Possible role of anthropogenic climate change in the record-breaking 2020 Lake Victoria levels and floods

Earth System Dynamics

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Contents

Abstract

This response letter contains the responses to comments from both anonymous reviewers. The following convention is applied to denote modifications in the original manuscript: new text ~~old text~~. To prevent confusion, the figures embedded within this response letter are called illustrations.

1 Reviewer 1

1.1 General comment

Reviewer 1 Comment 1

Pietroiusti et al. investigated the effect of anthropogenic climate change on the flood event of Victoria lake in 2020, using long-term in situ data, hydrological simulation and a large ensemble climate experiments with and without anthropogenic climate change. Authors found that the occurrence of the flood event has increased by a factor of 1.8 compared to a pre-industrial climate, and the anthropogenic climate change with the same return period would have led lake levels to rise by 7cm less without considering the anthropogenic climate change.
The background, purpose, and results of the study are clearly and well presented. In exchange for the very thorough explanations, there are a few redundant sections and low readability are the only weaknesses. However, these text would help researchers who do attribution for other hydrologic variables or in other places using similar experimental data, so if there is no limit to the number of words in the journal, I would not ask for a drastic reduction.

Response

We thank the Reviewer for their useful comments and suggestions to improve the manuscript. Based on these comments, we have made an effort to reduce some of the length and redundancy of the manuscript and move some non-essential material to the appendices. In particular, we have moved most of Section 3.3 to the appendix (see response to Reviewer 1 Comment 7) and have shortened Section 1.2 considerably and moved relevant points to the Discussion (see response to Reviewer 1 Comment 2). Moreoever, we have removed Appendix Figures C7 and C8 as we found they did not add value to the paper. Additionally, we add that we have modified the colors of Figures 8, 9 and Appendix Fig. C10 (now renumbered C8) so that the observed lake levels are always drawn in blue and the modelled lake levels are drawn in orange, so as to have consistency between the figures which previously had different color schemes.

1.2 Major comments

Reviewer 1 Comment 2

The future projection in 1.2 appears to be unnecessary. The description of future projections does not necessarily match climate change impacts on past events with projected changes in a warmer world in the future; differences in ENSO and IOD trends, changes in evapotranspiration, etc. will also change, so we felt that the description in the text, although background, could be minimized.

Response

We thank the reviewer for this suggestion. Indeed, we are attributing past changes and not looking at model projections. Nonetheless, we think it is valuable to frame the attribution study within (1) past observed trends and (2) a brief summary of what models show as the climate change signal we can expect in the region. These are signals we might expect for the future, but that might already be emerging in the present, which is why we carry out an attribution study. We think this framing increases the interpretability of the attribution results, by (1) explaining the underlying processes that might be below the weakly positive probability shift we estimate from GCMs and (2) showing that we should exercise caution in interpreting the results since previous literature has identified some intra-model differences (e.g. regional climate models capturing mesoscale changes over the lake that GCMs cannot capture) and disagreement between models and observations in some seasons (East African Precipitation Paradox).

Nonetheless, we have taken up the reviewer's comment and have shortened Section 1.2 considerably, which we believes also aids readability, and moved some of the relevant points to the Discussion. We have switched the order of the subsections, so that Section 1.2 is now Section 1.3, it has now been renamed from "Previous observed and projected trends in precipitation and hydrometeorological extremes" to "Precipitation variability, extremes and model representation in East Africa" and reads as follows:

> The Lake Victoria basin is located in the African Great Lakes region and characterized by a bimodal rainfall distribution pattern, with rains concentrated in the 'long rains' season in March, April and May, and the 'short rains' season in October, November and December (Thiery et al., 2015; Vanderkelen et al., 2018). The region exhibits strong inter-annual variability in precipitation, influenced by the El Niño Southern Oscillation (ENSO) and the Indian Ocean Dipole (IOD) (Nicholson, 2017; Ummenhofer et al., 2009; Black, 2005; Palmer et al., 2023). The spatial distribution of precipitation in the basin is influenced by topography and the presence of the lake, with high accumulated precipitation amounts and a tendency for hazardous night-time thunderstorms over the lake surface (Thiery et al., 2016; Van de Walle et al., 2020). The heavy 2019 short rains rainy season in East Africa was linked to a strong positive IOD event (Wainwright et al., 2021; Nicholson et al., 2022; Khaki and Awange, 2021), with anomalies in sea surface temperatures leading to weakened westerlies in the Indian Ocean and wetter than usual conditions in East Africa (Wainwright et al., 2021; Black, 2005; Nicholson, 2017).

