Dear Editor of NHESS

Thank you for your help in obtaining two reviews of our Brief Communication:

Drought Likelihood for East Africa.

The drought in East Africa has caused severe problems for millions of people, and including high numbers of deaths. Although there are plots of climate model projections of rainfall changes in the IPCC report, these are not specific to East Africa. Instead what we are trying to achieve in this short manuscript is a straightforward “show and tell” of future model projections of rainfall for this region, and for specific period August, September and October.

The research community needs to obtain a full meteorological understanding of what happened in year 2016, and then apply this knowledge to assess its occurrence in future projections by climate models. We hope a set of standard comprehensive climate research papers on African drought will appear over the years ahead. Our brief communication may act to encourage this, along with highlighting the need to refine future estimates of change.

We recognize our reviews are poor, and especially from Reviewer 2. We have, though, responded in full to all requests. This includes making all methods transparent, and in particular providing uncertainty bounds on (a) rainfall datasets and (b) bias correction methodology to scale climate model to measurement records. We believe our paper now provides a preliminary but robust assessment of Africa drought risk.

We hope that your journal will consider our responses, and in light of these that there might still be the possibility of publishing our analysis as a Brief Communications in NHESS. Our responses are described below. Adjusted manuscript text is repeated in red font. We believe we have satisfied all formatting requirements.

Thank you for all the help so far.

With kind regards,

Hui Yang

Hui Yang (and on behalf of Chris Huntingford).

Response to the reviewers

To Reviewer #1:

***Reviewer #1* General Comments:**

We thank Reviewer #1 for their help and time spent on this paper. Our responses are below, and revised text in the paper repeated in red font.

***METHOD**: The method is rather experimental and not well documented or explained. Even within the tight limits of this manuscript type, there would be plenty of room to explain the method and if it can indeed explain what is going on.*

[Response 1.1] We accept there is a need for a more complete description of the calculation methods used, which we have now done. The main change is that in the revised manuscript we now write: "A bias correction with two post-processing steps is applied to the GCM precipitation estimates. We first calculate modelled and ERA-based mean ASO rainfall estimates over the east Africa during the period 1979-2015. The GCM precipitation estimates, both past and future, are corrected by a GCM-specific mean correction factor, which is a ratio of the climatological mean of each GCM to that of the ERA-interim reanalysis product. Second, we then adjust the climatological standard deviation (STD) of GCM precipitation estimates by multiplying the ratio of the climatological STD of each GCM to that of the ERA-interim data. The adjustment of spread of rainfall distribution is an important additional procedure to further constrain GCM estimates (Sippel et al., 2016; Jeon et al., 2016; Angelil et al., 2017). Together this ensures all GCMs have the ERA-based mean and STD for period 1979-2015." (Page: 1, Lines: 28-31 and Page: 2, Lines: 1-4)

***FIGURES:** The figures are readable and do not have to be re-done. However, from the figures, rather than focusing on the very small changes for the current level of precipitation, it would be worthwhile focusing on the clear change in the overall distribution, showing a significant increase in inter-annual variability, which is strongly linked to socio-economic indicators (see e.g. Brown & Lall, 2006).*

[Response 1.2] We now added a new figure (i.e. Figure 3), which places an emphasis on GCM-specific changes in mean and standard deviation of ASO rainfall (See Response 1.17, where Figure 3 is shown). We also cite your suggested reference – thank you for alerting us to this paper. We quantify throughout variability by standard deviation (STD), recognizing that any auto-correlation means that strictly speaking, is not its inter-annual variability. We clarify this in the modified revised manuscript.

REFERENCES: *It is very surprising that no climate study is cited that looks at the impact of climate change on East African rainfall instead of just impact studies. Also, the impact of external forcings such as ENSO is not mentioned, although for East Africa that might be a major factor for the strong (and increasing) inter-annual variability.*

[Response 1.3] We thank the reviewer for this comment, and in the meantime have identified references that we should have used in the initial submission. Using key reference, we now note the potential driving factors of the East African rainfall deficits, and in particular the impact of ENSO. Please see our paper amendments, as follows: "Improving GCM projections also could involve on-going constraining of model components. For rainfall of east Africa predictions in particular, this will link to accurate forward projections of oceanic variability. Strong teleconnections are known to exist between El Niño Southern Oscillation (ENSO) and East African rainfall (Segele et al., 2009; Gissila et al., 2004), and with longer-term fluctuations in Pacific SSTs increasing/decreasing rainfall (Funk et al., 2014; Liebmann et al., 2014)." (Page: 3, Lines: 19-23)

LANGUAGE: *The English should be improved.*

[Response 1.4] We have polished the language in large parts of manuscript, and in addition the technical details are given in a more precise way. We hope the new paper version has a level of clarity as to be useful to a relatively broad audience.

CONCLUSION: *The conclusion offers a smorgasbord of other studies, and does not help the reader understand what the present study is able to contribute to the current research. Instead, it suggests that other methods may be more worthwhile exploring. It will have to be made much more clear what the benefit of this study is in order for it to be published.*

Page 2, Lines 2 – 7: this conclusion has to be improved. Some sentences suggest other approaches may be better suited to study this problem, while some bring up topics that should have been covered in the introduction. What is the conclusion from your own method?

[Response] We make clearer our contribution, which is to find we cannot yet make accurate projections of change, as this depends on GCM, any bias-correction method used, and the observation product used in such bias removal. Although this is a slightly negative find (i.e. answer is inclusive), we believe this is still important to have placed in the literature. We are targeting "Brief Communication" format, so the issues brought up are not expanded in full, but we would be grateful to mention in the context of our analysis.

The many issues raised are dealt with throughout the concluding paragraphs, and although it takes up space in our response, we list this in full as: “Our analysis reveals that current understanding of how future climate change will impact on East Africa ASO drought risk remains uncertain. This is based on a relatively simple assessment of 37 climate models, each given equal weight but after being corrected by observation-based rainfall products. We find the sources of uncertainty in drought prediction include: 1) the choice of bias correction methodology; 2) the choice of observational product used to correct bias in GCMs; and 3) the choice of GCMs used. Currently, for many geographical regions, GCM estimates of rainfall changes varies substantially across models (Knutti and Sedláček, 2013). Multi-model analyses such as ours consider uncertainty associated with different model parameterisation or scheme describing rainfall features. However, to give more definitive answers, the climate research community may need to be confident enough to rank climate models based on performance to refine future projections (Knutti et al., 2017). Improving GCM projections also could involve on-going constraining of model components. For rainfall of east Africa predictions in particular, this will link to accurate forward projections of oceanic variability. Strong teleconnections are known to exist between El Niño Southern Oscillation (ENSO) and East African rainfall (Segele et al., 2009; Gissila et al., 2004), and with longer-term fluctuations in Pacific SSTs increasing/decreasing rainfall (Funk et al., 2014; Liebmann et al., 2014). Larger ensembles of simulations by each model is also important, and especially when analysing the probability of extreme events. This enables a more complete sampling of probability distributions, describing more fully the internal variability of the climate system imposed over general climate change. In addition, some GCMs estimate an increase in future variability of east African ASO rainfall, and better knowledge of the magnitude of this is important. Research shows any variability increases as well as mean changes has strong impacts on society (Brown and Lall, 2006). Furthermore, food and water availability in East Africa has multiple socio-economic drivers, alongside climatic influences (Little et al., 2001; Adhikari et al., 2015). Although here we have focused on climate model projections of the future, more holistic approaches will combine climate and crop impact modelling. The hope is that climate model predictions for east Africa will move towards a consensus on expected changes, helping then better protection and disaster preparedness against future famine.” (Page: 3, Lines: 12-33)

***Reviewer #1* Detailed Comments:**

Page 1, Line 10: "merging" could be explained better

[Response 1.5] We have clarified this in the manuscript: "After bias correction to match contemporary rainfall mean, GCMs project small decreases in probability of drought of same severity for East Africa by the end of 21st century. However, further adjusting the variance of GCMs to match ERA-interim data, probability of drought increases slightly." (Page: 1, Lines: 9-11)

Page 1, Line 11: GCM is the acronym for "General Circulation Model"

[Response 1.6] Corrected.

Page 1, Line 11: make sure to distinguish ERAinterim from other ECMWF reanalyses

[Response 1.7] Done.

Page 1, Line 18: the reader would need at least some justification why there was a famine in East Africa and not in other regions, where according to Fig. 1a the rainfall deficiency is much worse

[Response 1.8] The east Africa is especially vulnerable to the impacts of drought because of a unique combination of several adverse factors. We now write in paper: "We concentrate on East Africa, as this region experienced particularly poor harvest and where famine was widely reported during 2016 (noting that regions outside black rectangle of Fig. 1a also experienced major rainfall deficits in 2016). East Africa is especially vulnerable to the impacts of drought (DEC, 2017). The region has long experienced widespread poverty and high levels of food insecurity (Von Grebmer et al., 2016). The high dependence of its population on rain-fed agriculture, sometimes in tandem with political instability, exacerbate the impacts of droughts (Love, 2009; Masih et al., 2014)." (Page: 1; Lines: 18-24).

Fig. 1: that does not look like the percentage of average rainfall, as suggested in the figure, rather it must be the percentage deviation from the mean rainfall.

[Response 1.9] Thank you for this. The Figure label now reads "Rainfall for Aug to Oct, 2016 as a percent change from the average (%)".

Page 1, Line 18: "this" = this region?

[Response 1.10] Done.

Page 1, Line 19: a list of the models would be helpful. Readers like to know which model they're looking at, and if these particular models were picked for a reason.

[Response 1.11] We list the CMIP5 ESMs that provide monthly precipitation of both historical simulations and RCP8.5 projections in this study, resulting in a list of 37 ESMs (Table S1). In addition, our new Figure 3 provides GCM-specific information on projections (see Response 1.17 for detailed explanations).

Table S1. CMIP5 global circulation models (GCMs) used in this study, and their components.

