Major revision 2 comments

Comments from Referees

The authors have improved the manuscript and the logic is clearer. In general, the interpretation in the result section is still weak. There are still some issues that the authors may consider addressing or clarifying in the manuscript before I can recommend it for publication on ESD.

1. The novelty of this research, as highlighted by the authors, is the usage of multiple methods and models to investigate the impact of precipitation and temperatures on drought trends in EA. According to tables 2 and 3, observational/reanalysis and model data have different spatial resolutions, have they been resampled to the same resolution or used directly in the analysis? Also, the resolution of model data, e.g. GFDL (2.02°*2.5°), the extent of one region NK (2°N-4.5°N, and 34°E-41°E), it means probably only 6 grids are used to study the trends in variables in this region, whether the global-scale model simulation data is applicable to detect changes over small regions divided in table 1 / Figure 1. For trends derived from datasets with different resolutions, how were they eventually synthesized?

Response:

We indeed use all data as it comes with no resampling. The precipitation and temperature data from GFDL thus has a low resolution and indeed the smaller regions are only represented by a few grid cells. As long as the decorrelation length of the drought phenomenon is larger than the grid size of the model, the model can (if validation tests are passed) describe the phenomenon. Compared to other higher resolution models however, the results from low-resolution GCMs do not consistently stand out and also do overlap with observational uncertainty.

Any data set can potentially be used individually to give (albeit unrobust) attribution results. We attempt to synthesize a range of outcomes that can result from individual analyses based on data sets with different properties to arrive at a robust result, i.e., with a representative confidence interval.

*Changes: We added "*resampling or downscaling*" to the sentence "*Note that we use the data as it is available without applying any additional bias correction, resampling or downscaling."

Furthermore we added "The results from low resolution GCMs do not consistently stand out compared to higher resolution models and also do overlap with observational uncertainty." to the results section."

2. About datasets in section 2.2, the authors selected 35yrs or longer, multiple datasets spanning different lengths of years were used, e.g. observation Berkeley from 1750-2019, CenTrends from 1900-2014, GCM MIROC from 1850-2018, for trend analysis, 5-10 years more or less may not largely influence the final trend, however, if it were a 50-100-year difference, could the trend be biased simply because of the different temporal coverage?

Response:

Note that in Section 3.2 (Assumptions and decisions),

- we explain (point 8) that "Differences in trends can arise due to different time periods and lengths of datasets, which are generally shorter for observations and reanalyses than for model simulations. However, we consider the use of all available observational and reanalysis data and different model framings to lead to a more complete and robust attribution statement."
- we specify that we use Berkeley from 1920 in region SS and from 1900 in all other regions. Thanks to the reviewer's comment we see now that this adjusted start date was not carried over to Table 2.

The model data sets (Table 3) have very similar time spans (except weather@home), where we should realise that most GMST rise occurs in the second half of the 20th century, so starting in 1850 or 1900 does not make a big difference. Some of the observational series e.g. ERA-I (1979-2018) miss the early part of the GMST rise, but due to the necessity of using observations we do not want to exclude these series even though they are shorter. We extrapolate trends from these observational series backwards in time but not without consequence: the extrapolation makes the uncertainty of the trend larger. We added this to assumption 8.

Looking at the 6 regions, ERA-I temperature data does not show a systematic difference: the trend is sometimes larger and sometimes smaller than for the Berkeley data set.

Changes:

The "time period used" for Berkeley Earth given in table 2 has been changed from 1750-2019 to 1900-2018. Also for CRU-TS4 and ERA-I the end date has been changed from 2019 to 2018.

Assumption 8: "Differences in trends can arise due to different time periods and lengths of datasets, which are generally shorter for observations and reanalyses than for model simulations. Extrapolation between the first half of the 20th century and pre-industrial does not make a big difference, as most GMST rise occurs in the second half of the 20th century. For shorter observational series the difference is larger. However, we consider the use of all available observational and reanalysis data and different model framings to lead to a more complete and robust attribution statement."

3. GCM simulated precipitation data have poor accuracy compared to temperature. Apparently, in Figure 5, observations (CenTrends) suggested an increasing trend in precipitation over region SS, and four GCM models suggested declining trends, in the end, the synthesized trend was declining. Similar in Figure S1 for EE and S4 for NK. This seems that the synthesized trend is largely influenced by less reliable model simulation instead of the observed trend. The authors may consider justifying this in the discussion section.

Response and changes:

Part of the reviewer's remarks probably concern the best estimate of the trend from CenTrends and GCM models. It is however extremely important not to rely on the best estimate as the uncertainties are large. The CenTrends confidence interval spans zero, with a substantial fraction of the interval on both the negative and positive side, i.e. although the best estimate lies on the positive side, the observational results clearly encompass 'no change'. We would say that only two of the four GCMs the reviewer mentions suggest declining trends whereas the other two GCM results span zero, with one weighted more towards the positive side and the other to the negative. The final synthesized result for region SS is communicated as a negative non-significant trend.

We would furthermore like to emphasize that first all model results are combined (into the dark red bar in the synthesis figures) and all observational results are combined (into the dark blue bar in the synthesis figures). Only afterwards the dark bars are combined (with weighting dependent on the uncertainties of these bars). So all models together and all observations together contribute to the synthesized value with one estimate (including uncertainty estimates).

On this topic we add: "Firstly, we compute the weighted average of **the synthesized values** for models and observations, neglecting model uncertainties beyond the model spread: this is indicated by the magenta bar. ... we also use the more conservative estimate of an unweighted average of the **synthesized values for** observations and models"

We furthermore assume that the reviewer means Figure S1 for WE (not EE). We agree that from the text it is not clear that models and observations do not always fully agree on the trend, although it is clear from the figures.

To clarify this in the text as well, we add to the synthesis results section:

"The more the magenta bar is centered in the white box, the better the models agree with observations and the more we trust our attribution statement"

And

"For precipitation, regions WE and NK show a positive but non-significant trend, although in region WE models and observations only partially overlap. In region NS there is a small positive trend, regions EE and CK show no trend (for EE only with partial overlap of models and observations), and region SS a negative, non-significant trend."

4. As mentioned earlier, the results section seems weak, the authors did point out the regional differences of trends in four variables, additional interpretations may need to be added regarding the regional differences, for example, from the perspective of regional climate etc.

Response:

We acknowledge that an interpretation from a regional climate perspective is missing. The division of the region into smaller subregions was necessary as we only want to study changes over a homogeneous region. The results do not change our motivation for this decision. However, taking all uncertainties into account, the differences between the regions are very small and not clearly related to the regional climate, so we cannot draw conclusions based on the different regional climates.

Changes:

We added to the end of the results section that "While it would be desirable to link the overall findings to differences in regional climate, the differences in the synthesized results between regions are too small relative to confidence intervals to be able to say anything meaningful. It was nevertheless necessary to divide the study area into homogeneous regions, so that extremes experienced within each region are representative for that region and inhomogeneity is not influencing the location of the occurrence of extremes."

5. The authors selected soil moisture because it is a better indicator of crop health than precipitation to study agricultural drought, in conclusion, it's concluded that soil moisture can not be relied upon due to the large uncertainties in both observations and simulations and precipitation should be included given more reliable simulations and observations. This can be confusing and contradictory. As the authors concluded, previous studies using precipitation and this study using soil moisture all detected no consistent trends on droughts. This implies that drought in the study area is not getting worse with increasing temperature and precipitation deficit from the perspective of both meteorology and agriculture. The authors may need to rewrite this properly.

Response: Thank you for bringing these sources of potential confusion to our attention.

Soil moisture is indeed more indicative of crop health than precipitation in the study of agricultural drought but we also know that precipitation records are longer and more widespread than soil moisture measurements. If there had been a strong trend in soil moisture our conclusion would have been based on this trend. However, as we see no trend in soil moisture emerging from natural variability, we can not make more robust statement on trends in drought based on soil moisture. After concluding this, we argue that in that case, we can also rely on results obtained from using the longer precipitation records.

Perhaps there is also confusion over the chronological order in which this study developed. Previous trend studies for this part of Africa indeed do not agree on the sign of the trend in precipitation. However, although there is disagreement in reported results, the disagreement lies within observational uncertainty, according to Philip et al., 2018a. We referred to this as detecting no consistent trend on (meteorological) drought. Motivated by reports of a cluster of recent droughts and the request to understand if, despite no evident trend in precipitation, increasing temperatures could be exacerbating drought, we investigated if more insight can be gained by additionally examining the variables PET and soil moisture that are more closely related to crop health than precipitation. We were aware that precipitation measurements are the most reliable, but it is in our opinion still worth investigating if soil moisture and PET show a signal.

Changes:

In the introduction we add: "In this study, we aim to understand if, despite no evident trend in precipitation, increasing temperatures could be exacerbating drought."

In the conclusion we change the relevant text to:

"Due to the large uncertainties in both soil moisture observations and simulations, we find no trend emerging from natural variability."
And:
"We conclude that, although soil moisture is the prefered indicator of agricultural drought, we recommend that any soil moisture analysis be supplemented with precipitation analysis due to the superior reliability of precipitation measurements and the large influence of precipitation on drought in this region. Besides, soil moisture also has a physical lower limit: once the soil is dry it will remain dry. In water-limited regions an analysis of precipitation is thus a helpful addition".

6. The discussion section is hard to read, please consider revising.

Response:

We revised the discussions section as follows:

- We shortened some paragraphs and deleted subjects that distracted the reader from the main results.
- We added information and moved text from other sections to the discussions section where we or the reviewer thought this was helpful.
- We reordered the discussions section to improve the flow.
- We revised some wordy interpretation.

Changes:
For the new discussions section see the revised manuscript.

Some minor revisions are suggested as follows:

1. Page 2 Line 3, particularly "thorough" or "through" threats to food security?

Response: Fixed the typo.

2. The author did mention that the study period was from the pre-industrial era to 2018 in abstract, but it’s hard to tell the study period from the datasets or introduction sections.

Response: Thank you for pointing to this, we will add the years 1900 and 2018 to the introduction as well.

Changes:

P3 L18-19. "Assessments will be based on both observations and climate and hydrological model output on the annual time scale**, between the years 1900 (to represent the pre-industrial era) and 2018**."

