

The First Emergence of Unprecedented Global Water Scarcity in the Anthropocene

Corresponding Author: Professor Christian Franzke

This file contains all reviewer reports in order by version, followed by all author rebuttals in order by version.

Version 0:

Reviewer comments:

Reviewer #1

(Remarks to the Author)

Revision of the manuscript "The First Emergence of Unprecedented Global Water Scarcity in the Anthropocene" by V. Ravinandrasana and C. Franzke.

General Comment.

In this study, the authors provide a definition of Day Zero Drought based on the duration and intensity of the drought event and the time required for the water reservoirs to dry. It is interesting approach as it combines both the atmospheric drivers of such events – the ones which have been mostly considered in the scientific literature so far – with the capabilities of water reservoirs and water consumption, which are instead associated with humans and as such are prone to be changed, modified and adapted to new climatic conditions. However, despite my overall positive impression, the work contains major deficiencies that must be addressed before it can be considered for publication in Nature Communications. A significant revision is necessary.

Major issues

- Overall, the manuscript is not very well written, which poses challenges for readers in understanding the results. First, I find it questionable that the results are presented immediately after the introduction without any prior explanation of key definitions, which are entirely located in the methods section. While detailed explanations of the methods belong in the "Methods" section, including at least a brief overview of the primary methods and their novelty between the introduction and the results would greatly benefit the reader and the readability of the paper. Additionally, there are several areas of the text that I find difficult to comprehend (refer to my minor comments), so I would recommend having your paper professionally edited for clarity and language.
- It is not clear how this study advances our current knowledge, particularly in comparison to similar recent studies. For example, the authors mention references 29 and 30 in the introduction, which address a very similar topic as this manuscript. How does this study differ from those? What new insights does it provide compared to references 29 and 30? Why is a different approach from these references necessary at this point?
- One of the main concerns regarding the conclusions of this study is that they rely solely on a single General Circulation Model (GCM), specifically CESM2. Can the authors justify why using only one model is sufficient? How do they account for the structural uncertainty that arises from differences between models? The manuscript does not address this issue at all, and I believe it should be discussed more thoroughly.
- The use of a large ensemble is justified primarily for obtaining reliable statistics, given the substantial number of equivalent years. However, this approach could also serve another purpose - quantifying the signal-to-noise ratio, which involves comparing anthropogenic forcing signals to internal variability noise. This could help explain the differences in the times of first emergence. Are there regions where the late emergence can be attributed to significant internal variability?
- The main result, shown in Figure 2b, indicates that the Time of First Engagement (ToFE) sharply rises from 2020 to 2030. Since we are currently in 2025, we find ourselves right in the middle of this timeframe, which means this statement applies not only to the future but also partially to the present. Shouldn't we be able to observe some verification of this surge of ToFE now? Additionally, how can we physically explain the rapid shift occurring during this decade?
- Lines 352-367. I find this point quite critical: the authors use a projected future water demand, which is highly uncertain, to fit data and extend them in the past, which should be more reliably known. The authors need to convince me that this approach is acceptable. Additionally, I do not understand what the "five Global Climate Models" mentioned in line 355 are,

as they are never explained.

Minor issues

- Line 40-48. Cape Town is not the only city in the world to have faces something like a DZD, so other examples which happened could be mentioned (for example, Chennai 2019 water crisis, India) or places which are very vulnerable and may face it soon (e.g., Los Angeles).
- Line 202. It would be interesting to know if this was related to internal natural variability at the interannual or decadal scale in different regions of the world.
- Fig. 4c-e, yellow line cannot be seen. Furthermore, in fig4d, it is not clear in which year these estimates are evaluated.
- Line 258. It should be said that here it is not accounted for how water reservoirs will change in the future, as they are assumed stationary. Re-planning of water reservoirs is one of the main adaption strategies, and in principle this could be included in the framework you present.
- Line 413. Who first introduces the SWSI?
- Line 436 Bias correction: why a reanalysis for precipitation and temperature and not observations? Also, can we implicitly assume that the bias will be the same in the future? Also, the method could be briefly explained and not just referenced.
- Line 47-48. Cape Town was on the brink of reaching a "Day Zero," but did not experience it because the winter of 2018 had slightly above-average rainfall, and the following years also saw above-average precipitation, which led to the postponement of Day Zero, and ultimately, it never occurred.
- Line 43. It's not clear what rivers are the authors talking about. Please specify.
- Reference 10 and 15 is the same but it is reported twice
- Line 55-56. I don't understand the logics of this sentence: why a long-term drought necessarily implies an increase in water demand?
- Line 58-59. This sentence is at best ambiguous, or at worst wrong: multi-year droughts are not necessarily associated with global warming but mostly to internal natural variability. The authors can find papers in the scientific literature on that. Human-caused climate change can of course make them more likely or exacerbate them, but this is not clear at all from what they authors wrote here.
- Line 65-66. I just can't understand what this sentence means.
- Line 66-67. Here it should specified that this mostly what future projections indicate, as historical trends on, e.g., annual mean precipitation, still do not show clear trend patterns.
- Line 75-77. I just don't understand what this sentence means. It is also not clear what a "reservoir feedback" is.
- Line 260-261. I just don't understand what this sentence means.
- Line 289-290. "as it reflects the interaction between the drought events and the reservoirs". It's not clear what this means.
- Line 387-388. I just don't understand this sentence.
- Line 400. It is not clear what are the variables used in the definition of SRFI.
- Line 421-422: here we have five GCM out of the blue, and that's a bit confusing as you say you are using only CESM2.
- Line 494-496. This sentence is awkward. It is not true that anthropogenic global warming necessarily decrease water supplies, in some regions it can actually increase them because precipitation is projected to increase.
- Line 503. Something is wrong with the grammar of this sentence.

Reviewer #2

(Remarks to the Author)

General Assessment:

The paper presents a comprehensive analysis of the emergence of unprecedented global water scarcity, focusing on the concept of "Day Zero Drought" (DZD) under anthropogenic climate change. The study employs a probabilistic framework and large-ensemble climate simulations under the SSP3-7.0 scenario to assess the time of first emergence (ToFE) of DZD, its duration, and its societal impacts. The authors use a combination of hydrological indices (SPEI, SRFI, SWSI) to evaluate multi-year droughts and water scarcity, and they incorporate reservoir dynamics to assess the severity of water shortages. The study highlights the role of climate change in driving water scarcity and emphasizes the need for proactive water management strategies.

The paper is well-structured and addresses a critical issue in the context of global climate change. The use of large-ensemble simulations and the integration of reservoir data are strengths of the study. However, there are several areas where the paper could be improved, particularly in terms of clarity, methodological rigor, and the interpretation of results. I suggest a major revision.

My major concerns are listed below.

1 Clarity and Focus:

- (1) The paper is dense and could benefit from a more streamlined presentation. The introduction and discussion sections are lengthy and could be condensed to improve readability.
- (2) The concept of "Day Zero Drought" (DZD) is central to the paper, but its definition and distinction from other types of droughts (e.g., meteorological, hydrological) could be clarified earlier in the manuscript. The authors should provide a clearer explanation of how DZD differs from other drought types and why it is particularly relevant in the context of climate change.
- (3) The relationship between "drought" and "water scarcity" is not well-explained. While drought is a natural phenomenon characterized by a temporary reduction in water availability, water scarcity often results from a combination of natural and anthropogenic factors, including drought, population growth, and mismanagement of water resources. The authors should explicitly clarify how drought contributes to water scarcity in their framework and how the two concepts interact in the context of DZD. This distinction is critical for understanding the compound nature of the events being studied.
- (4) In a 2017 paper, Water Scarcity Assessments in the Past, Present, and Future, authors explored the validation of water

scarcity using drought indicators. By analyzing modeling data over a 15-year period, they demonstrated that 6 out of 14 tested water scarcity indicators showed a statistically significant relationship with the occurrence of drought-related crises [Alcamo et al., 2008]. This foundational work suggests that it is feasible to validate water scarcity indicators, determine their appropriate range of application, and establish reliable scarcity thresholds. Further research in this direction would not only strengthen the scientific basis for estimating water scarcity but also accelerate the development of more robust and practical indicators for assessing water stress.

(5) The authors reference Liu et al. (30) but describe their work as "few studies" rather than acknowledging it as the first study to reveal the timing of the first emergence and disappearance of global water scarcity on a global scale. This is a significant oversight, as Liu et al. (30) provide a groundbreaking contribution to the field. A proper credit is required.

2 Methodological Concerns:

(1) The paper relies heavily on the SSP3-7.0 scenario, which represents a high-emission pathway. While this scenario is useful for understanding worst-case scenarios, the lack of comparison with lower-emission scenarios (e.g., SSP1-2.6 or SSP2-4.5) limits the broader applicability of the findings. The authors should consider including results from other scenarios to provide a more comprehensive view of future water scarcity under different climate trajectories.

(2) The bias correction method (Quantile Delta Mapping) is mentioned, but the details of its application are not sufficiently explained. The authors should provide more information on how the bias correction was applied to the hydrological indices and how it affects the results.

(3) The paper does not adequately address the uncertainties associated with the large-ensemble simulations. While the use of 100 ensemble members is a strength, the authors should discuss the range of variability within the ensemble and how this impacts the robustness of their conclusions.

3 Reservoir Dynamics:

(1) The treatment of reservoir dynamics is a key aspect of the study, but the assumptions made about reservoir operations (e.g., static TRD) are oversimplified. The authors acknowledge this limitation but do not fully explore its implications. A more dynamic approach to modeling reservoir operations, including time-varying management practices, would strengthen the study.

(2) The paper does not consider the role of groundwater in mitigating water scarcity. Groundwater is a critical resource in many regions (Kuang et al. 2024. The changing nature of groundwater in the global water cycle), and its exclusion from the analysis may lead to an underestimation of water availability during droughts. The authors should discuss this limitation and consider incorporating groundwater data in future work.

3 Interpretation of Results:

(1) The paper identifies several regions as hotspots for DZD emergence, but the discussion of these results is somewhat superficial. The authors should provide more context on why these regions are particularly vulnerable and how local factors (e.g., population growth, water management practices) contribute to the risk of water scarcity.

(2) The societal impacts of DZD are discussed in terms of population exposure, but the paper does not explore the potential economic or ecological consequences in detail. A more thorough discussion of the broader implications of DZD would enhance the paper's relevance to policymakers and stakeholders.

(3) The paper focuses primarily on water quantity, but water scarcity is a multidimensional issue that also includes water quality and environmental flow requirements. The authors should discuss the concept of three-dimensional water scarcity, which integrates water quantity, quality, and environmental flows, as highlighted in recent literature. Incorporating this perspective would provide a more holistic understanding of water scarcity and its implications for ecosystems and human societies.

4 Figures and Data Presentation:

(1) Some of the figures (e.g., Fig. 1, Fig. 2) are difficult to interpret due to the complexity of the information presented. The authors should consider simplifying these figures or providing additional explanatory text to guide the reader.

(2) The paper would benefit from a more detailed discussion of the data sources and their limitations. For example, the global reservoir database (Grand) is used extensively, but the authors do not discuss the potential biases or gaps in this dataset.

5 Broader Implications and Policy Relevance:

(1) While the paper highlights the need for proactive water management strategies, it does not provide specific recommendations for policymakers. The authors should consider including a section on potential mitigation and adaptation strategies, particularly in regions identified as DZD hotspots.

(2) The paper could also benefit from a discussion of how the findings align with the Sustainable Development Goals (SDGs), particularly SDG 6 (Clean Water and Sanitation). This would help to contextualize the study within the broader framework of global sustainability efforts.

6 Reevaluate the Critique of the Falkenmark Indicator:

(1) The authors critique the Falkenmark indicator, suggesting that it does not consider demand. However, this is a misinterpretation. The Falkenmark indicator, which measures water availability per capita, inherently incorporates demand through population data, as population is a proxy for water demand. While it is true that per capita water demand varies across countries, the indicator provides a useful high-level assessment of water scarcity. The authors should revise their critique to acknowledge that the Falkenmark indicator does, in fact, consider demand indirectly through population, even if it does not account for sectoral water use or regional variations in consumption patterns.

Reviewer #3

(Remarks to the Author)

This study investigates the emergence of water scarcity under global change. This is done with a comprehensive approach that infers water scarcity by considering meteorological, hydrological and demand vs. supply perspectives. The authors find that in future projections calculated with the CESM2 Earth system model, significant water scarcity emerges in the coming decades in some places across the globe. The paper analyzes the timing of the emergence across regions and the affected population. The results furthermore show that the duration and time between water scarcity events can be similar in the future in some regions.

Recommendation:

I think the paper requires major revisions.

The topic of this study is interesting and timely. With ongoing climate change, precipitation and evaporation are changing in many regions, and this can affect river runoff in concert with other changes such as of vegetation or cryosphere dynamics. Moreover, in addition to related changes in freshwater supply, also demand is changing as populations and economies change with time. This study makes an important contribution to understand when and where these changes lead to severe water scarcity. I particularly like the novel, comprehensive approach to characterise water scarcity across meteorological, hydrological and societal domains. This way, I think the manuscript is very relevant and interesting for the readership of Nature Communications.

However, before the paper can be published I would ask the authors to consider the concerns described below:

General comments:

(1)
While I appreciate the methodological approach used in this study, I think that readers can not understand (and therefore also not appreciate) the results and conclusions with the present main text as this fails to explain most of the key terms and methods used in the analysis. This is a critical shortcoming. I could only follow the results in the main text after reading the full methods section. For example, in line 125 "Our study reveals a co-occurrence..." comes as surprise and it is hard to understand what "co-occurrence" you are referring to. Shortly after, the terms "time of emergence", "fraction of attributable risk", and drying out of "global reservoirs" appear without any explanation. In this context, also the "thresholds" in line 156 not clear, and "TRD" in line 159 appears without explanation, and not even the abbreviation is introduced. Finally, also the waiting time as a central concept of Figure 3 appears without introduction in line 174. Furthermore, some of these terms and approaches are also used in the abstract ("hydrological compound extremes", "35%", "waiting time") which should instead describe the findings and conclusions more generally to allow readers to follow.

(2)
The results presented here are based on simulations with a single Earth system model, CESM2. I understand that this choice is necessary as the analyses require a large ensemble which is probably not readily available from many Earth system models. At the same time, it is known that trends in precipitation and evapotranspiration, which are key variables for water scarcity projections, differ across projections of different Earth system models (see e.g. Orth et al. 2016, Denissen et al. 2022). I wonder to which extent the CESM ensemble can capture such uncertainty, or whether this only emerges when comparing different models? In any case, the authors should add some discussion about this point in the discussion section.

(3)
I like the idea of analysing waiting times and durations of water scarcity events in Figure 3. At the same time, the comparison PDFs in the present Figure 3 does not allow to infer explicitly where and how often durations actually exceed waiting times. To me it seems that this aspect is most critical in terms of impacts and for informing future adaptation strategies, and therefore I would recommend to revise Figure 3 to highlight this more explicitly.

I do not wish to remain anonymous - Rene Orth.

Specific comments:

line 62: I think this is not always the case; the simultaneous occurrence of several climate extremes *can* lead to more severe impacts

line 66: "global warming disrupts the water cycle", this statement is too strong and too general, and comes without explanation and references;
a similar statement should be corrected in lines 494-496

line 74: What did these studies find, and how does this study move beyond them?

line 94: I know that this is a widely used index and agree that it fits well in this study, but It should be clarified that potential evapotranspiration is less relevant for the water cycle than actual evapotranspiration

line 100 & Figure 1: it should be explained that SPEI48 refers to SPEI at 48-month time scale (similar for the other indices)

line 135: It should be made clear that the time of emergence refers to pre-industrial conditions as a reference. This is a valid approach. Nevertheless, in the discussion section it should be explained that this perspective could provide limited information for future planning and adaptation measures because current infrastructures are not designed for pre-industrial conditions but rather for conditions prevailing during the previous decades.

line 137: not clear what you mean with “drive a DZD”

line 154: This seems to be the first supplementary figure that is referred to in the main text; make sure the numbering of the supplementary figures matches their appearance in the main text. In addition make sure to refer to, and explain, all supplementary figures in the main text.

lines 168/169: While I appreciate the consideration of reservoirs, I feel it would be needed to provide some analysis about potential inconsistencies in the spatial patterns that the different treatment of grid cells with reservoirs vs. grid cells without reservoirs may introduce.

line 171 and Figure 2: percentage of what?

line 179: abbreviation PDF not introduced

line 195: is water retention capacity changing over time in CESM2?

line 236: related *to* the baseline period

line 243: rephrase to “total population of 488 million”

lines 334/335: are maximum and minimum temperatures calculated from daily or hourly data?

line 419: evapotranspiration is not a water resource

lines 431-343: I find this quite relevant, and would suggest to move it to the main text.

line 451: How and why are trends removed and reintroduced?

line 455: please explain “as a single value”

lines 473/474: isn't it the duration to dry out the reservoir if there is *no* river water input, not if river water input continues to be the (only) source

line 537: “ex”?

lines 540-550: this should be moved to the beginning of the section

line 602-605: I do not understand this

Figures 1 and 2:

It feels a bit inconsistent that the time periods considered in Figure 1 do not include 2020 which turns out to be relevant in Figure 2.