Model Name	**Atmospheric Model**	**Land surface Model**	**Oceanic Model**	**Reference**
ACCESS1-0	HadGEM2 r1.1	MOSES	MOM4pl	*Bi et al.*(2012)
ACCESS1-3	Similar to GA 1.0	CABLE v1.8	MOM4p	
bcc-csm1-1	BCC_AGCM2.2	BCC_AVIM1.0	MOM4_L40	*Wu et al.* (2013)
bcc-csm1-1-m	BCC_AGCM2.2	BCC_AVIM1.0	MOM4_L40	
BNU-ESM	CAM3.5	CLM	MOM4p1	*Ji et al.* (2014)
CanESM2	CanAM4	CLASS2.7	CanOM4 and CMOC1.2	*Arora et al.* (2011)
CCSM4	CAM4	CLM4	POP2	*Gent et al.* (2011)
CESM1-BGC	CAM4	CLM4	POP2	*Neale et al.* (2010)
CESM1-CAM5	CAM5	CLM4	POP2	
CMCC-CESM	ECHAM5	SILVA	NEMO	*Scoccimarro et al.* (2011)
CMCC-CM	ECHAM5	SILVA	OPA 8.2	
CMCC-CMS	ECHAM5	SILVA	OPA 8.2	
CNRM-CM5	ARPEGE climate	SURPEXv5.1	NEMO3.3	*Voldoire et al.* (2011)
CSIRO-Mk3-6-0	AGCMv7.3.8	a soil-canopy scheme	GFDL MOM2.2	*Rotstayn et al.* (2010)
EC-EARTH	IFS	H-TESSEL	NEMO	Hazeleger et al. (2010)
GFDL-CM3	GFDL-AM3	LM3	MOM	*Donner et al.* (2011)
GFDL-ESM2G	GFDL-AM2.1	LM3	GOLD	*Dunne et al.* (2012)
GFDL-ESM2M	GFDL-AM2.1	LM3	MOM4	
GISS-E2-H-CC	GISS-E2	GISS-LSM-CC	HYCOM	*Schmidt et al.* (2014)
GISS-E2-H	GISS-E2	GISS-LSM	HYCOM	
GISS-E2-R-CC	GISS-E2	GISS-LSM-CC	Russell	
GISS-E2-R	GISS-E2	GISS-LSM	Russell	
HadGEM2-CC	HadGAM2	TRIFFID	HadGOM2	*Collins et al.* (2011)
HadGEM2-ES	HadGAM2	TRIFFID	HadGOM2	*Jones et al.* (2011)
INMCM4	INM	INM	HadGOM2	*Volodin et al.* (2010)
IPSL-CM5A-LR	LMDZ5A	ORCHIDEE	NEMO	*Dufresne et al.* (2012)
IPSL-CM5A-MR	LMDZ5A	ORCHIDEE	NEMO	
IPSL-CM5B-LR	LMDZ5B	ORCHIDEE	NEMO	
MIROC5	FRCGC-AGCM	MATSIRO	COCO4.5	*Watanabe et al.* (2011)
MIROC-ESM	FRCGC-AGCM	MATSIRO	COCO4.5	
MIROC-ESM-CHEM	FRCGC-AGCM	MATSIRO	COCO4.5	
MPI-ESM-LR	ECHAM6	JSBACH	MPIOM	*Ilyina et al.* (2013)
MPI-ESM-MR	ECHAM6	JSBACH	MPIOM	
MRI-CGCM3	MRIÒAGCM3	HAL	MRI.COM3	*Yukimoto et al.* (2012)
NorESM1-ME	CAM4-Oslo	CLM4	MICOM	*Tjiputra et al.* (2013)
NorESM1-M	CAM4-Oslo	CLM4	MICOM	

Page 1, Lines 20 – 23: describe the method more clearly.

Page 1, Line 22: "This is also...": this sentence is not clear.

[Response] Yes, the original manuscript version we now see could have been written more clearly. We now re-write the method in the revised manuscript as follows, and we think it now has ambiguity removed: "A bias correction with two post-processing steps is applied to the GCM precipitation estimates. We first calculate modelled and ERA-based mean ASO rainfall estimates over the east Africa during the period 1979-2015. The GCM precipitation estimates, both past and future, are corrected by a GCM-specific mean correction factor, which is a ratio of the climatological mean of each GCM to that of the ERA-interim reanalysis product. Second, we then adjust the climatological standard deviation (STD) of GCM precipitation estimates by multiplying the ratio of the climatological STD of each GCM to that of the ERA-interim data. The adjustment of spread of rainfall distribution is an important additional procedure to further constrain GCM estimates (Sippel et al., 2016; Jeon et al., 2016; Angelil et al., 2017). Together this ensures all GCMs have the ERA-based mean and STD for period 1979-2015." (Page: 1, Lines: 28-31 and Page: 2, Lines: 1-4)

Page 1, Line 22: precipitation estimates in reanalysis products tend to be comparably poor. It will need to be justified why this particular dataset was used and not some other precipitation dataset.

[Response 1.12] This is also noted by reviewer 2, and we answer this in full by now using a large ensemble of four additional global precipitation data sets (Table S2). These precipitation data sets are interpolated gauge observations only (i.e. PREC/L and CPC), gauge observations combined with satellite measurements (i.e. GPCP), or satellite observations (i.e. TRMM). This is alongside our original ERA-interim data product.

All the rainfall products show the August-to-October (ASO) rainfall in year of 2016 is less than the climatological mean of ASO rainfall (Table S2 and an additional Figure below which is not in paper). However, when we use all five products to correct climatological mean and STD of GCM rainfall estimates, such bias-correction influences strongly future projections. We illustrate these differences in a new Figure 2, which has one panel of future projections for each rainfall product. We are grateful for this reviewer request, now allowing better presentation of uncertainty.

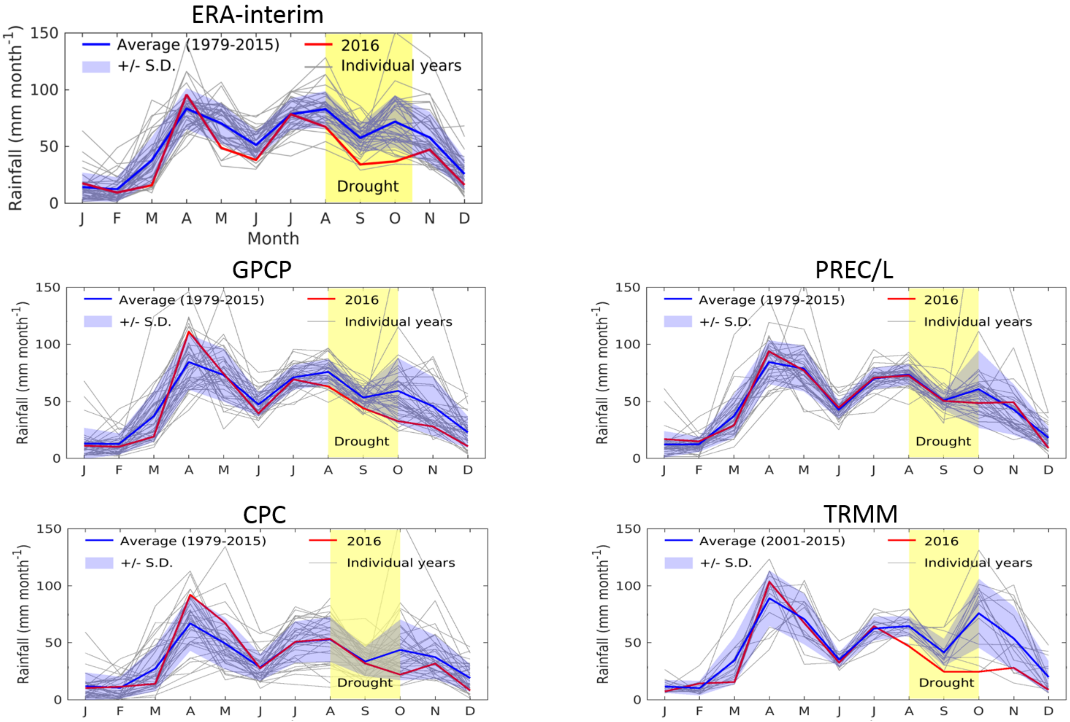
At lines 21-34 (Page 2) of the paper, we now write: "Given that large uncertainty in the observation-based precipitation products has been well reported (Angélil et al., 2016), we use four other precipitation estimates (GPCP, PREC/L, CPC and TRMM) to bias-correct

GCM estimates. In Fig. 2 we reproduce the insets of Fig 1c (no hatching) and Fig 1d (hatching) for ERA-Interim, and then for the four other precipitation products. Consistent with the conclusions based on the ERA-interim product only, the results from the other rainfall products also show that the probability of drought occurrence in the east Africa has decreased slightly from pre-industrial to present day, and irrespective of whether variance adjustment has occurred (Fig. 2, all blue and black bars, with and without hatching). Future projections, though, of drought likelihood do vary across different precipitation products. For the mean-corrected GCM estimates, 4 out of 5 rainfall product-corrected GCM projections give a slight decrease in drought occurrence likelihoods by the end of 21st century. The exception is the TRMM-corrected GCMs, which suggest the drought probability would increase slightly by 2070-2100 and relative to the present day. For the mean- and variance-corrected GCM estimates, relative to the present-day levels the GCM estimates corrected to the ERA-interim, GPCP, and TRMM products give an increase in drought occurrence probability. However PREC/L- and CPC-corrected GCM estimates suggest the probability of drought occurrence will decrease. This divergence is due to the strong differences in the climatological mean, standard deviation and year 2016 ASO rainfall levels among the different precipitation products (Table S2)."

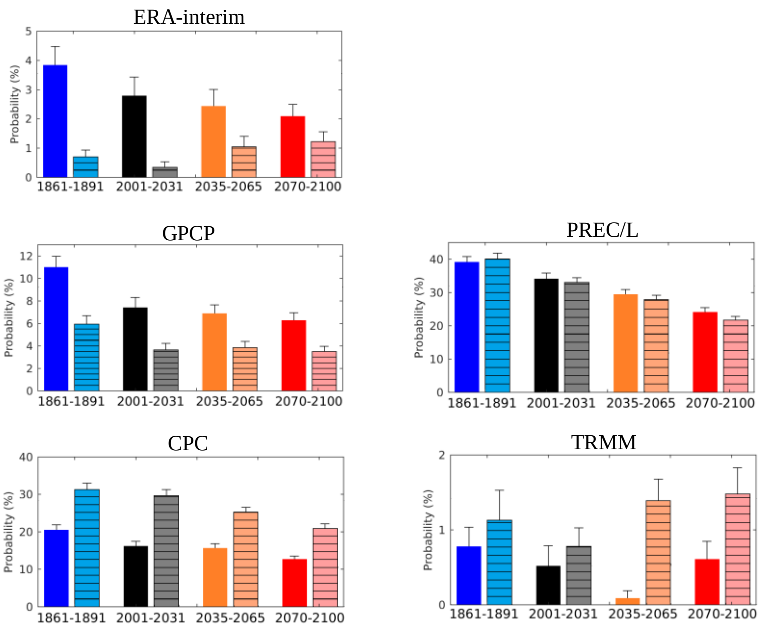
Table S2. The mean August-to-October (ASO) rainfall (mm month^{-1}) of year 2016, multi-year mean (not including 2016) and multi-year standard deviation (STD) over east Africa for years 1979 to 2016. The five global precipitation data sets used are listed. Four products of ERA-interim, GPCP, PREC/L, CPC and TRMM are available from 1979 to 2016. These four precipitation data sets are either interpolated gauge observations only (i.e. PREC/L and CPC), gauge observations combined with satellite measurements (i.e. GPCP), or reanalysis data (i.e. ERA-interim). The TRMM satellite observations are available from 2001 to 2016.

ASO rainfall (mm month^{-1})	ERA-interim	GPCP	PREC/L	CPC	TRMM
2016	46.10	46.56	57.16	35.78	32.05
Climatological mean (1979-2015)	70.76	62.78	61.68	43.44	60.69*
Climatological STD (1979-2015)	11.28	10.40	11.48	13.89	11.83*

* TRMM satellite precipitation data is only available from 2001 to 2016. The climatological ASO rainfall averages of the period 2001-2015 is computed.



Additional Figure for response (not in paper). The monthly total rainfall (mm per month) over study region (panel Figure 1a; land within black rectangle) for years 1979 to 2016. Year 2016 is red, other years are individual grey lines, and multi-year average (not including 2016) is blue. Blue shading is ± one standard deviation of monthly rainfall across years 1979-2015. The drought event (shaded in yellow) is defined as the three consecutive months of ASO when rainfall in year 2016 is below blue shading.



New Figure 2 in the revised manuscript. CMIP5-based histograms of probabilities of mean ASO rainfall falling below year 2016-based threshold values. Shown for periods 1861-1891 (blue), 2001-2031 (black), 2035-2065 (orange) and 2070-2100 (red). Each bar corresponds to merged normalized outputs from 37 CMIP5 models forced by historical emissions and RCP8.5 future scenario. The bars without horizontal hatching (left) are for the mean-corrected GCM precipitation estimates. The bars with hatching (right) are for the mean- and variance-corrected GCM estimates.

