EXPLAINING EXTREME EVENTS OF 2018

From a Climate Perspective

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EXPLAINING EXTREME EVENTS OF 2018 FROM A CLIMATE PERSPECTIVE

Editors

Stephanie C. Herring, Nikolaos Christidis, Andrew Hoell,
Martin P. Hoerling, and Peter A. Stott

BAMS Special Editors for Climate

Andrew King, Thomas Knutson,
John Nielsen-Gammon, and Friederike Otto

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CORRESPONDING EDITOR:

Stephanie C. Herring, PhD
NOAA National Centers for Environmental Information
325 Broadway, E/CC23, Rm 1B-131
Boulder, CO, 80305-3328
E-mail: stephanie.herring@noaa.gov

COVER CREDIT: iStock.com/Alena Kravchenko—River Thames receded during a heatwave in summer 2018 in London, United Kingdom.

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QUANTIFYING HUMAN-INDUCED TEMPERATURE IMPACTS ON THE 2018 UNITED STATES FOUR CORNERS HYDROLOGIC AND AGRO-PASTORAL DROUGHT

EMILY WILLIAMS, CHRIS FUNK, SHRADDHANAND SHUKLA, AND DANIEL McEVOY

Human-induced (HI) warming increased Four Corners' vapor pressure deficits and reduced the Normalized Difference Vegetation Index by ~18%–30%. Without HI warming, March snow water equivalent would have been ~20% higher.

In water year (WY) 2018 (October 2017 to September 2018), temperatures in the Four Corners region of the western United States (Fig. 1a) were the warmest on record. These high temperatures occurred during a severe meteorological drought (West Wide Drought Tracker; Abatzoglou et al. 2017). According to the U.S. Drought Monitor (USDM), nearly 95% of the region was in severe drought in February 2018, and 56% of the region was in exceptional drought in September 2018. The Navajo Nation issued a drought declaration, finding that “drought conditions...created a critical shortage of water and range feed for livestock” (Navajo Nation 2018). Widespread agricultural and ranching losses contributed to an estimated three billion U.S. dollars in losses (NOAA NCEI 2019). The drought was characterized by significant hydrologic (limited surface water) and agropastoral (poor soil and vegetation conditions) impacts; thus, this study examines the influence of elevated temperature on hydrologic and agropastoral drought.

Past studies indicate that above-normal temperatures have exacerbated droughts in the Southwest (McCabe et al. 2017; Weiss et al. 2009; Udall and Overpeck 2017; Woodhouse et al. 2016) by reducing snowpack and driving earlier snowmelt (Shukla et al. 2015; AghaKouchak et al. 2014; Cook et al. 2015) and increasing saturation vapor pressure (SVP), thereby increasing the vapor pressure deficit (VPD) (Seager et al. 2015). Increased VPD can lead to drying of the land surface, potentially stressing rangelands in late spring and summer months. Thus, above-normal temperatures co-occurring with meteorological drought may increase the risk of severe hydrologic and agropastoral drought (National Academies of Sciences, Engineering, and Medicine 2016, p. 98; Diffenbaugh et al. 2015; Williams et al. 2015; Shukla et al. 2015; Trenberth et al. 2014).

Given high probabilities that the twenty-first century will bring continued warming and the relatively uncertain influence of human-induced (HI) warming on precipitation in the Four Corners (Garfin et al. 2013), it is important to explore how temperature alone may contribute to enhancing hydrologic and agropastoral droughts. In this study, we estimate the potential temperature increase due to HI warming and subsequently examine the impacts of elevated temperature (i) on VPD using a statistical model, (ii) on agropastoral drought using a statistical model relating VPD and the Normalized Difference Vegetation Index (NDVI), and (iii) on hydrologic drought using a hydrologic model.

