EXPLAINING EXTREME EVENTS OF 2018

From a Climate Perspective

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EXPLAINING EXTREME EVENTS OF 2018 FROM A CLIMATE PERSPECTIVE

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

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ATTRIBUTION OF THE 2018 OCTOBER–DECEMBER DROUGHT OVER SOUTH SOUTHERN AFRICA

SHINGIRAI NANGOMBE, TIANJUN ZHOU, LIXIA ZHANG, AND WENXIA ZHANG

The HadGEM3 (CAM5) model suggests that anthropogenic emissions increased the chances of the October–December 2018 drought over the southernmost area of southern Africa by 1.4 (0.97–1.96) times [4.3 (3.43–5.46) times], with higher influence on reference evapotranspiration than on precipitation.

Across Africa, droughts are a major type of natural disaster and a household insecurity trigger. The south southern Africa region (SSA; encompassed by the 22°–35°S, 18°–32°E rectangle) experienced extremely poor rainfall during the first half [i.e., October–December 2018 (OND)] of the October 2018 to March 2019 rainfall season (Fig. 1a). The OND subseason marks the important first half of southern Africa's rainfall season (Landman and Mason 1999). Late rainfall onset dates normally lead to below normal seasonal rainfall in southern Africa (Dunning et al. 2016). Dry conditions during OND 2018 led to a 2-month delay in sowing in parts of southern Africa (SADC CSC 2018), which translated

to reduced regional crop yield, where livelihoods are principally agriculture-based. In South Africa's large cereal-producing provinces, 40%–50% reduced rains delayed plantings and curbed sown areas (FAO 2019; FEWSNET 2019). Late rain onset acted as a disincentive to farmers to take risks of sowing outside of the optimal planting window (FAO 2019). This contributed to Zambia and South Africa (the main regional grain suppliers) recording below-average harvests, thereby reducing exportable surplus from 7.5 to 1.4 million tons (SADC RVAA 2019), hence affecting regional food security.

The poor rains were also accompanied by water loss through above average reference evapotranspiration (Fig. 1b). This exacerbated the drought impact, considering the region's large population. Water loss worsened the water supply situation since dam and river water levels were already low due to the three previous consecutive droughts (Richman and Leslie 2018).

This study investigates how extreme the OND 2018 SSA drought was, and explores the related anthropogenic influences.

DATA AND METHODS. Gridded observational temperature, from the Global Historical Climatology Network Gridded v2 and Climate Anomaly Monitoring System dataset (GHCN-CAMS; Fan and van den Dool 2008) is used here available at 0.5° horizontal grid resolution. A precipitation average of the Global Precipitation Climatology Centre v2018 (GPCC-FD v2018; Schneider et al. 2015) dataset available at 1° horizontal grid resolution and the Climate Research Unit v4.0.3 (CRU-TS 4.03; Harris et al. 2014) dataset available since 1901 at 0.5° horizontal resolution is also utilized.

Two C20C+ Detection and Attribution project (Folland et al. 2014; Stone et al. 2019) global mod-

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FIG. 1. The OND 2018 anomalies of (a) precipitation derived from the GPCC and CRU averaged datasets, (b) reference evapotranspiration calculated from GHCN-CAMS, and (c) difference between precipitation and reference evapotranspiration (P -refET) denoting the drought index. (d) Map of geopotential height (shading; hPa) and moisture transport (vector; $\text{kg kg}^{-1} \text{m s}^{-1}$) anomalies at 850 hPa during OND 2018 derived from the JRA-55 reanalysis (Kobayashi et al. 2015). (e) SSA area-averaged OND P (blue) and P -refET (red) with overlaid refET (sky-blue and brown bars). (f) Map of OND 2018 outgoing longwave radiation flux anomalies (W m^{-2}). SSA is shown by a black box in (a)–(d) and (f). All the anomalies are calculated from a 1960–2013 climatology. The units are in mm day^{-1} unless stated otherwise.

els are employed here in evaluating anthropogenic influence on this drought occurrence: HadGEM3 (Ciavarella et al. 2018) and CAM5 (Risser et al. 2018). These comprise two suites of simulations representing the actual climate (All-Hist) and a hypothetical natural climate excluding anthropogenic influence (Nat-Hist). In HadGEM3, both All-Hist and Nat-Hist have 15 realizations ranging from 1960 to 2013; in CAM5, there are 50 realizations ranging from 1960 to 2017.

