Response letter of hess-2022-124-RC1

Dear Jakob Zscheischler,

Please find the responses to the comments.

Comments made by the reviewer were highly insightful. They allowed us to greatly improve the quality of the manuscript. We described the response to the comments.

Each comment made by the reviewers is written in italic font. We numbered each comment as (n.m) in which n is the reviewer number and m is the comment number.

Sincerely,

Yuya Kageyama and Yohei Sawada

Responses to the comments of Referee #1

General comments

This a valuable contribution as it links drought entries in a recently constructed disaster database (GDIS), which is based on EM-DAT, with actual droughts identified based on a state-of-the-art reanalysis dataset. The work is important because typically disaster databases are not based on information derived from meteorological variables and establishing such links gives credence to the databases but also serves to identify hazard thresholds and differences in vulnerability.

Generally the manuscript is very clear and easy to follow but it would benefit from a more in-depth discussion of a number of points that are only briefly mentioned. More detailed comments and suggestions follow below.
→ Many thanks for the comments and suggestions.

(1.1) *L10: "We found that ERA5-Land soil moisture accurately captured the socio-economic impacts of drought shown in GDIS." I think I understand what the authors mean but as it is this statement is not correct. ERA5-Land cannot capture "impacts of droughts", rather it provides information that droughts actually occurred when disasters labelled as drought-driven where recorded. Similar statements can be found in other places throughout the text. Please adjust the language to more correctly represent your findings and the relationship between drivers of disasters and the recorded impacts.*
→ We will change the sentences like "We found that the socio-economic impacts of drought shown in GDIS were generally represented by drought hazards quantified from ERA5-Land soil moisture."

(1.2) *L12: "were robust": better us "were less vulnerable"*
→ We appreciate this comment. We will replace "were robust" with "were less vulnerable."

(1.3) *L106: The authors specify some criteria for the analysed events but it seems the number of analysed events is not affected by this. In line 100 it says "The 282 drought events…were analysed", which suggests that this is the number of events contained in GDIS. In Line 162 it is stated that there are 282 drought events. Please clarify how many events are available in GDIS and how many are finally analysed in this study.*
→ Originally, there are 433 drought events in GDIS and 282 drought events were analyzed. Therefore, the number of analyzed events was indeed affected by our quality control. This point was indeed unclear in the original version of the paper. We will add this information in the revised

version of the paper.

(1.4) *L 163: "We recognized that the drought indices successfully capture the GDIS drought events if the two distributions are not statistically the same." This is only true for the full distribution, not at the individual event level. There could still be many events where no drought is evident from a soil moisture perspective (there is also a strong overlap in the distributions). Furthermore, the test doesn't tell you how the distributions differ. Theoretically it would be possible that all disaster events show less extreme drought conditions compared to the control and the KS test give significant results. Please adjust this statement accordingly and make it more nuanced. This should also be reflected in the abstract.*

→ We fully agree with this comment. In the results section 4.1 (L 208, L 212), we stated that the drought index during the GDIS drought periods was significantly higher than that of the whole period. We checked if the distribution is high/low, as well as the results of *K–S* test.

We will change "We recognized that the drought indices successfully capture the GDIS drought events if the two distributions are not statistically the same." to "We recognized that the GDIS drought events are generally represented by the drought indices quantified from ERA5-Land if the median of the drought index during the GDIS drought periods is higher than that of the whole period and the two distributions of the drought index are not statistically the same." In the results section (from L 217), we will add "Please note that although we confirmed a general linkage between drought hazards and the GDIS drought events, some GDIS events were not explained from a soil moisture perspective."

(1.5) *L 165: unclear what "socio-economic drought events in GDIS" means. I assume "socio-economic droughts" are the droughts events and impacts recodred in GDIS? Better use something like "drought disasters" or similar*

→ As the reviewer mentions, "socio-economic droughts" are the drought events and impacts recorded in GDIS. We will replace "socio-economic drought events in GDIS" with "drought events in GDIS", to be consistent with the expressions in other places of our manuscript.