DATA AND METHODS. The study region (34°–39°N, 112°–105°W) encompasses the spatial extent of exceptional drought in WY2018 as defined by the USDM (Fig. 1a). Observationally based gridded monthly means of daily minimum and maximum

AFFILIATIONS: WILLIAMS AND SHUKLA—University of California, Santa Barbara, Santa Barbara, California; FUNK—U.S. Geological Survey Earth Resources Observation and Science Center and University of California, Santa Barbara, Santa Barbara, California; McEVOY—Western Regional Climate Center, Desert Research Institute, Reno, Nevada

CORRESPONDING AUTHOR: Emily Williams, ewilliams@ucsb.edu

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FIG. 1. Context for the WY2018 drought. (a) Study region bounding box, encompassing large portions of New Mexico, Arizona, Utah, and Colorado, overlaid on USDM 9 Oct 2018 drought extent. **(b)** Scatterplot demonstrating observed annual precipitation and mean $T_{\min}$ and $T_{\max}$ for each water year. Blue and red lines show $T_{\min}$ and $T_{\max}$ regression lines, respectively. **(c)** Human-induced temperature increases for WY2018 spatially averaged over the study region. Each boxplot displays the distribution of spatially averaged differences between the seasonal RCP8.5 and PI simulations over the 2013–23 time period. The lower and upper extent of the boxes depict the 25th and 75th percentiles of the distribution of differences. The center bar represents the median and the whiskers represent the less extreme of the maximum/minimum value or the 3rd/1st quartile + 1.5 * (interquartile range).

temperature ($T_{\min}$, $T_{\max}$), minimum and maximum vapor pressure deficit ($VPD_{\min}$, $VPD_{\max}$), and precipitation data from 1895 to 2018 for the region were obtained from the PRISM Climate Group (www.prism.oregonstate.edu/; 4 km $\times$ 4 km resolution) and, alongside snow water equivalent (SWE) measurements from SNOTEL (Fig. ES2), were examined to place the WY2018 drought in historical context.

To attribute the role of HI forcing on the temperature anomaly, factual and counterfactual estimates of $T_{\min}$ and $T_{\max}$ were derived. To derive factual $T_{\min/\max}$ estimates, representative concentration pathway 8.5 (RCP8.5) simulations from two large ensembles (LENS) were chosen: the Canadian Earth System Model version 2 (CanESM2) (Kirchmeier-Young et al. 2017) (50-member ensemble, 1950–2100) and the Community Earth System Model version 1 (CESM1) (Kay et al. 2015) (40-member large ensemble; 1920–2100). We selected the two models with the largest ensembles to account for the internal variability in the climate system. Counterfactual estimates were based on pre-industrial (PI) CMIP5 simulations for the same models, obtained from the Climate Explorer (<https://climexp.knmi.nl/>). A bias correction (described in online supplemental material) was used to align the CESM1 PI (CMIP5) simulations (Taylor et al. 2012) with the 40 CESM1 LENS simulations (Kay et al. 2015). As WY2018 experienced a weak La Niña, only model simulations with similar Niño-3.4 SST anomalies (with $\pm 0.4^{\circ}\text{C}$ buffer) were used. HI influence on temperature was determined by comparing monthly $T_{\min}$ and $T_{\max}$ averages from RCP8.5

simulations for 2013–23 (sample sizes: $N_{\text{CESM1}} = 1439$; $N_{\text{CanESM2}} = 2012$) with those from the PI simulations ($N_{\text{CESM1}} = 760$; $N_{\text{CanESM2}} = 1103$).

To estimate counterfactual VPD (minimum and maximum), we calculated counterfactual SVP (SVP_{cf}) and combined these values with actual vapor pressure (AVP) to calculate VPD_{cf} . Since we focus on temperature dependencies in this set of experiments, and since 1895–2018 AVP shows no significant linear trend, we assume that human-induced warming did not change AVP. Actual SVP was first calculated using PRISM temperatures, then AVP was calculated using actual SVP and VPD. Then, the warming anomaly (from the counterfactual temperature experiment) was subtracted from PRISM temperature and used to calculate SVP_{cf} , based on the equation for VPD from Daly et al. (2015). Finally, SVP_{cf} and actual AVP were used to derive VPD_{cf} .

