test of anthropogenic effects than observations alone. Use of these large ensemble experiments allowed evaluations of extreme event probabilities to be directly calculated, which is a strength of the study, even though the models are not perfect representations of the Earth system. Our results are consistent with the regional precipitation decrease in a changing climate reported by Luong et al. (2017), which employed higher-resolution models that permit convection, although it should be noted that their study found precipitation decreases to be most prominent over Arizona.

An observed downward trend in June–September precipitation over the Four Corners states has not been observed as of 2020. However, the absence of such a trend is not sufficient evidence against an effect of anthropogenically forced drying. We note that some of the models can reproduce the small observed mean precipitation increase from past to recent climates (Fig. S1). Suggested hereby is that the absence of a drying trend over the last century could have resulted from internal variability masking a climate change drying.

One of five models indicate that climate change leads to a slight wetting of the region during June–September. This contrary indication of North American monsoon precipitation in a changing climate is consistent with Cook and Seager (2013), who found no significant change in total monsoon precipitation over Mexico and southern Arizona and New Mexico in CMIP5 models. However, He et al. (2020) found a significant drying of the core monsoon region over Mexico and Central America using CMIP5 and CMIP6 models, as did Moon and Ha (2020), Chen et al. (2020), and Cook et al. (2020) for projections of the end of the twenty-first century in CMIP6 ensembles. Cook et al. (2020) further points out that results from CMIP5 and CMIP6 are generally consistent, which suggests that the same sources of uncertainty remain the latest generation of climate models. The current study adds to these by focusing on the Four Corners region to the north, and future work would be wise to examine summer rainfall change across southwest North America. Such work would benefit, as here, from the use of large ensembles from which tail risks could be meaningfully evaluated.

Acknowledgments. The authors thank the editor and two anonymous reviewers for thoughtful and constructive comments that led to an improved manuscript. The authors also thank Mr. David Allured for conducting the ECHAM5 simulations and Dr. Judith Perlwitz for comments on an early version of this paper. The authors are grateful for the support of the NOAA MAPP Program and its Drought Task Force.

References

Bindoff, N. L., and Coauthors, 2013: Detection and attribution of climate change: From global to regional. *Climate Change 2013: The Physical Science Basis*, T. F. Stocker et al., Eds., Cambridge University Press, 867–952.

Chen, Z., T. Zhou, L. Zhang, X. Chen, W. Zhang, and J. Jiang, 2020: Global land monsoon precipitation changes in CMIP6 projections. *Geophys. Res. Lett.*, **47,** e2019GL086902, https://doi.org/10.1029/2019GL086902.

Cook, B. I., and R. Seager, 2013: The response of the North American monsoon to increased greenhouse gas forcing. *J. Geophys. Res. Atmos.*, **118,** 1690–1699, https://doi.org/10.1002/jgrd.50111.

——, J. S. Mankin, K. Marvel, A. P. Williams, J. E. Smerdon, and K. J. Anchukaitis, 2020: Twenty-first century drought projections in the CMIP6 forcing scenarios. *Earth's Future*, **8,** e2019EF001461, https://doi.org/10.1029/2019EF001461.

Crockett, J. L., and A. L. Westerling, 2018: Greater temperature and precipitation extremes intensify western U.S. droughts, wildfire severity, and Sierra Nevada tree mortality. *J. Climate*, **31,** 341–354, https://doi.org/10.1175/JCLI-D-17-0254.1.

Danabasoglu, G., J. F. Lamarque, J. Bacmeister, D. A. Bailey, A. K. DuVivier, J. Edwards, and W. G. Strand, 2020: The Community Earth System Model version 2 (CESM2). *J. Adv. Model. Earth Syst.*, **12,** e2019MS001916, https://doi.org/10.1029/2019MS001916.

Delworth, T. L., W. F. Cooke, A. Adcroft, M. Bushuk, J.-H. Chen, K. A. Dunne, and M. Zhao, 2020: SPEAR: The next generation GFDL modeling system for seasonal to multidecadal prediction and projection. *J. Adv. Model. Earth Syst.*, **12,** e2019MS001895, https://doi.org/10.1029/2019MS001895.

Eyring, V., S. Bony, G. A. Meehl, C. A. Senior, B. Stevens, R. J. Stouffer, and K. E. Taylor, 2016: Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization. *Geosci. Model Dev.*, **9,** 1937–1958, https://doi.org/10.5194/gmd-9-1937-2016.

Fu, R., A. Hoell, J. Mankin, A. Sheffield, and I. R. Simpson, 2021: Tackling challenges of a drier, hotter, more fire-prone future. *Eos, Trans. Amer. Geophys. Union*, **102,** https://doi.org/10.1029/2021EO156650.

He, C., T. Li, and W. Zhou, 2020: Drier North American monsoon in contrast to Asian–African monsoon under global warming. *J. Climate*, **33,** 9801–9816, https://doi.org/10.1175/JCLI-D-20-0189.1.

Hoerling, M., J. Barsugli, B. Livneh, J. Eischeid, X. Quan, and A. Badger, 2019: Causes for the century-long decline in Colorado River flow. *J. Climate*, **32,** 8181–8203, https://doi.org/10.1175/JCLI-D-19-0207.1.