Global and regional climate models generally project an increase in average annual precipitation amounts over East Africa with climate change (e.g. Rowell et al., 2015; Akurut et al., 2014; Dunning et al., 2018; Souverijns et al., 2016; Olaka et al., 2019), particularly during the short rains (Palmer et al., 2023), as well as an increasing frequency of extreme positive IOD events (Cai et al., 2014, 2018). At the same time, there is evidence of biases in coupled climate models in representing seasonal precipitation in East Africa, particularly with respect to the long rains (see Discussion Sect. 4; Wainwright et al., 2019; Palmer et al., 2023; Ayugi et al., 2021). Nonetheless, since our study is not restricted to the long rains season, and since coupled global climate models remain invaluable tools to simulate factual and counterfactual (i.e., in the absence of anthropogenic climate change) climate conditions in the most complete way (Otto, 2017), extreme event attribution studies of hydrological changes in the region using coupled GCMs and other modelling setups can still contribute to improving our understanding of ongoing changes in the region (e.g. Philip et al., 2018; Kew et al., 2021; Kimutai et al., 2022, 2023).

Reviewer 1 Comment 3

I also do not know the intent of presenting Table 4. The results can vary depending on the number of hist-nat samples for the total sample, and it is not clear what the message is beyond what is obtained in Table 3.

Response

We thank the reviewer for flagging this, and agree this could lead to some confusion. We have restructured Tables 3 ad 4 into a single table now numbered Table 3, which includes relevant results from (1) observations, (2) historical models and (3) hist and hist-nat models, and have moved the bottom section of Table 3 (which referred only to the hist-nat models and has now been removed from the Table) to the Appendix section. We have also edited the caption and sub-headers of Table 3 for clarification, as below:

Table 3: ~~Analysis results showing e~~Estimated return periods, probability ratios and magnitude changes of the flood event in a current ~~(2020)~~ and a pre-industrial ~~(1900)~~ climate based on observed lake levels for the period 1897–2020 (observations), lake levels simulated by the WBM driven by observational precipitation for the period 1983–2020 (observational WBM), factual (historical) and counterfactual (hist-nat) climate model simulations. In Methods 1 and 2 'current' corresponds to a 2020 climate and 'pre-industrial' corresponds to a 1900 climate. In Method 3 'current' corresponds to a 2020 climate in historical simulations and 'pre-industrial' corresponds to a 2020 climate in hist-nat simulations. ~~For historical simulations the return period in the current climate is held equal to that estimated from observations to estimate a model-specific magnitude threshold. For hist-nat simulations the model-specific magnitude threshold from the corresponding historical simulation is used to estimate the return periods. Magnitude changes indicate the difference in lake level rise expected during an event with the same return period.~~ Only models that passed the evaluation are shown.