To estimate the effects of VPD on the NDVI (Normalized Difference Vegetation Index; a measure of greenness and vegetative stress), counterfactual NDVI was derived using counterfactual SVP and observed precipitation. NDVI observations were obtained from MODIS Terra 16-day (Spruce et al. 2016). Seasonal 2000–18 June–August mean SVP and precipitation were regressed onto the spatially aggregated magnitude of change from April to August NDVI (ΔNDVI). Various SVP, AVP, and precipitation lags and combinations were tested to find the optimal regression (i.e., the best predicting months and variables). June–August SVP and precipitation proved to be the best for April–August ΔNDVI (the “greenup”

phase) ($\text{DNDVI} = 0.17 + -0.00558 \times \text{SVP} + 0.00073 \times \text{precip}$; $R^2 = 0.766$). These regression coefficients were then used with SVP_{cf} and actual precipitation means to calculate $\Delta\text{NDVI}_{\text{cf}}$.

Finally, the effect of elevated temperature on hydrologic drought (specifically SWE and runoff) was estimated by using the variable infiltration capacity (VIC) hydrologic model (Liang et al. 1994) which has been used in similar attribution studies (such as Shukla et al. 2015; Xiao et al. 2018). The VIC is a physically based hydrologic model that uses atmospheric forcings including precipitation, temperature, and wind speed to compute SWE, soil moisture (SM), evapotranspiration (ET), and runoff. The VIC was run using PRISM precipitation, T_{min} and T_{max} data, and climatological wind speed [as in Livneh et al. (2013)] (upscaled from $4 \text{ km} \times 4 \text{ km}$ to $6 \text{ km} \times 6 \text{ km}$). After a long-term spinup period, the VIC was run first to simulate the water budget given the observed WY2018 conditions, and then twice using counterfactual WY2018 temperatures obtained by adjusting the observed WY2018 temperatures using the difference between factual and counterfactual temperatures derived from CESM and CanESM while keeping precipitation the same.

RESULTS. WY2018 precipitation was the lowest on record ($\sim 220 \text{ mm}$) averaged over the study area. There is no significant correlation between precipitation and annual T_{min} ($\text{cor} = -0.03$; $p \text{ value} = 0.73$); however, a significant negative correlation exists between precipitation and annual T_{max} ($\text{cor} = -0.60$; $p \text{ value} = 0.16\text{e-}12$) (Fig. 1b). WY2018 T_{max} and T_{min} values were both among the warmest on record (Fig. 1b). Estimates of the human-induced temperature increases from the counterfactual experiment indicate substantial warming (Fig. 1c). The mean annual difference in temperature between RCP8.5 and PI ensemble runs is $\sim 2^\circ\text{C}$ for CanESM2 ($+2.0^\circ\text{C } T_{\text{max}}$, $+2.0^\circ\text{C } T_{\text{min}}$) and $\sim 1.3^\circ\text{C}$ for CESM1 ($+1.3^\circ\text{C } T_{\text{max}}$, $+1.4^\circ\text{C } T_{\text{min}}$) for the 2013–23 decade. PRISM suggests a temperature increase of $\sim 1.9^\circ\text{C}$ (T_{max}) and $\sim 0.9^\circ\text{C}$ (T_{min}) from 1895–1929 to 2013–18.

Figure 2a shows the climatological (1895–1980) VPD (black line), actual WY2018 VPD (red line), and “alternative” WY2018 VPD (blue line, CESM1-adjusted; green line, CanESM2-adjusted) estimated using the counterfactual T_{min} and T_{max} . In June–August, actual VPD_{max} (VPD_{min}) was on average 6.6 hPa (3.1 hPa) greater than the climatology. Counterfactual estimates (blue and green lines in Fig. 2a) suggest that the HI-induced temperature anomalies could account for $3.7\text{--}4.9 \text{ hPa}$ (VPD_{max}) and $0.7\text{--}2.2 \text{ hPa}$ (VPD_{min}), or $59\%\text{--}80\%$ (VPD_{max})

and $26\%\text{--}74\%$ (VPD_{min}), of the difference between the climatological VPD and 2018 actual June–August VPD. Average 2000–18 ΔNDVI (greenup) was 0.088 —the region experienced severe drought during the first decade. April–August modeled 2018 ΔNDVI (representing greenup) was 0.067 ; under counterfactual temperature conditions, ΔNDVI was estimated to have been $0.080\text{--}0.088$ based on CESM1- and CanESM2-estimated VPD_{cf} respectively (Fig. 2b).