Page 1, Line 24: "31 times 37 numbers": be more clear

[Response 1.13] We have improved all the related text to number of models and time-periods used. We now write "Bias-corrected mean ASO rainfall are presented in Fig. 1c for mean bias correction, and in Fig. 1d for mean and STD bias correction. These are derived from 37 GCMs, and for four 31-year periods (pre-industrial, present day, and two future periods)." (Page: 2, Lines: 5-7)

Page 1, Line 25: month-1 = per month?

[Response 1.14] Corrected.

Page 1, Line 27/28: is this a significant increase? It seems rather small.

[Response 1.15] Based on this, and to enable better assessment of whether these changes are significant, we now provide uncertainty bounds on probability of drought for different time periods. This allows far better visual comparisons of the changes within Figure 1 and new Figure 2. We do this via bootstrapping methods. In particular, the one standard deviations are estimated via bootstrapping with 80% replications from the 37 GCM precipitation data and for the 31-year periods.

Page 1, Line 28: "stretch in the distribution tail"? Maybe just describe that the mean of the distribution shifts to higher rainfall amounts, while the tails flatten.

Page 1, Line 29: "stretched left-tails": same here

[Response 1.16] As can be seen from our revised Figure 1, we no longer fit normal curves, and instead rely on direct presentation of the probability density functions of ASO rainfall estimates. Hence we have removed the sentences about the changes in the distribution tails in the reviewed manuscript.

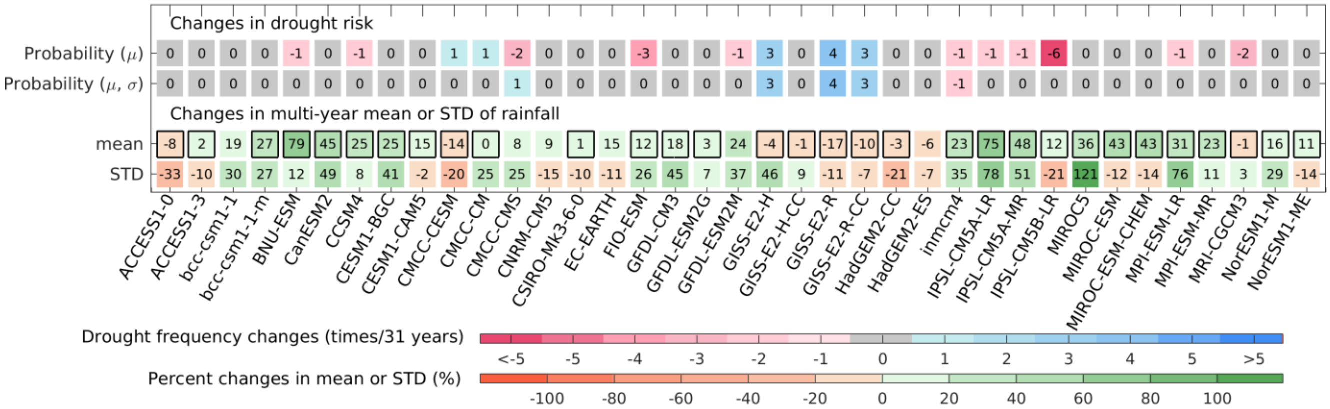
Page 1, Line 30: "a few models": which ones? How many?

Page 1, Line 30: "increased interannual variability": it would be helpful for the general reader to know the seasonal cycle of rainfall in this region. It seems there is a significant intermodal variability, and it does not become clear from the manuscript if these models can be trusted.

[Response 1.17] This request has led to new Figure 3 (repeated below), that shows individual model responses. Overall ASO mean rainfall levels increase in 28 out of 37 GCMs from the present period 2001-2031 to the period 2070-2100.

In terms of variability, this new figure in the revised manuscript shows changes in STDs for each GCM. We found enhanced STDs of 31-year rainfall variations in 22 out of 37 GCMs. We have taken the issue of whether the STD of models can be trusted by now including this in our bias-correction methods. Unlike the previous manuscript version, we now compensate for both the model mean and STD discrepancies (Figure 1c versus new Figure 1d, and within Figure 2).

Besides, we write in the text: "We also show individual model changes in mean and STD of ASO rainfall, for 31 years 2070-2100 compared to 2001-2031. Fig. 3 shows 28 out of 37 model estimates for this region become wetter, and most models (i.e. 22 out of 37 models) exhibiting increased distribution spreads reflected by raised STDs." (Page: 3, Lines: 6-9)



New Figure 3 in the revised manuscript. Changes in drought frequency, multi-year mean and standard deviations (STD) of 31 consecutive year rainfall amounts. Difference between present period 2001-2031 and period 2070-2100, as estimated by 37 GCMs. GCM estimates are corrected by the ERA-interim rainfall product. Changes to frequencies of drought occurrence are estimated from the mean bias-corrected GCM estimates (1st row), both mean- and variance bias-corrected GCM estimates (2nd row). The colored grids in the 3rd row with black borders indicate statistically significant differences in the 31-year rainfall mean between these two periods (*t*-test, with P < 0.05). The percentage changes are calculated as $[(x_{2070\text{-}2100}/x_{2001\text{-}2031})-1]\times100\%$.

Page 2, Line 1: "considers models equally": but the models are all modified to fit ERAinterim, so "equally" is maybe not the right term?

[Response 1.18] We now modify this sentence, as follow: "This is based on a relatively simple assessment of 37 climate models, each given equal weight but after being corrected by observation-based rainfall products." (Page: 3, Lines: 13-14). Please also note, as described above, our analysis now include five rainfall products, and so not just ERA-interim.

Figure 1b: is this year significantly different from other years? What about these other years when rainfall was low or even lower than this year? Were these also drought years?

[Response 1.19] The area-weighted spatial average of monthly rainfall from ERA reanalysis product over the August to October (ASO) of 2016 lies at least one standard deviation (STD) below the climatological mean of the other years (i.e. 1979-2015) (see Figure 1b).

There are other five years (1986, 1990, 1991, 1993 and 2010) where the ASO rainfall also lies at least one standard deviation below the climatological mean during 1979-2015.

One year in particular has been studied, that of 2010, and this also caused widespread famine and loss of life. We now write: "For this region, the spatial average of monthly rainfall during ASO of 2016 lies at least one standard deviation below the climatological mean of the other years (Fig. 1b). The year of 2016 is the third driest year in the past four decades. Other years with rainfall at least one standard deviation below the climatological mean during 1979-2015 are 1986, 1990, 1991, 1993 and 2010. Year of 2010 also suffered from the severe famine (Dutra et al., 2013)." (Page: 1; Lines: 15-18)

Figure 1c: the PDFs look surprisingly smooth, it would have been nicer to see some structure. Or at the very least explain the smoothing that has been used.

[Response 1.20] Please note we responded rapidly to this, as we accept the smoothness is misleading. Please see our earlier response on NHESS website, as to why we reverted to presenting directly the pdf of ASO seasonal rainfall, rather than a smoothed fit to these.

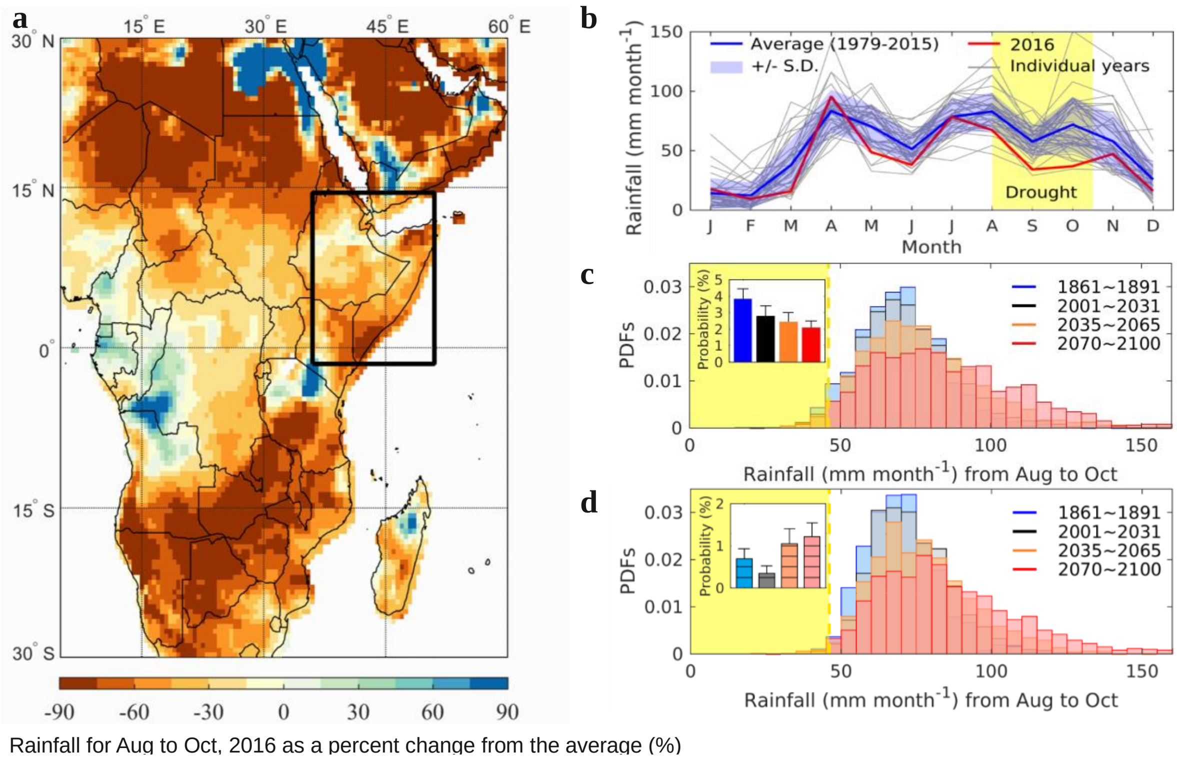


Figure 1 in the revised manuscript. (**a**) Black rectangle is location of study region (14.5°N~1.5°S, 36°E~51°E). Plotted is mean rainfall for 2016 and months August to October inclusive (ASO), presented relative changes (as %) to long-term average ASO values (1979-2015). Values based on ERA-interim reanalysis product. (**b**) ERA-based monthly total rainfall (mm month^{-1}) over study region (panel a; land within black rectangle) for years 1979 to 2016. Year 2016 is red, other years are individual grey lines, and multi-year average (not including 2016) is blue line. Blue shading is ± one standard deviation of monthly rainfall across years 1979-2015. The drought event (shaded in yellow) is defined as the three consecutive months of ASO, and when rainfall in year 2016 is below blue shading. (**c**) CMIP5-based PDFs of mean ASO rainfall for periods 1861-1891 (blue), 2001-2031 (black), 2035-2065 (orange) and 2070-2100 (red). Each curve corresponds to the mean-corrected combined outputs from 37 CMIP5 models forced by historical emissions and RCP8.5 future scenario. Individual GCM bias correction is based on the ERA-interim reanalysis product. Yellow shading is mean ASO rainfall less than 46 mm month-1, which is the ERA-interim 2016-based threshold (mean of ASO, red curve in panel b). Inset shows probabilities of mean rainfall of ASO falling below the threshold for the same modelled periods (colours match those of curves). The error bars are the standard deviations (estimated via bootstrapping 80% replications from the 37 GCM precipitation data for the 31-year periods). (**d**) same as (**c**), but based on the mean- and variance-corrected GCM rainfall estimates.