3. Some one-sentence paragraphs can be considered to combine with the others based on the logic.

Response: We have worked throughout the paper to eliminate these, and to sharpen (and simplify) the writing in general.

Changes:

4. Tables 2, 3, and 4 seem outside of the right sections.

Response:

We assume that the layout of tables, such as these, are adjusted according to the journal's requirements during the typesetting stage.

Changes:

5. In section 3.2, more convincing references should be included to justify those assumptions and decisions, for example, the authors assumed that using RefET doesn’t influence the overall conclusion, does this mean that the crop coefficients are the same across different regions, if not, PET may vary stronger than RefET.

Response:

Firstly, we acknowledge that, locally, strong long term trends in land cover could enhance or counteract the reported trends, however this was not the focus of our study. We focus on climate-induced changes rather than land cover-induced changes. Our conclusions are therefore valid for the chosen large study regions, under the condition that there are no strong changes in land use or soil physical conditions in time. Secondly, we remark that in the context of this paper, we don't convert reference ET to PET, nor would we convert reference ET to crop ET using crop coefficients, because it would not be relevant to our research purposes. This study neither needs nor uses crop coefficients as we are only interested in evaporative demand in its purest sense—i.e., as the atmospheric control driving upward moisture flux in the land-atmosphere system. One would use crop coefficients to mediate reference ET towards an estimation of crop evaporation, a value that would then not be a measure of evaporative demand but would instead approach actual evapotranspiration (ET). Even if we were to want to apply crop coefficients to our estimate of reference ET, any crop coefficients we used would be (i) so inaccurate as to be meaningless at the large spatial scales of our analysis, and (ii) different for each of the different metrics of E_0 that we use. Further, many hydrologists would start from the perspective of the differences between PET and ET_0 being predicated mostly on the surface assumptions involved (open water for PET, a reference crop for reference ET) to argue that assumption #6 in the text mis-states the relationship between PET and reference ET.

A few words on the mix of metrics that we use for evaporative demand (Hamon, Priestley-Taylor, Penman-Monteith). First, even though we have used the abbreviation "PET," we are not actually using PET; instead, we use evaporative demand (E_0), which is the name for the concept of (i) the theoretical thirst of the atmosphere, or (ii) the energy limit on evaporation, or (iii) the amount of water that would evaporate were there enough water to meet the need--they're all conceptually the same in the context of this paper. Second, E_0 is an umbrella term that has three specific definitions:

1. potential ET (PET), which is the original, defined by Penman in 1948 as evaporation from an open-water surface or well-watered grass (depending on one's reading of Penman (1948));
2. reference ET (ET_0), which is defined as the water evaporating from a specific, well-defined crop surface (the reference crop)--and is what we've used to estimate Eo;
3. and pan evaporation, which is a physical observation of evaporation from the small open-water surface in a pan.

Third, as each of these three E_0 definitions assumes (or observes) evaporation from a surface at a variety of spatial scales, and has a variety of parameterizations (in the case of PET and ET_0) or instruments (in the case of pan evaporation) that all make different assumptions about which drivers are important (temperature; temperature and radiation; and temperature, radiation, wind speed, and humidity in Hamon, Priestley-Taylor, and Penman-Monteith, respectively), it is no surprise that they all yield different values of E_0. In the case of PET and ET_0, an inexhaustive list of parameterizations includes Thornthwaite, Blaney-Criddle, Hamon, Hargreaves-Samani, Turc, Makkink, Penman, Priestley-Taylor, and Penman-Monteith. Of these, we use Hamon, Priestley-Taylor, and Penman-Monteith. Penman and Blaney-Criddle are described as both PET and ET_0, depending on whom you're reading: this is clumsy writing. Penman-Monteith can be both PET and ET_0, depending on which parameter values one is using: this is a flexible equation. In the face of all of these uncertainties, the ensemble of models, drivers, and E_0 parameterizations employed in this study is a proven technique for estimating the overall effect of evaporative demand--in this case, on drought. In fact, this convergence-of-evidence approach is the backbone of operational drought monitoring. To sum up: we do not use crop coefficients nor do we need to; and we should not have stated that we're concluding on PET, but have instead now defined E_0 as above and used the abbreviation "E_0" where we previously had "PET" and the term "evaporative demand" where we previously used "potential evaporation" (or "potential evapotranspiration").

Changes:

We added the following text in the introduction:

"Ideally, we would study the influence of temperature on soil moisture via ET, however observational records are very limited in time and space and, as the spatial decorrelation lengths of ET are short, their informational value is limited. We therefore analyse evaporative demand (E_0); sometimes also referred to as "potential evapotranspiration,'" or PET, although this is strictly only one metric of E_0. E_0 is the amount of evaporation that would occur under prevailing meteorological conditions, if an unlimited supply of water were available; in that sense, E_0 measures the thirst of the atmosphere. E_0 is calculable as a function of temperature, humidity, solar radiation, and wind speed. We use a variety of common parameterizations of E_0 that includes both potential evapotranspiration and reference evapotranspiration and that ranges in physical representation and complexity from simple estimates based solely on temperature (the Hamon equation), through estimates that also include solar radiation as a driver (the Priestley-Taylor equation), to ultimately, fully physical estimates that further include humidity and wind speed as drivers (the Penman-Monteith equation). All necessary drivers are available for both observations and model simulations. In this manner, we bracket the complexity in E_0 parameterizations in a convergence-of-evidence approach familiar to the drought-monitoring community.

We investigate E_0 as a means to study the influence of temperature on soil moisture, however, for regions that are irrigated or where irrigation is being considered, E_0 itself can be regarded as more relevant than soil moisture as a measure of drought tendency."

We added an assumption to the list in section 3.2:

"In using our variety of E_0 metrics, we do not convert reference evapotranspiration (such as that drawn from the MERRA-2 dataset (Hobbins et al., 2018) to PET, nor do we use crop coefficients to convert reference evapotranspiration to crop evapotranspiration because doing so would not be relevant to the research purposes. Our study is only interested in evaporative demand in its purest sense - i.e., as the atmospheric control driving upward moisture flux in the land-atmosphere system. In any case, crop coefficients we used would be (i) so inaccurate as to be meaningless at the large spatial scales of our analysis, and (ii) different for each of the different metrics of E_0 that we use. The ensemble of E_0 values generated by our variety of E_0 metrics will ensure that significant trends generated are robust."

And we changed PET into E_0 throughout the paper.

6. Line 24-28 in the conclusion section should be placed in discussion sections.

Response: We agree that these lines are written in a way that belongs more to the discussion. One of our conclusions is, however, that precipitation should still be considered a good drought indicator in this region, so we will add a sentence to that effect in the conclusions.

Changes: We moved lines 24-28 from the conclusions to the discussion. To the conclusions we added "Soil moisture is the prefered indicator of agricultural drought, however we recommend that any soil moisture analysis be supplemented with precipitation analysis due to the superior reliability of precipitation measurements and the large influence of precipitation on drought in this region".

7. Units of trends in four variables should be added in Figures 5 and 6 and S1-DS6 in the Supplement figures.

Response: trends are in [units of the study variable]/K, so we add for precipitation and PET [mm/day/K], for Temperature [K/K] and for soil moisture [/K].

Changes: we added the units to the paper

8. Please consider revising some wordy interpretation, e.g. page 13, We therefore assume for ... We therefore..... and the discussion section is so lengthy that readers can easily get lost.

Response: We agree the text was sometimes too wordy and the discussions section contained information that could easily distract the reader from the main results. We revised wordy interpretation throughout the whole manuscript, and rearranged the discussions section.

Changes: see revised manuscript.

Impact of precipitation and increasing temperatures on drought trends in ~~eastern~~ Eastern Africa

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Abstract. In ~~eastern~~ Eastern Africa droughts can cause crop failure and lead to food insecurity. With increasing temperatures, there is an ~~a priori~~ *a priori* assumption that droughts are becoming more severe~~, however,~~ . However, the link between droughts and climate change is not sufficiently understood. ~~In the current study~~ Here we investigate trends in long-term agricultural drought and the influence of increasing temperatures and precipitation deficits.

Using a combination of models and observational datasets, we studied trends, spanning the period from 1900 (to ~~represent the~~ approximate pre-industrial ~~era~~conditions) to 2018, for six regions in ~~eastern~~ Eastern Africa in four drought-related annually averaged variables — soil moisture, precipitation, temperature and, ~~as a measure of evaporative demand , potential evapotranspiration (PET~~evaporative demand (E_0). In standardized soil moisture data, we found no discernible trends. ~~Precipitation was found to have a stronger~~ The strongest influence on soil moisture variability ~~than temperature or PET~~was from precipitation, especially in the drier, or water-limited, study regions~~. The~~ ; temperature and E_0 did not demonstrate strong relations to soil moisture. However, the error margins on precipitation-trend estimates are ~~however~~ large and no clear trend is evident~~. We find~~ , whereas significant positive trends were observed in local temperatures. ~~However, the influence of these on soil moisture annual trends appears limited.~~ The trends in ~~PET~~ E_0 are predominantly positive, but we do not find strong relations between ~~PET~~ E_0 and soil moisture trends. Nevertheless, the ~~PET-trend~~ E_0-trend results can still be of interest for irrigation purposes because it is ~~PET~~ E_0 that determines the maximum evaporation rate.

We conclude that, until now, the impact of increasing local temperatures on agricultural drought in ~~eastern~~ Eastern Africa is limited and we recommend that any soil moisture analysis be supplemented by an analysis of precipitation deficit.

1 Introduction

In ~~eastern~~ Eastern Africa, drought has occurred throughout known history ~~and the phenomenon has incurred~~ with significant impacts on the agricultural sector and the economy, particularly ~~thorough~~ through threats to food security. It is therefore important to examine the role of anthropogenic climate change in drought, particularly in the face of the large-scale droughts of 2010/11, 2014 and 2015 in Ethiopia, and the 2016/17 drought in Somalia, Kenya, and parts of Ethiopia and surrounding countries, which have ~~recently~~ raised the spectre of climate change as a risk multiplier in the region.