VIC estimates of SWE (for elevations $> 2,000 \text{ m}$) and runoff are summarized in Figs. 2c and 2d. Evapotranspiration results are shown in the supplemental material. Climatologically, peak SWE months are February–April, whereas peak runoff months are May–June. The simulated 2018 March SWE peak (annual WY runoff) was $\sim 71\%$ ($\sim 57\%$) less than the climatological average. Comparing VIC simulations—those driven with adjusted temperature forcings versus those driven with WY 2018 actual temperature—reveals that March SWE would have been $\sim 24\%$ (CanESM) or $\sim 19\%$ (CESM) higher than WY 2018 observation-based SWE. Likewise, annual WY runoff would have been $\sim 1.3\%$ (CanESM) or $\sim 1.43\%$ (CESM) higher than WY 2018 observed temperature-based simulated annual runoff. These results indicate that human-induced temperature increases had a measurable impact on SWE, but little discernable impacts on runoff; the SWE effects, however, were secondary to the influence of record-low precipitation during WY 2018 (Fig. 1b).

DISCUSSION AND CONCLUSIONS. WY2018 was exceptionally warm and dry (Figs. 1a,b), and an assessment of the CESM1 and CanESM2 simulations suggested that HI warming increased air temperatures by $\sim 1.3^\circ$ to $\sim 2^\circ\text{C}$, respectively (Fig. 1c). Relatively small changes in temperature can result in large changes in VPD; thus, if AVP remains constant, human-induced warming, alone, could explain $\sim 60\%\text{--}80\%$ of the observed WY2018 VPD_{max} anomalies (Fig. 2a). WY2018 experienced low NDVI values as reflected in the poor rangeland conditions reported by the USDM for much of New Mexico, Utah, and Arizona during the same period. HI increases in SVP values likely contributed to reduced August NDVI; the magnitude of greenup was smaller in actual 2018 NDVI compared to the counterfactuals (Fig. 2b). VIC simulations suggest that without the HI warming March SWE would have been $\sim 24\%$ (CanESM) or $\sim 19\%$ (CESM) higher and annual WY runoff would have been $\sim 1.3\%$ (CanESM) or $\sim 1.43\%$ (CESM) higher (Figs. 2c,d).

This study did not assess the potential effect of positive land–atmosphere feedbacks under drought conditions, in which HI temperature anomalies can

FIG. 2. Hydrologic and agropastoral effects of HI-forced temperature anomalies. Climatology of each variable is shown in black [in (a) and (b) only], WY2018 actual (“observed”/factual) conditions in red, and counterfactual estimates in blue (CESM1-adjusted) and green (CanESM2-adjusted). (a) Comparison between climatological VPD, WY2018 VPD, and estimated counterfactual WY2018 VPD, estimated using the difference between counterfactual and factual temperatures as shown in Fig. 1c. VPD_{max} is shown using an asterisk (*) and VPD_{min} using an open circle (o). (b) PDF of spatially aggregated actual NDVI greenup (or magnitude of change in NDVI from April to August) in black for 2000–18, modeled 2018 NDVI greenup (red), and counterfactual estimates of greenup without HI temperature increases (blue and green). Also shown are VIC model-based estimates of (c) SWE and (d) runoff derived from CanESM2- and CESM1-adjusted (counterfactual) temperatures, and actual (“observed”/factual) temperatures for WY2018. SWE is aggregated over only those grid cells at >2,000-m mean elevation.

yield even greater observed anomalies as energy is released as sensible heat instead of latent heat (as suggested by the negative correlation between precipitation and annual average T_{max}). Therefore, our estimates of climate change-induced temperature increase on hydrology (particularly SWE) and VPD (and its influence on NDVI) may be conservative estimates. Future research will expand this analysis to cover the full time series (1900–present), allowing us to assess potential temperature impacts under less extreme precipitation deficits.

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