To Reviewer #2:

***Reviewer #2* General Comments:**

We thank Reviewer #2 for their help and time spent on this paper. Our responses are below, and revised text in the paper repeated in red font.

This study by Yang and Huntingford uses a combination of historical data from a single reanalysis product (ERA-Interim), combined with models from the CMIP5 suite, to quantify changes in drought risk over the East Africa region under a high-warming scenario (RCP8.5). The study does not include validation analysis to determine whether the models being considered can in fact provide a reasonable representation of the observed climate for the region of interest – this is particularly problematic given the long-recognised absence of high-quality observational records over these regions. There have also been several other studies analysing changes to East African drought in recent years, which the authors have failed to acknowledge. Finally, there is little to no treatment of statistical uncertainty estimates accompanying the results, which is fundamentally misleading to the reader.

[Response 2.1] Thank you for these thoughtful and valuable comments on previous version of this manuscript. Following those comments and suggestions, we have thoroughly revised the manuscript. Main changes in the revised manuscript correspond to the three requests above:

1. Given that the large uncertainty in the observation-based precipitation products has been well reported, we have advanced our calculations to include other precipitation products (e.g. GPCP, PREC/L, CPC and TRMM). This allows assessment of the robustness any conclusions.
2. We have cited the recent published papers related to the east African drought.
3. We perform additional analysis, and now apply bootstrapping techniques to provide uncertainty bounds on revised diagrams.

Please see below detailed responses to each specific comment.

***Reviewer #2* Specific Comments:**

1) Why was ERA-Interim reanalysis chosen? Has there been any sensitivity analyses using other reanalysis products, or comparison with observational rainfall products for common time periods? I would like to see some demonstration as to whether the results would vary if NCEP2, JRA or 20th Century Reanalysis products were used instead, as well as some consideration of actual observational data (such as TRMM, CRU-TS, or individual station-

based records).

The authors are referred to the following papers for reference:

- *Angelil et al (2016, Weather and Climate Extremes,)*
- *Sillmann et al (2013, JGR Atmospheres, doi:10.1002/jgrd.50203)*

[Response 2.2] Based on this request, we now use an ensemble of five global precipitation data sets (Table S2). In addition to our original ERA-interim product, we now use four additional precipitation data sets. These are interpolated gauge observations only (i.e. PREC/L and CPC), gauge observations combined with satellite measurements (i.e. GPCP), or satellite observations (i.e. TRMM).

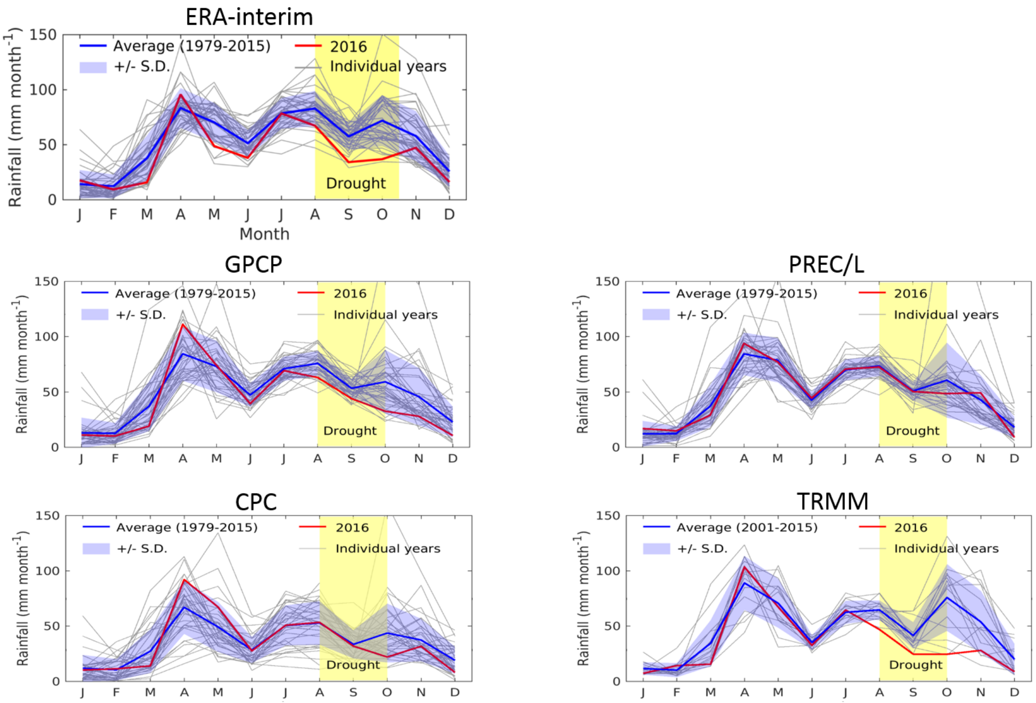
Although the uncertainty in rainfall changes over Africa is large, all the rainfall products show the August-to-October (ASO) rainfall in year of 2016 is less than the climatological mean ASO rainfall to each (Table S2 and an additional Figure below which is not in paper). However, when using the different datasets to bias-correct the GCM rainfall estimates (their climatological mean and SD), we do find our estimated probabilities of future drought are dependent on precipitation product used. We are grateful for the encouragement to do this, and it has led to a new Figure 2 in the manuscript (please see below).

For completeness, below we repeat here the revised part of the manuscript that describes the differences found in our results from between using five precipitation products to do the bias-correction (and after that follows Table S2, and two Figures mentioned above). At lines 21-34 (Page 2) of the paper, we now write: "Given that large uncertainty in the observation-based precipitation products has been well reported (Angélil et al., 2016), we use four other precipitation estimates (GPCP, PREC/L, CPC and TRMM) to bias-correct GCM estimates. In Fig. 2 we reproduce the insets of Fig 1c (no hatching) and Fig 1d (hatching) for ERA-Interim, and then for the four other precipitation products. Consistent with the conclusions based on the ERA-interim product only, the results from the other rainfall products also show that the probability of drought occurrence in the east Africa has decreased slightly from pre-industrial to present day, and irrespective of whether variance adjustment has occurred (Fig. 2, all blue and black bars, with and without hatching). Future projections, though, of drought likelihood do vary across different precipitation products. For the mean-corrected GCM estimates, 4 out of 5 rainfall product-corrected GCM projections give a slight decrease in drought occurrence likelihoods by the end of 21st century. The exception is the TRMM-corrected GCMs, which suggest the drought probability would increase slightly by 2070-2100 and relative to the present day. For the mean- and variance-corrected GCM estimates, relative to the present-day levels the GCM estimates corrected to the ERA-interim, GPCP, and TRMM products give an increase in drought occurrence probability. However PREC/L- and CPC-corrected GCM estimates suggest the probability of drought occurrence will decrease. This divergence is due to the strong differences in the climatological mean, standard deviation and year 2016 ASO rainfall levels among the different precipitation products (Table S2)."

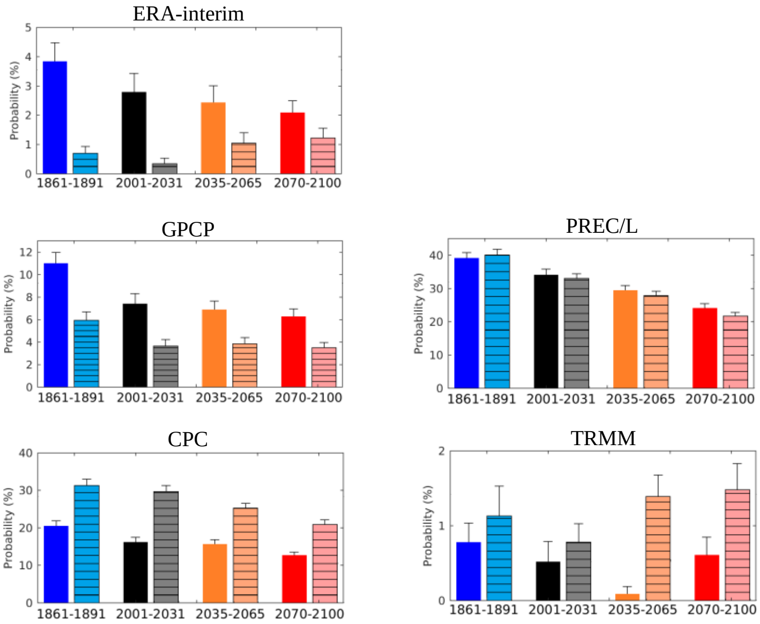
Table S2. The mean August-to-October (ASO) rainfall (mm month^{-1}) of year 2016, multi-year mean (not including 2016) and multi-year standard deviation (STD) over east Africa for years 1979 to 2016. The five global precipitation data sets used are listed. Four products of ERA-interim, GPCP, PREC/L, CPC and TRMM are available from 1979 to 2016. These four precipitation data sets are either interpolated gauge observations only (i.e. PREC/L and CPC), gauge observations combined with satellite measurements (i.e. GPCP), or reanalysis data (i.e. ERA-interim). The TRMM satellite observations are available from 2001 to 2016.

ASO rainfall (mm month^{-1})	ERA-interim	GPCP	PREC/L	CPC	TRMM
2016	46.10	46.56	57.16	35.78	32.05
Climatological mean (1979-2015)	70.76	62.78	61.68	43.44	60.69*
Climatological STD (1979-2015)	11.28	10.40	11.48	13.89	11.83*

* TRMM satellite precipitation data is only available from 2001 to 2016. The climatological ASO rainfall averages of the period 2001-2015 is computed.



Additional Figure for response (not in paper). The monthly total rainfall (mm per month) over study region (panel Figure 1a; land within black rectangle) for years 1979 to 2016. Year 2016 is red, other years are individual grey lines, and multi-year average (not including 2016) is blue. Blue shading is ± one standard deviation of monthly rainfall across years 1979-2015. The drought event (shaded in yellow) is defined as the three consecutive months of ASO when rainfall in year 2016 is below blue shading.



New Figure 2 in the revised manuscript. CMIP5-based histograms of probabilities of mean ASO rainfall falling below year 2016-based threshold values. Shown for periods 1861-1891 (blue), 2001-2031 (black), 2035-2065 (orange) and 2070-2100 (red). Each bar corresponds to merged normalized outputs from 37 CMIP5 models forced by historical emissions and RCP8.5 future scenario. The bars without horizontal hatching (left) are for the mean-corrected GCM precipitation estimates. The bars with hatching (right) are for the mean- and variance-corrected GCM estimates.

2) Why is there no broader consideration of the suitability of the climate models used, beyond a bias correction based on climatological mean precipitation? This approach to bias correction has been widely considered inadequate in the context of analysing precipitation extremes, and especially so for within an attribution context. For example, if the width of the distribution of precipitation is unrealistically narrow, than even a 'realistic' shift in the mean of the distribution would result in an overestimation of the increased likelihood of future low-precipitation extremes.

The authors are referred to the following papers for reference:

-Sippel et al (2016, Earth System Dynamics, doi:10.5194/esd-7-71-2016)

-Jeon et al (2016, Weather and Climate Extremes)

-Angelil et al (2017, Journal of Climate, https://doi.org/10.1175/JCLI-D-16-0077.1)

[Response 2.3] We have performed new analysis in response to this request. In particular, we now additionally bias-correct and ensure the standard deviation of GCMs equals the standard deviation in the observational data products. This has led us to re-calculate the likelihoods of east African drought, and a new panel in Figure 1 (Figure 1d in the revised manuscript). We are grateful for this request to address distribution width issue - our results suggest the choice of bias correction methodology (i.e. with/without additional STD bias-correction) is a major source of uncertainty in drought likelihood projection.