Droughts are triggered and maintained by a number of factors and their interactions, including meteorological forcings and variability, soil and vegetation feedbacks, and human factors such as agricultural practices and management choices, including irrigation and grazing density (van Loon et al., 2016). Accordingly, there are several definitions of drought in common use (Wilhite and Glantz, 1985): meteorological drought (precipitation deficit), hydrological drought (low streamflow), agricultural drought (low soil moisture) and socioeconomic drought (including water supply and demand). This complexity of droughts poses challenges for their attribution. It is not straightforward to disentangle these interacting factors, but over ~~a long time period~~ long periods it may be possible ~~that a signal can be detected~~to detect a climate change signal.

Previous attribution studies for ~~eastern~~ Eastern Africa have mainly focussed on meteorological drought drivers (precipitation deficit), with recent studies finding little or no change in the risk of low-precipitation periods due to anthropogenic climate change (e.g., Philip et al., 2018a; Uhe et al., 2018). Some weather stations in ~~eastern~~ Eastern Africa have recorded a decrease in precipitation in recent years, however climate models generally project an increase in mean precipitation but give conflicting results for the probability of very dry rainy seasons ~~(e.g. Shongwe et al., 2011)~~ (e.g., Shongwe et al., 2011) . The reasons for the recent observed decrease in precipitation thus ~~remains~~ remain unclear, but the trend is within the large observed natural variability in the region, at least for the historical and current climate.

However, precipitation only covers one aspect of drought — that of the supply side of the water balance. The demand side is represented by actual evapotranspiration (ET), which is a function of moisture availability and evaporative demand. With increasing temperatures, there is an a priori assumption that rising evaporative demand will increase the demand side of the water balance and, all else equal, droughts will become more severe. However, this assumption is not based on analyses, which motivates an objective study. In this study, we aim to understand if, despite no evident trend in precipitation, increasing temperatures could be exacerbating drought.

In the current study we wish to align our drought definition as closely as possible with the major human impact of drought — the threat to food security. Across ~~eastern~~ Eastern Africa, the quality and quantity of food production for domestic consumption is intimately linked to agricultural conditions. We therefore use the agricultural definition of drought — low soil moisture — because soil moisture is a better indicator of crop health than precipitation alone and it embodies the net effect of the supply and demand side of the water balance ~~,~~ in regions without irrigation. Whilst short term single-season drought episodes can be severe, we choose to analyse changes in drought on annual rather than sub-annual time scales because the worst crises in food security in this region have occurred with ~~multiple season~~ multiple-season droughts (Funk et al., 2015). We will also investigate the influence of the main meteorological drivers of soil moisture trends, i.e., precipitation and temperature.

Ideally, we would study the influence of temperature on soil moisture via ~~evapotranspiration (ET)~~ET, however observational records are very limited in time and space and, as the spatial decorrelation lengths of ~~evapotranspiration are short~~ET are short, their informational value is limited. We therefore analyse evaporative demand ~~, which is~~ (E_0; sometimes also referred to as "potential evapotranspiration~~" PET. PET~~ ", or PET, although this is strictly only one metric of E_0). E_0 is the amount of evaporation that would occur under prevailing meteorological conditions, if an unlimited supply of water were available~~, which is calculable or available for both observations and model simulations and is~~ ; in that sense, E_0 measures the thirst of the atmosphere. E_0 is calculable as a function of temperature, humidity, solar radiation, and wind speed. We use a variety of common parameterizations of E_0 that includes both potential evapotranspiration and reference evapotranspiration and that ranges in physical representation and complexity from simple estimates based solely on temperature (the Hamon equation), through estimates that also include solar radiation as a driver (the Priestley-Taylor equation), to ultimately, fully physical estimates that further include humidity and wind speed as drivers (the Penman-Monteith equation). All necessary drivers are available for both observations and model simulations. In this manner, we bracket the complexity in E_0 parameterizations in a convergence-of-evidence approach familiar to the drought-monitoring community.

We investigate ~~evaporative demand~~ E_0 as a means to study the influence of temperature on soil moisture, however, for regions that are irrigated or where irrigation is being considered, ~~evaporative demand~~ E_0 itself can be regarded as more relevant than soil moisture as a measure of drought tendency.

Whilst attribution studies ~~specifically for the east~~ specific to the East African region have not previously used soil moisture or ~~PET~~ E_0 to explore drought, ~~PET~~ E_0 has been used in various attribution or trend studies outside ~~our regionof study~~this region, to explore for example, the influence of climate change on the ~~hydrological~~ hydrologic cycle in China ~~(e.g. Yin et al., 2010; Li et al., 2014; Far~~ trends and variability at sites in West Africa ~~Obada et al. (2017)~~ (Obada et al., 2017) and compound events of low precipitation and high ~~PET in Europe Manning et al. (2018)~~ E_0 in Europe (Manning et al., 2018) .

Summarizing, the objectives of this study are~~to (i)~~ , first, consider the attribution question "do increasing global temperatures contribute to drier soils and thus exacerbate the risk of agricultural drought (low soil moisture) in ~~eastern~~ Eastern Africa?" and~~(ii)~~ , second, to investigate if global-warming driven trends in precipitation or local temperature via ~~PET~~ E_0 explain any emerging trend in agricultural drought. Our approach to attribution comprises the following steps: (1) ~~Definition~~ definition of the study variables and explanation of the study regions~~,~~ ; (2) ~~Description~~ description of observational data and detection of trends in observations; (3) ~~Model~~ model evaluation including description of the models~~,~~ ; (4) ~~Attribution~~ attribution of trends in models~~,~~ ; and (5) ~~Synthesis~~ synthesis of the results. Assessments will be based on both observations and climate and hydrological model output on the annual time scale~~.~~ , between the years 1900 (to represent the pre-industrial era) and 2018. We will illustrate the method using examples of recent droughts in ~~eastern~~ Eastern Africa.

~~The outline of the remainder of the paper is as follows: In~~ Section 2 of this paper presents the chosen study regions~~are presented~~ , followed by a description of the datasets used in the study. ~~In~~ Section 3 ~~we describe~~ describes the stepwise approach to attribution used~~in this paper~~, including assumptions and decisions made and illustrative examples. ~~In~~ Section 4 ~~, the results~~

Table 1. The six study regions. See also Fig. 1

Region	Long name	Latitude	Longitude	~~Seasonal~~ Months of seasonal precipitation peak(s)	Primary livelihood zone
WE	~~West~~ Western Ethiopia	7°N-14°N	34°E-38°E	Aug	agropastoral/mixed land
EE	~~East~~ Eastern Ethiopia	8°N-13°N	38°E-43°E	Apr, Jul/Aug	pastoral
NS	~~North~~ Northern Somalia/Somaliland region and ~~East~~ Eastern Ethiopia	5°N-12°N	43°E-52°E	Apr/May, Oct	pastoral
NK	~~North~~ Northern Kenya	2°N-4.5°N	34°E-41°E	Apr, Oct/Nov	pastoral
CK	Central Kenya	1.5°S-1.5°N	35°E-38.5°E	Apr, Nov	agropastoral/mixed land
SS	~~South~~ Southern Somalia	2°S-5°N	41°E-48°E	Apr/May, Oct/Nov	pastoral/agropastoral

~~are synthesized per~~ synthesizes the results by region. Finally, ~~the discussion and conclusions are presented in~~ Sections 5 and 6 present the discussion and conclusions.

2 Study variables, region and datasets

In this section, we present the chosen study variables and study regions in ~~eastern~~ Eastern Africa and the datasets used to provide the variables to be analysed. Brief descriptions of the projects from which the datasets originate are provided in the supplement.

2.1 Study variables and region

We analyse four different variables: soil moisture, precipitation, temperature, and ~~PET~~E_0. We average these variables over six non-overlapping regions, as trend analyses of time series of regionally averaged quantities are more robust than the same analyses for point locations. This is especially true for precipitation, which shows small-scale spatial variability if the time period is not long enough to sufficiently sample the distribution from multiple precipitation events. It is however necessary to select homogeneous ~~zones~~regions, so that the signals present are not averaged out.

The focus of the study is on ~~eastern~~ Eastern Africa — Ethiopia, Kenya, and Somalia (including the Somaliland region). We selected six regions based on precipitation zones, in which the annual mean precipitation and seasonal cycle are homogeneous (Fig. 1a), livelihood zones (see Fig. 1b) and discussions with local experts from the Kenya Meteorological Department and the National Meteorological Agency (NMA) of Ethiopia and the Famine Early Warning Systems Network (FEWS NET). The regions are shown in Fig. 1 and listed in Table 1. Data is annually and spatially averaged over the study regions.

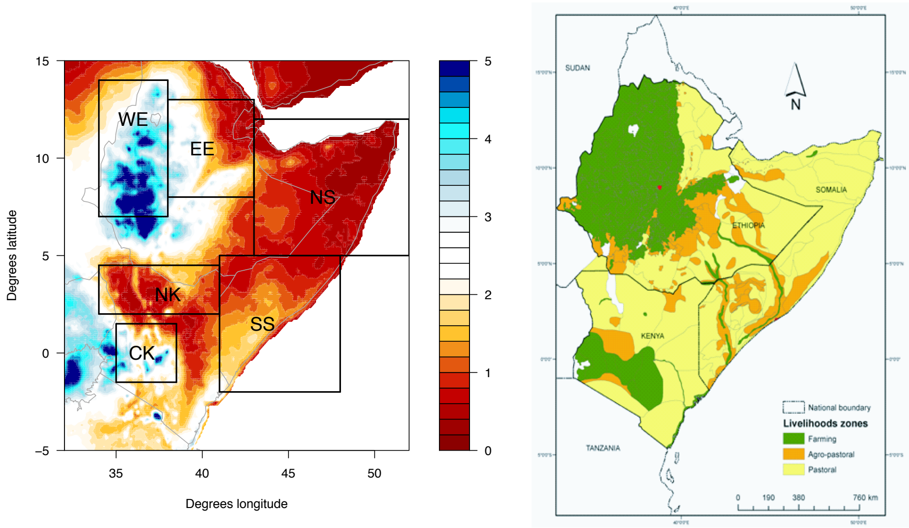

Figure 1. ~~Left:~~ (a) annual mean precipitation [mm/day] and the six study regions. Note that only land values are used. ~~Right:~~ (b) livelihood zones after Pricope et al. (2013), which were also used to define the study regions.