(1.6) *L170: Initially I wasn't completely sure what the purpose of the drought clustering is. I assume the idea is to check whether spatially large droughts typically also lead to impacts (as recorded by EMDAT/GDIS). Given that the drought definition is percentile-based, every location experiences drought with the same frequency, and differences from a rather homogeneous distribution (as for instance visible in the US, Canada and Russia in Fig. 8) are driven by the distribution of continents and the choice of the spatial cutoff (100000km2). With this background, this could be a useful* *analysis but it would be good to motivate it better and discuss the results in more detail (e.g. it seems that some regions experience more contiguous/large-scale droughts than others, why?). The finding that drought disasters tend to occur in regions that are characterise by frequent large-scale droughts is then quite interesting and novel, especially because from a meteorological perspective and at a pixel level, the frequency of drought occurrence is the same everywhere (20% of the time in this study). So it seems that drought disasters occur when droughts occur over large areas. These findings could be described and discussed in more detail.*

→ As the reviewer mentions, the idea of drought clustering is to check whether spatially large hydro-meteorological droughts typically lead to disasters that can be seen in GDIS. In the revised version of the paper, we will clarify the role of drought clustering more by the following sentences.

"The consistency between hydro-meteorological drought-prone areas in ERA5-Land and socio-economic drought-prone areas in GDIS shows that spatially large hydro-meteorological droughts (we analyzed at least 100,000 km^2) typically lead to impacts as shown in GDIS. Although the drought frequency defined by simulated soil moisture is the same everywhere at the grid level (we set the 20th percentile as a drought threshold), there was considerable heterogeneity in the spatially large drought-prone areas (Fig. 8)."

To reinforce our idea, a sensitivity analysis with different thresholds of the size of drought clusters will be described in the supplement material (see the results in the lowermost part of this response). We have already found that drought-prone areas found in GDIS cannot be reproduced by ERA5-based drought-prone areas when we used too small or large thresholds. We will mention it in the revised version of the paper by describing "See also the supplement material for a sensitivity analysis with different thresholds of the size of drought clusters (Fig. S3), showing that drought-prone areas found in GDIS cannot be reproduced by ERA5-based drought-prone areas when we used too small or large thresholds that are used to identify drought clusters."

We will also discuss the results more deeply focusing on the underlying climatological mechanisms which are useful to interpret the drought-prone areas. In the revised version of the paper, we will add, "There are some factors that contribute to the emergence of drought-prone areas, such as El Niño-Southern Oscillation (ENSO), La Niña, intertropical convergence zone (ITCZ), monsoon, land-atmosphere coupling, and anticyclones (Christian et al., 2021). La Niña affects the Horn of Africa, northern China, and western India and has caused severe drought impacts (Funk, 2011; Jain et al., 2021). Ummenhofer et al. (2011) clarified the effect of El Niño–Indian monsoon relationship on drought in western India. Quite large spatio-temporal events such as La Niña might cause drought to persist, which leads to drought impacts as shown in GDIS. However, the drought factors are complex, and much future work is needed to reveal the mechanism of the emergence of drought-prone areas. "

These two points (i.e., the role of drought clustering and climatological mechanisms) will be included in the discussion section of the revised paper.

Supplement material

S3 Sensitivity of drought cluster centroids map to the size of drought clusters

Upscaled map of the drought cluster centroids was generated using four thresholds of the size of drought clusters: 10,000km^2, 50,000km^2, 100,000km^2, and 500,000km^2, shown in Fig. S3. The drought clusters were generated from the third layer's soil moisture. In the results part, we showed the case of 100,000km^2. This shows that drought-prone areas identified by drought indices are not well consistent with those found in GDIS, whether the size of drought clusters is too large or too small.