Then state here we now use those reference, and repeat the sentences here: "Second, we then adjust the climatological standard deviation (STD) of GCM precipitation estimates by multiplying the ratio of the climatological STD of each GCM to that of the ERA-interim data. The adjustment of spread of rainfall distribution is an important additional procedure to further constrain GCM estimates (Sippel et al., 2016; Jeon et al., 2016; Angelil et al., 2017)." (Page: 1; Line: 31 and Page: 2, Lines: 1-3)

3) Moreover, the authors fail to consider the many other contributions beyond low precipitation which can contribute to a severe drought. In this context, an exploration of more robust drought metrics would be helpful.

[Response 2.4] Thank you for this comment. We respectfully request that we don't expand our paper to alternative drought metrics, in part as some involve socio-economic and governance implications which would take beyond the remit of a Brief Communications. This, hopefully, will be a component of full size climate - socio-economic studies in over the years ahead.

However, we do want to change the manuscript to acknowledge this issue. In particular, other African regions also suffered from rainfall deficits in 2016, and yet there were fewer media reports of famine. This supports, therefore, that drought-induced famine has more aspects than simply low rainfall. For this reason, we want to stress this point, and by guiding readers to observe the low rainfall also recorded beyond East Africa, and as show in Figure 1. We have now amended the manuscript to say: "We concentrate on East Africa, as this region experienced particularly poor harvest and where famine was widely reported during 2016 (noting that regions outside black rectangle of Fig. 1a also experienced major rainfall deficits in 2016). East Africa is especially vulnerable to the impacts of drought (DEC, 2017). The region has long experienced widespread poverty and high levels of food insecurity (Von Grebmer et al., 2016). The high dependence of its population on rain-fed agriculture, sometimes in tandem with political instability, exacerbate the impacts of droughts (Love, 2009; Masih et al., 2014)." (Page: 1; Lines: 18-24)

4) The absence of uncertainty estimates in Figure 1c is troubling. Most attribution studies *provide, at the very least, bootstrapping estimates of uncertainty. I suspect that if error bars did accompany the probability changes in the inset panel, the changes for 2001-2031 and 2035-2065 would be statistically insignificant relative to 1861-1891. Further, it is not clear as to whether the future probabilities of witnessing less than 46mm month-1 have been calculated using raw model data, or the excessively-smoothed PDF constructions.*

[Response 2.5] We have address all issues raised. We now calculate the bootstrapping estimates of uncertainty and add the uncertainty bounds on to the insets of Figure 1c, 1d and also on new Figure 2. The one standard deviations are estimated via bootstrapping with 80% replications from the 37 GCM precipitation data and for the 31-year periods. As the reviewer predicted, these uncertainty bounds do overlap, allowing a visual interpretation that changes may not be detectable.

We accept the reviewers' questioning of appropriateness of smoothing in our original panel 1c, and this revealed a factual error. In the revised manuscript, we now simply show bias-corrected GCM projections as a probability density function. These revised a plot (Figures 1c and 1d) – please see below.

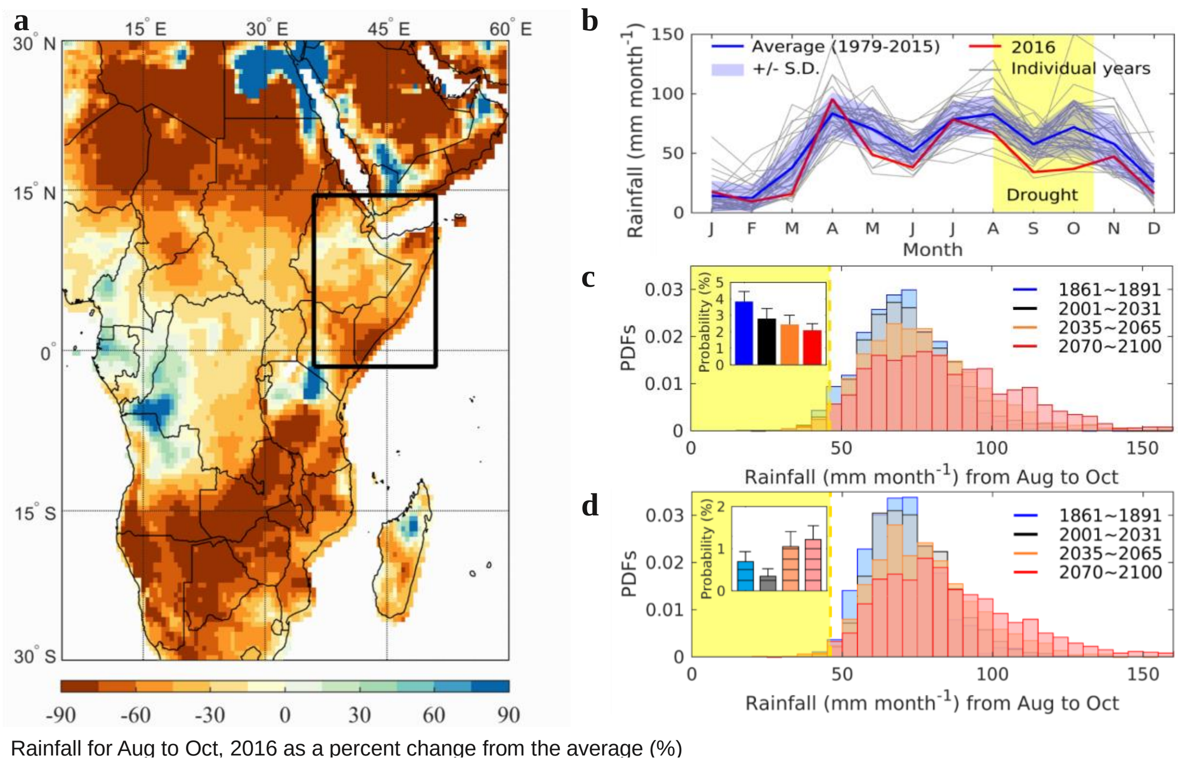


Figure 1 in the revised manuscript. (**a**) Black rectangle is location of study region (14.5°N~1.5°S, 36°E~51°E). Plotted is mean rainfall for 2016 and months August to October inclusive (ASO), presented relative changes (as %) to long-term average ASO values (1979-

2015). Values based on ERA-interim reanalysis product. (**b**) ERA-based monthly total rainfall (mm month^{-1}) over study region (panel a; land within black rectangle) for years 1979 to 2016. Year 2016 is red, other years are individual grey lines, and multi-year average (not including 2016) is blue line. Blue shading is ± one standard deviation of monthly rainfall across years 1979-2015. The drought event (shaded in yellow) is defined as the three consecutive months of ASO, and when rainfall in year 2016 is below blue shading. (**c**) CMIP5-based PDFs of mean ASO rainfall for periods 1861-1891 (blue), 2001-2031 (black), 2035-2065 (orange) and 2070-2100 (red). Each curve corresponds to the mean-corrected combined outputs from 37 CMIP5 models forced by historical emissions and RCP8.5 future scenario. Individual GCM bias correction is based on the ERA-interim reanalysis product. Yellow shading is mean ASO rainfall less than 46 mm month-1, which is the ERA-interim 2016-based threshold (mean of ASO, red curve in panel b). Inset shows probabilities of mean rainfall of ASO falling below the threshold for the same modelled periods (colours match those of curves). The error bars are the standard deviations (estimated via bootstrapping 80% replications from the 37 GCM precipitation data for the 31-year periods). (**d**) same as (**c**), but based on the mean- and variance-corrected GCM rainfall estimates.

5) The use of 1861-1891 is a misleading representation of 'pre-industrial' as it includes the influences of the Krakatoa volcanic eruption, and associated cooling effects. I strongly recommend changing the baseline period, perhaps to 1861-1880 in accordance with the IPCC's definition.

[Response 2.6] We have checked this. We are keen to keep each period containing 31 years, so all statistics are comparable between timeframes analyzed. We check probability for two 31 year segments of (i) 1861-1891 and (ii) split period 1861-1881 and 1890-1899. We find for ASO East Africa rainfall, there is no difference in probabilities, and so we request keeping the pre-industrial representative years as in the original paper version.

***Reviewer #2* Technical Comments:**

P1, L5: East Africa, not East African.

[Response 2.7] Corrected.

P1, L10: It's not really an analysis 'merging' ERA-Interim data with CMIP5 data. Instead you are using ERA-Interim as a basis for bias-correcting the model data.

[Response 2.8] We thank the reviewer pointing it out. We now have clarified this and revised this sentence in the manuscript: "After bias correction to match contemporary rainfall mean, GCMs project small decreases in probability of drought of same severity for East Africa by the end of 21st century. However, further adjusting the variance of GCMs to match ERA-interim data, probability of drought increases slightly." (Page: 1, Lines: 9-11)

P1, L14: '... shows that during August to October'?

[Response 2.9] Corrected.

P1, L20: RCP8.5 is not designed as a 'business-as-usual' scenario. It is in fact an acceleration of the present-day rates of increase in radiative forcing. The closest to 'business-as-usual' would be RCP6.0. I suggest the authors modify this particular phrase.

[Response 2.10] To avoid confusion, the phrase of "business-as-usual scenario" is modified to "high emission future scenario".

P1, L20-L23: This is poorly phrased. So you are bias-correcting based on climatological mean precipitation for ERA-Interim?

[Response 2.11] Yes, we bias correction on climatological mean precipitation. In light of your comment 2.3 above, we also bias-correct on variance. We now re-write the method in the revised manuscript, which we hope removes previous ambiguities. We write: "A bias correction with two post-processing steps is applied to the GCM precipitation estimates. We first calculate modelled and ERA-based mean ASO rainfall estimates over the east Africa during the period 1979-2015. The GCM precipitation estimates, both past and future, are corrected by a GCM-specific mean correction factor, which is a ratio of the climatological mean of each GCM to that of the ERA-interim reanalysis product. Second, we then adjust the climatological standard deviation (STD) of GCM precipitation estimates by multiplying the ratio of the climatological STD of each GCM to that of the ERA-interim data. The adjustment of spread of rainfall distribution is an important additional procedure to further constrain GCM estimates (Sippel et al., 2016; Jeon et al., 2016; Angelil et al., 2017). Together this ensures all GCMs have the ERA-based mean and STD for period 1979-2015." (Page: 1, Lines: 28-31 and Page 2: 1-4)

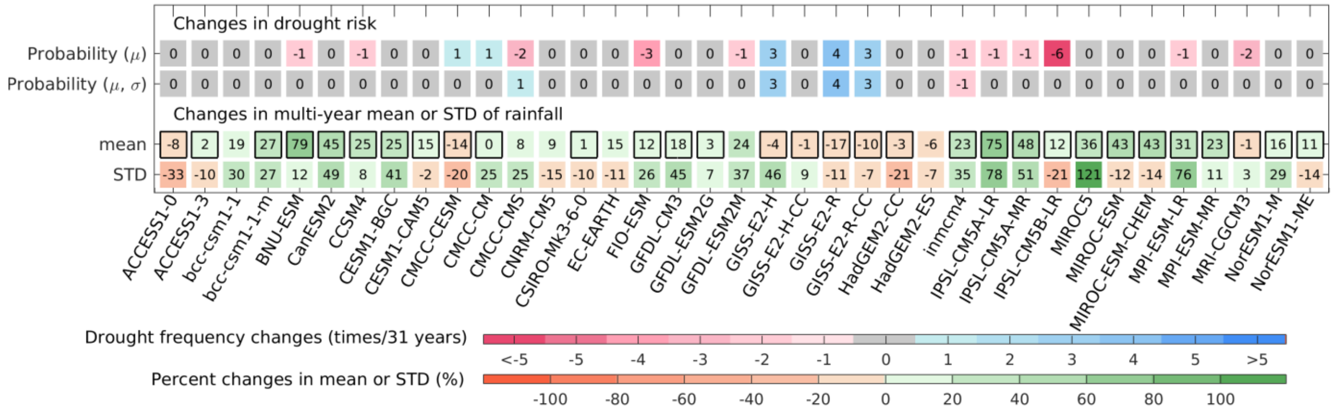
P1, L27-28: I suspect a change from 5.6 to 5.8% is not statistically significant in any way, and repeating these calculations with even just two or three models removed could lead to a completely different answer. What is the range in answers of this probabilistic increase for *each individual model?*

[Response 2.12] Following your helpful suggestion, we have answered this in two ways.