2.2 Datasets

For the four study variables, we use ~~as many datasets as readily available~~ all readily available datasets over the study area, provided that (i) the data are sufficiently complete over a ~~time~~ period long enough to be used for trend calculations, and (ii) the model data pass the validation tests (see Sect. 3). For this purpose, we ~~decided to~~ use time series of at least 35 years~~and longer~~. As the focus of this paper is on annual time scales, using monthly data is sufficient. The observational and model datasets used in this study are shown in Fig. 2 and listed in ~~tables~~Tables **??** and 3 below. (For brief descriptions of the projects from which these data originate, ~~please~~ see the Supplement.) Note that we use the data as ~~it is~~ they are available without applying any additional bias correction, resampling or downscaling. Some of the data has undergone bias correction within ~~project~~ their projects of origin, as described in the Supplement.

The following subsections address the observational datasets and modelling datasets in turn.

Observational datasets: For observations of precipitation and daily mean near-surface temperature, we use gridded observational data sets and reanalyses.

For soil moisture and ~~PET~~E_0, no direct observations meeting the above criteria exist. Instead, we use observational estimates of soil moisture and ~~PET~~ E_0 resulting from various combinations of observational forcing data and models (see Fig. 2a).

~~Concerning soil moisture , observational series are fewand~~ Observational series of soil moisture are few, generally too short to use for trend analysis~~and they~~ , and do not correlate well with reanalysis or model data over ~~eastern~~ Eastern Africa (McNally et al., 2016). It is therefore important to use multiple observationally forced model estimates to span the large uncertainties from inter-dataset differences. There being no a priori reason to favour one soil moisture dataset over another, we treat all resulting soil moisture datasets equally. For ~~all~~ both observed and modelled soil moisture data sets, ~~observed and modelled,~~

we use the topmost layer (see Fig. 2 for the depth of the topmost layer) provided by each dataset~~and scale each time series to have a standard deviation of 1 in order to make comparisons in trends possible. An exception to this is~~ , except for the model weather@home where the available soil moisture variable is an integrated measure of all four layers of soil moisture~~in the model~~, including the deep soil. Each time series is scaled to have a standard deviation of 1 in order to make comparisons in trends possible.

~~PET~~ E_0 is a function of temperature, humidity, solar radiation, and wind speed~~, and as such is not a directly observable variable~~. Observational estimates of ~~PET~~ E_0 used here originate from reanalysis data sets or reanalysis-driven impact models. For both observed and modelled ~~PET~~E_0, there are various ~~ways of parametrizing PET~~parameterizations, ranging from simple ~~temperature~~ temperature- or radiation-based schemes to sophisticated schemes based on all the aforementioned components. Whilst the Penman-Monteith scheme is often considered superior ~~(e.g. Hobbins et al., 2016)~~ (e.g., Hobbins et al., 2016) , one is often constrained from using a Penman-Monteith parameterization due either to the lack of accurate or reliable input data or because the choice of ~~PET~~ E_0 parameterization within a given hydrological model setting is already prescribed, as in the ISIMIP ensemble. We thus chose to use a variety of ~~PET parameterizations~~ E_0 parameterizations (mostly the PET metric) and input datasets in order to cover the range of possible ~~PET~~ E_0 values and trends in ~~PET. The PET~~ E_0. The E_0 scheme used by each data set is noted in Fig. 2.

~~Concerning model data sets, most~~ Modelled datasets: Most simulations stem from the ISIMIP project, which provides output of the variables under investigation for four different impact models driven by four different GCMs. These simulations are complemented by other readily available model runs (EC-Earth-PCRGLOB-WB and weather@home) with different (but compatible) framings.

~~With the datasetswe use we~~ Using these various observations and modelled datasets, we cover a wide range of different factors that influence ~~PET~~ E_0 and soil moisture. The different factors include meteorological forcing, model choice, RCP scenario for the greenhouse gas concentration trajectory, ~~PET~~ E_0 scheme, number of soil layers and depth of topsoil layer, dynamic vegetation modelling (LPJmL only), and transient versus ~~time slice~~ time-slice runs (see ~~next section on~~ 'Methods').

3 Methods

In this section~~we describe first the method we use~~ , we first describe the method for detection and attribution of trends in the four variables, including model validation and the synthesis of observational and model results. ~~Furthermore, in subsection~~ Subsection 3.2 ~~we describe~~ describes the assumptions and decisions that are made concerning the data/model setup~~and in subsection~~ ; and Subsection 3.3 ~~we provide~~ provides an example of how the method is applied to real data.

3.1 Detection and attribution of trends

In this section we detect trends in observations and analyse whether these trends, if present, can be attributed to human induced climate change. In doing so, the approach taken to communicating uncertainty is to

Table 2. Observational data used in this study.

Observational dataset	**Full name**	**Time period used**	**Spatial resolution (°lat x °lon)**	**~~Reference~~Citations(s)**
Observatational/reanalysis data set				
CenTrends (prcp)	Centennial Trends data set	1900–2014	0.1x0.1	Funk et al. (2015)
CRU TS4 (temp)	CRU TS4.01	~~1901–2019~~ 1901–2018	0.5x0.5	Harris et al. (2014)
Berkeley (temp)	Berkeley Earth	~~1750–2019~~ 1900–2018	1.0x1.0	Rohde et al. (2013b, a)
ERA-I	ERA-Interim	~~1979–2019~~ 1979–2018	0.5x0.5	Dee et al. (2011)
Observation-driven hydro/impact model				
LPJmL-WFDEI (soil moisture)	Lund-Potsdam-Jena managed Land - WATCH-Forcing-Data-ERA-Interim	1971–2010	0.5 x 0.5	Bondeau et al. (2007); Rost et al. (2008); Schaphoff et al. (2013); Weedon et al. (2014)
PCRGLOB-WFDEI (soil moisture)	PCRaster GLOBal Water Balance model - WATCH-Forcing-Data-ERA-Interim	1971–2010	0.5 x 0.5	Sutanudjaja et al. (2018); Weedon et al. (2014)
CLM-ERA-I (soil moisture, ~~PET~~E_0)	Community Land Model version 4 - ERA-Interim	1979–2016	0.5 x 0.5	Oleson et al. (2010)
CLM-WFDEI (soil moisture, ~~PET~~E_0)	Community Land Model version 4 - WATCH-Forcing-Data-ERA-Interim	1979–2013	0.5 x 0.5	Lawrence et al. (2011); Weedon et al. (2014)
FLDAS (soil moisture)	Famine Early Warning Systems Network (FEWS NET) Land Data Assimilation System	1981–2018	0.1 x 0.1	McNally et al. (2017)
MERRA Ref-ET (~~PET~~E_0)	Modern-Era Retrospective analysis for Research and Applications Reference Evapotranspiration	1980–2018	0.125 x 0.125	Hobbins et al. (2018)

Table 3. Model data used in this study.

Model dataset	**Full name**	**Time period used**	**Spatial resolution (°lat x °lon)**	**~~Reference~~Citations(s)**
GCM/RCM				
GFDL	GFDL-ESM2M, Geophysical Fluid Dynamics Laboratory - Earth System Model 2M	1861–2018	2.02x2.5	Dunne et al. (2012, 2013)
HadGEM	HadGEM2-ES, Hadley Centre Global Environmental Model version 2-ES	1859–2018	1.25x1.88	Collins et al. (2011); Jones et al. (2011)
IPSL	IPSL-CM5A-LR, Institut Pierre Simon Laplace - CM5A-LR	1850–2018	1.89x3.75	Dufresne et al. (2013)
MIROC	MIROC5, Model for Interdisciplinary Research on Climate - version 5	1850–2018	1.4x1.4	Watanabe et al. (2010)
EC-Earth	EC-Earth 2.3	1850–2018	1.12x1.125	Hazeleger et al. (2012)
w@h (temp, prcp, soil moisture)	Weather@home	2005–2016 and counterfactual climate	0.11x0.11	Massey et al. (2015); Guillod et al. (2017)
Hydro/impact models				
H08 (soil moisture, ~~PET~~E_0)	H08	1861–2018	0.5x0.5	Hanasaki et al. (2008a, b)
LPJmL (soil moisture, ~~PET~~E_0)	Lund-Potsdam-Jena managed Land model	1861–2018	0.5x0.5	Bondeau et al. (2007); Rost et al. (2008); Schaphoff et al. (2013)
PCRGLOB (soil moisture, ~~PET~~E_0)	PCRGLOB-WB, PCRaster GLOBal Water Balance model	1861–2018	0.5x0.5	Sutanudjaja et al. (2018)
WaterGAP2 (soil moisture, ~~PET~~E_0)	Water Global Analysis and Progress Model version 2	1861–2018	0.5x0.5	Müller Schmied et al. (2016)

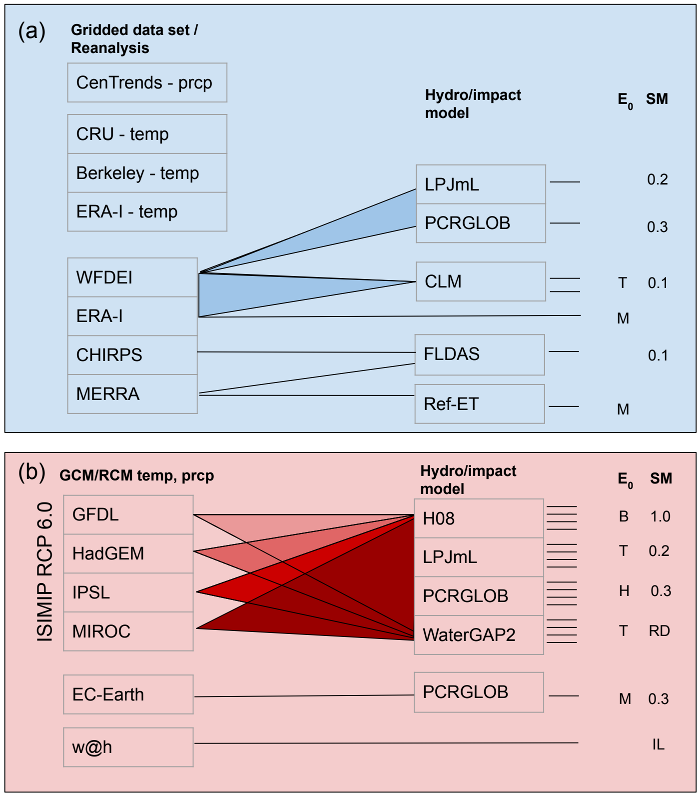

Figure 2. Datasets used in this paper. ~~Top~~(a): observational precipitation (prcp) and near-surface temperature (temp) datasets, ~~bottom~~(b): models. Listed under ~~PET~~ E_0 is the ~~PET~~ E_0 scheme (T: Priestley-Taylor, M: Penman-Monteith, H: Hamon, B: Bulk formula) and, under SM, is the depth of the top soil moisture layer available (RD: depends on rooting depth (0.1-1.5m for WaterGAP2); IL: integrated over all layers). Shading indicates an experiment with either multiple input datasets or multiple hydrological models. The number of resulting hydrological model simulations are indicated by horizontal lines on the right side of the figure.