Data	**Return period in current climate** (years)	**Return period in pre-industrial climate** (years)	**Probability ratio (PR)**	**Magnitude change** (m)
~~Observations and observational WBM~~ Method 1: Observation-based time period comparison (shift fit)				
Observations	63 (27, 395)	104 (43, 1100)	1.7 (0.3, 3.9)	0.11 (0, 0.23)
Observational WBM	34 (12, ∞)	79 (16, ∞)	2.3 (0, 6.6)	0.14 (-0.18, 0.53)
~~GCM historical-ssp370 (ISIMIP3BASD)~~ Method 2: GCM historical-ssp370 time period comparison (shift fit)				
CanESM5	63 (21, 335)	142 (57, 1160)	2.2 (0.4, 6.6)	0.08 (-0.03, 0.21)
CNRM-CM6-1	63 (23, 307)	66 (34, 253)	1.1 (0.2, 2.9)	0.01 (-0.13, 0.16)
GFDL-ESM4	63 (16, 711)	88 (43, 464)	1.4 (0.1, 5.4)	0.03 (-0.08, 0.15)
IPSL-CM6A-LR	63 (28, 300)	85 (42, 813)	1.3 (0.3, 3)	0.04 (-0.07, 0.15)
MRI-ESM2-0	63 (26, 358)	86 (43, 383)	1.4 (0.2, 3.3)	0.05 (-0.09, 0.19)
Method 3: GCM hist and hist-nat comparison				
CanESM5	63 (21, 335)	170 (58, ∞)	2.7 (0.5, ∞)	0.1 (-0.05, 0.29)
CNRM-CM6-1	63 (23, 307)	97 (46, 1634)	1.5 (0.3, 22.8)	0.05 (-0.12, 0.24)
GFDL-ESM4	63 (16, 711)	69 (28, 1580)	1.1 (0.08, 31.4)	0.01 (-0.17, 0.2)
IPSL-CM6A-LR	63 (28, 300)	129 (50, 4910)	2 (0.4, 74.6)	0.07 (-0.09, 0.22)
MRI-ESM2-0	63 (26, 358)	139 (54, ∞)	2.2 (0.35, ∞)	0.09 (-0.11, 0.31)

Reviewer 1 Comment 4

Changes in lake levels due to climate change tend to be smoothed out, possibly due to increased runoff, which increases in response to inflows, or human activity. Therefore, I found it difficult to adequately detect climate change signals. For example, if there is a large year-to-year variation in accumulated precipitation over the lake, it is possible that a more robust climate change signal could be detected if the accumulated precipitation is attributed. I thought it would be a good idea to add an addendum to the Discussion about this.
No Major concerns raised.

Response

We thank the reviewer for this point, which is in part are already addressed in the discussion section, where we mention the important role of human water management (e.g. L555 and L611). First, we realise this is a limitation of using lake level time series as observations for statistical attribution, but find this is more than balanced by (1) the possibility to attribute a variable closer to the impacts of the 2020 event and (2) having a long timeseries of observations that goes further back than many station timeseries in the region.

Second, we have added a sentence in the discussion that mentions the role inter-annual variability might play in increasing the frequency of high ΔL/Δt events and how these might not necessarily correspond to high absolute lake levels (see also response to Reviewer 2 Comment 4), which reads as follows:

> [...] the variable relates only indirectly, through backflow effects, to tributary river floods, which caused a large part of the impacts in 2020. Moreover, an increased frequency of high $\Delta L/\Delta t$ events can be caused by increased interannual variability in seasonal precipitation, which, if not preceded by already high lake levels, would not necessarily represent a high-impact flooding event.

1.3 Minor comments

Reviewer 1 Comment 5

P.3, L75 : The main objective of this study is to investigate the effects of past climate change on the probability and magnitude of the past flood event in the lake Victoria. Since target period of future projection in precipitation and hydrometeorological extremes by CMIP5 and CMIP5, witten in 1.2, is not consistent with the target period of this study,

Response

See response to Reviewer 1 Comment 2.

Reviewer 1 Comment 6

P.4, L85: Specify the time period of the average of precipitation.

Response

We have amended L85 as follows:

> Despite a projected increase in average annual precipitation ~~levels~~ amounts over East Africa in most global and regional climate models [...]

Reviewer 1 Comment 7

P.19, L375-418: Since this paper already has many Appendixes, but 3.3 is not the main result either, I thought it would be better to put only the essence in Chapter 2 (Methods) of the main text and move the rest to the Appendix.

Response

We thank the reviewer for this suggestion, which we believe makes the manuscript more readable. We have left only the essential points of section 3.3 in the results, which now reads as below, and have moved the rest to a new subsection in the Appendix.