First, in response to your comment 2.5 above, we now undertake bootstrapping to provide estimates of uncertainty (Figure 1c, d; new Figure 2). These uncertainty bounds place in a much better context GCMs estimates of changes in the probability of drought occurrence in east Africa.

Second, we also calculate the changes in probabilities of drought estimated from each of individual GCMs between period 2001-2031 and period 2070-2100. This creates a new Figure 3 (please see below). For the mean-corrected GCM estimates, the changes in probabilities of drought range from -19.4% (-6 times per 31 years) to +12.9% (+4 times per 31 years). For the mean- and variance-corrected GCM estimates, drought probabilities changes range from -3.2% (-1 times per 31 years) to 12.9% (+4 times per 31 years). These values are made clear from Figure 3.

We appreciate being asked to present understanding at the individual GCM scale. This demonstrates that the choice of GCMs used is a major source of uncertainty of future drought risk analysis. Figure 3 also highlights the relatively small number of years in simulations for understanding changes in extreme events. Ideally, there would be a large ensemble of simulations by each model to refine the probability of extreme events, enabling a more complete sampling of probability distributions. Based on this, we now write in the concluding paragraph: "We find the sources of uncertainty in drought prediction include: 1) the choice of bias correction methodology; 2) the choice of observational product used to correct bias in GCMs; and 3) the choice of GCMs used." (Page: 3; Lines: 14-16) and "For rainfall of east Africa predictions in particular, this will link to accurate forward projections of oceanic variability. Strong teleconnections are known to exist between El Niño Southern Oscillation (ENSO) and East African rainfall (Segele et al., 2009; Gissila et al., 2004), and with longer-term fluctuations in Pacific SSTs increasing/decreasing rainfall (Funk et al., 2014; Liebmann et al., 2014). Larger ensembles of simulations by each model is also important, and especially when analysing the probability of extreme events. This enables a more complete sampling of probability distributions, describing more fully the internal variability of the climate system imposed over general climate change." (Page: 3; Lines: 21-26)



New Figure 3 in the revised manuscript. Changes in drought frequency, multi-year mean and standard deviations (STD) of 31 consecutive year rainfall amounts. Difference between present period 2001-2031 and period 2070-2100, as estimated by 37 GCMs. GCM estimates are corrected by the ERA-interim rainfall product. Changes to frequencies of drought occurrence are estimated from the mean bias-corrected GCM estimates (1st row), both mean- and variance bias-corrected GCM estimates (2nd row). The colored grids in the 3rd row with black borders indicate statistically significant differences in the 31-year rainfall mean between these two periods (t-test, with $P < 0.05$). The percentage changes are calculated as $[(x_{2070\text{-}2100}/x_{2001\text{-}2031})-1]\times100\%$.

P1, L29: 'stretched left-tails' is a poor description, and I suggest changing this.

[Response 2.13] We now have removed the sentences about the changes in the distribution tails in the reviewed manuscript. This is due to Review Comment 2.5.

P2, L2-7: This is a very poor concluding paragraph. You do not summarize the key results of the study, but instead offer reasons why significance testing is needed (reliability of different models), before highlighting all of the reasons why monthly-mean precipitation deficits may in fact be a poor proxy for drought impacts over East Africa.

[Response 2.14] We have completely re-written the concluding paragraph, and mainly in light of comments from both Reviewer 1 and Reviewer 2. The main difference in paper versions, is that the requested changes have placed all results in a more complete uncertainty analysis framework. We summarize these main results, noting future predictions of drought likelihood depend on the GCMs used, any bias correction algorithm, and the choice of observation product used to correct bias. Although this is a slightly negative find (i.e. answer is inclusive), we believe this is still important to have placed in the literature.

Based on Review 1 comment 1.3 above, we mention the importance of accurate representation of oceanic drivers, via teleconnections, to East Africa rainfall. In terms of drought proxy, we use the literature better in our discussion, to re-iterate that there are other factors (e.g. social drivers) of importance in terms of ability to deal with low rainfall totals.

Although it takes up space in our response, we list this in full as: "Our analysis reveals that current understanding of how future climate change will impact on East Africa ASO drought risk remains uncertain. This is based on a relatively simple assessment of 37 climate models, each given equal weight but after being corrected by observation-based rainfall products. We find the sources of uncertainty in drought prediction include: 1) the choice of bias correction methodology; 2) the choice of observational product used to correct bias in GCMs; and 3) the choice of GCMs used. Currently, for many geographical regions, GCM estimates of rainfall changes varies substantially across models (Knutti and Sedláček, 2013). Multi-model analyses such as ours consider uncertainty associated with different model parameterisation or scheme describing rainfall features. However, to give more definitive answers, the climate research community may need to be confident enough to rank climate models based on performance to refine future projections (Knutti et al., 2017). Improving GCM projections also could involve on-going constraining of model components. For rainfall of east Africa predictions in particular, this will link to accurate forward projections of oceanic variability. Strong teleconnections are known to exist between El Niño Southern Oscillation (ENSO) and East African rainfall (Segele et al., 2009; Gissila et al., 2004), and with longer-term fluctuations in Pacific SSTs increasing/decreasing rainfall (Funk et al., 2014; Liebmann et al., 2014). Larger ensembles of simulations by each model is also important, and especially when analysing the probability of extreme events. This enables a more complete sampling of probability distributions, describing more fully the internal variability of the climate system imposed over general climate change. In addition, some GCMs estimate an increase in future variability of east African ASO rainfall, and better knowledge of the magnitude of this is important. Research shows any variability increases as well as mean changes has strong impacts on society (Brown and Lall, 2006). Furthermore, food and water availability in East Africa has multiple socio-economic drivers, alongside climatic influences (Little et al., 2001; Adhikari et al., 2015). Although here we have focused on climate model projections of the future, more holistic approaches will combine climate and crop impact modelling. The hope is that climate model predictions for east Africa will move towards a consensus on expected changes, helping then better protection and disaster preparedness against future famine." (Page: 3, Lines: 12-33)

Brief Communication: Drought Likelihood for East Africa

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Abstract. ~~The on-going effects of severe~~East Africa autumn drought in ~~East Africa are causing high levels of~~ 2016 caused malnutrition, ~~hunger,~~ illness and death. Close to 16 million people across Somalia, Ethiopia and Kenya ~~need~~needed food, water and medical assistance ~~(DEC, 2017).~~. Many factors influence drought stress and ~~ability to respond.~~response. However, inevitably it is asked: are elevated ~~atmospheric~~ greenhouse gas ~~(GHG)~~ concentrations altering ~~the likelihood of~~ extreme rainfall ~~deficits?~~deficit frequency? We ~~find small increases~~ investigate with General Circulation Model (GCMs). After bias correction to match contemporary rainfall mean, GCMs project small decreases in probability of ~~this~~drought of same severity for East ~~African, based on merging the observation-based reanalysis dataset~~Africa by the ~~European Centre for Medium-Range Weather Forecasts (ECMWF) (Dee et al., 2011) with Global Climate Models (GCMs) in the CMIP5 database (Taylor et al., 2012).~~end of 21st century. However, further adjusting the variance of GCMs to match ERA-interim data, probability of drought increases slightly.

ECMWF re-analysis data (ERA-interim; Dee et al., 2011) shows that during August to October (ASO) of 2016, large parts of Somalia, Ethiopia and Kenya (Black rectangle, Fig. 1a) had a reduction of 30% or more in rainfall compared to a baseline ASO period 1979-2015. For this region, the spatial average of monthly rainfall during ASO of 2016 lies at least one standard deviation below the climatological mean of the other years (Fig. 1b). ~~During these months, other parts of Africa also experienced severe rainfall deficits. We concentrate on East Africa, as this experienced poor harvest and where famine is widely reported.~~ The year of 2016 is the third driest year in the past four decades. Other years with rainfall at least on standard deviation below the climatological mean during 1979-2015 are 1986, 1990,1991, 1993 and 2010. Year of 2010 also suffered from the severe famine (Dutra et al., 2013). We concentrate on East Africa, as this region experienced particularly poor harvest and where famine was widely reported during 2016 (noting that regions outside black rectangle of Fig. 1a also experienced major rainfall deficits in 2016). East Africa is especially vulnerable to the impacts of drought (DEC, 2017). The region has long experienced widespread poverty and high levels of food insecurity (Von Grebmer et al., 2016). The high dependence of its population on rain-fed agriculture, sometimes in tandem with political instability, exacerbate the impacts of droughts (Love, 2009; Masih et al., 2014).

To assess any influence of increasing atmospheric GHG concentrations, we use monthly rainfall data from 37 GCMs simulations for the historical period and for a high emission future ~~“business-as-usual” RCP8.5~~ scenario~~.~~ RCP8.5. These are from the Coupled Model Intercomparison Project Phase 5 (CMIP5, Taylor et al., 2012). A summary of the main characteristics of the models are provided in Table S1. A bias correction with two post-processing steps is applied to the GCM precipitation estimates. We ~~multiply~~first calculate modelled and ERA-based mean ASO rainfall estimates over the east Africa during the period 1979-2015. The GCM precipitation estimates, both past and future, ~~with~~are corrected by a GCM-specific ~~value such that~~ mean correction factor, which is a ratio of the climatological mean of each GCM ~~during the period 1979-2015 equals~~ to that of the ERA-interim reanalysis product. Second, we then adjust the climatological standard deviation (STD) of GCM precipitation estimates by multiplying the ratio of the climatological STD of each GCM to that of the ~~ECMWF reanalysis. This is also for the spatial average over our study region (Fig. 1a).~~ERA-interim data. The adjustment of spread of rainfall distribution is an important additional procedure to further constrain GCM estimates (Sippel et al., 2016; Jeon et al., 2016; Angelil et al., 2017). Together this ensures all GCMs have the ERA-based mean and STD for period 1979-2015. Each GCM is considered equally plausible. ~~Considering different~~ Bias-corrected mean ASO rainfall are presented in Fig. 1c for mean bias correction, and in Fig. 1d for mean and STD bias correction. These are derived from 37 GCMs, and for four 31-year periods~~, Probability Density Functions (PDFs) of mean ASO rainfall (e.g. 31 times 37 numbers) are constructed.~~ (pre-industrial, present day, and two future periods).