- Perform a multi-model and multi-observation analysis that summarises what we currently know, using readily available data and methods.
- Apply simple evaluation techniques to readily available data, treating datasets that satisfy evaluation criteria equally and rejecting the others.
- Communicate uncertainties from synthesis. A simple 'yes' or 'no' is not appropriate if there is no significant trend. Rather, the uncertainties (confidence intervals) and their origin (e.g., natural variability or model spread) are given.

We use a multi-method, multi-model approach to address attribution. We use global mean surface temperature (GMST) as a measure for anthropogenic climate change for calculating trends. We calculate trends for all variables, regions and datasets and synthesize results into one overarching attribution statement for each of the four variables (soil moisture, precipitation, temperature, and E_0) in each of the six regions. We use this method, following the approach applied in earlier studies on drought in ~~eastern~~ Eastern Africa (e.g., Philip et al., 2018a; Uhe et al., 2018) and other drought- and heat-attribution studies (e.g., Philip et al., 2018b; van Oldenborgh et al., 2018; Kew et al., 2019; Sippel et al., 2016) ~~, which~~ as it represents the current state of the art in extreme event attribution. The method is extensively explained in van Oldenborgh et al. (2019), Philip et al. (2019), van Oldenborgh et al. (2018), and van der Wiel et al. (2017).

In this study, for transient model runs and observational time series, we statistically model (i.e., fit) the dependency of annual means of the different variables on GMST, (the model GMST for models, and GISTEMP surface temperature GMST (Hansen et al., 2010) for observations and reanalyses) as follows:

After inspection of whether a Gaussian or a General Pareto Distribution fits the observational ~~or~~ and reanalysis data best, we use the following distributions:

- for soil moisture: a Gaussian distribution that scales with GMST, focussing on low values,
- for precipitation: a General Pareto Distribution (GPD) that scales ~~to~~ with GMST, analyzing low extremes
- for temperature: a Gaussian distribution that shifts with GMST, focussing on high values, and
- for ~~PET~~ E_0: a Gaussian distribution that scales with GMST, focussing on high values.

When the distribution is shifted, a linear trend α is fitted by making the location parameter μ dependent on GMST as

$$\mu = \mu_0 + \alpha T, \tag{1}$$

with α in [units of the study variable]/K. When the distribution is scaled,

$$\mu = \mu_0 \exp(\alpha T/\mu_0), \tag{2}$$

$$\sigma = \sigma_0 \exp(\alpha T/\mu_0), \tag{3}$$

which keeps the ratio of the location and scale parameter σ/μ invariant. In each case, the fitted distribution is evaluated twice: once for the year 1900 and once for the year 2018. Confidence intervals (CI) are estimated using a non-parametric bootstrapping procedure. This allows us to calculate the return period of an event as if it ~~would have~~ had happened in the year 1900 or in the year 2018. To obtain a first-order approximation of the percentage change in the magnitude of the study variable between the two reference years, α is multiplied by 100% times the change in GMST and divided by μ_0 (for the shift fit this is exact). Note that for some variables — e.g., precipitation — it is appropriate to scale rather than shift the distribution with GMST ~~(see van Oldenborgh et al., 2019; Philip et al., 2019, for an explanation)~~ (van Oldenborgh et al., 2019; Philip et al., 2019) . For the very large weather@home ensemble simulations of actual and counterfactual climates, it is not necessary to use a fitting routine as the large amount of data permits a direct estimation of the trend. This also provides an opportunity to check the assumptions made in the fitting, notably that the values follow an extreme-value distribution and that the distribution shifts or scales with the smoothed GMST. We calculate trends for the time series of spatially and annually averaged data of all four variables and all six regions for all datasets by dividing the difference in the variable between the two ensembles by the difference in GMST.

Figures 3 and **??** present the methods applied to transient series and time slices, respectively. For reference and to aid interpretation of the return-period diagrams, the magnitude of a hypothetical event with a 20-year return period in the year 2018~~or~~, i.e., in the current climate, is shown as a horizontal line or square. Reading the return period at which this line crosses the fit for the reference year 1900 shows how frequent an event with a 20-year return period in today's climate would have been then.

4 Synthesis results

In this section, ~~to~~ we illustrate the synthesis method~~, intermediate~~. Intermediate synthesis figures, which not only show the overall synthesis but also the results for individual models, are presented for the region SS for each of the four variables~~.~~ ~~See the caption of Fig. 4 for more information. The~~ ; the intermediate synthesis figures of all six regions can be found in the Supplementary Information. Table 4 and Fig. 5 summarize ~~all~~ final synthesized findings for all regions. Using both the intermediate and final synthesis results, we first draw conclusions based on different GCMs and hydrological models and then turn to conclusions ~~per~~ for each variable.

First, we look for consistent behaviour in the trends from individual GCMs across the four variables. We note that the results from low resolution GCMs do not consistently stand out compared to higher resolution models and also do overlap with observational uncertainty. Some general conclusions about the different GCMs are as follows: (i) for GCM-driven model runs with stronger positive trends in temperature, there is a tendency ~~that~~ for the positive trends in ~~PET are also~~ E_0 also to be stronger and vice versa for weaker trends; (ii) the uncertainty in precipitation trends is high compared to the trend magnitudes~~.~~ ~~This is one of the reasons~~ , which partially explains why a clear relation with soil moisture trends is not evident; (iii) no clear relation between local temperature trends and soil moisture trends is evident.

Looking at the different hydrological models, we conclude that the trend in PCR-GLOBWB ~~PET~~E_0, which uses the Hamon ~~PET~~ E_0 scheme that depends only on temperature, is generally higher than the trend in in EC-Earth ~~PET~~E_0, which uses the more-complex Penman-Monteith ~~PET~~ E_0 scheme that additionally depends on humidity, wind ~~and~~ speed, and solar radiation. Using this more complex scheme can influence the trend in soil moisture, especially in wetter regions.

The analyses of the individual model runs, stratifying by GCM or hydrological model, do not lead to a clear conclusion on the relation between the trends in soil moisture, precipitation, temperature, ~~PET and soil moisture~~and E_0. We therefore turn to the analysis of the synthesized values ~~,~~ (see Table 4 and Fig. 5 for a summary of the outcome and Fig. 4 and Figs. S1 to S6 in the Supplementary Information for synthesis diagrams~~. The table gives a concluding~~). Table 5 summarizes the interpretation of the synthesized results shown in Fig. 5. The more the magenta bar is centered in the white box, the better the models agree with observations and the more we trust our attribution statement.

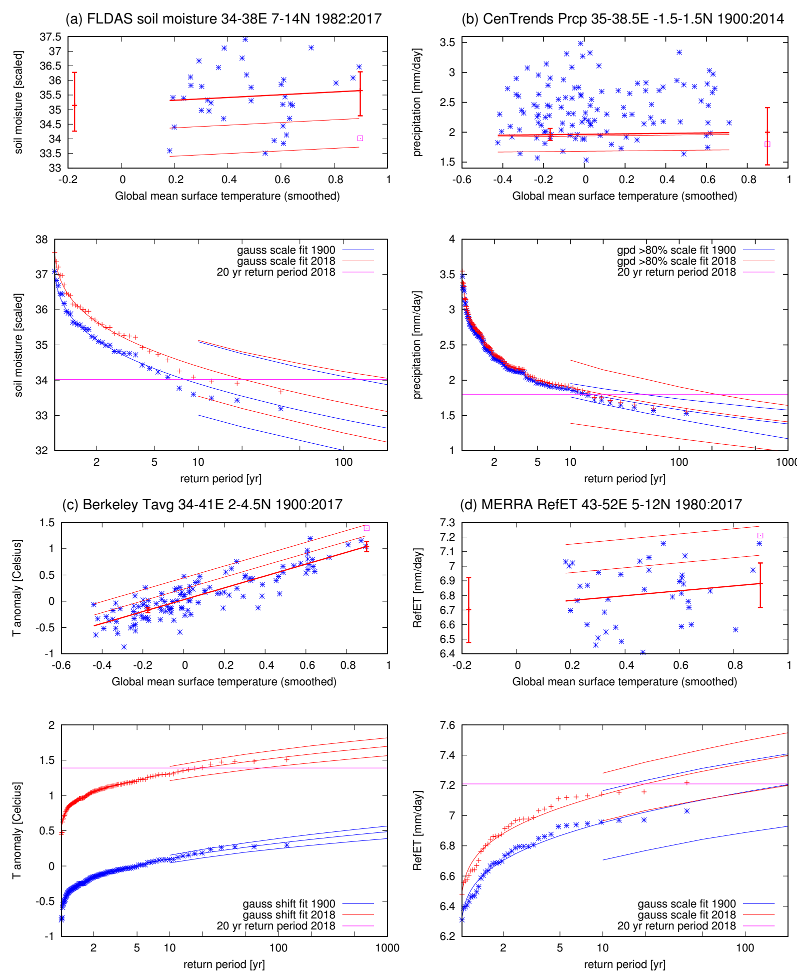

Figure 3. Illustrative examples of the fitting method for each variable, for selected study regions. (a) FLDAS soil moisture (Gauss fit, low extremes, region WE); (b) CenTrends precipitation (GPD fit, low extremes, region CK); (c) Berkeley temperature anomaly (Gauss fit, high extremes, region NK); (d) MERRA E_0 (Gauss fit, high extremes, region NS). Top of each panel: annually averaged data (stars) against GMST and fit lines - the location parameter μ (thick), $\mu\pm\sigma$ and $\mu\pm 2\sigma$ (thin lines, Gaussian fits) and the 6- and 40-year return values (thin lines, GPD fit). Vertical bars indicate the 95% confidence interval on the location parameter μ at the two reference years 2018 and 1900. The magenta square illustrates the magnitude of an event constructed to have a 20-year return period in 2018 (not included in the fit). Bottom of each panel: return period diagrams for the fitted distribution and 95% confidence intervals, for reference years 2018 (red lines) and 1900 (blue lines). The annually averaged data is plotted twice, shifted or scaled with smoothed global mean temperature up to 2018 and down to 1900. The magenta line illustrates the magnitude of a hypothetical event with a 20-year return period in 2018.