Figure 2 and 4:

Figures 2b and 4c are similar but quite distant from each other in the flow of arguments.

References:

Orth, R., J. Zscheischler, and S.I. Seneviratne, Record dry summer in 2015 challenges precipitation projections in Central Europe, *Sci. Rep.* 6, 28334, doi: 10.1038/srep28334 (2016).

Denissen, J.M.C., A.J. Teuling, A.J. Pitman, S. Koirala, M. Migliavacca, W. Li, M. Reichstein, A.J. Winkler, C. Zhan, and R. Orth, Widespread shift from ecosystem energy to water limitation with climate change, *Nature Climate Change*, 12, 677–684, doi: 10.1038/s41558-022-01403-8 (2022).

Version 1:

Reviewer comments:

Reviewer #1

(Remarks to the Author)

The authors did a great and careful job in revising their manuscript. I am happy with their responses and now I can recommend the manuscript for publications.

Reviewer #3

(Remarks to the Author)

Second Review of Ravinandrasana et al., manuscript number NCOMMS-25-13170A
"The First Emergence of Unprecedented Global Water Scarcity in the Anthropocene"

I appreciate the efforts made by the authors to address my and the other reviewers' comments which have improved the paper. After a few more refinements and expansions the paper is ready for publication in my opinion:

Regarding changes made in response to main comment (1) from my previous review:

I appreciate the clarifications in the revised manuscript. However, still many of the key concepts are introduced quite late (after 1/3-1/2 of the entire manuscript) such that readers can not fully understand and appreciate the motivation, approach and first results of the study. For example, FAR is mentioned in lines 109/110 without further explanation where readers can not understand what is attributed and why.

Furthermore, in this context I also suggest to move the first two paragraphs of the results section to the end of the previous section as this text is about methods rather than results.

Regarding changes made in response to main comment (2) from my previous review:

I appreciate the inclusion of data of a second Earth system model which is very relevant to assess the reliability and (un)certainly of the main conclusions of the study. I disagree with the authors that detected hot spot regions are "very similar" between both models (lines 251/252). I feel that the maps in Fig. S21 are substantially different with e.g. new hot spot regions in South America or Australia detected in the CNRM model but not in the CESM model. On a related aspect: it would be great to also reproduce Figure 2b in Figure S21, and not only Figure 2a as presently done.

More generally, this important uncertainty needs to be better reflected in the abstract which so far does not include this information and instead provides seemingly accurate numbers (35%, 14%) which may be (very) different in other Earth system models. This issue is very relevant as the abstract will be read by people from outside the field including practitioners and policy-makers such that special care is necessary to also communicate the existing uncertainty to them.

Other specific comments:

lines 245/246: Please add information on the source of the CMIP6 model data. I suggest to use the Earth System Grid Federation (ESGF) public data repository, <https://aims2.llnl.gov/search/?project=CMIP6/>. Maybe you can find the required data from more models there, incase you have not yet checked it?

There is a typo in the caption of Figure S7, CES2-LE should be CESM2-LE.

I do not wish to remain anonymous - Rene Orth.

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In cases where reviewers are anonymous, credit should be given to 'Anonymous Referee' and the source.

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Dear Reviewers,

We would like to express our sincere gratitude for the thorough and insightful review of our manuscript. We deeply appreciate the valuable comments provided by the reviewers to improve our study. In light of these comments, the manuscript has been carefully revised to address all three reviewers' suggestions, which have considerably strengthened the methodological rigour and clarity of our study. Below you will find a detailed response to each point raised. We have carefully considered all comments and made revisions accordingly. We have presented the comments in blue first for clarity, followed by our responses.

As part of the major revisions, we expanded our analysis by incorporating simulations from the Centre National de Recherches Météorologiques (CNRM) models under both SSP2-4.5 and SSP3-7.0 scenarios, sourced from the Coupled Model Intercomparison Project Phase 6 (CMIP6). We now include 10 members from the CNRM model. This choice was driven by limitations in available river discharge datasets, as CNRM was the only model that provided multiple ensemble members, including both atmospheric and river discharge variables. However, due to the coarser spatial resolution and limited ensemble size of the CNRM simulations compared to CESM2-LE, the CNRM model is used solely for sensitivity analysis of the event emergence time. This addition enables us to evaluate the robustness of Day Zero Drought (DZD) emergence against differences in model structure and emission scenarios.

More broadly, we have revised the manuscript along the following key points:

- We now explicitly consider uncertainties in the Time of First Emergence (ToFE) of DZD in the results section. Specifically, we address the uncertainties arising from: the use of different climate model such as CESM2-LE and CNRM; the focus on surface water; the definition of DZD as a socio-physical water scarcity metric that does not include water quality or environmental flow requirements; limitations and inaccuracies in the reservoir datasets; and uncertainties in the reconstruction of water consumption data.
- We have dedicated a section to Adaptation pathways and policy implications for regions vulnerable to DZD in the results section. This section highlights the broader relevance of our findings for policymakers and stakeholders in decision-making under increasing drought stress. In particular, we discuss how our study informs progress toward the Sustainable Development Goals (SDGs) targets 6.1, 6.4, 13.1, and 13.2.
- We have extended the study and updated the methodology section, and at the same time, performed some sensitivity analysis of ToFE. These analyses explore:
 - the sensitivity of using different thresholds of the multi-year compound drought extremes to define DZD,
 - the importance of using reservoirs,
 - the effect of varying the duration of TRD by doubling and quadrupling,
 - the influence of the model structure between the CESM2-LE members and with CNRM models in ToFE,
 - and the sensitivity of ToFE relative to future socioeconomic scenarios (SSP2-4.5 vs SSP3-7.0).

REVIEWER COMMENTS

Reviewer #1 (Remarks to the Author):

Revision of the manuscript "The First Emergence of Unprecedented Global Water Scarcity in the Anthropocene" by V. Ravinandrasana and C. Franzke.

General Comment.

In this study, the authors provide a definition of Day Zero Drought based on the duration and intensity of the drought event and the time required for the water reservoirs to dry. It is interesting approach as it combines both the atmospheric drivers of such events – the ones which have been mostly considered in the scientific literature so far – with the capabilities of water reservoirs and water consumption, which are instead associated with humans and as such are prone to be changed, modified and adapted to new climatic conditions. However, despite my overall positive impression, the work contains major deficiencies that must be addressed before it can be considered for publication in Nature Communications. A significant revision is necessary.

Response: Thank you for your insightful recommendation and suggestions to improve our manuscript. We are grateful to you for taking the time to review our manuscript and for giving us the opportunity to improve our study. We appreciate your recognition of our approach that integrates both atmospheric drivers and human-related factors to define Day Zero Drought. We acknowledge your concerns regarding the major deficiencies in the manuscript. We have meticulously addressed each of the concerns, and the necessary changes have been made to improve the relevance and clarity of the study.

Major issues

- Overall, the manuscript is not very well written, which poses challenges for readers in understanding the results. First, I find it questionable that the results are presented immediately after the introduction without any prior explanation of key definitions, which are entirely located in the methods section. While detailed explanations of the methods belong in the "Methods" section, including at least a brief overview of the primary methods and their novelty between the introduction and the results would greatly benefit the reader and the readability of the paper. Additionally, there are several areas of the text that I find difficult to comprehend (refer to my minor comments), so I would recommend having your paper professionally edited for clarity and language.

Response: We have revised the manuscript to include a brief and informative overview of the key definitions and the novelty of the study in the introduction and results sections. This addition provides a conceptual bridge between the background and the results section, helping readers better understand the scope and objectives of our study before delving into the technical details in the methods section. We have also ensured that the beginning of the results section briefly explains the methodology context to maintain continuity and enhance comprehension. Furthermore, we have thoroughly revised the manuscript for clarity and coherence, carefully addressing your comments. To further improve the overall readability and quality of the manuscript, we have reviewed and rewritten several sections for enhanced clarity and flow.

• It is not clear how this study advances our current knowledge, particularly in comparison to similar recent studies. For example, the authors mention references 29 and 30 in the introduction, which address a very similar topic as this manuscript. How does this study differ from those? What new insights does it provide compared to references 29 and 30? Why is a different approach from these references necessary at this point?

Response: In the revised manuscript (lines 91-101), we now clarify how our study differs from Satoh et al. (2022) and Liu et al. (2024). Satoh et al. (2022) analysed the Time of First Emergence (ToFE) of unprecedented hydrological droughts based solely on abnormally low river flow discharge. On the other hand, Liu et al. (2024), to our knowledge, is the only study that has estimated the ToFE of water scarcity and its disappearance using a per-capita water availability metric, with water scarcity being defined as per-capita water availability falling below the threshold of 1000 m³/person/year.

In our study, we adopt a fundamentally different framework: we define water scarcity based on the simultaneous occurrence of climate-induced droughts and water supply-demand imbalances. Specifically, we consider the prolonged depletion of water sources through decreases in rainfall, river flow, and reservoir levels as triggers of water stress. We introduce the concept of Day Zero Drought (DZD) as a compound water scarcity event driven by prolonged drought, where drought-induced reductions in water supply can no longer meet human demand. This event-based, compound approach goes beyond prior single-indicator studies and allows us to capture the interaction between droughts and emerging water scarcity under climate change.

Lines 91-101:

“To the best of our knowledge, few studies have assessed the Time of First Emergence (ToFE) of extreme events such as unprecedented hydrological drought³⁸ and water scarcity³⁹, under human-induced climate change. For instance, Liu et al.³⁹ estimated the ToFE of water scarcity and its potential disappearance based on a per-capita water availability metric. However, the ToFE of water scarcity driven by the compound effects of hydrological drought and socio-economic growth remains limited. Here, water scarcity arises when freshwater demand exceeds the available supply, including reservoir storage, under compound drought conditions. Reservoirs are essential for managing local water availability and assessing the severity of water scarcity under climate change⁴⁰. However, reservoir feedback^{41,42} due to reservoir dependence can increase vulnerability to water shortages during prolonged drought, as increased storage capacity encourages greater water consumption.”

• One of the main concerns regarding the conclusions of this study is that they rely solely on a single General Circulation Model (GCM), specifically CESM2. Can the authors justify why using only one model is sufficient? How do they account for the structural uncertainty that arises from differences between models? The manuscript does not address this issue at all, and I believe it should be discussed more thoroughly.

Response: We acknowledge that relying on a single GCM, in this case CESM2-LE, may limit the generalizability of our conclusion. Our initial choice was driven by the availability of a large ensemble, which offers high consistency and ensemble robustness for probabilistic analysis. CESM2-LE is particularly valuable for estimating the Fraction of Attributable Risk

(FAR) because it provides a large number of simulations under both historical and future scenarios. The spread across the ensemble members (100 members) enables us to quantify the uncertainty in event attribution more accurately. This structure allows for a robust separation of the human-induced signal from natural climate variability, which is critical for reliable FAR estimations. Moreover, CESM2-LE is highly practical for event attribution studies as it offers the necessary framework, ensemble size, and physical realism to carry out a reliable and nuanced FAR analysis, especially for rare events such as Day Zero Drought.

However, we agree that structural uncertainty across models is a critical aspect that should be addressed. In response, we have investigated model structure uncertainty across CESM2-LE, as detailed in lines 999-1025.

Furthermore, to assess the model structural uncertainty in the ToFE of the DZD event, we have extended our analysis beyond CESM2-LE by incorporating hydro-climatic data from the Centre National de Recherche Météorologiques (CNRM) models under both SSP2-4.5 and SSP3-7.0 scenarios from the Coupled Model Intercomparison Project Phase 6 (CMIP6). This extended analysis is described in lines 533-543 and further elaborated in lines 1027-1118 of the revised manuscript. Specifically, we selected 10 ensemble members from the CNRM model that include both atmospheric and river discharge variables across both SSP2-4.5 and SSP3-7.0 scenarios: CM6-1 (r2ilplf2, r3ilplf2, r4ilplf2, r5ilplf2, r6ilplf2), ESM2-1 (r2ilplf2, r3ilplf2, r4ilplf2, r5ilplf2), and CM6-1-HR r1ilplf2. We introduce a dedicated sensitivity section to evaluate the influence of model structure and emission scenarios on DZD ToFE, as detailed in lines 1027-1118, as follows:

In addition, we have included a discussion of the limitations associated with using CESM2-LE and CNRM (in the uncertainty section, lines 422-429) and the implications this may have on our findings, as well as suggesting directions for future work involving multi-model comparisons (in the discussion section, lines 508-510).

To directly address the concern regarding ensemble variability within CESM2-LE and to support the robustness of our findings, we computed the Time of First Emergence (ToFE) for each ensemble member (100 members) of CESM2-LE, shown in the figure below (now provided in Supplementary Figure S20a). We plot the Probability Density Functions (PDFs) of ToFE in considering all grid points of DZD-prone regions for each ensemble member. In Fig. S20a, the dark green line represents the PDF of the ToFE based on the ensemble sum of all DZD events (as defined in equation 4), while the aquamarine lines represent the PDFs of ToFE for individual ensemble members, calculated based on the FAR formulation provided below (as defined in equation 5):

$$FAR_i(t) = 1 - \frac{P_{preindustrial,i}}{P_{forcing,i}(t)} \text{ with } \begin{cases} P_{preindustrial,i} = \frac{event_{preindustrial,i}(DZD)}{N_{preindustrial,i}} \\ P_{forcing,i}(t) = \frac{event(t)_{forcing,i}(DZD)}{N_{forcing,i}(t)} \end{cases}$$

Where $P_{preindustrial,i}$ is the probability of the counterfactual for member i , which is the ratio between the summation of the event of the DZD event within the preindustrial period (1850-

1899) and the number of samples within the same period ($N_{\text{preindustrial}}$). While $P_{\text{forcing}, i}(t)$ is the probability of the factual for member i , which is the ratio between the decadal summation of the frequency of the DZD event of the member i during each decade from 1900 to 2100 and the number of samples during the decade ($N_{\text{forcing}}(t)$). The ToFE of DZD has been considered as the first decade of FAR greater than 0.99, where a 99% probability of the impact of the acute water scarcity that has emerged can be associated with a human-induced signal after the decade of completion of reservoirs.

The results exhibit substantial variability among ensemble members between 1900 and 1990, reflecting high uncertainty during this early period when the anthropogenic signal is still weak relative to internal variability, showing that structural uncertainty arising from the use of a single model remains an important caveat. After 1990, the results indicate strong agreement across ensemble members, with the highest density of emergence concentrated between 2020 and 2030. Agreement increases over time, particularly toward the end of the 21st century, underscoring the robustness of the signal under CESM2-LE. This ensemble-based approach provides a meaningful and reliable estimation of FAR and ToFE, though we now explicitly address the sensitivity of the ToFE in the context of model dependency and structural uncertainty (see lines 999-1025 and Fig. S20a)

To further address the structural uncertainty arising from differences between climate models, we extended our analysis using data from the Centre National de Recherche Météorologiques (CNRM) models under both SSP2-4.5 and SSP3-7.0 scenarios from CMIP6. This choice was driven by limitations in available river discharge datasets, as CNRM was the only model that provided multiple ensemble members, including both atmospheric and river discharge variables. To ensure methodological consistency and data completeness, we selected 10 CNRM ensemble members that include both atmospheric variables and river discharge across both scenarios, SSP2-4.5 and SSP3-7.0 (for details, please find in the methodology, in the Sensitivity analysis section, lines 1027-1118).

The results (now provided in Supplementary Figure S20b-c) show that model structural differences play a critical role in shaping projections of hydrological extremes. The PDFs of DZD ToFE for individual members (derived from equation 5) exhibit greater dispersion and multiple flattened peaks across ensemble members. The thick green line (ToFE derived from equation 4, based on aggregated event) is broader and flatter, indicating considerable variability in ToFE across ensemble members and highlighting the uncertainty in the timing of DZD emergence. This variability emphasized the challenge of detecting a robust probabilistic signal from a limited ensemble size, shown in the figure below (Fig. S20b-c).

Furthermore, probabilistic attribution methods such as the FAR require large ensemble sizes to confidently characterize forced emergence signals. The limited ensemble size available for CNRM under SSP2-4.5 and SSP3-7.0 limits the reliability of such analysis and reinforces the need for larger multi-model ensemble frameworks to robustly assess future water scarcity risks.