To factor in high temperatures, a drought index that incorporates reference evapotranspiration is used: specifically, OND averaged P -refET, where P and refET denote precipitation and reference evapotranspiration, respectively. The Hamon method is used to estimate refET (Haith and Shoemaker 1987) from temperature data using the *refevt_hamon* function (Brown et al. 2019). The online supplemental

information and Eq. (7) in Haith and Shoemaker (1987) provide details of refET calculation.

The Gaussian distribution (Wellmer 1998) was fitted to the observed OND averaged data, and return period of the 2018 event derived, separately for P , refET, and P -refET. Using 810 and 2900 model years from HadGEM3 and CAM5 All-Hist simulations respectively, OND averaged P , refET, and P -refET indices were extracted. Then Gaussian distributions are fitted to the All-Hist-based indices and used to derive the drought events that have similar return periods as the 2018 observed one. Last, as in Stott et al. (2004) and Ma et al. (2017), the probability ratio ($\text{PR} = P_1 / P_0$) and the fraction of attributable risk ($\text{FAR} = 1 - P_0 / P_1$) are estimated, where P_1 (P_0) is the likelihood of an event occurring in the All-Hist (Nat-Hist) simulations. Here, a null hypothesis of existing human influence against an alternative hypothesis of no human influence on the drought occurrence is used.

However, in some cases like precipitation where high model uncertainty exists, the null hypothesis may be disproved. A total of 1,000 bootstrapping samples are used to estimate the 5th–95th confidence intervals for PR and FAR.

RESULTS. The observed OND precipitation area-averaged over SSA in 2018 was 0.68 mm day^{-1} (46%) below normal (1960–2013 baseline), while refET was 0.23 mm day^{-1} above normal (Fig. 1e). These precipitation and refET anomalies were ranked as the second lowest and third highest since 1950, respectively. Consequently, P -refET was the second record-breaking event with $-0.91 \text{ mm day}^{-1}$ (−60%) anomaly (Figs. 1c,e) and a 72-yr return period. Precipitation (refET) had a 40-yr (32-yr) return period (not shown).

SSA in OND is normally characterized by northeasterly moisture transport from the tropical Indian Ocean (Fig. S1a), leading to precipitation. However, in 2018, there was weak southerly moisture flux into SSA (Fig. 1d). A cyclonic anomaly in the Indian and Atlantic Oceans dominated the 850-mb moisture flux, hence diverting moisture flow away from SSA (Fig. 1d). Moreover, late 2018 was associated with El Niño conditions (Fig. S1b). Typically, during El Niño in austral summer, southern Africa receives drought (Hoell and Cheng 2018; Manatsa et al. 2017) while temperatures are usually above average (Nangombe et al. 2018). Likewise, Figs. S1c and S1d show a positive (negative) relationship between the OND ENSO index and OND SSA refET (*P*-refET) index.

Meanwhile, using outgoing longwave radiation (OLR) as a proxy for tropical temperate trough (TTT) events, anomalously high OLR over SSA in OND 2018 indicates a decrease in convection linked to TTTs (Fig. 1f). TTTs are the main rainfall bearers to SSA (Cook et al. 2004). Therefore, sea surface temperatures in the Pacific and Indian Oceans accompanied by anomalous low TTTs over SSA contributed to below normal 2018 OND precipitation in SSA.

On evaluating the model performance, correlation coefficients of *P*-refET, *P*, and refET area-averaged over SSA between the HadGEM3 (CAM5) All-Hist ensemble-mean and observation are 0.36, 0.31, and 0.38 (0.34, 0.21, and -0.1), respectively, with about 1 to 2 mm day⁻¹ overestimation of the models. All the correlations based on the HadGEM3 (CAM5) model are significant (insignificant) at the 0.05 level. Nonetheless, results from both models under All-Hist and Nat-Hist cover the observed range (Figs. S2a,b). Additionally, there are statistical similarities between the density distributions of the All-Hist simulations and observation/reanalysis (Figs. S2c,d), hence our confidence in using these models.