For soil moisture we find no significant synthesized trends: there is practically no change in region EE and no trend to a small~~positive~~ , positive but non-significant trend in regions WE, NS, NK, CK and SS.

Table 4. Summary of synthesis results for each region and study variable. Note that ‘0’ means no *significant* change~~and~~ , a ‘+’ sign indicates a positive trend, ~~where in soil moisture this means~~ and a ~~change towards~~ ‘-’ sign indicates a ~~*wetter*~~ ~~soil~~negative trend. The uncertainties associated with each result are depicted in Fig. 5

Region	**Soil moisture**	**Precipitation**	**Temperature**	**~~PET~~E_0**
WE	0/+	0/+	+	+
EE	0	0	+	+
NS	0/+	+	+	+
NK	0/+	0/+	+	0/+
CK	0/+	0	+	0/+
SS	0/+	0/-	+	+

For precipitation, regions WE and NK show a positive but non-significant trend, ~~in region~~ although in region WE models and observations only partially overlap. In region NS there is a small positive trend, regions EE and CK show no trend ~~and~~ (for EE only with partial overlap of models and observations), and region SS a negative, non-significant trend.

As expected from global climate change, the local annually averaged temperatures all have a significant positive trend, with best estimates between 1.0°and 1.3°per degree of GMST increase. Related to this, trends in ~~PET~~ E_0 are also positive in four of the six regions but lower than for temperature and generally with larger confidence intervals. The regions NK and CK are the exceptions. Although weighted averages show positive trends, models show tendencies opposite to observations. This incompatibility renders the results uncertain.

We can identify the following relationships between different variables: (i) Precipitation trends have a (small) influence on soil moisture trends in regions WE, NS and NK; (ii) in regions WE, EE, NS, NK and CK, temperature and ~~PET~~ E_0 have no discernible influence on soil moisture trends; (iii) in region SS, the non-significant negative trend in precipitation does not lead to lower soil moisture and neither do the trends in temperature or ~~PET.~~ E_0. While it would be desirable to link the overall findings to differences in regional climate, the differences in the synthesized results between regions are too small relative to confidence intervals to be able to say anything meaningful. It was nevertheless necessary to divide the study area into homogeneous regions, so that extremes experienced within each region are representative for that region and inhomogeneity is not influencing the location of the occurrence of extremes.

5 Discussion

In this section, we ~~discuss the interpretation of~~ interpret our results in the light of how our choices and assumptions ~~made~~ may have influenced the ~~outcome~~ outcomes and we compare ~~previous studies on similar topics~~them to previous studies.

~~We study drought trends on annual as opposed to sub-annual time scales, as long-term drought presents a greater risk for food security. We define the annual period to be from January to December. This definition is a natural choice for each of our study regions, where the single or dual seasonal cycle peaks in precipitation (rainy seasons) and temperature do not extend~~

~~beyond December into the next year. The Jan–Dec definition has the consequence that multi-season droughts out of phase with this period do not appear extreme in the observational time series used here, whilst they would appear extreme in~~ Whilst it may be preferable to use soil moisture as a ~~Jul–Jun series. For example, in the well-documented 2010/2011 drought event in eastern Africa, only the second rainy season in 2010 and first rainy season of 2011 were exceptionally dry. This choice however does not affect the resulting annual trends, which are similar for both the Jan–Dec and Jul–Jun annual definition.~~

~~On the annual time scale, we do not see strong explanatory relationships between the *trends* in the four studied variables. To gain insight in the relationships between the variables, we additionally looked at correlations on a sub-annual time scale. Simple correlations between monthly precipitation, temperature, PET and soil moisture(not shown) support the conclusions of Manning et al. (2018) on the influence of precipitation and PET on soil moisture at dry sites in Europe.They found that at water-limited sites the influence of precipitation on soil moisture is much larger than the influence of temperature, via PET, on soil moisture.In our study, we find the same for the driest regions and the driest months in the wetter regions, and for the more temperature-based PET schemes.~~

drought indicator, observations and simulations of precipitation are more reliable in this region (Coughlan de Perez et al., 2019). Precipitation has a large influence on agricultural droughts and is therefore appropriate to use in attribution studies in Eastern Africa, supplementing the analysis of soil moisture. The outcome of previous studies that have focussed on precipitation deficits only (e.g., Philip et al., 2018a; Uhe et al., 2018) are thus still relevant and compare well with our results—i.e., that no consistent significant trends in droughts are found. ~~Looking at seasonal cycles — monthly means averaged over recent decades — a~~ A comparison between seasonal cycles of the different variables (averaging the monthly means over recent decades) shows that the seasonal cycle of soil moisture is similar to that of precipitation in all six study regions. In contrast, the inverse seasonal cycle of temperature is not similar to that of soil moisture. Whether the ~~PET~~ E_0 seasonal cycle reflects elements of the soil moisture cycle or not depends on the ~~PET~~ E_0 scheme used: temperature- or radiation-based schemes show a seasonal cycle that is similar to that of temperature, whereas more advanced schemes reflect a mixture between the seasonal cycles of precipitation and temperature~~.~~, as they also synthesize the seasonal cycle in humidity, which is strongly correlated to that of precipitation. We thus conclude that the influence of precipitation on soil moisture is higher than that of temperature or ~~PET~~most E_0 schemes. This is supported by the synthesized results that show negligible or no trends in soil moisture and precipitation whereas the trends in temperature and ~~PET~~ E_0 are strongly positive.

If temperature has ~~, via PET,~~ an influence on trends in soil moisture (through E_0), we expect to see that the positive trend in temperature is coupled to a drying ~~trend in soil moisture~~ soil moisture trend. As we average over the annual scale, we may miss parts of the season when this effect is strongest. Therefore we selected a region and period outside the rainy season, in which the seasonal peak in temperature corresponds to a dip in soil moisture (region CK, months Feb–Mar), to inspect sub-annual trends (not shown). Even then, we find that there is no negative trend in soil moisture accompanying the positive temperature trends.

~~While improving the data with respect to some characteristics, an additional uncertainty arises from the bias correction of the GCM data prior to use in the hydrological model. The bias correction in ISIMIP was set up to preserve the~~ We study drought trends on annual as opposed to sub-annual time scales, as long-term ~~trend, but it also decreases the daily variability~~

~~by truncating extreme high values (e. g., in precipitation) (Hempel et al., 2013) . The most important element for our analysis is that it also increases the daily variability by removing excessive drizzle, which is often present in GCM precipitation data. Prudhomme et al. (2014) noted that such a statistical bias correction can influence the signal of runoff changes but that~~ drought presents a greater risk for food security. On the annual time scale, we do not see strong explanatory relationships between the *trends* in the four studied variables (soil moisture, precipitation, temperature, and E_0). To gain insight into the relationships between the variables, we additionally looked at correlations on a sub-annual time scale. Simple correlations between monthly soil moisture, precipitation, temperature, and E_0 (not shown) support the conclusions of Manning et al. (2018) on the influence of precipitation and E_0 on soil moisture at water limited sites in Europe. They found that at water-limited sites the influence of precipitation on soil moisture is much larger than that of temperature via E_0. In our study, we find the same for the driest regions and the ~~effect generally remains smaller than the uncertainty from GCMs and global impact models. By far the largest difference we found in our analysis between trends in original and bias-corrected data was for temperature for IPSL in region NK: we found 1.9 K/K (95% CI 1.8 to 2.1 K/K)for the original trend and 1.4 K/K (95% CI 1.3 to 1.5 K/K)for the trend in bias-corrected data~~ driest months in the wetter regions, and for the more temperature-based E_0 schemes. This is presumably because temperature-based schemes (such as the Hamon approach) do not reflect land surface-atmosphere interactions as well as those that are also driven by humidity and wind speed (such as the Penman-Monteith approach) or, to a lesser degree, by radiation (such as the Priestley-Taylor approach).

~~All other differences were smaller and non-significant.~~

Previous studies have shown that both the E_0 scheme and their input data can have a large influence on E_0 values (Trambauer et al., 2014; We confirm this using the CLM-ERA-PT (Priestley-Taylor), CLM-WFDEI-PT and CLM-ERA-PM (Penman-Monteith) datasets (not shown). In our study regions, E_0 values are consistently higher when using PM than when using PT. The differences in trends in E_0 using ERA or WFDEI input or using PT or PM input are sometimes significant. However, comparing study regions, there is no consistency in the difference; in four out of the six regions the PM data shows a higher trend than the PT data and in four out of the six regions WFDEI data shows a higher trend than the ERA data.