When comparing the spatial patterns of DZD ToFE between CESM2-LE and CNRM, we found that approximately 76% of the land area is classified as uncertain with respect to future DZD emergence, illustrating substantial inter-model disagreement in the DZD-prone region (now provided in Supplementary Figure S21). The model structure contributes to these

spatial discrepancies (Fig. S21a-b and d-e): CESM2-LE projects broader DZD emergence in northern Africa, whereas CNRM (coarser resolution) highlights different regions. However, CESM2-LE and CNRM agree on DZD occurrence across 24 % of the DZD-prone land area, though within this overlap, CESM2-LE projects later emergence over 14% of the area and earlier emergence over 10% compared to CNRM, as detailed in lines 1027-1069.

Lastly, we assessed scenario sensitivity by comparing SSP2-4.5 and SSP3-7.0 using the CNRM model (Fig. S21b-c and f). The results show that the influence of emission scenarios on DZD ToFE is region-specific, due to the interaction between regional climate drivers and human water use. Under the high-emission scenario (SSP3-7.0), DZD emergence can either advance or be delayed depending on the region. Notably, spatial discrepancies in DZD-prone regions persist across scenarios, with 43% of the land area remaining uncertain between the SSP2-4.5 and SSP3-7.0 scenarios within the CNRM model. However, both scenarios, SSP2-4.5 and SSP3-7.0, agree on DZD emergence across 57 % of the DZD-prone land area. Within this overlap, SSP3-7.0 projects later emergence over 17% of the area and earlier emergence over 18% compared to SSP2-4.5, while 22% of the area shows no change in the ToFE between the two scenarios, as detailed in lines 1071-1118.

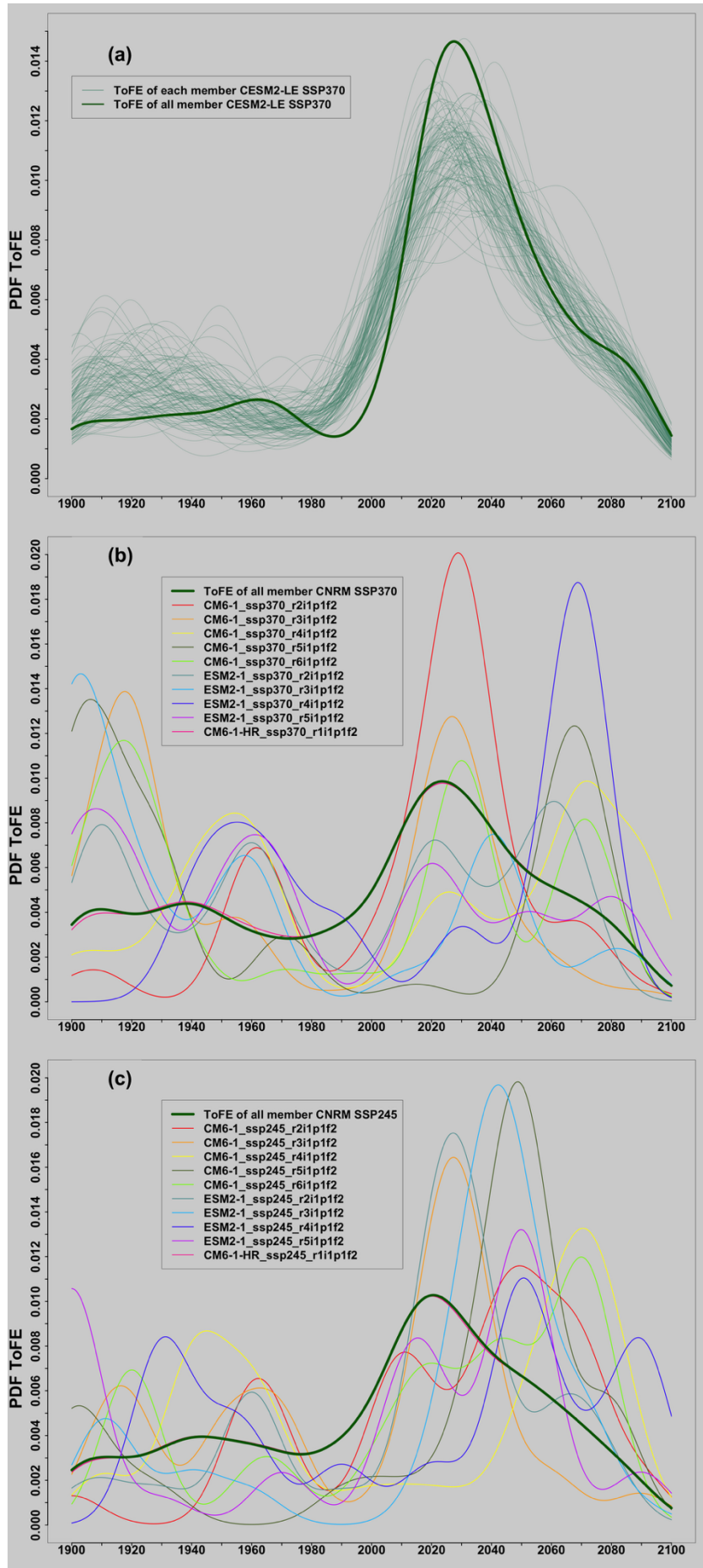


Fig S20: Probability Density Function (PDF) of Time of First Emergence of DZD events, in considering all grid points for each ensemble member across different models and scenarios. (a) ToFE PDFs from CESM2-LE under SSP3.7-0. Thick dark green line represents the PDF of the ToFE based on the sum of all DZD events (as defined in equation 4), while the thin aquamarine lines represent the PDFs of the ToFE for individual ensemble members, based on equation (5) of FAR. (b) ToFE PDFs for different ensemble members from CNRM-CM6-1 and CNRM-ESM2-1 models under SSP3.7-0. (c) Same as (b) but for SSP2.4-5. Colored thin lines represent individual ensemble members distinguished by the CNRM model (as defined in equation 5). The thick dark green line in each panel shows the ToFE based on equation (4). While our primary objective was to emphasize the externally forced signal, hence the use of aggregated events across the ensemble, to assess the internal variability and its influence on our results, we conducted a Time of First Emergence (ToFE) analysis across each ensemble member, to transparently assess the spread and uncertainty within the ensemble. This allows us to examine the spread of emerging timing of Fay Zero Droughts (DZD) and to evaluate the inter-member agreement. We computed the probability density functions (PDFs) of ToFE for each member across all global land covered by DZD. The figure (a) exhibits substantial variability among ensemble members between 1900 and 1990, reflecting high uncertainty during this early period when the anthropogenic signal is still weak relative to internal variability, showing that structural uncertainty arising from the use of a single model remains an important caveat. However, a strong ensemble consensus emerged after 2000, with most members indicating emergence between 2020 and 2030, and increasing agreement toward the end of the 21st century. This coherence across members supports the robustness of our findings in terms of both the timing and magnitude of anthropogenic influence on DZD events. Figure (b) and (c) shows a disagreement between the model in CNRM along all periods, 1900-2100. The dark green line from both models of each panel shows a high density of ToFE between the decades of 2020 and 2030. In terms of the scenario, the emergence under SSP2.4-5 is more delayed and spread out compared to SSP3.7-0. Peaks occur later, and the PDFs are broader compared to Fig. S18b. This suggests that under moderate forcing (SSP2.4-5), DZD emergence is slower and more uncertain. These results highlight the influence of both model structure and emissions scenarios on the DZD emergence.

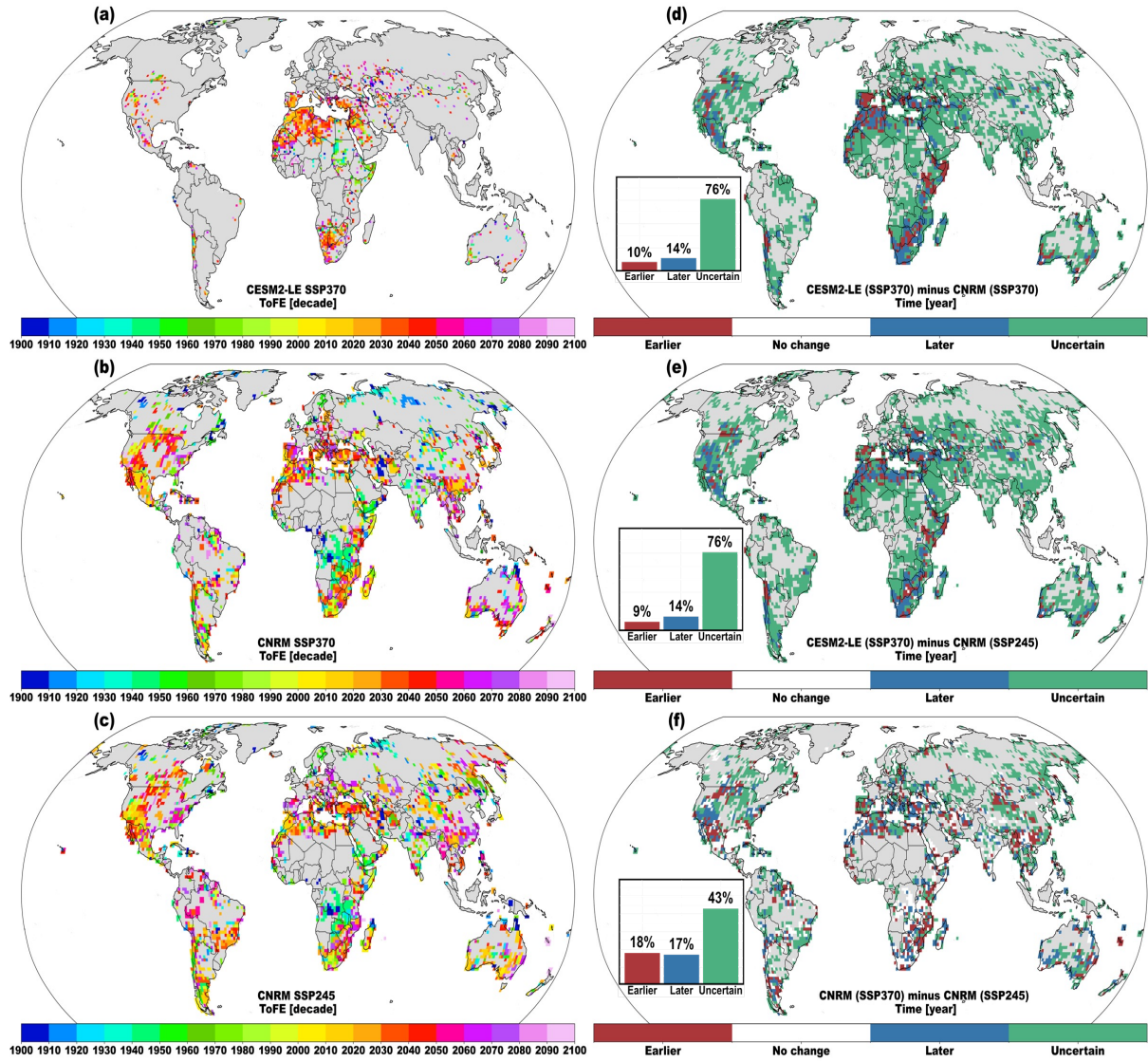


Figure S21: Spatial distribution of the Timing (ToFE) and associated uncertainties of Day Zero Drought (DZD) events across climate models and emission scenarios (CESM2-LE under SSP3-7.0 and CNRM under SSP2-4.5 and SSP3-7.0). Panels (a-c) depict the decadal ToFE of DZD events for each grid cell, calculated as the first decade in which the Fraction of Attributable Risk (FAR) exceeds 0.99, indicating that over 99% of DZD risk is attributable to anthropogenic climate change, based on the cumulative count of DZD events (Equation 4). Results are shown for (a) CESM2-LE under SSP3-7.0, (b) CNRM under SSP3-7.0, and (c) CNRM under SSP2-4.5. Panels (d-f) illustrate inter-model and scenario-based differences in ToFE for grid cells where DZD emergence is detected under those compared cases. Panel (d) represents the difference between CESM2-LE (SSP3-7.0) and CNRM (SSP3-7.0), reflecting structural uncertainty between models. For consistency, ToFE values from CESM2-LE (a) are interpolated to the CNRM resolution to compute the difference between the ToFE between CESM2-LE (SSP3-7.0) and CNRM (SSP3-7.0) as shown in (d) and (e). Panel (e) compares CESM2-LE (SSP3-7.0) and CNRM (SSP2-4.5), highlighting scenario- and model-driven uncertainty. Panel (f) compares CNRM (SSP3-7.0) and CNRM (SSP2-4.5), isolating internal model sensitivity emissions pathways. Inset bar plots in panels (d-f) quantify the proportion of DZD-prone land grid cells experiencing earlier and later emergence, as well as regions with

divergent DZD emergence (uncertain DZD-prone regions). Red and blue shading denote areas where ToFE occurs earlier or later, respectively, in the first model or scenario listed. The green shading indicates regions with inconsistent DZD emergence among the inter-model and scenarios cases (i.e., emergence only occurs in one of the models or scenarios), underscoring uncertainty in projections. The results show that CNRM projects broader emergence in parts of Asia, Australia, and America, while CESM2-LE projects earlier and later emergence across the Mediterranean and Africa. Grey areas indicate locations with no emergence of DZD condition during the analysis period. These results highlight the importance of model structure and emissions scenario in assessing the timing and spatial distribution of DZD emergence.

- The use of a large ensemble is justified primarily for obtaining reliable statistics, given the substantial number of equivalent years. However, this approach could also serve another purpose - quantifying the signal-to-noise ratio, which involves comparing anthropogenic forcing signals to internal variability noise. This could help explain the differences in the times of first emergence. Are there regions where the late emergence can be attributed to significant internal variability?

Response: You are absolutely right that a large ensemble can be used to assess the signal-to-noise ratio (SNR), particularly in studies focused on emergence and internal variability. However, in the context of our study, where we use the Fraction of Attributable Risk (FAR) to quantify human influence on water scarcity, SNR is not a suitable metric for several reasons.

First, the Day Zero Drought (DZD) events are defined based on the simultaneous occurrence of extreme conditions across three drought indicators, 48-month time scale of Standardized Precipitation-Evapotranspiration index (SPEI48), Standardized River Flow Index (SRFI48), and Standardized Water Scarcity Index (SWSI48), integrates both water supply and demand components, and their duration to dry the reservoir (TRD). The inclusion of SWSI48, as described in lines 640-661, which incorporates both climatic drivers and water consumption, means that the emergence of DZD can result from both stochastic variability in drought occurrence and an increase in human water demand. Each indicator plays a distinct but interrelated role in defining DZD; therefore, none is weighted as more important than another. Their simultaneous exceedance is necessary to identify a DZD event, filtering out less severe or isolated events. For instance, precipitation deficits alone may not result in a crisis without demand pressure. i.e., in low low-demand case, just as high demand may not lead to scarcity if the supply is still enough. Similarly, even in the absence of climate variability, unsustainable consumption alone can trigger water scarcity if water use surpasses the available resource. We identify the DZD event when all four indicators simultaneously fall below predefined thresholds, indicating a compound extreme drought condition, as detailed in equation 3 and lines 824-849. The model output is therefore transformed into binary outcomes (event occurred or not), and we count the number of events that occur within each ensemble member and each time window. The detection of DZD focused on counting events, i.e., discrete events, counting over 1850 to 2100.

Second, the discrete-events framework is then used to estimate the FAR. FAR is a probabilistic attribution method that compares the likelihood of extreme events between historical (1850-1899) and forcing scenarios (1900-2100). It does not rely on trends or absolute

magnitudes of anomalies but rather on the change in the probability of occurrence of extremes. This makes it more directly applicable for event attribution. In addition, we identify ToFE with a very high attribution confidence ($\text{FAR} \geq 0.99$) of human-induced signal relative to the pre-industrial period (1850-1899). Thus, the late emergence can be attributed to the late attribution of $\text{FAR} \geq 0.99$ of the simultaneous occurrence of a compound extreme event condition:

$$\begin{cases} \text{SPEI48} \leq -1.5 \cap \text{SRFI48} \leq -1.5 \cap \text{SWSI48} \leq 0.6, \text{dur}_{\text{ce}} \geq \text{TRD}, \text{if reservoir exists.} \\ \text{SPEI48} \leq -1.5 \cap \text{SRFI48} \leq -1.5 \cap \text{SWSI48} \leq 0.6, \text{if there is no reservoir.} \end{cases}$$

Third, SNR requires continuous variables to calculate a meaningful ratio between the signal and the noise. However, when dealing with discrete event counts, especially rare events, SNR can become problematic, especially if no events occur during the baseline period (1850-1899), which is common for rare extremes like severe drought and water scarcity. In such cases, the standard deviation approaches zero, leading to undefined SNR values. This makes the metric tendentially misleading in our context.