In exploring the anthropogenic influence, CAM5 depicts a distinct leftward shift of the probability functions of the OND *P*-refET in All-Hist compared to Nat-Hist, while HadGEM3 suggests a slight shift (Figs. 2a,b). This signifies a likely anthropogenic influence on *P*-refET in the SSA. The shift is even more pronounced for refET, albeit in the rightward direction (Figs. 2e,f). Conversely, for precipitation, there is no obvious shift in All-Hist compared to Nat-Hist simulations of HadGEM3, while CAM5 depicts a moderate shift (Figs. S2e,f). In HadGEM3 (CAM5), -2.02 mm day⁻¹ (-1.79 mm day⁻¹) of *P*-refET is selected as the threshold for attribution of SSA drought since it has a return period similar to the observed 2018 *P*-refET. For refET (*P*), the thresholds used are

3.32 (1.33) mm day⁻¹ and 3.59 (1.84) mm day⁻¹, respectively. The HadGEM3 (CAM5) model estimates PR and FAR to be 1.36 (0.97–1.96) [4.34 (3.43–5.46)] and 26% (-3% to 49%) [77% (71%–82%)], respectively, for *P*-refET. The attributable influence from anthropogenic forcings is weaker in HadGEM3 than in CAM5, as the lower bound of the confidence interval of PR from HadGEM3 is slightly less than 1. Nonetheless, HadGEM3 simulations suggest PR and FAR values of 157.16 (86.90–310.74) and 99% (99%–100%) for refET while CAM5 suggests 105.75 (77.04–146.45) and 99% (99%–99%), respectively. We note that the PR and FAR estimates calculated from the CAM5 simulations are substantially affected by the nonstationarity of the ALL-Hist simulations (in terms of greenhouse gas concentrations) compared to estimates from the HadGEM3 simulations (not shown).

Furthermore, using simulations from composite El Niño years in estimating *P*-refET, HadGEM3 and CAM5 estimate PR values of 0.75 (0.24–2.77) and 2.19 (0.68–8.03) respectively. Thus, comparing with the other PR values, this portrays a reduction in the anthropogenic influence on drought of similar magnitude to that of OND 2018 in SSA during El Niño years.

Examining precipitation associated with the 2018 drought, CAM5 estimates the related PR (FAR) to be 1.95 (1.63–2.33) [49% (39%–57%)], whereas HadGEM3 suggests 0.76 (0.59–0.98) and -32% (-2% to -69%) PR (FAR) values, respectively, hence implying a reduced probability of occurrence due to anthropogenic forcing. Thus, comparing the two models, the anthropogenic forcing impact on precipitation-based drought in SSA is uncertain. Also, Yuan et al. (2018) highlighted that the major sources of uncertainty in detecting/attributing flash droughts over southern Africa are soil moisture and precipitation variation. Plus, the interannual variability of precipitation is much higher in African regions, hence making it difficult to distinguish anthropogenic signal from noise (Otto et al. 2013). Nonetheless, although low precipitation seasons such as OND 2018 are not necessarily more likely due to anthropogenic emissions, they may have severe impacts in an anthropogenically warmed world due to increased temperatures and hence increased refET.

CONCLUDING REMARKS. SSA experienced an extreme drought event in OND 2018 accompanied by extremely low rainfall and high reference evapotranspiration. This translated to substantial delay in the planting season hence affected the regional 2018/19 crop yield where livelihoods are largely agriculture-based.

FIG. 2. HadGEM3's probability density functions (PDFs) of October–December (a) *P*-refET from all years, (c) *P*-refET El Niño years, (e) refET all years, and (g) refET El Niño years, area-averaged over the SSA region. (b),(d),(f),(h) As in (a),(c),(e),(g), but for the CAM5 model. All-Hist simulations and Nat-Hist simulations are represented by red and blue PDFs, respectively. The PDFs of HadGEM3 are based on 15-member realizations of both All-Hist and Nat-Hist ranging from 1960 to 2013 while CAM5 PDFs are based on 50-member realizations of both All-Hist and Nat-Hist ranging from 1959 to 2016. The dashed lines are the thresholds similar to the observed 2018 values. PDFs are calculated by the Gaussian kernel density estimator.

Here, the HadGEM3 model suggests that anthropogenic influence may have increased the probability of SSA droughts, such as the OND 2018 drought (*P*-refET), by 1.4 times [0.97, 1.96], and the CAM5 model indicates 4.3 times [3.43, 5.46]. The high anthropogenic influence on refET mostly contributed to this drought occurrence. El Niño conditions may also have had an influence. Therefore, the increase in temperature accompanied by rainfall decrease projected over southern Africa might result in increase in drought occurrence of at least OND 2018 magnitudes in the future (Kusangaya et al. 2014; Niang et al. 2014; Maure et al. 2018; Nikulin et al. 2018; Nangombe et al. 2018).

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