> As outlined in Sect. 1.1, we focus on the rate of change in lake levels ($\Delta L/\Delta t$) instead of on absolute lake levels to define the event, choosing a time window

(Δt) of intermediate length, corresponding to 180 days and subsequently extract annual block maxima of the $\Delta L/\Delta t$ time series. The 2020 event thus defined corresponds to a lake level increase of 1.21 m that occurred in the 180 days leading up to 17 May 2020, and is the third most extreme event since 1897, ranking after 1998 (1.39 m) and 1962 (1.30 m; Fig. 7). Lake levels usually rise by approximately 0.28 m in the period November - May, meaning the 2020 event represents approximately a 0.93 m anomaly compared to the whole time series. No clear temporal trend is visible in the resulting time series, although a clustering of high values is visible between 1960 and 1962 (Fig. 7b). We test the sensitivity to this choice of event definition in Sect. B3.

Reviewer 1 Comment 8

P.21, L424: The difference between model and observation around 2005-2015 appears to be due to the fact that there is less of a decrease in water levels between 2006 and 2007 in the model; the decrease in water levels since 2003 stops around 2005 in the model, but continues to fall through 2007 in the observation. The shape of the trend is similar to that of the rapid increase in water levels and the interannual variability of water levels since 2007. Is the difference in the drop in water level from 2003-2005 due to outflow?

Response

We thank the reviewer for this suggestion. The difference between modelled and observed lake levels in 2005-2015 is unlikely to be due to outflow in the period 2003-2005, since for these years we have observational measurements for outflow (see paper Fig. C3). Moreover the lake levels are actually quite similar in the period 2003-2005 (see paper Fig. 8 and Illustration 1), with a mean bias of -0.02 m in 2003-2004 and a mean bias of 0.18 m in 2005. This bias increases rapidly from 2005 onwards, suggesting most of the modelling error is actually introduced from 2005 onwards. In the period 2006-2020 we no longer have observational outflow but use the agreed curve approximation, suggesting this could be introducing an important part of the bias, since literature has also suggested in the period from 2006 on outflow was above agreed curve levels (e.g. Vanderkelen et al., 2018).

We have amended the text in L424 and ff. as follows to point readers to the figure showing the sources of outflow data in the appendix:

> The large and consistent overestimation from 2005 to 2015 could be due to the modelled outflow, which was assumed to follow the Agreed Curve from 2005 on (Fig. C3), while in this period, the real outflow likely exceeded the Agreed Curve, resulting in lower lake levels (Vanderkelen et al., 2018).

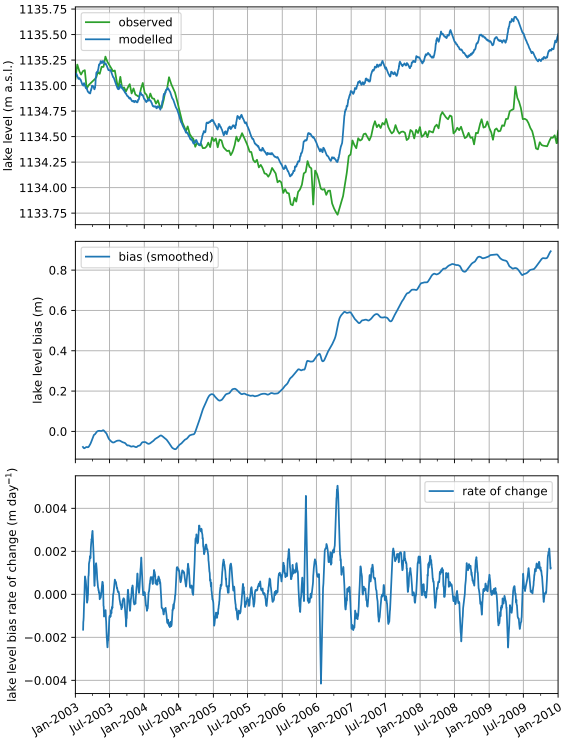

Illustration 1: Water balance model bias in the period January 2003–December 2010: (a) observed and modelled lake levels; (b) lake level bias (i.e. difference modelled minus observed curves from top panel) smoothed with a centered 60-day moving average low-pass filter; (c) daily rate of change in smoothed lake level bias (i.e. approximation of first derivative of bias curve from central panel).