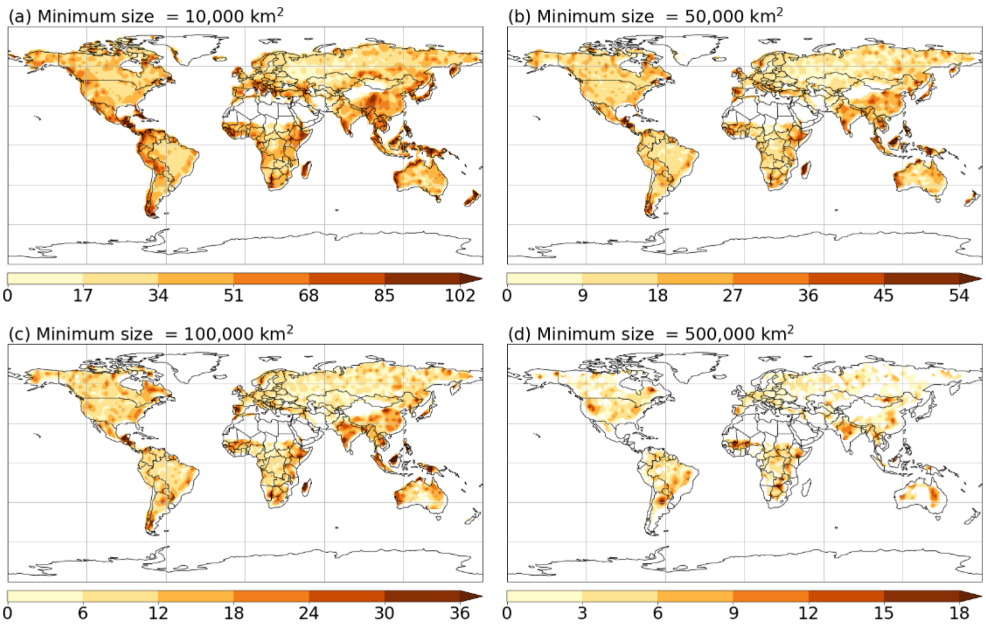

Figure S3: Sensitivity of drought cluster centroids map to the size of drought clusters. (a) 10,000km^2, (b) 50,000km^2, (c) 100,000km^2, and (d) 500,000km^2.

(1.7) *Another point to discuss is that you're using a relative percentile, which means that in generally wet regions, a drought de fined in this way might not be that impactful because the absolute amount of available water is still quite high. This will to some extent also determine where drought disasters occur and might confound the vulnerability assessment. It makes sense to use a relative percentile given that ecosystems/societies are usually adapted to the water availability in their region. However, it is worth discussing this choice.*

→ We appreciate this comment. The major limitation of using an absolute value of soil moisture is that it is difficult to conduct a unified drought analysis across multiple regions. As the reviewer mention, the thresholds of drought impact occurrences are different in different regions because ecosystems/societies are usually adapted to the water availability in their region. Another point is the uncertainty of using data with different reanalysis products or different observation locations. Many climate studies have used relative values rather than absolute values, for which climate model biases are less important (Liu and Key, 2016). Palecki (2018) also stated the uncertainties of absolute soil moisture product from different soil moisture observation networks with different measurement equipment and calibrations.

The limitation of a relative percentile-based drought quantification is that the drought in extreme wet regions might not be represented as the reviewer points out. In the drought clustering analysis, we showed that Indonesia was hydro-meteorological drought-prone areas in ERA5-Land, which were not included in drought-prone areas found in GDIS. We attributed this inconsistency to the abundance of absolute water availability in Indonesia (from L287 to L290).

The issues discussed above will be included in the revised version of the paper: "We used the percentile soil moisture, deviation from the normal condition, to quantify drought following many previous studies (e.g., Sheffield and Wood, 2011; Hanel et al., 2018). However, the inconsistency for Indonesia between hydro-meteorological drought-prone areas and drought-prone areas found in GDIS implies that the drought in extreme wet regions might not be well represented. It implies that our drought quantification method based on relative values of soil moisture cannot accurately consider the amount of regularly available water resources. An alternative way to quantify drought is to use an absolute soil moisture value, but it is not straightforward to quantify drought events by absolute soil moisture values. The thresholds of drought impact occurrences in absolute values are different in different regions, because ecosystems/societies are usually adapted to the water availability in their region. This means that a unified drought analysis across multiple regions is difficult. Another limitation of the absolute value is the uncertainty of using data with different reanalysis products or different observations. Many climate studies have used relative values rather than absolute values, for which climate model biases are less important (Liu and Key, 2016). Palecki (2018) stated the uncertainties of absolute soil moisture product from different soil moisture observation networks with different measurement equipment and calibrations."

(1.8) *L206: You could mention some more details in the results. For instance, how large are the differences between the medians for the different soil moisture layers in Figs 3 and 4. I assume the SDI for the whole period is approx 1 by definition (Fig. 4)? I would also mention that for* *clarification.*

→ We will describe how large are the differences. The mean value of SDI for the whole period is approximately 1 by the definition (Fig. 4).