Therefore, while SNR is valuable in other emergence studies, it does not align well with the objectives or methodology of our work, where FAR provides a more robust and meaningful measure of anthropogenic influence on the risk of extreme events. FAR is specifically designed to handle probabilistic event-based analysis.

• The main result, shown in Figure 2b, indicates that the Time of First Engagement (ToFE) sharply rises from 2020 to 2030. Since we are currently in 2025, we find ourselves right in the middle of this timeframe, which means this statement applies not only to the future but also partially to the present. Shouldn't we be able to observe some verification of this surge of ToFE now? Additionally, how can we physically explain the rapid shift occurring during this decade?

Response: We acknowledge that the critical 2020-2030 decades indeed encompass the present year, 2025, as depicted in Figure 2b. Implying that the projected emergence of DZD is not only future-oriented but should be partly observable in the present.

Regarding the physical drivers of the rapid shift in ToFE between the decades of 2020 and 2030, this transition arises from the compound effects of increasing climate-induced water stress and accelerating anthropogenic water demand. Specifically, intensifying evapotranspiration, declining precipitation and river flow, and increasing water consumption are collectively considered as drought-driven triggers of acute water scarcity, such as DZD. Our framework captures these interactions through the use of compound indicators at a 48-month time scale: Standardized Precipitation-Evapotranspiration index (SPEI48), Standardized River Flow Index (SRFI48), Standardized Water Scarcity Index (SWSI48), and their duration to dry the reservoir (TRD). These indicators integrate both water supply and demand components, allowing us to represent water scarcity conditions during prolonged drought periods.

To further address your comment, we evaluate the temporal variations of these three water stress indices (SPEI48, SRFI48, and SWSI48) across each grid cell within the DZD-prone regions, as shown below (now presented in Supplementary Figure S7), where a more detailed explanation is provided in the figure caption. The results show that SPEI48, SRFI48, and SWSI48 exhibit synchronized declining trends after 2020, indicating a concurrent intensification of water stress and scarcity across these regions.

SPEI48 (Fig. S7a) shows a pronounced negative trend after 2000, indicating intensifying long-term aridity driven by decreasing precipitation and increasing evapotranspiration. SRFI48 (Fig. S7b) exhibits a relatively weaker negative trend toward the end of the 21st century, alongside increased variability in hydrological extremes. SWSI48 (Fig. S7c) is presented on a logarithmic scale to capture the wide range of supply-demand imbalance conditions. SWSI48 shows a substantial decline in magnitude over time. This trend suggests that future water consumption will increasingly exceed the available water supply, indicating a severe future water scarcity by the end of the 21st century. SWSI48 reflects the compound effects of climate stress and human water use in DZD-prone regions. The vertical dashed line between 2020 and 2030 highlights a critical decade during which a simultaneous decline in all three indices is observed across many grid cells, marking the emergence of compound water stress extremes. The combined pattern of SPEI48, SRFI48, and SWSI48 highlights a severe and persistent decline in water availability and an increase in water demand, underscoring the growing vulnerability of DZD-prone regions under future climate scenarios.

Together, these factors explain why the 2020s represent a critical decade for the ToFE of DZD. As for a DZD event to be considered valid, all three thresholds of the definitions of DZD (equation 3) must be met simultaneously at the same time and location. The prolonged simultaneous occurrence of severe climate-driven drought (SPEI48), severe river flow shortages (SRFI48), and acute water scarcity driven by human use (SWSI48) is required. This compound condition ensures that DZD captures the most severe and impactful water scarcity situations, driven jointly by both climatic stress (atmospheric and hydrologic) and human water demand.

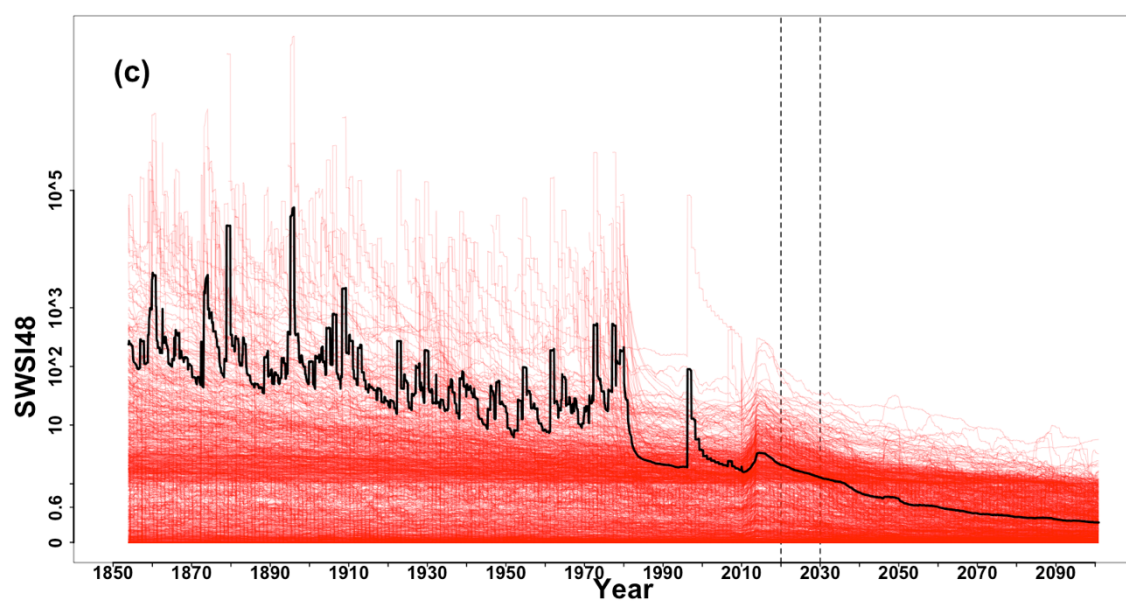
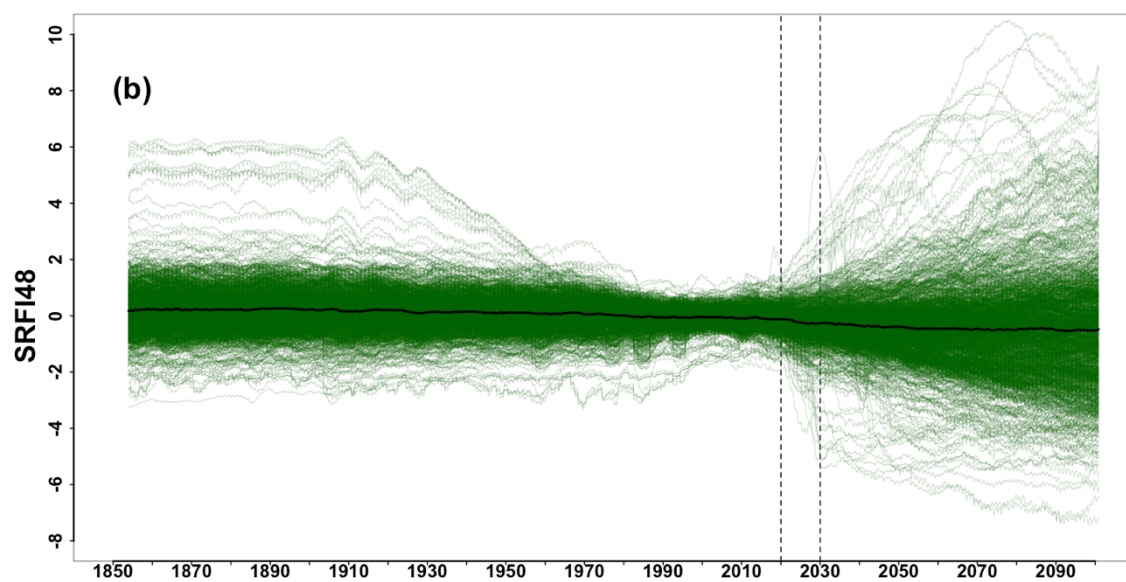
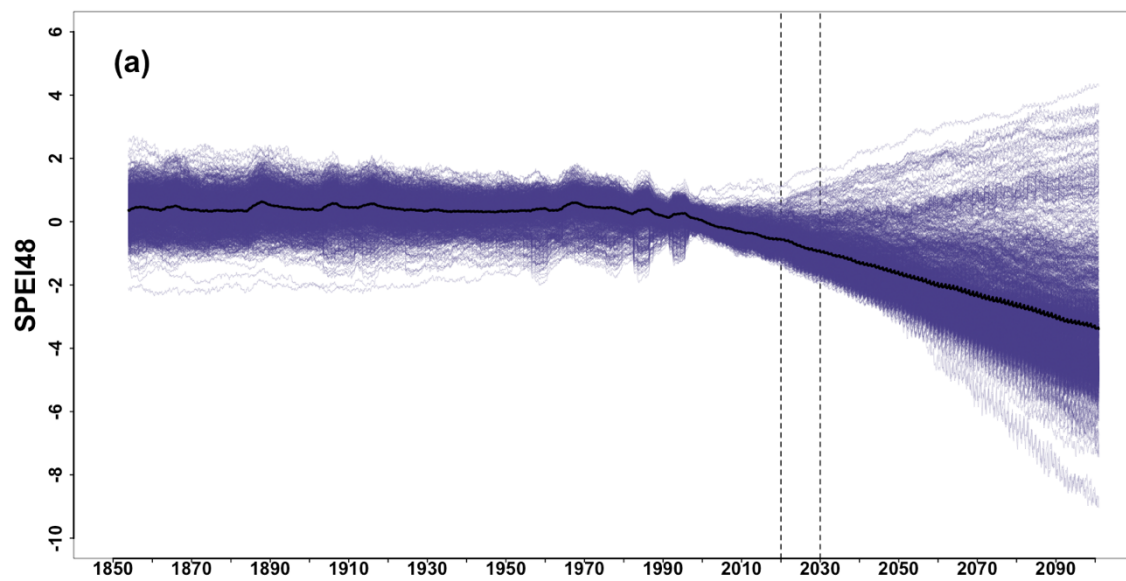
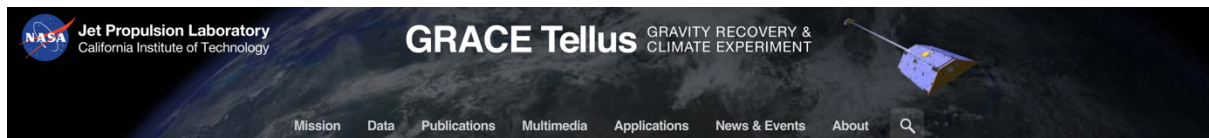


Fig. S7: Time series of ensemble-mean of water stress indices from CES2-LE across each grid cell within Day Zero Drought (DZD)-prone regions (as shown in Fig. 2a). Each panel displays time series from 1850 to 2100 for: (a) the 48-month Standardized Precipitation-Evapotranspiration index (SPEI48), (b) the 48-month Standardized River Flow Index (SRFI48), and (c) the 48-month Standardized Water Scarcity Index (SWSI48). Thin lines represent values from individual grid cells, while the thick black line indicates the ensemble mean across those grids. All three indices exhibit declining trends after 2020. SPEI48 shows a pronounced negative trend after 2000, indicating intensifying long-term aridity driven by decreasing precipitation and increasing evapotranspiration. SRFI48 shows a relatively weaker negative trend toward the end of the 21st century, alongside increased variability in hydrological extremes. SWSI48 is presented on a logarithmic scale to capture the wide range of supply-demand imbalance conditions. SWSI48 shows a substantial decline in magnitude over time. This trend suggests that future water consumption will increasingly exceed the available water supply, indicating a severe future water scarcity by the end of the 21st century. SWSI48 reflects the compound effects of climate stress and human water use in DZD-prone regions. The vertical dashed line between 2020 and 2030 highlights a critical decade during which a simultaneous decline in all three indices occurs across many grid cells, making the emergence of compound water stress extremes. The patterns of SPEI48, SRFI48, and SWSI48 highlight a severe and persistent decline in water availability and increase in water demand, underscoring the growing vulnerability of DZD-prone regions under future climate scenarios.

Concerning observational verification: while our study is based on CESM2-LE projections, we also compare our results with recent observational data and real-world events. Recent global and regional hydrological events from 2020 to 2025 (including the 2020 decade) demonstrate a clear acceleration in water scarcity and drought impacts, consistent with the CESM2-LE projection of ToFE:

- Satellite-Derived Freshwater Storage (2020-2025): Data from NASA's GRACE-FO mission reveal that many DZD-prone regions were already experiencing minimum freshwater storage during the early 2020s, directly supporting our model's projection of an early onset of compound drought risk. Source: <https://grace.jpl.nasa.gov/>, consulted in April 2025.



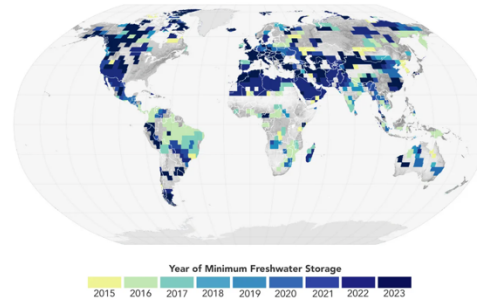
Measuring Earth's Surface Mass and Water Changes

NASA Satellites Reveal Abrupt Drop in Global Freshwater Levels

An international team of scientists using observations from NASA-German satellites found evidence that Earth's total amount of freshwater dropped abruptly starting in May 2014 and has remained low ever since.

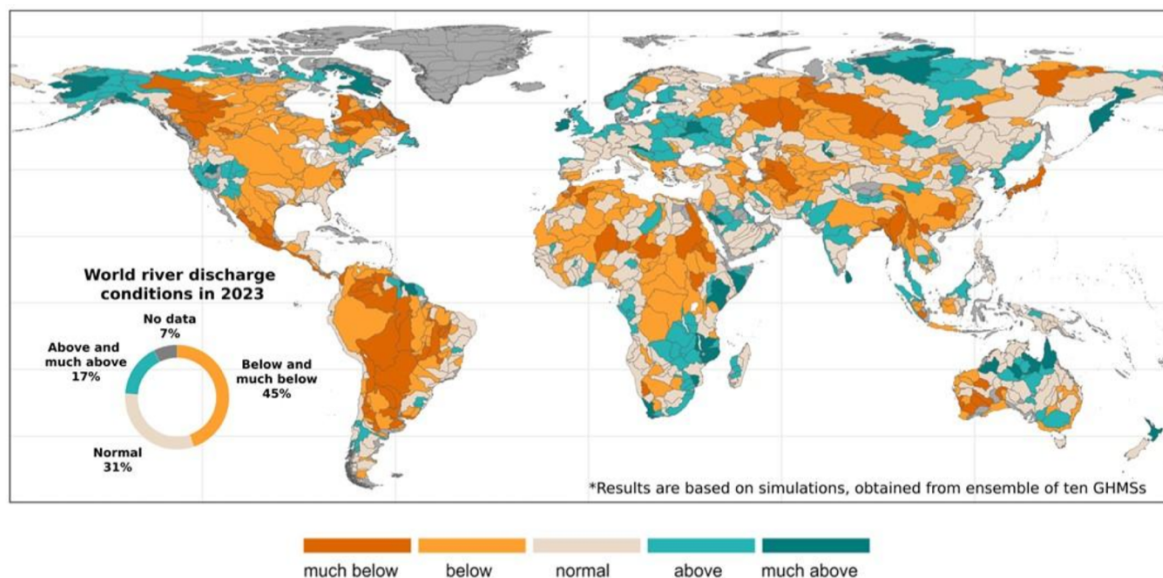
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Map of Year of Minimum Freshwater Storage. Source: <https://grace.jpl.nasa.gov/>, consulted in April 2025.

- The World Meteorological Organization (WMO) Report on Global River and Reservoir Conditions (2023): The WMO reported that 2023 was the driest year for global rivers over three decades. Below-normal river flows and reservoir inflows were widespread, particularly across North, South, and Central America, as well as parts of Australia. Prolonged drought conditions were also reported in North America and Europe. In addition, groundwater levels in Chile and Jordan fell below normal, largely due to over-abstraction rather than climatic factors.



Map of world river discharge conditions in 2023. World Meteorological Organization (WMO) Report. Where half of the globe had dry river flow conditions. (published 07 October 2024) Source <https://public.wmo.int/news/media-centre/wmo-report-highlights-growing-shortfalls-and-stress-global-water-resources?>, assessed on April 2025.

- Southern Africa water stress (2024): Countries like Zimbabwe and Botswana experienced extreme drought conditions, leading to a severe water crisis, resulting in failed crops, food insecurity, and humanitarian assistance requests for emergency food aid. These impacts are consistent with DZD-characteristic conditions, where compound hydrological stress overwhelms local resilience.