Reviewer 1 Comment 9

P.25, Fig.11: I cannot see the upper side of the width of the preindustrial uncertainty. Could you please shade it or write it in with a dotted line, etc.?

Response

Thank you for this suggestion. We have remade the figure with the boundaries of the confidence intervals of the return periods in a darker color (Illustration 3).

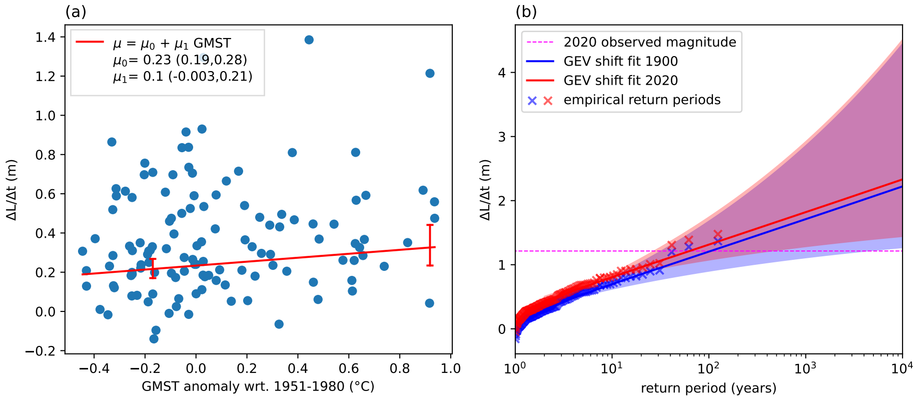

Illustration 2: Fig. 11 old version

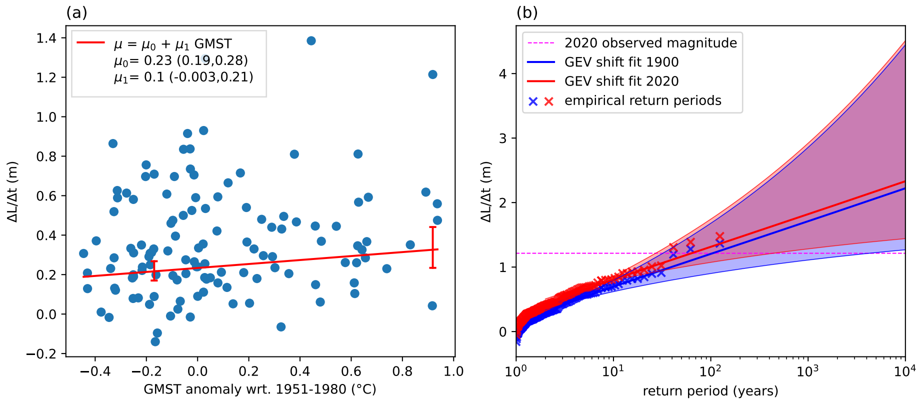

Illustration 3: Fig. 11 new version

Reviewer 1 Comment 10

P.29, Fig.12: I can't understand why you need the purple bar. What is the intention of averaging models and observations? Are you assuming that the observations are an ensemble of pasts that were not obtained by the model?

Response

Indeed, we are following the probabilistic extreme event attribution methodology outlined in (Philip et al., 2020) and applied in many extreme event attribution studies, whereby changes in the return period or magnitude of the event due to anthropogenic climate change are estimated from (a) each model and (b) from observations. Then, the results of each individual model in (a) is averaged, resulting in the red bar Fig. 12. Subsequently this model average is itself averaged with (b, i.e. the blue bar), resulting in the purple bar in Fig. 12, which corresponds to the final results cited in the study. This means all models are collectively given the same weight as observations, and that observations play a relatively larger role in the final synthesis result. As suggested by the Reviewer, in Fig. 12, the preliminary results from each model and from the observations are all treated as a separate samples, which contribute to the final result. A key strength of this approach is that it quantitatively combines multiple lines of evidence, by (i) not being based only on models but also on real-world observations and (ii) being flexible to the inclusion of various statistical methods (see discussions in van Oldenborgh et al., 2021). Importantly, if the results from models (orange and red bars) and observations (blue bar) in Fig. 12 were to disagree very much, e.g. one suggesting an increase and one suggesting a decrease in likelihood due to anthropogenic climate change, this would make it impossible to make an attribution statement (Philip et al., 2020, p. 194 and Fig. 9c).