(1.9) *L219: It maybe worth checking how these regions differ in their absolute SM values (averaged over time). Regions with lower water availability in general might experience drought disasters more frequently even though the relative deviation from normal conditions is small (see the comment higher up). Independent of the findings, the interpretation that the identified regions are more vulnerable to drought probably still holds, but I think it can slightly change the interpretation and consequences for resilience planning. If water is typically abundant, it's much easer to be drought resistant.*

→ We appreciate this implication. We will replace Fig. 5 with the one shown below, whose colors of the violins show the averaged absolute soil moisture value in each region. Sub-Saharan Africa, which was vulnerable to drought, shows lower water availability. This may be one of the reasons for the difficulty for Sub-Saharan Africa to manage the drought hazards. We will add this point in the results and discussion sections of the revised paper.

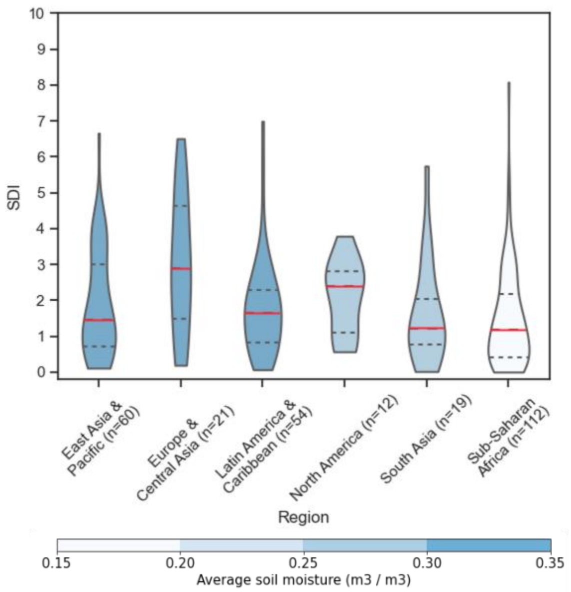

Figure 5: Comparison of the root-zone SDI by geographical regions. The red line shows the median value and grey dotted lines show the 25th and 75th percentile values of each distribution. The color shows the average soil moisture over the study period (1964–2018).

(1.10) *L258: Note that the results of Fig. 5 also confirm results from Tschumi & Zscheischler (2020)* *who also found smaller climate anomalies in less developed countries during EMDAT disasters for different climate variables (their Fig. 9).*

→ We appreciate this comment. We will discuss that our result is consistent with this work in the revised version of the paper.

(1.11) *L280: unclear what "reproducibility of ERA5-Land" means. Please clarify.*

→ "Reproducibility of ERA5-Land" means the performance of ERA5-Land to simulate soil moisture. We will rephrase "The lack of the reproducibility of ERA5-Land might affect these inconsistencies." to "The performance of ERA5-Land to simulate soil moisture might affect these inconsistencies."

(1.12) *L295: again, unclear what "reproducibility" of reanalysis products means. It seams the authors mean that using different climate datasets, one obtains similar drought maps (which makes sense) whereas this does not hold for socioeconomic impacts. This of course depends on how these things are defined. If the same drought definition is used, the choice of (climate) dataset has only little effect on the analysis as this information is comparably well constrained by observations. For socio-economic impacts, no clear/objective definition of disasters etc. exists and uncertainties in impact estimates are usually high. So a comparison across datasets is difficult also because different datasets use different definitions.*

→ The "reproducibility" (L295) means the performance of reanalysis products to simulate hydrometeorological variables. We believe that the validation of the performance has not been fully conducted in terms of whether the anomalies of simulated variables are consistent with the socio-economic impact of drought events in disaster databases. This "reproducibility" does not imply the similarity of results with different reanalysis products. We believe that this comment is provided because we failed to deliver this point using the misleading word of "reproducibility". In the revised version of the paper, this wording is no longer used. We will change this section (from L 295) to, "Although various reanalysis products have been developed and their validations have been conducted by comparing them with earth observation data (e.g., Muñoz-Sabater et al., 2021; Reichle et al., 2017; Rodell et al., 2004), few studies have examined the validation in terms of the disaster occurrence. Sawada (2018) compared the areas identified as drought quantified from a reanalysis product with the disaster records from EM-DAT, but only in a country-scale. As seen in Fig. 7, national-level information does not provide accurate views of disaster locations, so that it is insufficient for validation data. The use of sub-national disaster databases such as GDIS opens the door to validate reanalysis products in terms of the disaster occurrence."

(1.13) *L328: "GDIS only covers about 60% of droughts in EM-DAT" Can you comment on why this* *is the case? Was more detailed information on the remaining events not available?*

→ This is due to vague or unknown location names in EM-DAT. We will add this point in the revised version of the paper.

Additional References

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