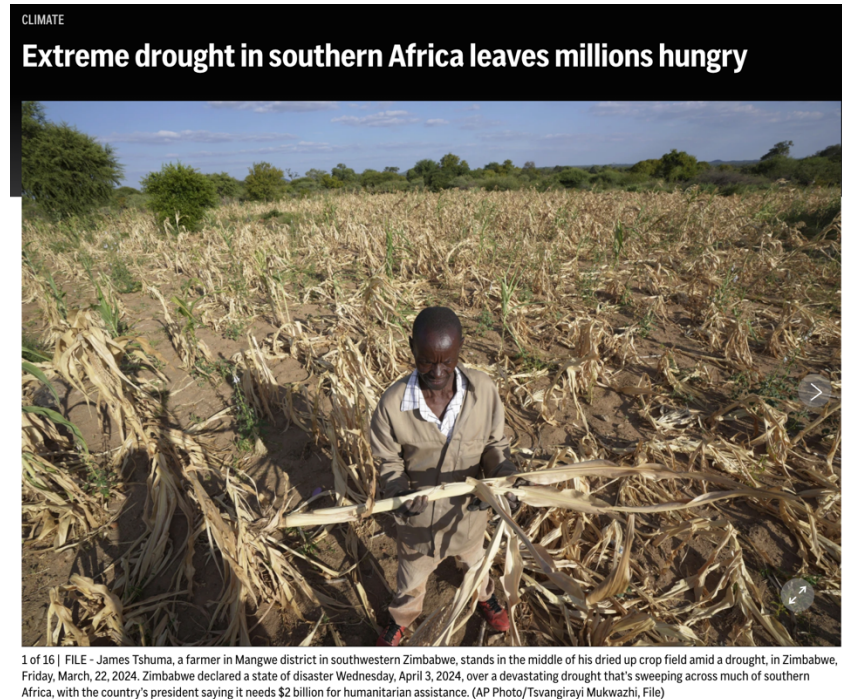


Photo of a farmer in Zimbabwe stands amidst his parched and failing crops during a severe drought. Source: The Associated Press: <https://apnews.com/article/southern-africa-drought-hunger-food-climate-2ef702abc386f7182dbc5f8f4192be3c>,



A woman sits in a wheelbarrow while waiting to receive food aid in Mangwe district in southwestern Zimbabwe, Friday, March 22, 2024. (AP Photo/Tsvangirayi Mukwazhi)



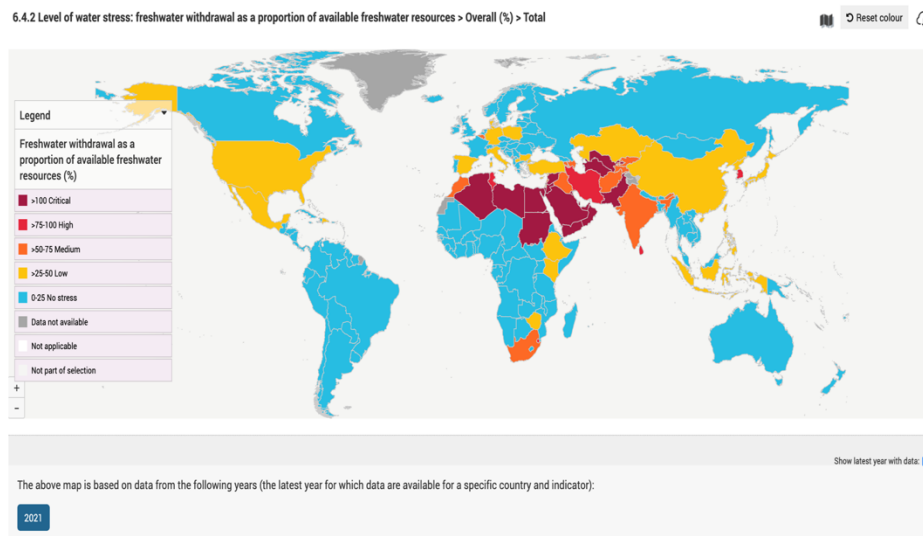
Women share peas during a food aid distribution in Mangwe district in southwestern Zimbabwe, Friday, March 22, 2024. (AP Photo/Tsvangirayi Mukwazhi)

Photo of scenes from food aid distribution in Mangwe, Southwestern Zimbabwe. Source: The Associated Press: <https://apnews.com/article/southern-africa-drought-hunger-food-climate-2ef702abc386f7182dbc5f8f4192be3c>, assessed April 2025.

- Water scarcity in South Texas, USA, and Mexico (2024): Texas and Mexico continue to face a worsening water crisis, exacerbated by rising temperatures and declining runoff. Agricultural productivity is under threat, and local communities are experiencing increasing water stress. This situation reflects the interconnected role of

climate and water demand in shaping ToFE dynamics. Cross-border cooperation will be essential for sustainable water management. Source: <https://www.edengreen.com/blog-collection/texas-mexico-water-crisis>, assessed April 2025.

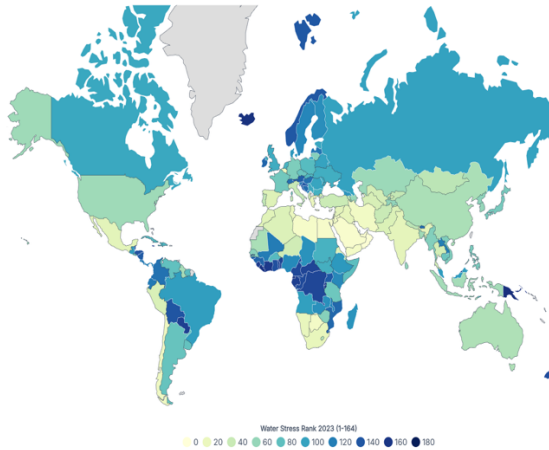
- Lake Mead, USA (observations and projections to 2025): U.S. government assessments indicate a 66% probability that Lake Mead will reach a critically low elevation by 2025. As this reservoir supplies 90% of the water for parts of Nevada, including rapidly expanding Las Vegas, this situation exemplifies the compounding effects of growing water demand and diminishing water supply. Source: <https://www.weforum.org/stories/2021/10/water-scarcity-in-a-warming-climate-a-story-in-four-visuals/>, assessed April 2025.
- Water Stress (2023): In November 2023, Spain encountered water stress, with national agencies warning of supply insecurity. This trend is reflected in global SDG 6.4.2 water stress maps (below), which show that Northern Africa, the Middle East, Southern Africa, the Mediterranean region, and parts of the Americas, all DZD hotspots, are under acute freshwater pressures. Source: <https://www.realinstitutoelcano.org/en/commentaries/spains-stressful-water-problem/>; <https://sdg6data.org/en/maps>, assessed April 2025.



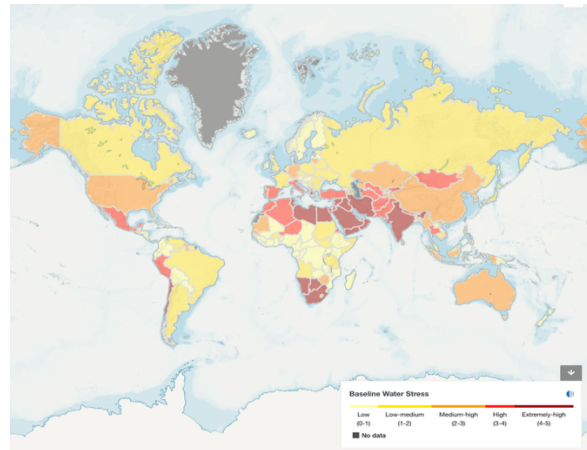
Map of Indicator 6.4.2 (SDG6) level of water stress: freshwater withdrawal as a proportion of available freshwater resources in 2021. Source: <https://sdg6data.org/en/maps>, assessed April 2025. The map is showing how much the freshwater that is being withdrawn by economic activities, compared to the total renewable freshwater resources available. It also takes into account environmental flow requirements.

- Water stress ranking by country (2025): The latest global rankings from the World resources Institute (WRI) Aqueduct tool show that many regions identified as DZD hotspot, including the Middle East, Southern Africa, Mediterranean Regions, Chile, Mexico, Northern Africa, and USA, are among the regions experiencing extremely high to medium-high levels of baseline water stress. This alignment provides us further empirical support for our modelled surge in the ToFE and underscores the convergence

between compound droughts-driven water scarcity risks (DZD) and observed water scarcity pressures. Source: <https://worldpopulationreview.com/country-rankings/water-stress-by-country#title>; <https://www.wri.org/applications/aqueduct/country-rankings/?indicator=bws>, assessed in April 2025.



Map of Water Stress by Country 2025. Source: <https://worldpopulationreview.com/country-rankings/water-stress-by-country#title>



Map of Baseline Water Stress from the WRI Aqueduct. Source: <https://www.wri.org/applications/aqueduct/country-rankings/?indicator=bws>

These observed cases from 2020 to 2025 demonstrate the real-world manifestation of the modelled surge in ToFE between 2020 and 2030. This pattern is substantiated by recent observational data and can be physically explained by the interplay between climate-induced hydrological changes and increasing water demand. These findings underscore the urgency of implementing integrated water resource management strategies to mitigate the impacts of compound drought events.

• Lines 352-367. I find this point quite critical: the authors use a projected future water demand, which is highly uncertain, to fit data and extend them in the past, which should be more reliably known. The authors need to convince me that this approach is acceptable. Additionally, I do not understand what the "five Global Climate Models" mentioned in line 355 are, as they are never explained.

Response: We thank the reviewer for this important and thoughtful comment.

Regarding the identity of the five Global Climate Models mentioned: these refer to the five Global Climate Models (GCMs) from Khan et al (2023), which provide monthly global gridded water consumption data for sectoral water use under SSP3- RCP6.0 scenario covering the period 2010 to 2100. We have clarified the identities of the five GCMs of the water consumption datasets used in our analysis. Specifically, these GCMs are: GFDL, HADGEM, IPSL, MIROC, and NORESM. This clarification has been added to lines 554-561 of the revised manuscript. Additionally, we note that the monthly sectoral water demand datasets used for this study, both SSP2-RCP4.5 and SSP3-RCP6, are publicly available via <https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/VIQEAB>, assessed in April 2025, to support transparency and reproducibility (lines 1131-1134).

Regarding the approach to reconstructing water consumption for the period 1850 to 2009, we agree that using projected future water demand to reconstruct historical trends requires careful justification, as this approach introduces potential uncertainty. We have expanded our explanation in the revised manuscript and added further discussion of limitations (lines 561-590). Specifically, we clarify that due to the lack of globally available sectoral water demand observations (across domestic, irrigation, industry, electricity, livestock, and mining sectors) for the full period 1850 to 2009, direct historical reconstruction from observation is not feasible. In this context, our method treats future projections as structured representations of plausible socio-economic trajectories under SSP2-RCP4.5 and SSP3-RCP6. The backward extrapolation is performed using a nonlinear or logarithmic dose-response regression model (drc package in R, specifically the `DRC.logCurve()` function), which captures the path-dependent dynamics of sectoral water use. This method allows flexible nonlinear curve fitting. Importantly, comprehensive observed water demand data across all sectors, such as domestic, irrigation, industry, electricity, livestock, and mining, are not globally available for the historical period (1850-2009). This data gap necessitates a reconstruction approach to provide plausible estimates consistent with future socio-economic narratives. The model is applied separately for each grid cell and month to reflect spatial-seasonal variability for each GCM model: GFDL, HADGEM, IPSL, MIROC, and NORESM. To estimate past water demand trends, we first fitted monthly-specific decay curves to the 2010-2100 water consumption data using the `DRC.logCurve()`. We then used these fitted models to extrapolate and predict water demand for each respective month during the historical period (1850-2009). This method provides a physically plausible reconstruction of historical water demand trends. This reconstruction is necessary to support the computation of the Standardized Water Scarcity Index (SWSI48) across the full period 1850-2100. We fully acknowledged the limitations of this method, and now explicitly discuss these uncertainties in the revised manuscript, as detailed in lines 456-462 and 576-584.

To provide further transparency, we now include a figure (Supplementary Figure S3, shown below) that presents the spatial distribution and temporal evolution of water demand after the reconstruction of monthly water demand, based on the GFDL model under the SSP3-RCP6.0 scenario. In addition to directly addressing the reviewer's concern, we also present additional figures below, illustrating monthly trends of water demand (1850-2100) for selected regions. These regional trends are provided specifically in response to this comment to demonstrate the plausibility of our reconstruction approach.

The use of `DRC.logCurve()` helps to capture the historical trends in water consumption. The figure illustrates reconstructed monthly water demand over the historical period (1850-2009) and projected into the future (2010-2100) for different regions. The backward regression extrapolation captures the expected declining trends when extending backward from 2009 to 1850, under the SSP3-RCP6 pathway in the GFDL model. Importantly, to preserve the seasonal cycle and interannual variability, the nonlinear model was fitted independently for each month: for example, the curve was fitted using all January values from 2010-2100 to reconstruct the backward trend for January from 2009 to 1850; this process was repeated separately for each calendar month (January to December), in each grid cell of each GCMs. This month-by-month fitting approach ensures that the extrapolated water demand retains the characteristic seasonal

patterns of each region. The results show that the historical baseline (1850-1899) is characterized by relatively low water demand, while future periods (especially 2080-2100) exhibit strong intensification in water usage under the SSP3-RCP6 pathway in the GFDL model.

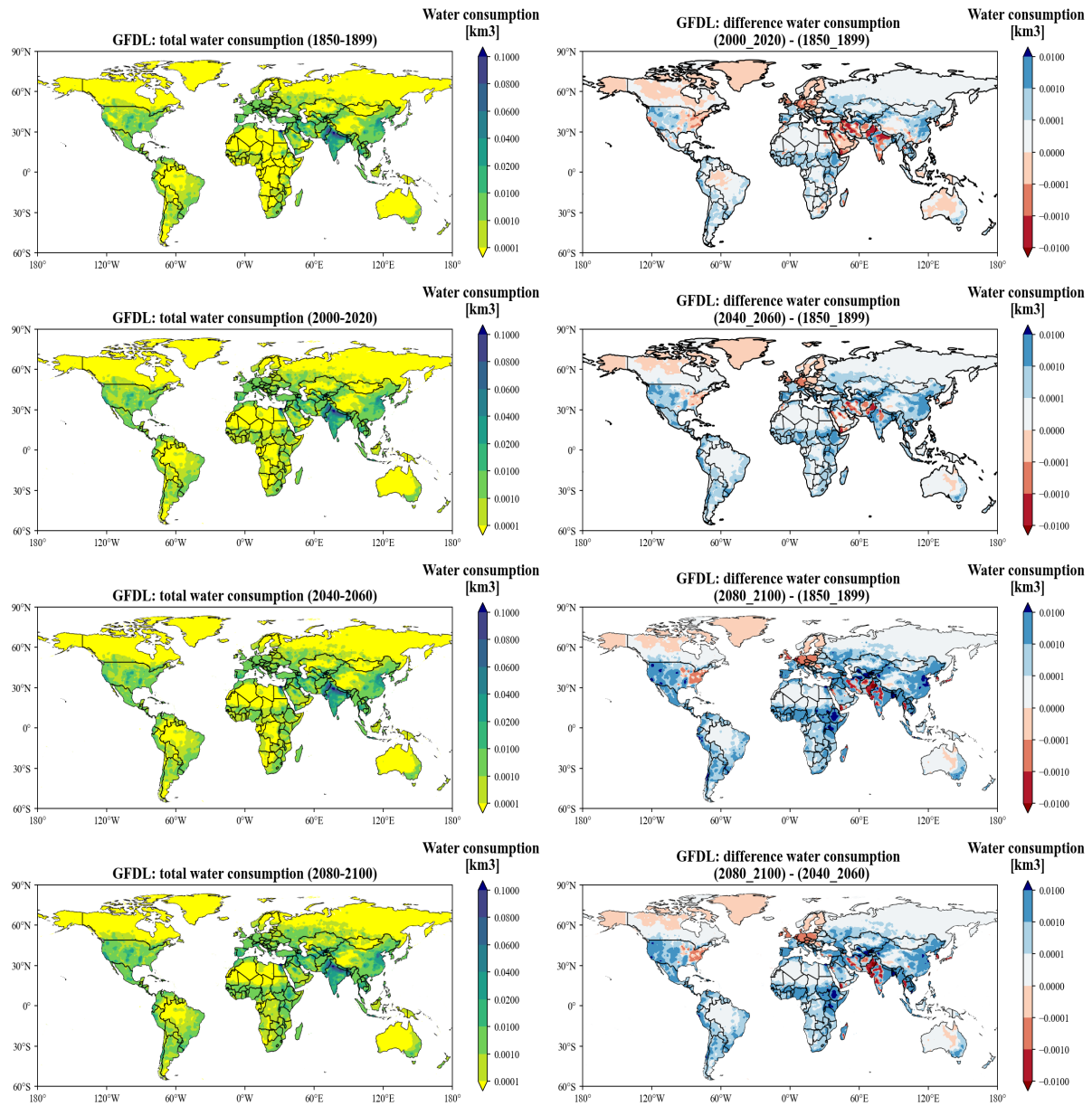


Fig. S3: Spatial distribution and evolution of mean total water consumption (km3) simulated by the GFDL model under the socio-economic pathways SSP3-RCP6.0. The left panels show the average water consumption for the preindustrial period (1850-1899), the present (2000-2020), the near future (2040-2060), and the far future (2080-2100). The right panels display the differences in water consumption. The results indicate that the historical baseline (1850-1899) reflects relatively low water demand, whereas future periods (especially 2080-2100) demonstrate an intensification in water usage. The historical period (1850-2009) is reconstructed using nonlinear backward extrapolation (`DRC.logCurve()` fitting) based on modelled future water demand (2010-2100) under SSP3-RCP6.0. The results show that the historical baseline (1850-1899) is characterized by relatively low water demand, while future periods (especially 2080-2100) exhibit strong intensification in water usage.