A study by Rowell et al. (2015) discussed the possibility that climate model precipitation trends in East Africa are influenced by the inability of the models to reliably represent key physical processes~~reliably. In attribution studies on drought, especially for this region, it is therefore high priority to extend model evaluation techniques to assess models' representation of key physical processes. The approach taken in this paper has been to apply simple evaluation techniques on the seasonal cycle and frequency distributions of readily available data and that results from models passing validation tests represent the status of our current knowledge.~~ . Rainy seasons in this region are governed by large-scale processes, such as El Niño-Southern Oscillation (ENSO) dynamics and the shifting of the ~~ITCZ and ENSO dynamics. The ability of a model to capture the seasonal cycle in precipitation and temperature thus provides~~ Intertropical Convergence Zone (ITCZ). We view the tests we perform on seasonal cycle and frequency distributions, which provide some assurance that large-scale physical processes are reasonably well described~~by the model. We see the tests we perform as~~ , to be a minimum requirement for model validation. ~~However, to~~ To improve the performance of models and to understand the discrepancies between models and observations, a much more thorough investigation into the models' representation of physical processes and feedbacks is required, such as demonstrated by James et al. (2018) and encouraged by the IMPALA (Improving Model Processes for African Climate) project (https://futureclimateafrica.org/project/impala/).

~~It is still unknown how vegetation will respond to substantial increases of CO_2 concentration. Two counteracting effects — physiological (restriction of stomatal openings leading to decreased evapotranspiration) and structural (increased leaf area leading to more stomata and increased evapotranspiration) responses — are expected, but their net effect is unknown (e.g. Wada et al., 2013) . So-called 'dynamic vegetation models' include these CO_2 effects and there are indications that these models show a weaker response of drought to climate change (Wada et al., 2013; Prudhomme et al., 2014) . In this study our selection of hydrological models is restricted by the variables we require, however, out of the four ISIMIP hydrological models that match our criteria, one (LPJmL) uses dynamic vegetation modeling. The soil moisture response to increasing GMST in LPJmL simulations is mid-range amongst the ISIMIP results. The PET response for LPJmL simulations is, however, somewhat on the low side of the ISIMIP results. It has not been verified if this behaviour is linked to dynamic vegetation modelling, but with confidence intervals generally overlapping with the synthesized model outcome, there is no exceptional difference.~~

~~The approach taken in this paper towards uncertainty has been to Perform a multi-model and multi-observation analysis that summarises what we know at the present moment, using readily available data and methods. Apply simple evaluation techniques to readily available data, treating datasets that satisfy evaluation criteria equally and rejecting the others. Communicate uncertainties from synthesis. A simple 'yes' or 'no' is not appropriate in this analysis where there is no clear significant positive or negative trend. Rather, the uncertainties (confidence intervals) and their origin (e.g. natural variability or model spread) are given.~~

In the long term, a trend in ~~PET~~ E_0 only has meaning for crop growth if there is water available for ~~evaporation~~evapotranspiration. Much of ~~eastern~~ Eastern Africa is in a water-limited ~~evaporation regime. In the case that irrigation would be locally applied, more water would become available for evaporation, shifting the situation away from a~~ hydroclimate, requiring irrigation for crop growth. In irrigated areas within larger water-limited regions, the increased water availability shifts the local hydroclimate away from the surrounding water-limited regime ~~and towards an energy limited regime. A trend in PET~~ towards a locally energy-limited regime. Positive trends in E_0 seen in our analyses (especially if the ~~analysis using~~ variety of different schemes produces a robust ~~PET~~ E_0 trend) could then signify a trend in ~~real evaporation~~ actual ET and would therefore be accompanied by an increase in both irrigation water demand ~~. Note~~ and, if that demand can be met, in crop growth. However, it should be noted that irrigation is not accounted for by the models or reanalysis datasets used here.

~~Previous studies have shown that both the PET scheme and the input data used for calculation of PET can have a large influence on PET values (Trambauer et al., 2014; Wartenburger et al., 2018) . We confirm this using the CLM-ERA-PT (Priestley-Taylor), CLM-WFDEI-PT and CLM-ERA-PM (Penman-Monteith) datasets (not shown).In our study regions, PET values are consistently higher when using PM then when using PT.The differences in trends in PET using ERA or WFDEI input or using PT or PM input are sometimes significant. However, comparing study regions, there is no consistency in the difference; in four out of the six regionsthe PM data shows a higher trend than the PT data and~~ Trends in E_0 away from irrigated regions (i.e., in ~~four out of the six regionsWFDEI data shows a higher trend than the ERA data~~water-limited regions) will generally denote lower ET rates (through the complementary dynamics between E_0 and ET that dominate in such regions), higher sensible heating of the atmosphere from a drier surface, and consequent greater drought exposure.

~~There~~ There are some factors influencing droughts and attribution results that are beyond the scope of this paper. For example, there is some evidence that warm spells are increasing in length, particularly in Ethiopia and ~~northern~~ Northern Somalia/Somaliland region (Gebrechorkos et al., 2019), as is the number of consecutive dry days in some parts of ~~eastern~~ Eastern Africa, which may have an impact on drought length and increase the rapidity of onset and the intensity of drought (Trenberth et al., 2014).

~~However, the overall impact on crops and food security during long-duration droughts on annual timescales is probably insensitive to this.~~

~~It is possible~~ Furthermore, it is likely that increasing temperatures have a negative impact on food security during droughts ~~in ways that are beyond the scope of this study~~through, e.g., decreased immunity of livestock, or increased water demand for cooling and water supply (Gebrechorkos et al., 2019, and references therein). In addition, in regions suffering from recent meteorological drought, non-meteorological factors such as increasing population and land-use changes also play a role in worsening the declining vegetation conditions, even after precipitation returns to normal (Pricope et al., 2013).

It is also still unknown how vegetation will respond to substantial increases in CO_2 concentration. Two counteracting effects — physiological (restriction of stomatal openings leading to decreased evapotranspiration) and structural (increased leaf area leading to more stomata and increased evapotranspiration) responses — are expected, but their net effect is unknown (e.g., Wada et al., 2013) . There are indications that ‘dynamic vegetation models’ that include these CO_2 effects and show a weaker response of drought to climate change (Wada et al., 2013; Prudhomme et al., 2014) . One of the hydrological models used in this study (LPJmL) uses dynamic vegetation modeling but there were no notable effects.

6 Conclusions

In this first multi-model, multi-method attribution study using several drought estimates in ~~eastern~~ Eastern Africa, we address the recurring question on whether increasing global temperatures exacerbate drought. Previous attribution studies for the ~~eastern~~ Eastern Africa region have examined drought from a meteorological perspective (precipitation deficit) and have found no clear trends above the noise of natural variability. In this study, we examined trends in ~~eastern~~ Eastern African drought from an agricultural perspective (soil moisture) as well as the meteorological perspective (precipitation, temperature~~and PET)~~ , and E_0 for six regions in ~~eastern~~ Eastern Africa. We also investigate whether global-warming driven trends in these meteorological variables can be seen to contribute to trends towards drier soils. In this section, we draw conclusions for each variable in turn and make recommendations.

~~Out of~~ Of the four studied variables, soil moisture is most closely related to food security, via crop health. In standardized soil moisture data, we found no discernible trends. The uncertainties in trends from model runs were found to be large and there are no long observational runs available. This emphasizes that the use of an ensemble of models is imperative. Due to the large uncertainties in both soil moisture observations and simulations, we ~~conclude that soil moisture cannot be relied upon on~~

~~its own as a drought indicator and it is therefore important to examine other drought indicators as well. Besides, soil moisture also has a physical lower limit: once the soil is dry it will remain dry. In water limited regions an analysis of precipitation is thus a helpful addition.~~ find no trend emerging from natural variability.

Precipitation was found to have a stronger influence than temperature or ~~PET~~ E_0 on soil moisture variability, especially in the drier study regions (the significant positive trend in temperature is not reflected by a decrease in soil moisture). However, the confidence intervals on precipitation trend estimations are large and no clear trend is evident.

As expected from the increase in global temperatures, we find significant positive trends in local temperatures in all six regions. The synthesized trend is between 1.0 and 1.3 times the trend in GMST, which corresponds to a local temperature rise of 1.1 to 1.4 degrees from pre-industrial times to 2018. However, the influence of this warming on annual soil moisture trends appears limited.

~~PET has a more direct link via evaporation to soil moisture than temperature. The trends in PET~~ Soil moisture is more directly linked to E_0 (via ET) than it is to temperature. Trends in E_0 are predominantly positive, although in the regions NK and CK the uncertainty in this trend is large. This generally agrees with the positive trends in temperature. Similar to the results for temperature, we do not find strong relations between ~~PET~~ trends in E_0 and soil moisture~~trends~~. Nevertheless, the results can still be of interest, ~~especially in irrigated regions~~ both for irrigated regions where crop growth is limited only by meteorological conditions and for water-limited regions where the availability of water to evaporate greatly constrains forage growth. Due to large differences in results from different hydrological model runs, we recommend that ~~PET~~ E_0 attribution analyses be carried out using an ensemble of hydrological models. These should use various (observational) input datasets and driving GCMs~~and cover various PET schemes , in order~~ , although the decision to cover various E_0 schemes is a trade-off between the desire to be representative of the uncertainty surrounding all ~~valid approaches and~~ approaches currently in use not bias results towards a particular method ~~.~~ (which is what we leant towards here by including, for example, the temperature-based Hamon approach) and the need to adhere to physical rigor in using the complete suite of drivers and an E_0 parameterization that reflects all relevant dynamics (e.g., in the Penman-Monteith approach).

~~Whilst it may be preferable to use soil moisture as a drought indicator , observations and simulations of precipitation are more reliable~~ We conclude that, although soil moisture is the prefered indicator of agricultural drought, we recommend that any soil moisture analysis be supplemented with precipitation analysis due to the superior reliability of precipitation measurements and the large influence of precipitation on drought in this region~~(Coughlan de Perez et al., 2019) . Precipitation has a large influence on agricultural droughts and is therefore appropriate to use in attribution studies in eastern Africa, supplementing the analysis of soil moisture. The outcome of previous studies that have focussed on precipitation deficits only (e.g., Philip et al., 2018a; Uhe et al., 2018) are thus still relevant and compare well with our results, that no consistent significant trends on droughts are found~~. Besides, soil moisture also has a physical lower limit: once the soil is dry it will remain dry. In water-limited regions an analysis of precipitation is thus a helpful addition.