~~Our PDFs enable estimation of~~

We estimate the probability, in any year, of rainfall being less than 46 mm ~~month-1 (shaded, Fig. 1c), which is~~ per month. This threshold is 35% less than the climatological ASO mean, and is the ASO mean rainfall level in 2016 (red curve within yellow highlight, Fig. 1b). ~~We compare~~For the mean-corrected GCM estimates, we compare (inset, Fig. 1c) modelled period 1861-1891, representative of pre-industrial, with present day (period 2001-2031), and find this probability ~~increases~~decreases slightly from ~~5.3% to 5.6% (inset, Fig. 1c). This is caused by a stretch in the distribution tail, as overall rainfall increases.~~3.8% (STD ± 0.5%) to 2.8% (STD ± 0.5%). The one standard deviations are estimated via bootstrapping with 80% replications from the 37 GCM precipitation data and for the 31-year periods. These trends continue, giving probabilities ~~6~~2.3% (± 0.5%) and ~~7~~2.1% (± 0.4~~%~~%) for periods 2035-2065 and 2070-2100 respectively. ~~The stretched left-tails are caused by a few models that estimate this region becomes drier, and some models~~For the mean- and variance-corrected GCM estimates (Fig. 1d), we found the probability of east African drought is smallest at present (0.4% ± 0.2%, period 2001-2031). Such probability would become larger in the future, giving probabilities 1.1% (± 0.4%) and 1.2% (± 0.3%) for periods 2035-2065 and 2070-2100 respectively. Hence we find accounting for model biases in the variance of GCM distributions has the potential to significantly alter the predictions of drought events occurrence over the east Africa.

Given that large uncertainty in the observation-based precipitation products has been well reported (Angélil et al., 2016), we use four other precipitation estimates (GPCP, PREC/L, CPC and TRMM) to bias-correct GCM estimates. In Fig. 2 we reproduce the insets of Fig 1c (no hatching) and Fig 1d (hatching) for ERA-Interim, and then for the four other precipitation products. Consistent with the conclusions based on the ERA-interim product only, the results from the other rainfall products also show that the probability of drought occurrence in the east Africa has decreased slightly from pre-industrial to present day, and irrespective of whether variance adjustment has occurred (Fig. 2, all blue and black bars, with and without hatching). Future projections, though, of drought likelihood do vary across different precipitation products. For the mean-corrected GCM estimates, 4 out of 5 rainfall product-corrected GCM projections give a slight decrease in drought occurrence likelihoods by the end of 21st century. The exception is the TRMM-corrected GCMs, which suggest the drought probability would increase slightly by 2070-2100 and relative to the present day. For the mean- and variance-corrected GCM estimates, relative to the present-day levels the GCM estimates corrected to the ERA-interim, GPCP, and TRMM products give an increase in drought occurrence probability. However PREC/L- and CPC-corrected GCM estimates suggest the probability of drought occurrence will decrease. This divergence is due to the strong differences in the climatological mean, standard deviation and year 2016 ASO rainfall levels among the different precipitation products (Table S2).

The multi-model ensemble forecast, corrected by the ERA-interim rainfall product and merging the individual forecasts with equal weights, shows that the east African mean ASO rainfall for 2070-2100 will increase significantly, compared with the present period 2001-2031 (main PDFs, Fig 1c.,d.). It is these general increases that even in conjunction with larger future distribution spreads, imply no significant increase of drought occurrence probability (Fig 1c., d.). In Fig. 3, we present for the individual models, changes in numbers of years of mean ASO rainfall falling below 46 mm per month. We also show individual model changes in mean and STD of ASO rainfall, for 31 years 2070-2100 compared to 2001-2031. Fig. 3 shows 28 out of 37 model estimates for this region become wetter, and most models (i.e. 22 out of 37 models) exhibiting increased ~~interannual variability.~~distribution spreads reflected by raised STDs. Models generally agree on the direction of these changes, but the magnitude of changes in GCMs remains uncertain.

Our ~~simple~~ analysis ~~that considers models equally, suggests~~reveals that current understanding of how future climate change will impact on East Africa ASO drought risk ~~is increasing, although general rainfall levels are rising. The~~remains uncertain. This is based on a relatively simple assessment of 37 climate models, each given equal weight but after being corrected by observation-based rainfall products. We find the sources of uncertainty in drought prediction include: 1) the choice of bias correction methodology; 2) the choice of observational product used to correct bias in GCMs; and 3) the choice of GCMs used. Currently, for many geographical regions, GCM estimates of rainfall changes varies substantially across models (Knutti and Sedláček, 2013). Multi-model analyses such as ours consider uncertainty associated with different model parameterisation or scheme describing rainfall features. However, to give more definitive answers, the climate research community may need to be confident enough to rank climate models based on performance to refine future projections (Knutti et al., ~~2017). Which models are most accurate for East Africa?~~2017). Improving GCM projections also could involve on-going constraining of model components. For rainfall of east Africa predictions in particular, this will link to accurate forward projections of oceanic variability. Strong teleconnections are known to exist between El Niño Southern Oscillation (ENSO) and East African rainfall

(Segele et al., 2009; Gissila et al., 2004), and with longer-term fluctuations in Pacific SSTs increasing/decreasing rainfall (Funk et al., 2014; Liebmann et al., 2014). Larger ensembles of simulations by each model is also important, and especially when analysing the probability of extreme events. This enables a more complete sampling of probability distributions, describing more fully the internal variability of the climate system imposed over general climate change. In addition, some GCMs estimate an increase in future variability of east African ASO rainfall, and better knowledge of the magnitude of this is important. Research shows any variability increases as well as mean changes has strong impacts on society (Brown and Lall, 2006). Furthermore, ~~under global warming, raised evaporation may offset rainfall gains, affecting crop photosynthesis (Adhikari et al., 2015). Food~~food and water availability in East Africa has multiple socio-economic drivers, alongside climatic influences (Little et al., ~~2001). Any~~2001; Adhikari et al., 2015). Although here we have focused on climate model projections of the future, more holistic ~~approach, including~~approaches will combine climate and crop impact modelling~~, will hopefully create better protections~~. The hope is that climate model predictions for east Africa will move towards a consensus on expected changes, helping then better protection and disaster preparedness against future famine.

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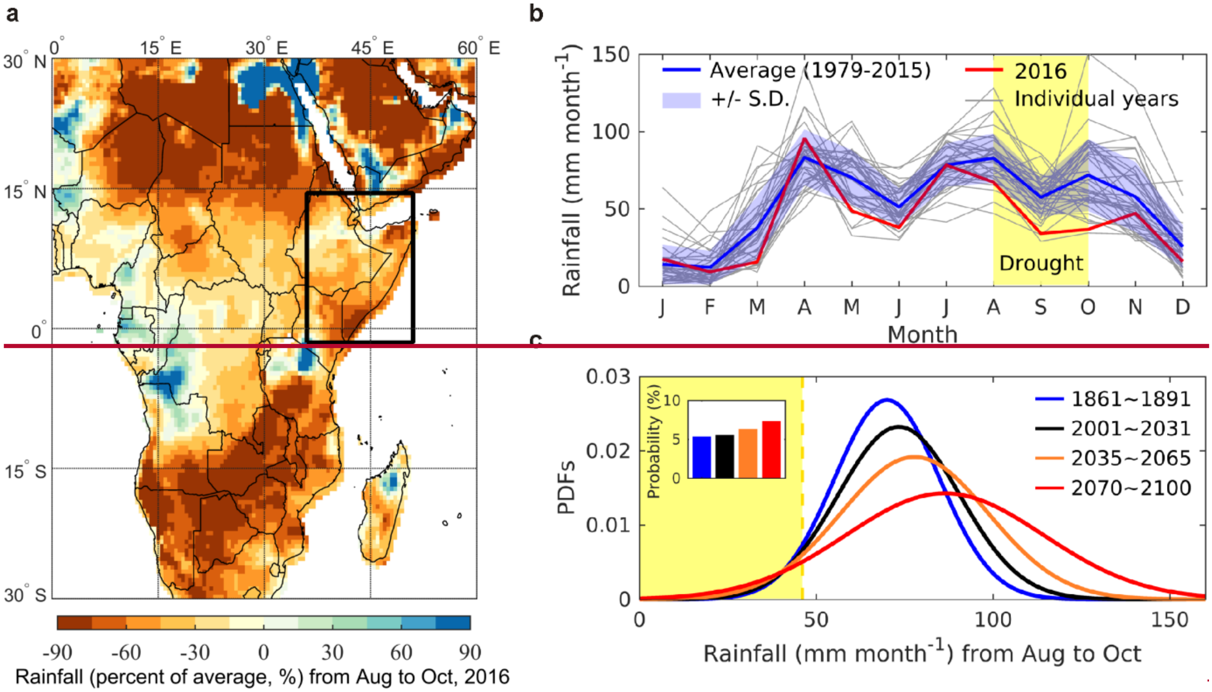
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Rainfall (mm month-1)
Month
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Probability (%)
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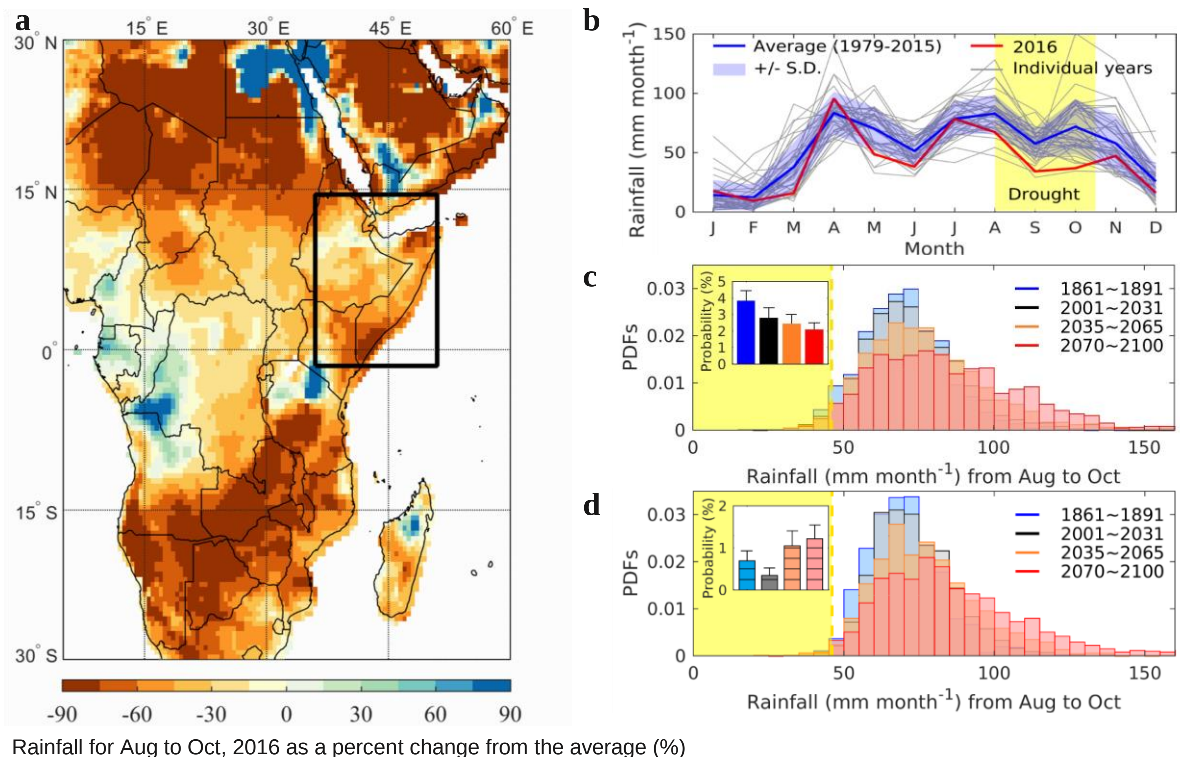
2001~2031
2035~2065
2070~2100
Rainfall (mm month-1) from Aug to Oct
Rainfall (percent of average, %) from Aug to Oct, 2016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Drought
Rainfall (mm month-1)
Month
PDFs
Probability (%)
1861~1891
2001~2031
2035~2065
2070~2100
Rainfall (mm month-1) from Aug to Oct
Rainfall for Aug to Oct, 2016 as a percent change from the average (%)