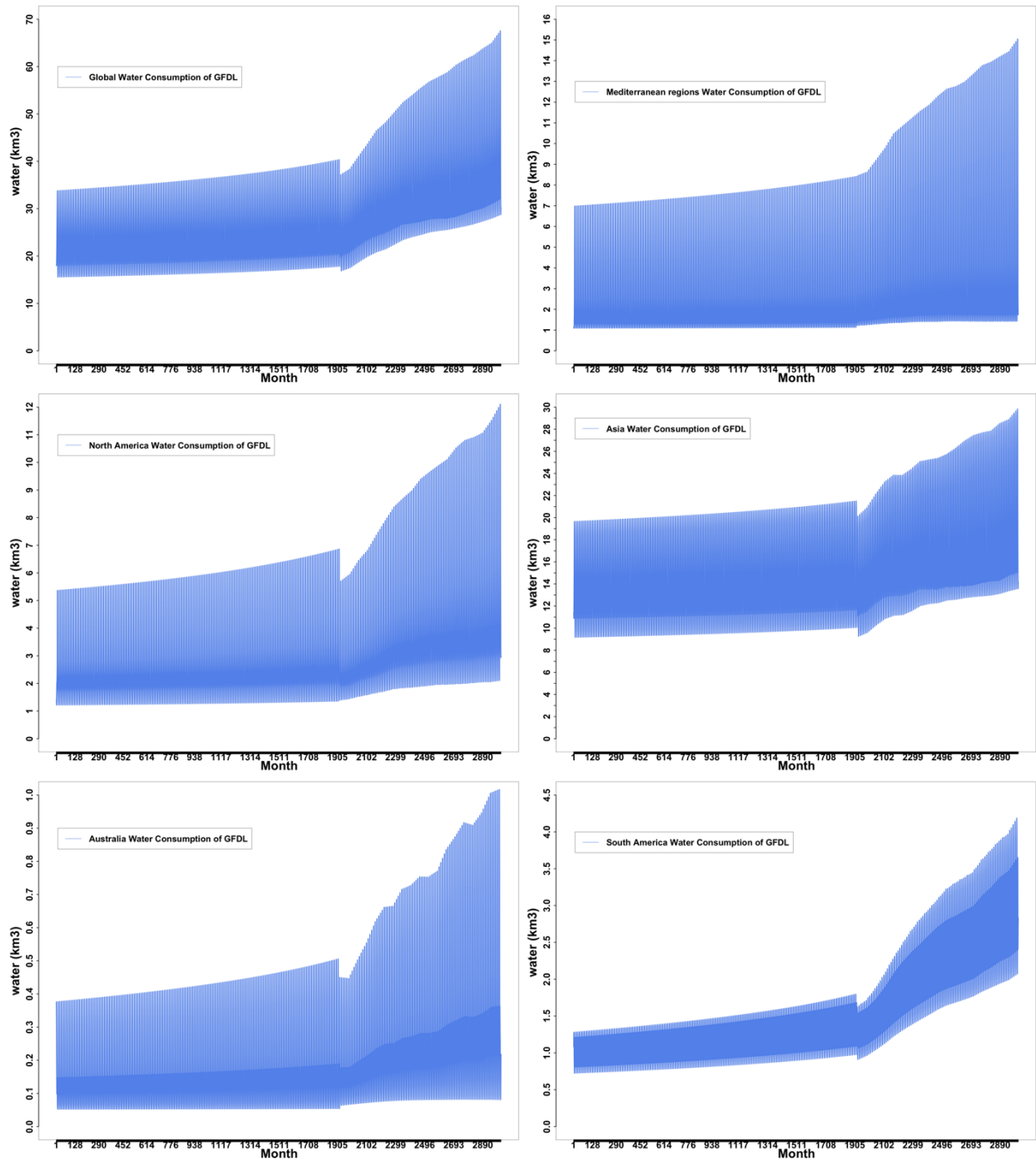


Figure: Global and regional water demand reconstruction from 1850 to 2100 based on the GFDL model. Water demand is expressed in cubic kilometers (km³) and represents the total demand across all sectors (domestic, agriculture, industry, electricity, livestock, mining) for the following regions: Global (top left), Mediterranean (to right), North America (middle left), Asia (middle right), Australia (bottom left), and South America (bottom right). The historical period (1850-2009) is reconstructed using nonlinear backward extrapolation (DRC.logCurve() fitting) based on modelled future water demand (2010-2100) under SSP3-RCP6.0 scenario.

Reference:

Khan, Z. *et al.* Global monthly sectoral water use for 2010–2100 at 0.5° resolution across alternative futures. *Sci. Data* **10**, 201 (2023).

Minor issues

• Line 40-48. Cape Town is not the only city in the world to have faces something like a DZD, so other examples which happened could be mentioned (for example, Chennai 2019 water crisis, India) or places which are very vulnerable and may face it soon (e.g., Los Angeles).

Response: We have revised the manuscript and have included additional examples of cities that have experienced or are at risk of facing the water crisis, like Day Zero Drought. In particular, we now mention the 2019 Chennai water crisis in India and the increasing vulnerability of cities such as Los Angeles. These additions help to contextualize Cape Town's experience in a broader global context of the urban water scarcity challenge trend. This update is reflected in lines 51-52 of the revised manuscript, as follows:

“Similar crises occurred in cities like Chennai in 2019⁷, while other cities like Los Angeles⁸ remain highly vulnerable.”

• Line 202. It would be interesting to know if this was related to internal natural variability at the interannual or decadal scale in different regions of the world.

Response: We agree that internal natural variability can influence hydrological extremes at interannual to decadal scales. However, our analysis indicates that the detection of Day Zero Drought (DZD) is primarily driven by compound interactions among climate stressors and human water use, rather than internal variability alone.

Specifically, DZD is defined based on the simultaneous exceedance of thresholds in four indicators: SPEI48 (climate), SRFI48 (hydrology), SWSI48 (water supply–to–demand balance), and TRD (reservoir depletion), making it inherently a compound and region-specific phenomenon. This multi-year indicator framework captures the compounding and interdependent nature of drought-driven water scarcity, such as DZD. DZD events only occur when these factors occur simultaneously and reinforce each other; none can be viewed in isolation. Regions where all these stressors align frequently, such as long droughts, reduced river flow, high consumption, and limited storage, are more likely to experience longer-lasting DZD and more frequent DZD events (short waiting time between DZD events), highlighting the critical role of local and regional conditions in DZD events. This underscores the compound, multi-dimensional nature of DZD and the need to consider all contributing factors together to fully understand its characteristics. Therefore, our findings suggest that the characteristics of Day Zero Drought, particularly duration and waiting time between events, are more strongly shaped by regional and local factors than by internal variability alone. Our analysis further reveals that the integration of the Standardized Water Scarcity Index (SWSI) and TRD plays a pivotal role in regionalizing DZD by incorporating not only climatic variables but also human-driven factors, particularly water consumption and reservoirs. Water consumption varies substantially across regions due to differences in demographic pressures, agricultural irrigation practices, industrial development, and other socio-economic sectors. Therefore, even if two regions are exposed to similar climatic drought conditions, their vulnerability to DZD can differ

significantly based on the water quantity and pattern used locally. These factors can vary significantly across regions, meaning the severity of the event is determined not just by climatic conditions (like precipitation, evapotranspiration, and river flow) but also by how water is used in a given area. For example, a region with intensive agriculture or rapid urban and industrial expansion is more likely to face water scarcity during dry conditions than a region with lower consumption, even if the climatic conditions are similar (without considering water management). This study underscores that DZD duration and waiting time are not merely products of natural variability but are deeply rooted in region-specific socio-hydrological dynamics. Therefore, the inclusion of water consumption ensures that DZD events are not only linked to the broader climate system but are also deeply embedded in local and regional socio-economic contexts. We have further clarified this point in lines 802-850 of the revised manuscript.

• Fig. 4c-e, yellow line cannot be seen. Furthermore, in fig4d, it is not clear in which year these estimates are evaluated.

Response: We have adjusted the color scheme in Fig.4 (changing the yellow line to green) to improve its visibility, shown below. Additionally, we have revised the caption (see lines 388-401) to clarify that the estimated population shown in Fig. 4d corresponds to the population exposed to DZD at the ToFE in their respective regions. In other words, the population is evaluated at their respective decade of the ToFE (Fig. 4a, c-d), and the GWL (Fig. 4e) occurs in each region.

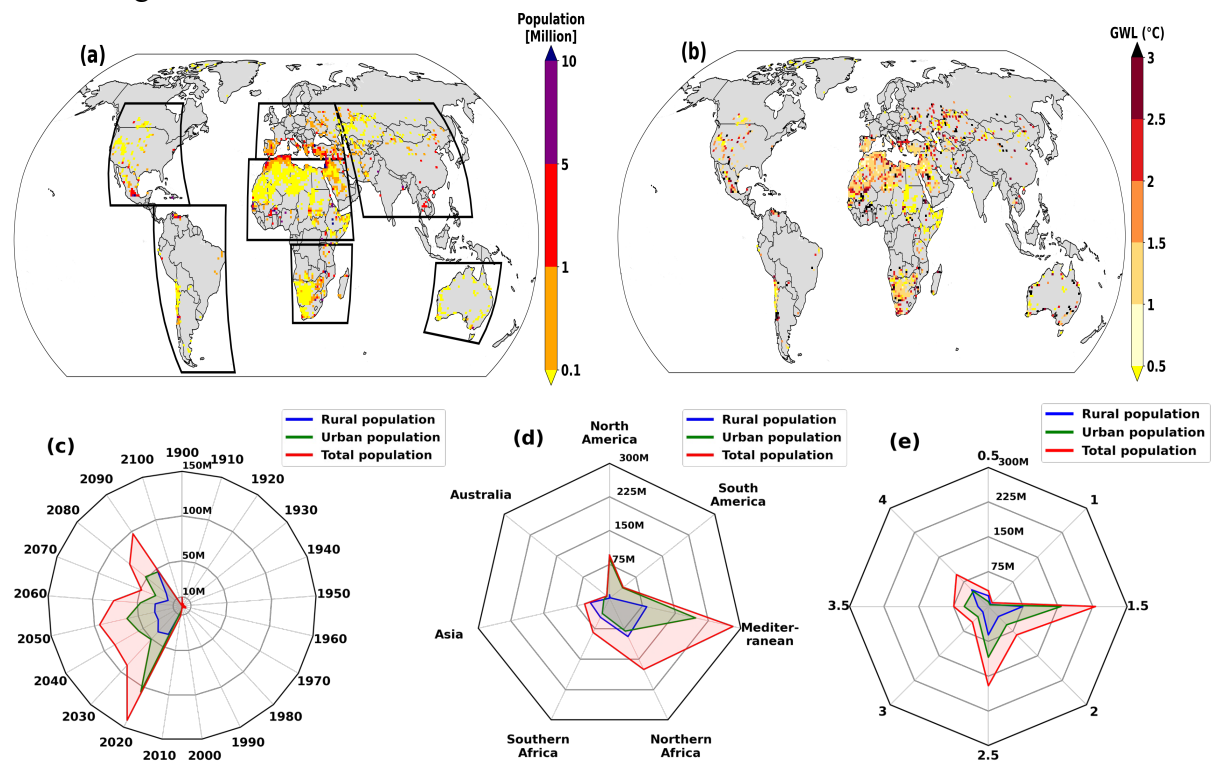


Fig. 4: Population exposure and global warming levels associated with the Time of First Emergence (ToFE) of Day Zero Drought (DZD) based on CESM2-LE ensemble simulations under the SSP3-7.0 scenario. (a) Spatial distribution of the total population exposure at the ToFE of DZD across the global DZD-prone regions. The color scale indicates the total population (urban and rural) exposed when DZD first emerges in each grid cell. (b) Global

distribution of the Global Warming Level (GWL, in °C above preindustrial) corresponding to the ToFE of DZD, providing insight into the warming levels associated with the onset of DZD events. (c) Circular diagram illustrating the rural, urban, and total population exposure to DZD at the ToFE, spanning the period from 1900 to 2100. (d) Regional distribution of rural, urban, and total populations affected by DZD, computed as the sum exposed respective rural, urban, and total population within each regional hotspot (demarcated black box in panel a) at their respective ToFE. (e) Distribution of population exposure relative to the GWL at ToFE. Radar plots (c-e) emphasize the relative contributions of rural and urban populations to total exposure, highlighting disparities in vulnerability and exposure across both time and regions.

• Line 258. It should be said that here it is not accounted for how water reservoirs will change in the future, as they are assumed stationary. Re-planning of water reservoirs is one of the main adaption strategies, and in principle, this could be included in the framework you present.

Response: We agree that changes in reservoir capacity and management are important components of future water scarcity and adaptation strategies. In our current framework, reservoir storage is assumed to remain stationary over time, due to the lack of a globally available dataset. We now explicitly clarify this assumption in the manuscript (see lines 759-771) and acknowledge it as a limitation of this study (see lines 446-455). Additionally, we have provided some discussion of the sensitivity of our results to reservoir inclusion in the Results section (see lines 224-242) and the Sensitivity Analysis section (see lines 971-992).

We found that excluding both drought duration and TRD increases the event occurrence in both historical and future periods, thereby raising their probability. This will delay the human-induced signal ($FAR \geq 0.99$), leading to later ToFE compared to Fig.2, particularly in the Mediterranean regions (now presented in Supplementary Figure S12). In contrast, DZD emerges earlier in other regions because the probability of future events exceeds the pre-industrial baseline earlier, enabling earlier detection of $FAR \geq 0.99$.

When considering the reservoir component, we find that the longer it takes for an unprecedented drought to drain water in reservoirs, the later the ToFE will occur, particularly in Mediterranean regions. An increase in TRD, quadrupling the TRD, will affect the ToFE of the 8% of the DZD-prone regions, causing later emergence than shown in Fig. 2a (Fig. S11). Therefore, the duration of drier conditions, combined with rising human water consumption, can dry the reservoirs and trigger severe DZD, including reservoir-dependent regions.

In addition, we have dedicated a section on Adaptation pathways and policy implications (lines 403-420), which outlines strategies for mitigating the risks of DZD and building resilience in vulnerable regions, including the re-planning of water reservoirs (lines 416-418).

• Line 413. Who first introduces the SWSI?

Response: The Standardized Water Scarcity Index (SWSI) used in this study is conceptually equivalent to the Supply and Demand Balance Index (SDBI) introduced by Huang and Yin (2017). The SDBI is defined as the ratio of total water supply to total water demand (represented in this study by water consumption) and serves as an indicator of water scarcity based on supply-demand imbalances. However, since Huang and Yin (2017) did not intend for

the SDBI to be used as a time-scale-based index, we adopt the alternative name, SWSI, to respect the original conceptual framework and avoid misrepresenting the intent of the SDBI index.

To the best of our knowledge, however, no prior study has applied this ratio-based index using multi-timescale accumulations, such as monthly or multi-year aggregations. In this study, we extend this approach by calculating the index over a 48-month timescale accumulation period and adopt the term Standardized Water Scarcity Index (SWSI48) to emphasize both the standardization of the index and its use for evaluating long-term imbalances between accumulated total water supply and demand. SWSI48 represents the standardized form of the imbalance between the 48-month accumulated total water supply and the 48-month accumulated total water demand. The clarification has been added to the revised manuscript in the methodology section, see lines 640-661.