Finally, communication of the uncertainties in the analyses of soil moisture, precipitation, temperature~~and PET~~ , and E_0 (and any drought indicators) to policy makers, the media, and other stakeholders is crucial. ~~Without~~ Decision-makers need to properly weight and synthesise streams of potentially competing information from the variety of models, but without insight into the uncertainties in ~~synthesized~~ trends in the different drought indicators, ~~conclusions become meaningless and results can easily be misinterpreted~~ they are missing this crucial information. They need to know how much the scientists trust their own conclusions, lest results are misinterpreted and conclusions become meaningless.

Data availability. Almost all time series used in the analysis are available for download under https://climexp.knmi.nl/EastAfrica_timeseries.cgi (last access: 29 April 2019).

Author contributions. Sarah Kew and Sjoukje Philip designed and coordinated the study, analysed all data and led the writing of the manuscript. Mathias Hauser contributed the CLM datasets including E_0 calculations and substantially contributed to writing. Mike Hobbins produced the RefET dataset and substantially contributed to writing. Niko Wanders and Karin van der Wiel collaborated to create the EC-Earth - PCR-GLOBWB data, including E_0 calculations and bias correction. Niko Wanders additionally advised on the use and validation of E_0 and soil moisture data for the analysis of drought. Geert Jan van Oldenborgh contributed analysis tools, monitored progress and contributed to writing. Ted I.E. Veldkamp provided guidance on the use of ISIMIP data and contributed to discussions. Joyce Kimutai and Chris Funk provided local information. Friederike E.L. Otto conceived the idea for the study, monitored development, provided weather@home results and contributed to writing.

Competing interests. We declare that there are no competing interests.

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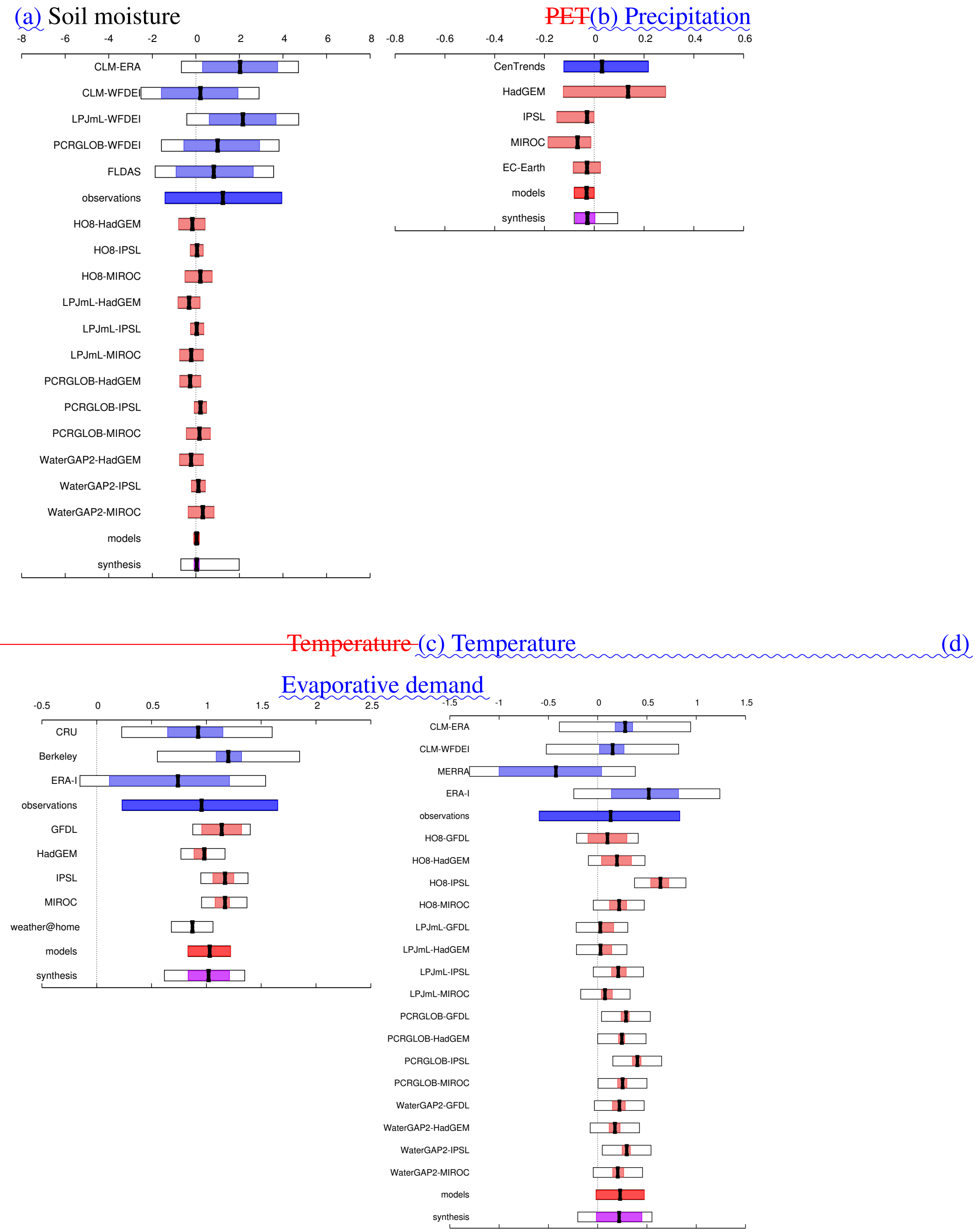

Figure 4. Illustrative examples of the synthesized values of trends per ~~degree~~ 1K GMST rise for soil moisture [/K] (~~top left~~a), ~~PET~~ precipitation [mm/day/K] (~~top right~~b), ~~precipitation~~ temperature [K/K] (~~bottom left~~c) and ~~temperature~~ E_0 [mm/day/K] (~~bottom right~~d) for region SS. Black bars are the average trends, colored boxes denote the 95% CI. Blue represents observations and reanalyses, red represents models and magenta the weighted synthesis. Coloured bars denote natural variability, white boxes also take representativity / model errors into account, if applicable (see Sect. 3). In the synthesis, the magenta bar denotes the weighted average of observations and models and the white box denotes the unweighted average. Soil moisture trends are based on standardized data, the other trends are absolute trends.

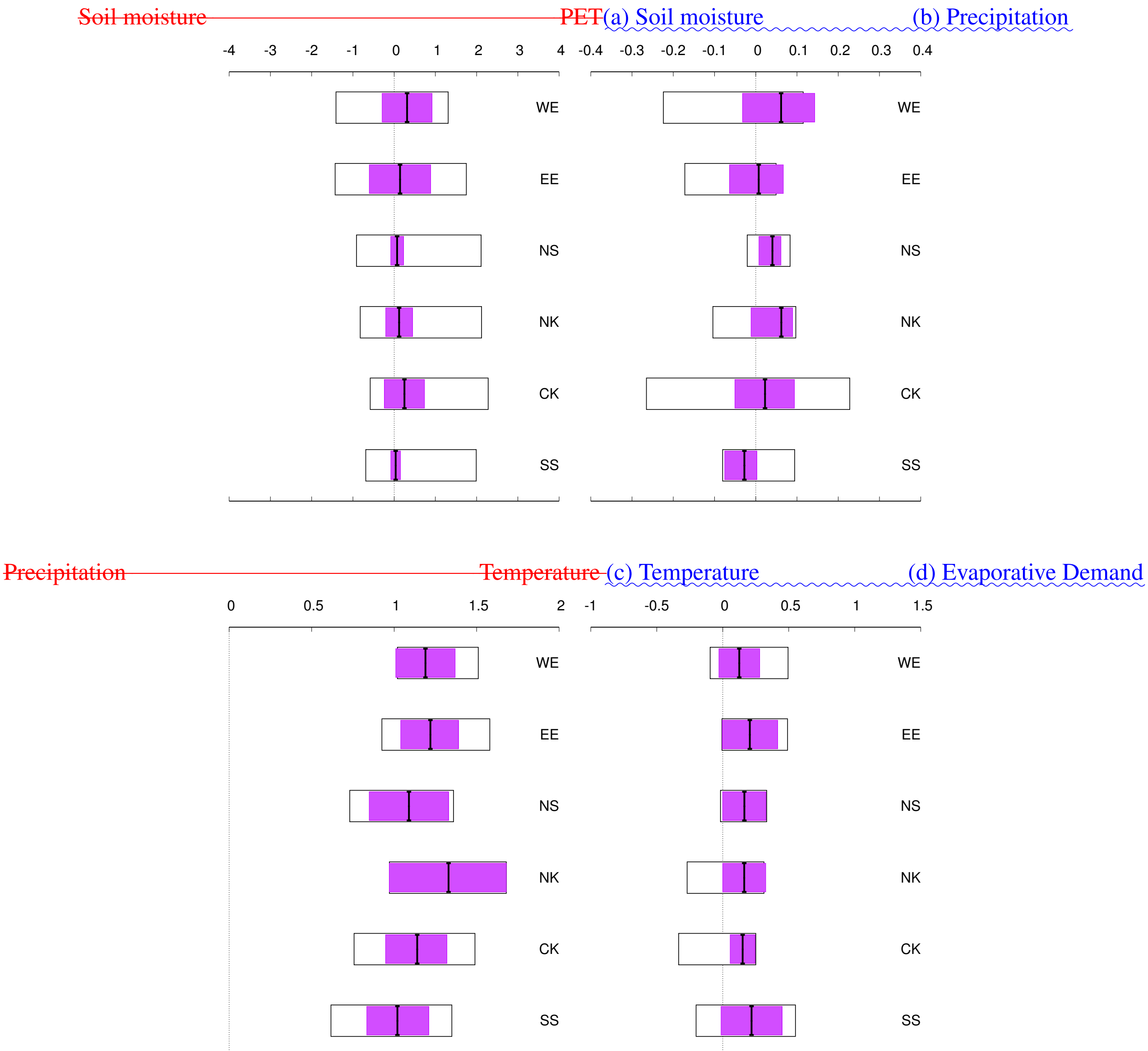

Figure 5. Summary of the synthesized values for soil moisture in [/K], ~~PET,~~ precipitation ~~and~~ in [mm/day/K], temperature in [K/K], and E_0 in [mm/day/K] in the six regions. The magenta bars denote the weighted averages of observations and models and the white boxes denote the unweighted averages.