To direct readers to the above-cited literature, we have amended the caption in paper Fig. 12 as follows:

> Synthesis of (a) PR and (b) change in magnitude estimates from observations and models between a current factual climate and a counterfactual or pre-industrial climate, following the methodology explained in Philip et al. (2020). Colored bars indicate the 95% CI, with the best estimate shown as a black line. Uncertainty denotes natural variability and takes model representativity into account, but neglects intrinsic epistemic model uncertainty. The red bar is an average of model results, computed through an unweighted synthesis methodology. The purple bar shows the average of observations and models.

And we have expanded upon this point in the Methodology section 2.2.3:

> **(iv) Synthesis of attribution statement.** Finally, we synthesise the results from observations and climate models to derive final estimates for a probability ratio and magnitude change with their 95% confidence intervals, following Philip et al. (2020). To this end, the probability ratios and magnitude changes obtained in step iv are first averaged for all GCMs, assuming these are respectively log-normally and normally distributed , using ~~We use~~ an 'unweighted' synthesis methodology ~~, whereby models with more uncertain results are not penalized, but contribute equally to the final result,~~ to avoid artificially reducing uncertainties. The resulting model-derived average is then averaged with the estimate obtained from observations in step ii, which is treated as a separate sample that contributes to the final result. This means all climate models are collectively given the same weight as observations, and that observations play a relatively larger role in the final synthesis result. ~~meaning that in the final results observations are given the same weight as all GCMs combined.~~ The synthesis step is carried out using the KNMI-WMO Climate Explorer.

2 Reviewer 2

2.1 General comment

Reviewer 2 Comment 1

Pietroiusti et al. examines the influence of anthropogenic climate change on the flooding of Lake Victoria in 2020, by applying a water-balance model in combination with a very well-established attribution methodology. This work advances the attribution field by using a new metric (rate of change of lake levels) more closely linked to impacts, compared with most studies that use meteorological variables without hydrological modelling. It also addresses the lack of attribution studies in the region examined. The authors find that anthropogenic climate change has likely increased the magnitude of the lake levels by 7cm (CI: 0-14 cm) and that the event was 1.8 (CI: 0.8-15.8) times more likely, based off a synthesis of results from the observations and climate models used. This work also gives an estimate of the impacts of the wider regional flooding event in 2020 using a remote sensing analysis. The methodology, analysis and calculations are well described. The detail provided is important and could be very useful for others working in the field. Some of it could be moved from the paper into the supplementary material - if required.

Response

We thank the Reviewer for their comments and useful feedback to improve the manuscript. Below, we address the comments and explain the corresponding changes made in the manuscript. We have also made an effort to reduce the length of the manuscript and move some non-essential material from the appendices to the supplementary material. See the response to Reviewer 1 Comments 1, 2 and 7.

2.2 Major comments

Reviewer 2 Comment 2

Line 50: Is this the first attribution study looking at rainfall or flooding in the Eastern Africa region? If so, this might be worth mentioning in the introduction, and if not - it would be good to know what other studies have found.

Response

We thank the reviewer for this suggestion. We have added a short paragraph after Line 50, which briefly summarizes previous attribution studies looking at low/high rainfall amounts and drought/flood events in East Africa. This reads as follows:

> The East African region is comparatively under-studied in relation to flood attribution, with most previous studies having focused on drought events, generally finding either no attributable role of anthropogenic climate change (e.g. Uhe et al., 2018; Philip et al., 2018; Otto et al., 2018; Kew et al., 2021), or a significant increase in the likelihood of drought events (e.g. Funk et al., 2016, 2019; Marthews et al., 2019; Kimutai et al., 2023), depending on the specific location,

> framing and variable being attributed in the study. One study has analysed the flood-inducing heavy long rains seasons that occurred in Kenya in 2012, 2016 and 2018, finding no significant trend attributable to human-induced climate change (Kimutai et al., 2022). To our knowledge, this study is the first to use water balance or hydrological modelling to attribute flood events in the region.