Huang, B., and Coauthors, 2017: Extended Reconstructed Sea Surface Temperature, version 5 (ERSSTv5): Upgrades, validations, and intercomparisons. *J. Climate*, **30,** 8179–8205, https://doi.org/10.1175/JCLI-D-16-0836.1.

Kay, J. E., and Coauthors, 2015: The Community Earth System Model (CESM) large ensemble project: A community resource for studying climate change in the presence of internal climate variability. *Bull. Amer. Meteor. Soc.*, 96, 1333–1349, https://doi.org/10.1175/BAMS-D-13-00255.1.

Lehner, F., C. Deser, I. R. Simpson, and L. Terray, 2018: Attributing the U.S. Southwest's recent shift into drier conditions. *Geophys. Res. Lett.*, **45,** 6251–6261, https://doi.org/10.1029/2018GL078312.

Luong, T. M., C. L. Castro, H. Chang, T. Lahmers, D. K. Adams, and C. A. Ochoa-Moya, 2017: The more extreme nature of North American monsoon precipitation in the southwestern United States as revealed by a historical climatology of simulated severe weather events. *J. Appl. Meteor. Climatol.*, **56,** 2509–2529, https://doi.org/10.1175/JAMC-D-16-0358.1.

Moon, S., and K. J. Ha, 2020: Future changes in monsoon duration and precipitation using CMIP6. *npj Climate Atmos. Sci.*, **3,** 45, https://doi.org/10.1038/s41612-020-00151-w.

Murray, D., and Coauthors, 2020: Facility for Weather and Climate Assessments (FACTS): A community resource for assessing weather and climate variability. *Bull. Amer. Meteor. Soc.*, **101** (7), E1214–E1224, https://doi.org/10.1175/BAMS-D-19-0224.1.

NCEI, 2021: U.S. billion-dollar weather and climate disasters. National Centers for Environmental Information, https://www.ncdc.noaa.gov/billions/.

Otto, F. E. L., S. Philip, S. Kew, S. Li, A. King, and H. Cullen, 2018: Attributing high-impact extreme events across timescales—A case study of four different types of events. *Climatic Change*, **149,** 399–412, https://doi.org/10.1007/s10584-018-2258-3.

Pascale, S., S. Bordoni, S. B. Kapnick, G. A. Vecchi, L. Jia, T. L. Delworth, S. Underwood, and W. Anderson, 2016: The impact of horizontal resolution on North American monsoon Gulf of California moisture surges in a suite of coupled global climate models. *J. Climate*, **29,** 7911–7936, https://doi.org/10.1175/JCLI-D-16-0199.1.

——, and Coauthors, 2017: Weakening of the North American monsoon with global warming. *Nat. Climate Change*, **7,** 806–812, https://doi.org/10.1038/nclimate3412.

Rayner, N. A., and Coauthors, 2003: Global analyses of sea surface temperature, sea ice, and night marine air temperature since the late nineteenth century. *J. Geophys. Res.*, **108,** 4407, https://doi.org/10.1029/2002JD002670.

Roeckner, E., and Coauthors, 2006: Sensitivity of simulated climate to horizontal and vertical resolution in the ECHAM5 atmosphere model. *J. Climate*, **19,** 3771–3791, https://doi.org/10.1175/JCLI3824.1.

Schubert, S. D., and Coauthors, 2016: Global meteorological drought: A synthesis of current understanding with a focus on SST drivers of precipitation deficits. *J. Climate*, **29,** 3989–4019, https://doi.org/10.1175/JCLI-D-15-0452.1.

Sun, L., D. Allured, M. Hoerling, L. Smith, J. Perlwitz, D. Murray, and J. Eischeid, 2018: Drivers of 2016 record Arctic warmth assessed using climate simulations subjected to factual and counterfactual forcing. *Wea. Climate Extremes*, **19,** 1–9. https://doi.org/10.1016/j.wace.2017.11.001.

Svoboda, M., and Coauthors, 2002: The Drought Monitor. *Bull. Amer. Meteor. Soc.*, **83,** 1181–1190, https://doi.org/10.1175/1520-0477-83.8.1181.

Taylor, K. E., R. J. Stouffer, and G. A. Meehl, 2012: An overview of CMIP5 and the experiment design. *Bull. Amer. Meteor. Soc.*, **93,** 485–498, https://doi.org/10.1175/BAMS-D-11-00094.1.

Udall, B., and J. Overpeck, 2017: The twenty-first century Colorado River hot drought and implications for the future. *Water Resour. Res.*, **53,** 2404–2418, https://doi.org/10.1002/2016WR019638.

U.S. Bureau of Reclamation, 2021: Annual operating plan for Colorado River reservoirs 2021. https://www.usbr.gov/lc/region/g4000/aop/AOP21.pdf.

USGCRP, 2018: *Impacts, Risks, and Adaptation in the United States: Fourth National Climate Assessment, Volume II*, D. R. Reidmiller et al., Eds., U.S. Global Change Research Program, 1515 pp., https://doi.org/10.7930/NCA4.2018.

Vose, R. S., and Coauthors, 2014: Improved historical temperature and precipitation time series for U.S. climate divisions. *J. Appl. Meteor. Climatol.*, **53,** 1232–1251, https://doi.org/10.1175/JAMC-D-13-0248.1.

Williams, A. P., and Coauthors, 2020: Large contribution from anthropogenic warming to an emerging North American megadrought. *Science*, **368,** 314–318, https://doi.org/10.1126/science.aaz9600.