Figure 1: (**a**) Black rectangle is location of study region (14.5°N~1.5°S, 36°E~51°E). Plotted is mean rainfall ~~from~~for 2016 and months August to October inclusive (ASO), presented relative changes (as %) to long-term average ASO values (1979-2015~~) and~~). Values based on ERA-~~Interim~~interim reanalysis product. (**b**) ERA-based monthly total rainfall (mm month^{-1}) over study region (panel a; land within black rectangle) for years 1979 to 2016. Year 2016 is red, other years are individual grey lines, and multi-year average (not including 2016) is blue line. Blue shading is ± one standard deviation of monthly rainfall across years 1979-2015. The drought event (shaded in yellow) is defined as the three consecutive months of ASO, and when rainfall in year 2016 is below blue shading. (**c**) CMIP5-based PDFs of mean ASO rainfall for periods 1861-1891 (blue), 2001-2031 (black), 2035-2065 (orange) and 2070-2100 (red). Each curve corresponds to ~~merged normalised~~the mean-corrected combined outputs from 37 CMIP5 models forced by historical emissions and RCP8.5 future scenario. Individual GCM bias correction is based on the ERA-interim reanalysis product. Yellow shading is mean ASO rainfall less than 46 mm month^{-1}, which is the ERA-interim 2016-based threshold (mean of ASO, red curve in panel b). Inset shows probabilities of mean rainfall of ASO falling below the threshold for the same modelled periods (colours match those of curves). The error bars are the standard deviations (estimated via bootstrapping 80% replications from the 37 GCM precipitation data for the 31-year periods). (**d**) same as (**c**), but based on the mean- and variance-corrected GCM rainfall estimates.

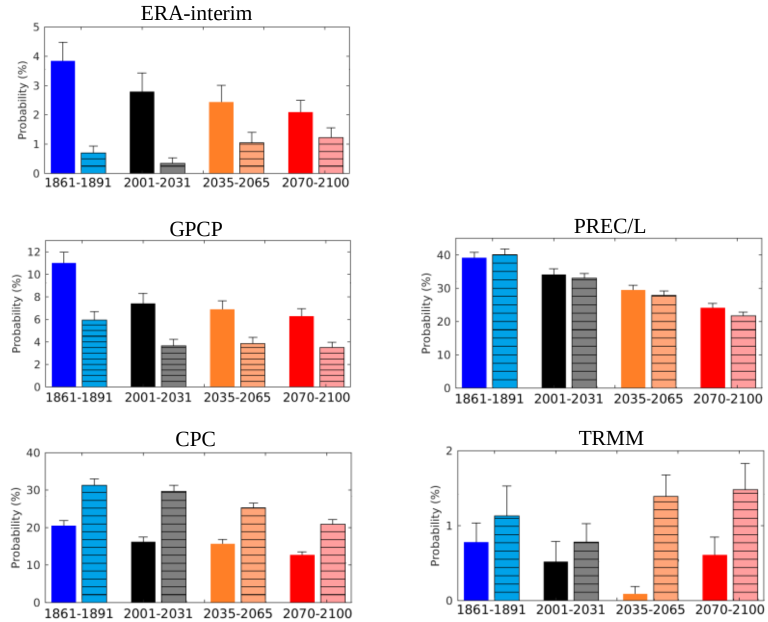

Figure 2: CMIP5-based histograms of probabilities of mean ASO rainfall falling below year 2016-based threshold values. Shown for periods 1861-1891 (blue), 2001-2031 (black), 2035-2065 (orange) and 2070-2100 (red). Each bar corresponds to merged normalized outputs from 37 CMIP5 models forced by historical emissions and RCP8.5 future scenario. The bars without horizontal hatching (left) are for the mean-corrected GCM precipitation estimates. The bars with hatching (right) are for the mean- and variance-corrected GCM estimates.

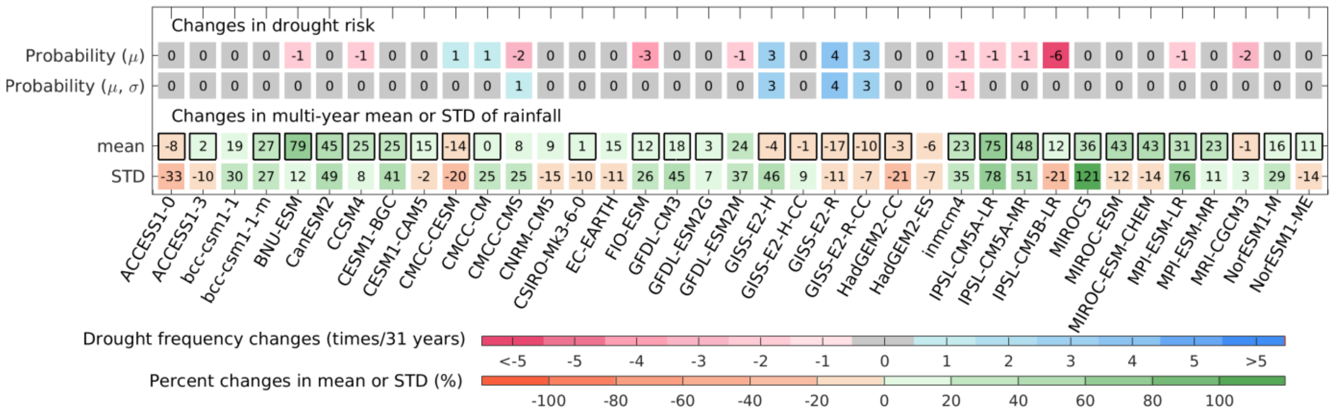

Figure 3: Changes in drought frequency, multi-year mean and standard deviations (STD) of 31 consecutive year rainfall amounts. Difference between present period 2001-2031 and period 2070-2100, as estimated by 37 GCMs. GCM estimates are corrected by the ERA-interim rainfall product. Changes to frequencies of drought occurrence are estimated from the mean bias-corrected GCM estimates (1st row), both mean- and variance bias-corrected GCM estimates (2nd row). The colored grids in the 3rd row with black borders indicate statistically significant differences in the 31-year rainfall mean between these two periods (*t*-test, with $P < 0.05$). The percentage changes are calculated as $[(x_{2070\text{-}2100}/x_{2001\text{-}2031})-1]\times 100\%$.

Supplementary Information

Table S1. CMIP5 global circulation models (GCMs) used in this study, and their components.

Model Name	**Atmospheric Model**	**Land surface Model**	**Oceanic Model**	**Reference**
ACCESS1-0	HadGEM2 r1.1	MOSES	MOM4pl	*Bi et al.*(2012)
ACCESS1-3	Similar to GA 1.0	CABLE v1.8	MOM4p	
bcc-csm1-1	BCC_AGCM2.2	BCC_AVIM1.0	MOM4_L40	*Wu et al.* (2012)
bcc-csm1-1-m	BCC_AGCM2.2	BCC_AVIM1.0	MOM4_L40	
BNU-ESM	CAM3.5	CLM	MOM4p1	*Ji et al.* (2014)
CanESM2	CanAM4	CLASS2.7	CanOM4 and CMOC1.2	*Arora et al.* (2011)
CCSM4	CAM4	CLM4	POP2	*Gent et al.* (2011)
CESM1-BGC	CAM4	CLM4	POP2	*Neale et al.* (2010)
CESM1-CAM5	CAM5	CLM4	POP2	
CMCC-CESM	ECHAM5	SILVA	NEMO	*Scoccimarro et al.* (2011)
CMCC-CM	ECHAM5	SILVA	OPA 8.2	
CMCC-CMS	ECHAM5	SILVA	OPA 8.2	
CNRM-CM5	ARPEGE climate	SURPEXv5.1	NEMO3.3	*Voldoire et al.* (2011)
CSIRO-Mk3-6-0	AGCMv7.3.8	a soil-canopy scheme	GFDL MOM2.2	*Rotstayn et al.* (2010)
EC-EARTH	IFS	H-TESSEL	NEMO	Hazeleger et al. (2010)
GFDL-CM3	GFDL-AM3	LM3	MOM	*Griffies et al.* (2011)
GFDL-ESM2G	GFDL-AM2.1	LM3	GOLD	*Dunne et al.* (2012)
GFDL-ESM2M	GFDL-AM2.1	LM3	MOM4	
GISS-E2-H-CC	GISS-E2	GISS-LSM-CC	HYCOM	*Schmidt et al.* (2014)
GISS-E2-H	GISS-E2	GISS-LSM	HYCOM	
GISS-E2-R-CC	GISS-E2	GISS-LSM-CC	Russell	
GISS-E2-R	GISS-E2	GISS-LSM	Russell	
HadGEM2-CC	HadGAM2	TRIFFID	HadGOM2	*Collins et al.* (2011)
HadGEM2-ES	HadGAM2	TRIFFID	HadGOM2	*Jones et al.* (2011)
INMCM4	INM	INM	HadGOM2	*Volodin et al.* (2010)
IPSL-CM5A-LR	LMDZ5A	ORCHIDEE	NEMO	*Dufresne et al.* (2012)
IPSL-CM5A-MR	LMDZ5A	ORCHIDEE	NEMO	
IPSL-CM5B-LR	LMDZ5B	ORCHIDEE	NEMO	
MIROC5	FRCGC-AGCM	MATSIRO	COCO4.5	*Watanabe et al.* (2011)
MIROC-ESM	FRCGC-AGCM	MATSIRO	COCO4.5	
MIROC-ESM-CHEM	FRCGC-AGCM	MATSIRO	COCO4.5	
MPI-ESM-LR	ECHAM6	JSBACH	MPIOM	*Ilyina et al.* (2013)
MPI-ESM-MR	ECHAM6	JSBACH	MPIOM	
MRI-CGCM3	MRIǑAGCM3	HAL	MRI.COM3	*Yukimoto et al.* (2012)
NorESM1-ME	CAM4-Oslo	CLM4	MICOM	*Tjiputra et al.* (2013)
NorESM1-M	CAM4-Oslo	CLM4	MICOM	

Table S2. The mean August-to-October (ASO) rainfall (mm month^{-1}) of year 2016, multi-year mean (not including 2016) and multi-year standard deviation (STD) over east Africa for years 1979 to 2016. The five global precipitation data sets used are listed. Four products of ERA-interim, GPCP, PREC/L, CPC and TRMM are available from 1979 to 2016. These four precipitation data sets are either interpolated gauge observations only (i.e. PREC/L and CPC), gauge observations combined with satellite measurements (i.e. GPCP), or reanalysis data (i.e. ERA-interim). The TRMM satellite observations are available from 2001 to 2016.

ASO rainfall (mm month^{-1})	ERA-interim	GPCP	PREC/L	CPC	TRMM
2016	46.10	46.56	57.16	35.78	32.05
Climatological mean (1979-2015)	70.76	62.78	61.68	43.44	60.69*
Climatological STD (1979-2015)	11.28	10.40	11.48	13.89	11.83*

* TRMM satellite precipitation data is only available from 2001 to 2016. The climatological ASO rainfall averages of the period 2001-2015 is computed.

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