Reviewer 2 Comment 3

The result for the change in magnitude of the lake levels due to anthropogenic climate change seems more meaningful (in both how useful it is and its confidence intervals), compared to the risk ratio. In the conclusion the magnitude change only gets one line compared to the risk ratio which is discussed a lot more. It would probably be better the other way round. It might be worth comparing the anthropogenic magnitude change to the overall lake level rise, and the rise due to anomalous precipitation over the 180 days.

Response

We thank the reviewer for this suggestion. We have accordingly added this sentence to section 3.3 (i.e. we have quantified the lake level rise as an anomaly based on observations):

> Lake levels usually rise by approximately 0.28 m in the period November - May, meaning the 2020 event represents approximately a 0.93 m anomaly compared to the whole time series.

We note that this is not excessively sensitive to the time period, e.g. choosing a 1980-2020 baseline results in quantifying the 2020 event as a 0.94 m anomaly.

And have modified the conclusion as follows:

> Based on observational data, the flood event has an estimated return period of 63 years (CI 27 - 395 years) in the current climate, and in a pre-industrial climate lake levels would have risen 0.11 m (0 - 0.23 m) less than observed, with uncertainty including the possibility of no attributable change. ~~and is 1.7 (CI 0.3 - 3.9) times as likely today as in a pre-industrial climate.~~ This change in ~~probability~~ magnitude is however associated with a relatively large uncertainty, including the possibility of no forced change. [...] Based on a synthesis of observations and climate model simulations, the observed event is slightly more likely in the current climate than in a pre-industrial climate, by a factor of 1.8 (CI 0.8 - 15.8), although the uncertainty is relatively large and includes the possibility of no change. Similarly, we estimate that in the absence of anthropogenic climate change a 63-year event would have resulted in lake levels rising 7 cm (CI 0 - 14 cm) less than observed, which corresponds to approximately 6% (0% - 13%) of the total November-May rise in lake levels.

Reviewer 2 Comment 4

The main metric used (delta L/delta t for delta t=180 days) is well justified taking into account the influence of both rainfall and evaporation over the 180-days, with sensitivity tests carried out on the length of time chosen. This metric however, will naturally cover time periods where the rainfall/evaporation ratio is relatively high. Any change in evaporation due to climate change during the drier part of the year (relatively), which will likely influence the lake-level before the 180-day extreme lake-level rise, may be missed. This doesn't change, the anthropogenic influence on rate of change of lake level rise seen in 2020- but is probably worth including in the limitations. However, in general, the limitations and assumptions have been covered and addressed in great detail.

Response

We thank the reviewer for flagging this important point (see also response to Reviewer 1 Comment 4). We have added a few sentences in the discussion about this:

> [...] the variable relates only indirectly, through backflow effects, to tributary river floods, which caused a large part of the impacts in 2020. Moreover, an increased frequency of high $\Delta L/\Delta t$ events can be caused by increased interannual variability in seasonal precipitation, which, if not preceded by already high lake levels, would not necessarily represent a high-impact flooding event. Further, lake levels preceding the $\Delta L/\Delta t$ event would be influenced by evaporation rates, particularly during dry seasons, which do not vary in our study but might change under climate change.

2.3 Minor comments

Reviewer 2 Comment 5

Line 444: Typo section title 3.4.2- 'modelling'

Response

Thank you, this has been corrected in the manuscript.

Reviewer 2 Comment 6

Line 682-683: This line or similar would be good to have in the introduction - to give some context.

Response

Contextual information similar to the indicated lines has been added to the introduction in a short paragraph that situates this study in the broader context of previous drought and flood event attribution studies in East Africa (see response to Reviewer 2 Comment 2).

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