Reference: Huang, L. & Yin, L. Supply and Demand Analysis of Water Resources based on System Dynamics Model. *J. Eng. Technol. Sci.* **49**, 705–720 (2017).

• Line 436 Bias correction: why a reanalysis for precipitation and temperature and not observations? Also, can we implicitly assume that the bias will be the same in the future? Also, the method could be briefly explained and not just referenced.

Response: We acknowledge the importance of carefully selecting an appropriate reference dataset for bias correction. In our study, we chose to use reanalysis data instead of direct observations because reanalyses provide more complete spatial and temporal coverage (1979-2022 for this study), as well as an internally consistent representation of climate variables. This is especially advantageous in regions or time periods where observational records are limited, inconsistent, or spatially sparse. The reanalysis data bridges the gap between observations and numerical modelling. While reanalyses are not free from biases, their physical consistency and coverage make them a practical reference choice for large-scale climate applications. This rationale has been clarified in the revised manuscript (see lines 676-727).

We also recognize that Quantile Delta Mapping (QDM), like most bias correction methods, assumes that model biases are based on the present reference dataset. While this assumption simplifies the correction process, it may not always hold under evolving climate conditions. To address this, we have included a brief explanation in the methodology section of the revised manuscript, highlighting this limitation and its potential impact on future projections (see lines 743-750).

• Line 47-48. Cape Town was on the brink of reaching a "Day Zero," but did not experience it because the winter of 2018 had slightly above-average rainfall, and the following years also saw above-average precipitation, which led to the postponement of Day Zero, and ultimately, it never occurred.

Response: We are grateful you brought this to our attention. We acknowledge that Cape Town ultimately did not reach Day Zero Drought and have revised the manuscript accordingly to clarify that although the city was on the brink of DZD, it was ultimately averted. The updated

paragraph now reflects this nuance and avoids implying that DZD occurred. These changes have been incorporated in lines 49-51 of the updated manuscript, as follows:

“Although Cape Town ultimately avoided reaching DZD, due to the slightly above-average rainfall in winter 2018 and subsequent wetter years, this event remains the major urban drought in recent history.”

- Line 43. It’s not clear what rivers are the authors talking about. Please specify.

Response: To improve clarity, we have revised the sentence to specify that the Sonderend River is the main river supplying inflow to the Theewaterskloof Reservoir, which is the largest dam in the Western Cape water supply system. Exceptionally low river flows contributed to the critical depletion of this reservoir, which was one of the most severely affected during the drought. The revisions can be found in lines 43-45 of the updated manuscript, as follows:

“This event was characterized by the lowest river flows recorded since 1904² in the Sonderend River and drained the largest reservoir³, Theewaterskloof to critical levels.”

- Reference 10 and 15 is the same but it is reported twice

Response: Thank you for your careful and helpful observation. We have corrected this redundancy and updated the references accordingly to ensure consistency throughout the manuscript. The corrected reference now appears as reference 19.

- Line 55-56. I don’t understand the logics of this sentence: why a long-term drought necessarily implies an increase in water demand?

Response: We apologize for the confusion. The sentence was intended to describe the compound nature of DZD, where the long-term drought, reduction in water storage levels, and the challenges in meeting existing water demand occur simultaneously, triggering the crisis. We have revised the sentence for clarity, and the updated version can be found in lines 59-61 of the revised manuscript, as follows:

“However, DZD represents an acute water scarcity triggered by the simultaneous occurrence of multi-year precipitation deficits, river flow depletion, and high-water demand, leading to a critical depletion of reservoirs.”

- Line 58-59. This sentence is at best ambiguous, or at worst wrong: multi-year droughts are not necessarily associated with global warming but mostly to internal natural variability. The authors can find papers in the scientific literature on that. Human-caused climate change can of course make them more likely or exacerbate them, but this is not clear at all from what they authors wrote here.

Response: We agree that multi-year droughts are primarily driven by natural variability, while human-induced climate change can contribute to their likelihood or severity. The aim of our study is to reflect the contribution of global warming to the emergence of water scarcity driven by drought conditions. To address your concern, we have revised the sentence for clarity and precision. The updated version can be found in lines 65-67 of the manuscript, as follows:

“Multi-year meteorological drought, driven by insufficient precipitation and potentially exacerbated by global warming, can lead to hydrological droughts characterized by abnormally low river flows, reducing water availability.”

- Line 65-66. I just can't understand what this sentence means.

Response: We sincerely apologize for the lack of clarity in the sentence. Our intention was to highlight that the increasing water demand driven by economic development, population growth, and modern agriculture can exceed the available water supply, especially when compounded by unsustainable water use practices and the effects of drought. To address this, we have revised the sentence in the manuscript to improve clarity and convey the intended meaning more precisely. The updated version can be found in lines 79-81, as follows:

“Intensive water consumption due to economic development, population growth, and modern agriculture, heightens the risk that water resources, depleted by drought, will not be able to meet sectoral water demands.”

- Line 66-67. Here it should specified that this mostly what future projections indicate, as historical trends on, e.g., annual mean precipitation, still do not show clear trend patterns.

Response: We have revised the manuscript to clarify that the projected disruptions in the water cycle and associated dry conditions are primarily based on future climate projections. These clarifications can be found in lines 81-85 of the revised manuscript, as follows:

“On a global level, future climate projections indicate that global warming is expected to disrupt and intensify the water cycle variability²⁴, leading to more severe wet-dry fluctuation periods²⁵, enhancing evapotranspiration²⁶, and reducing precipitation and surface runoff²⁴ in many regions. These changes are expected to increase the likelihood of both climatological and hydrological water stress^{27–30}. ”

- Line 75-77. I just don't understand what this sentence means. It is also not clear what a “reservoir feedback” is.

Response: We apologize for the ambiguity in the original sentence. By “reservoir feedback”, we refer to the feedback loop created by over-reliance on the reservoir to buffer drought. Increased reservoir storage capacity can encourage higher water consumption, which in turn increases vulnerability to shortages when reservoirs are depleted during prolonged droughts. Reservoirs are essential for managing local water availability and assessing water scarcity severity under climate change. However, this dependence can mask underlying water stress and delay necessary adaptation measures. To improve clarity and address this point, we have revised the sentence accordingly. The updated version is provided in lines 97-102 of the revised manuscript, as follows:

“Reservoirs are essential for managing local water availability and assessing the severity of water scarcity under climate change⁴⁰. However, reservoir feedback^{41,42} due to reservoir dependence can increase vulnerability to water shortages during prolonged drought, as increased storage capacity encourages greater water consumption. Reservoirs help mitigate hydrological extremes, but over-reliance can mask water stress and delay adaptation strategies.”

- Line 260-261. I just don't understand what this sentence means.

Response: We have revised the sentence to improve its clarity. Please refer to lines 479-484 of the revised manuscript for the updated version, as shown below:

“Note that SWSI on its own can identify water scarcity driven by high water consumption, but that can occur without climate-caused drought conditions. This distinction is important in the context of our study, as we define DZD as a prolonged anthropogenic drought-driven water scarcity caused by socio-physical factors, including water supply, human-made reservoirs, lakes, and sectoral water consumption. Therefore, it is essential to consider multiple indicators for assessing extreme events⁶⁸, including SPEI48, SRFI48, and SWSI48.”

- Line 289-290. “as it reflects the interaction between the drought events and the reservoirs”. It's not clear what this means.

Response: Thank you for your comment. We acknowledge that the sentence was unclear and have revised it to improve clarity. The sentence emphasizes the importance of incorporating the Time for Reservoir to dry (TRD) metric dynamically in water scarcity assessments, as reservoir operations can influence how drought conditions affect water availability. A longer TRD indicated that it takes more time for the compound drought to deplete reservoir storage, thereby delaying the onset of water scarcity impacts. These clarifications and the revised sentence can be found in lines 446-455, as follows:

“The GRand database provides valuable reservoir data but lacks information on real-time-varying hydrological dynamic details and includes unverified entries, limiting the number of reservoirs used. Although our study assumes stationary TRD, the static TRD effectively defines the minimum drought duration required to deplete reservoirs below critical storage levels, but it limits the ability to capture the future dynamic reservoir operations during drought. In the era of ongoing dam construction, time-varying TRD is essential for understanding how reservoir strategies influence water scarcity, but such data are currently unavailable. The interaction between socio-physical drivers and reservoir management is essential for defining compound climate extreme events^{31,66} and assessing DZD impact. Despite data limitations, our approach provides a practical and reproducible framework for vulnerability assessment.”

- Line 387-388. I just don't understand this sentence.

Response: We have revised the sentence to highlight that the SPEI is a flexible index that captures multi-year water deficits that can lead to long-term storage declines. This makes SPEI particularly valuable for assessing how prolonged drought trends affect hydrological systems, as well as water storage levels. The revised sentence now provides a clearer and more transparent description of SPEI's relevance for identifying prolonged drought impacts. Please refer to lines 610-614 of the revised manuscript, as shown below:

“Moreover, the SPEI allows comparisons between regions across different climatic conditions and considers the onset and duration of drought. The SPEI can be used to investigate the impact of prolonged multi-year drought trends on hydrological and ecological variables, as well as on water storage deficits^{90,91}.”

- Line 400. It is not clear what are the variables used in the definition of SRFI.

Response: Thank you for pointing this out. The SRFI is based on river discharge data, which reflects non-precipitation-driven water inputs. We provide a clearer definition of SRFI and explicitly state the variables it is based on. The revised sentences can be found in lines 625-630, as written below:

“This is where the Standardized River Flow Index (SRFI) plays a crucial role, as it captures river drought conditions based on streamflow variations, reflecting both precipitation-driven and non-precipitation-driven water inputs. Therefore, we use a single input standardized drought index, called SRFI, the same as Vicente-Serrano et al.⁹⁶, to represent and categorize the severity of the river flow resource depletion. The river discharge data was used as the input to calculate SRFI.”

- Line 421-422: here we have five GCMs out of the blue, and that’s a bit confusing as you say you are using only CESM2.

Response: Thank you for the observation. We primarily used CESM2-LE simulation under the SSP3-7.0 scenario to analyze climate and hydrological data. However, sectoral water use data, both historical and projected, are not available under CESM2-LE. Therefore, we used water demand, specifically water consumption data of the SSP3-RCP6.0 from five Global Climate Models (GCMs): GFDL, HADGEM, IPSL, MIROC, and NORESM, provided by Khan et al. (2023), solely to represent future socio-economic water demand. We have clarified this point in lines 554-559 and 652-655 of the revised manuscript, as follows:

Lines 554-559: *“The monthly global gridded water consumption data for sectoral water use under SSP3 and SSP2, and the Representative Concentration Pathways scenario, RCP6.0 and RCP4.5, covering the period from 2010 to 2100, were downloaded from Khan et al⁷⁶. Both scenarios are available from the same five Global Climate Models (GCMs): GFDL, HADGEM, IPSL, MIROC, and NORESM. We use the available SSP3-RCP6.0 data due to the unavailability of sectoral water use data for SSP3-RCP7.0.”*

Line 652-655: *“Therefore, to calculate SWSI⁴⁸, the total water consumption from the five Global Climate Models (GCMs) provided by Khan et al⁷⁶ (GFDL, HADGEM, IPSL, MIROC, and NORESM) is randomly distributed across the total water supply from the CESM2-LE and CNRM (see Fig. S1 for further details).”*

Reference:

Khan, Z. et al. Global monthly sectoral water use for 2010–2100 at 0.5° resolution across alternative futures. *Sci. Data* **10**, 201 (2023).

- Line 494-496. This sentence is awkward. It is not true that anthropogenic global warming necessarily decrease water supplies, in some regions it can actually increase them because precipitation is projected to increase.

Response: We fully agree that the effects of climate change on precipitation are not uniform across regions; some areas may experience increased precipitation, while others may face reductions. Similarly, river discharge can vary spatially, with some regions becoming more prone to hydrological drought while others may see increased flow. Moreover, even in regions with increasing precipitation, higher evapotranspiration driven by rising temperatures can counteract precipitation increases, reducing net water availability (precipitation minus evapotranspiration, P-E) and leading to dry conditions.

We acknowledge that in regions where both precipitation and river discharge increase, and water consumption remains stable, water supply can exceed demand, and thus water scarcity may not occur. However, in many regions, rising water demand (due to population growth or economic development) can still outpace supply, even when climate-driven increases in water availability are observed. In this study, our primary focus is on water scarcity driven by long-term drought. Specifically, we examine scenarios where prolonged drought conditions reduce water supply below the level of water demand, thereby triggering water scarcity. We have clarified this point in lines 802-812 of the revised manuscript, as shown below:

“ However, global warming is expected to disrupt and intensify the variability of the water cycle²⁴, leading to increasingly frequent and severe fluctuations between excessively wet and dry periods²⁵. Warmer climates are projected to enhance the evapotranspiration, resulting in dry conditions²⁶. Additionally, reductions in precipitation and surface runoff are expected in many regions²⁴, further increasing the likelihood of both climatological and hydrological droughts^{27–30}. Moreover, population growth, economic development, and expansion of modern agriculture drive the rise in water consumption, placing additional pressure on water resources. Therefore, dry conditions driven by anthropogenic climate change and socio-economic development are jointly altering the global balance between water supply and demand, thereby amplifying the risk of DZD. Our concept distinguishes between drought and water scarcity, while also capturing their interaction in driving the DZD event.”

• Line 503. Something is wrong with the grammar of this sentence.

Response: We have revised the sentence to improve the grammar and clarity of the manuscript. Please find in lines 825-829 of the revised manuscript, written as below:

“Therefore, DZD is considered as an extreme water scarcity event, characterized by the fact that the water resources available in a region are largely below the limited reservoir’s capacity compared to the pre-industrial period. This is attributed to both anthropogenic climate change and an increase in water use. To our knowledge, this study is the first global-scale assessment of the timing of the emergence of Day Zero Drought conditions and its characteristics.”

Reviewer #2 (Remarks to the Author):

General Assessment:

The paper presents a comprehensive analysis of the emergence of unprecedented global water scarcity, focusing on the concept of "Day Zero Drought" (DZD) under anthropogenic climate change. The study employs a probabilistic framework and large-ensemble climate simulations under the SSP3-7.0 scenario to assess the time of first emergence (ToFE) of DZD, its duration, and its societal impacts. The authors use a combination of hydrological indices (SPEI, SRFI, SWSI) to evaluate multi-year droughts and water scarcity, and they incorporate reservoir dynamics to assess the severity of water shortages. The study highlights the role of climate change in driving water scarcity and emphasizes the need for proactive water management strategies.

The paper is well-structured and addresses a critical issue in the context of global climate change. The use of large-ensemble simulations and the integration of reservoir data are strengths of the study. However, there are several areas where the paper could be improved, particularly in terms of clarity, methodological rigor, and the interpretation of results. I suggest a major revision.

Response: We appreciate your thoughtful and constructive evaluation of our manuscript. We sincerely value your acknowledgment of the study's strengths, particularly the use of large-ensemble simulations, the integration of hydrological and reservoir data to investigate the Time of First Emergence (ToFE) of Day Zero Drought (DZD) under climate change. We also carefully consider your concerns regarding clarity, methodological rigor, and result interpretation. We value your recommendation for major revision and have carefully revised the manuscript to address each comment and suggestion.

My major concerns are listed below.

1 Clarity and Focus:

(1) The paper is dense and could benefit from a more streamlined presentation. The introduction and discussion sections are lengthy and could be condensed to improve readability.

Response: We fully understand your concern regarding the density of the manuscript and your suggestion to streamline the introduction and discussion sections. At the same time, we have also considered the request from another reviewer who highlighted the importance of providing more detailed explanations, particularly in the introduction, as well as a clearer articulation of the limitations of the study, which we now address in a newly added Uncertainty section. In revising the manuscript, we have sought to strike a balance by enhancing the clarity and details where necessary, while tightening the text to improve overall readability.

(2) The concept of "Day Zero Drought" (DZD) is central to the paper, but its definition and distinction from other types of droughts (e.g., meteorological, hydrological) could be clarified earlier in the manuscript. The authors should provide a clearer explanation of how DZD differs from other drought types and why it is particularly relevant in the context of climate change.

Response: We have revised the introduction to more explicitly define DZD and to clarify how it differs from conventional drought categories such as meteorological and hydrological droughts. We now emphasize that DZD is an acute physical water scarcity driven by the

simultaneous occurrence of multi-year precipitation deficits, river flow depletion, and high-water demand, leading to critical reservoir depletion. DZD is therefore conceptualized as a multi-year compound extreme event. Unlike traditional drought, DZD captures the interactions between climate drivers and anthropogenic water use that contribute to large-scale and severe impacts on water supply. We have incorporated this expanded explanation in lines 54-71 of the revised manuscript to better establish the distinctiveness and relevance of DZD within the broader context of climate change, drought, and water scarcity, as shown below:

“Traditional droughts, meteorological, agricultural, and hydrological, are typically assessed in isolation based on deficits in precipitation, soil moisture, or streamflow. In contrast, water scarcity is a multidimensional event arising from insufficient quantity, compromised quality, and unmet environmental flow requirements, constraining the sustainable availability of water sources for human and ecological systems⁹. This study focuses on socio-physical water scarcity, driven by anthropogenic supply-demand imbalances. However, DZD represents an acute water scarcity triggered by the simultaneous occurrence of multi-year precipitation deficits, river flow depletion, and high-water demand, leading to a critical depletion of reservoirs. Therefore, DZD is a multi-year compound extreme event that is determined by the concurrent occurrence of several interdependent events¹⁰. A compound extreme event refers to a simultaneous occurrence of multiple extreme events that can have drastic effects on a large scale, far greater than the impact of an individual event^{11,12}. Multi-year meteorological drought, driven by insufficient precipitation and potentially exacerbated by global warming, can lead to hydrological droughts characterized by abnormally low river flows, reducing water availability. Such combined events considerably increase the risk of water scarcity when the available supply is less than the demand. Hence, the simultaneous occurrence of several climate extremes can lead to more severe impacts¹³ on water supply¹⁴ and subsequently on society and ecosystems¹⁵, highlighting the need for integrated drought assessment frameworks that account for compound events.”

(3) The relationship between "drought" and "water scarcity" is not well-explained. While drought is a natural phenomenon characterized by a temporary reduction in water availability, water scarcity often results from a combination of natural and anthropogenic factors, including drought, population growth, and mismanagement of water resources. The authors should explicitly clarify how drought contributes to water scarcity in their framework and how the two concepts interact in the context of DZD. This distinction is critical for understanding the compound nature of the events being studied.

Response: We have revised the manuscript to explicitly articulate the relationship between “drought” and “water scarcity”. Water scarcity arises from an imbalance between the reduced water supply and the increasing demand. While this imbalance is shaped by multiple anthropogenic factors, such as socio-economic growth, increased water use (domestic, agricultural, and industrial), climate change can exacerbate it by reducing water supply through decreased precipitation, diminished river flow, and depletion of reservoir levels.

Within the context of DZD, we conceptualize drought as the key physical trigger of water scarcity. Specifically, multi-year meteorological and hydrological droughts reduce water availability at the same time as demand pressures intensify. DZD events occur when these

drought-driven supply reductions coincide with high and often growing demand, limited alternative water sources, and strong reliance on surface water reservoirs. This interaction between drought and anthropogenic demand factors is central to the compound nature of DZD. This compound interaction is now more clearly articulated in both the introduction (lines 54-71) and methods section (lines 784-850) of the revised manuscript, as written below:

Lines 54-71: *“Traditional droughts, meteorological, agricultural, and hydrological, are typically assessed in isolation based on deficits in precipitation, soil moisture, or streamflow. In contrast, water scarcity is a multidimensional event arising from insufficient quantity, compromised quality, and unmet environmental flow requirements, constraining the sustainable availability of water sources for human and ecological systems⁹. This study focuses on socio-physical water scarcity, driven by anthropogenic supply-demand imbalances. However, DZD represents an acute water scarcity triggered by the simultaneous occurrence of multi-year precipitation deficits, river flow depletion, and high-water demand, leading to a critical depletion of reservoirs. Therefore, DZD is a multi-year compound extreme event that is determined by the concurrent occurrence of several interdependent events¹⁰. A compound extreme event refers to a simultaneous occurrence of multiple extreme events that can have drastic effects on a large scale, far greater than the impact of an individual event^{11,12}. Multi-year meteorological drought, driven by insufficient precipitation and potentially exacerbated by global warming, can lead to hydrological droughts characterized by abnormally low river flows, reducing water availability. Such combined events considerably increase the risk of water scarcity when the available supply is less than the demand. Hence, the simultaneous occurrence of several climate extremes can lead to more severe impacts¹³ on water supply¹⁴ and subsequently on society and ecosystems¹⁵, highlighting the need for integrated drought assessment frameworks that account for compound events.”*

Lines 784-850: **“Day zero drought definition.** We define “Day zero drought” (DZD) as an acute water scarcity event driven by a compound multi-year hydrological drought, during which water demand exceeds water supply under prolonged drought conditions. DZD occurs due to a critical imbalance between supply and demand, driven both by climate-induced reduction in supply and anthropogenic pressures increasing demand.

In fact, water can be retained in the reservoir through different parts of the hydrological cycle and different resident times (time of water spent in reservoirs) considered similar to TRD. As the river flow contributes to the long-term storage of water in the reservoir, we considered the river discharge to be an appropriate parameter. DZD is the impact of the simultaneous occurrence of a long-term (48-month) critical rainfall deficiency and extreme dearth of water of low-flow river discharge during a prolonged drought in the context of global warming and long duration exceeding the time for the reservoirs to run out of water. This is formalized as follows:

$$DZD \text{ occurs if} \tag{3}$$

$$\begin{cases} SPEI_{48} \leq -1.5 \cap SRFI_{48} \leq -1.5 \cap SWSI_{48} \leq 0.6, dur_{ce} \geq TRD, \text{ if reservoir exists.} \\ SPEI_{48} \leq -1.5 \cap SRFI_{48} \leq -1.5 \cap SWSI_{48} \leq 0.6, \text{ if there is no reservoir.} \end{cases}$$

where dur_{ce} is the duration of the compound extreme. The identification of DZD was carried out at each grid cell across each of the 100 members of the CESM2-LE model, offering a comprehensive and probabilistic perspective on future water scarcity risk.

However, global warming is expected to disrupt and intensify the variability of the water cycle²⁴, leading to increasingly frequent and severe fluctuations between excessively wet and dry periods²⁵. Warmer climates are projected to enhance the evapotranspiration, resulting in dry conditions²⁶. Additionally, reductions in precipitation and surface runoff are expected in many regions²⁴, further increasing the likelihood of both climatological and hydrological droughts^{27–30}. Moreover, population growth, economic development, and expansion of modern agriculture drive the rise in water consumption, placing additional pressure on water resources. Therefore, dry conditions driven by anthropogenic climate change and socio-economic development are jointly altering the global balance between water supply and demand, thereby amplifying the risk of DZD. Our concept distinguishes between drought and water scarcity, while also capturing their interaction in driving the DZD event. Drought refers to a reduction in water availability either through decreased precipitation, increased evaporation, or reduced river flow. In contrast, water scarcity arises when water demand exceeds the available water supply. Water Scarcity is often human-driven from anthropogenic pressure, such as population, growth, agricultural expansion, industrial use, and mismanagement of water resources. Water scarcity can occur even in the absence of climate change if water use is unsustainable. In this study, we focused on water scarcity driven by drought, where the reduction of water supply is driven by dry conditions. In this context, the water stress is considered as a result of a compound event due to atmospheric conditions (precipitation and evaporative demand; SPEI48), streamflow conditions (SRFI48), and demand condition (SWSI48) of 48-months occur with important depletion of water supply and increase of water demand; and where the duration of the event is longer than the time of the closest reservoirs to dry (TRD). This study offers a global-scale assessment of DZD emergence and its characteristics, capturing the interactions between climate human-driven factors.

Therefore, DZD is considered as an extreme water scarcity event, characterized by the fact that the water resources available in a region are largely below the limited reservoir's capacity compared to the pre-industrial period. This is attributed to both anthropogenic climate change and an increase in water use. To our knowledge, this study is the first global-scale assessment of the timing of the emergence of Day Zero Drought conditions and its characteristics. DZD is characterized by the concurrent exceedance of critical threshold in four indicators: (i) The standardized Precipitation-Evapotranspiration Index (SPEI48) below minus 1.5 ($SPEI48 \leq -1.5$, exceedance of 1.5 standard deviations, signifying 1.5 standard deviation droughts to classify the extremely dry atmospheric condition, through prolonged deficits in precipitation and increased evapotranspiration, leading to a long-term surface water stress and can significantly influence the change in groundwater (Fig. S13). (ii) The Standardized River Flow Index (SRFI48) below minus 1.5 ($SRFI48 \leq -1.5$, exceedance of 1.5 standard deviation), signifying 1.5 standard deviation droughts, to detect the depletion of river flow conditions, representing the state of the severe drought in river flow during dry periods. (iii) The

Standardized Water Scarcity Index (SWSI48) below 0.6 ($SWSI48 \leq 0.6$) is used to quantify the imbalance between total water supply and demand and to represent the long-term average insufficiency of resources relative to demand during periods of drought, leading to an acute water scarcity. (iv) The duration of the compound event (dur_{ce}) exceeding the estimated time for reservoir depletion (TRD), when reservoirs exist. If no reservoir is present, the DZD is defined by the first three indicators. This framework reflects the reality that water scarcity emerges from the convergence of multiple stressors. Each indicator plays a distinct but interrelated role in defining DZD; therefore, none is weighted as more important than another. Their simultaneous exceedance is necessary to identify a DZD event, filtering out less severe or isolated events. For instance, precipitation deficits alone may not result in a crisis without demand pressure. i.e., in low low-demand case, just as high demand may not lead to scarcity if the supply is still enough. Similarly, even in the absence of climate variability, unsustainable consumption alone can trigger water scarcity if water use surpasses the available resource.”

(4) In a 2017 paper, *Water Scarcity Assessments in the Past, Present, and Future*, authors explored the validation of water scarcity using drought indicators. By analyzing modeling data over a 15-year period, they demonstrated that 6 out of 14 tested water scarcity indicators showed a statistically significant relationship with the occurrence of drought-related crises [Alcamo et al., 2008]. This foundational work suggests that it is feasible to validate water scarcity indicators, determine their appropriate range of application, and establish reliable scarcity thresholds. Further research in this direction would not only strengthen the scientific basis for estimating water scarcity but also accelerate the development of more robust and practical indicators for assessing water stress.

Response: We appreciate the reference paper on the validation of water scarcity indicators, which indeed provides a valuable foundation for assessing the robustness of such metrics. While Liu et al (2017) provided a comprehensive review of water scarcity assessments and highlighted the importance of validating scarcity indicators, their analysis was limited in temporal scope and did not fully exploit the potential of integrating drought and water scarcity indicators across long-term climate trajectories. They also emphasized the progress made in quantifying water availability and use through spatially explicit models, while pointing to persistent challenges in incorporating green water, water quality, and environmental flow requirements. Importantly, they stressed the need to account for the temporal dynamics of water scarcity, a dimension often overlooked in studies using annual data. Addressing this gap, our study employs monthly data and a 48-month timescale to better capture the duration, onset, and persistence of water scarcity, particularly under extended drought conditions.

In parallel, Almaco et al. (2008) introduced an innovative inference modelling approach to assess drought vulnerability using qualitative indicators and fuzzy set theory. While this method advanced the understanding of regional vulnerability, it remained primarily qualitative and case-specific, with limited integration of climate model data or long-term projections. Our work complements and extends these contributions by leveraging bias-corrected CESM2-LE simulations, adjusted using quantile delta mapping with ERA5 reanalysis as reference, due to the lack of global observed in-situ data, to jointly analyse standardized drought indices (SPEI48

and SRFI48) and water scarcity indicator (SWSI48) over the period 1850-2100. This enables a robust evaluation of how climatic drought and anthropogenic water stress co-evolve across time and space. By integrating physically based indicator with long-term climate projections and correcting for model biases, our study offers a more dynamic, quantitative, and forward-looking framework for assessing water scarcity, one that aligns with and advances the foundational insight of Liu et al. (2017) and Alcamo et al. (2008), while addressing the need for integrating, temporally explicit assessments of water stress under a changing climate.

Nonetheless, a key limitation of the present study is its focus on the quantity of water availability without explicitly accounting for water quality (as noted in the Uncertainty section, lines 442-445). This focus is a deliberate methodological choice, driven by the study's emphasis on Day Zero-like drought events, in which the primary concern is the extreme depletion of water resources to critically low levels, often resulting in the physical unavailability of water for essential human and ecological needs, regardless of its quality. These events, exemplified by the Cape Town crisis, are driven by an acute imbalance between water supply and demand, making the quantification of available water the most urgent and policy-relevant priority. While water quality and environmental flow requirements are undoubtedly an essential component of broader water security, the immediate risks associated with Day Zero scenarios are primarily linked to a decline in the quantity of supply.

Lines 442-445: *“Notwithstanding anthropogenic global warming, population growth and economics remain the major drivers of the water crisis by increasing demand^{27,34}. Our study considers the socio-physical aspects of water security and excludes factors like national water policies, governance, quality, and environmental flow requirements.”*

As emphasized Liu et al. (2017), water scarcity is a multi-dimensional issue, and the availability of water for human and ecological use is not solely a matter of quantity but also quality. Degraded water sources can exacerbate water stress, especially in regions where freshwater supplies are already limited. While this study focuses on socio-physical water scarcity, we acknowledge in the Discussion section that incorporating water quality and environmental flow considerations is essential for a more comprehensible understanding of future water risks. This point is discussed in lines 485-487, as written below:

“Although this study focuses on socio-physical water scarcity, incorporating water quality and environmental flows, as highlighted by Liu et al.⁹, is critical for a holistic understanding of future water risks.”

Reference:

- Liu, J. et al. (2017), Water scarcity assessments in the past, present, and future, *Earth's Future*, 5, 545–559, doi:10.1002/2016EF000518.
- Alcamo et al. (2008), A new approach to quantifying and comparing vulnerability to drought, *Reg Environ Change* (2008) 8:137–149, doi:10.1007/s10113-008-0065-5

(5) The authors reference Liu et al. (30) but describe their work as "few studies" rather than acknowledging it as the first study to reveal the timing of the first emergence and disappearance of global water scarcity on a global scale. This is a significant oversight, as Liu et al. (30) provide a groundbreaking contribution to the field. A proper credit is required.

Response: We now fully acknowledge that Liu et al. (2024) represent a groundbreaking contribution to the field, particularly in being among the first to reveal the timing of the emergence and potential disappearance of global water scarcity. We recognize that our original phrasing may have inadvertently understated the pivotal role of Liu et al. (2024) in advancing global water scarcity research. In response, we have revised the manuscript to clearly and explicitly acknowledge Liu et al. (2024) as a landmark study, one of the first to reveal the timing of both the emergence and potential disappearance of global water scarcity on a global scale. Their work represents a major milestone in the field, and we are grateful for the opportunity to appropriately highlight and credit this important contribution in our revised text. These revisions can be found in lines 91-94 of the revised manuscript, as shown below:

"To the best of our knowledge, few studies have assessed the Time of First Emergence (ToFE) of extreme events such as unprecedented hydrological drought³⁸ and water scarcity³⁹, under human-induced climate change. For instance, Liu et al.³⁹ estimated the ToFE of water scarcity and its potential disappearance based on a per-capita water availability metric."

Reference:

- Liu, J. et al. Timing the first emergence and disappearance of global water scarcity. Nat. Commun. 15, 7129 (2024).

2 Methodological Concerns:

(1) The paper relies heavily on the SSP3-7.0 scenario, which represents a high-emission pathway. While this scenario is useful for understanding worst-case scenarios, the lack of comparison with lower-emission scenarios (e.g., SSP1-2.6 or SSP2-4.5) limits the broader applicability of the findings. The authors should consider including results from other scenarios to provide a more comprehensive view of future water scarcity under different climate trajectories.

Response: We appreciate the reviewer's insightful observation regarding the reliance on a single emission scenario (SSP3-7.0). In the revised manuscript, we have addressed this methodological concern by incorporating a comparative analysis of the ToFE of DZD under SSP3-7.0 (high emission) and SSP2-4.5 (intermediate-emission) pathways. Specifically, we have expanded our analysis to include comparisons with a structural uncertainty that arises from model differences and scenario dependence, using simulation from the Centre National de Recherche Météorologiques (CNRM) models under both SSP2-4.5 and SSP3-7.0, sourced from the Coupled Model Intercomparison Project Phase 6 (CMIP6). The new results are presented in the Supplementary Figures S20 and S21, as shown below. We included ten ensemble members from the CNRM model under SSP2-4.5 and SSP3-7.0, enabling a direct

comparison with the CESM2-LE SSP3-7.0 ensembles. This addition allows us to evaluate the sensitivity of DZD relative to different models and climate trajectories.

Our findings indicate that under the lower-emission SSP2-4.5 scenario, the Probability Density Function (PDF) of ToFE is generally delayed and less concentrated, with more widespread emergence, reflecting lower likelihood and slower onset of DZD conditions. In contrast, SSP3-7.0 projects a high likelihood of DZD emergence between 2020-2040 due to stronger climate and hydrological forcing. While our primary focus remains on the CESM2-LE SSP3-7.0 simulations due to their large ensemble size and ability to capture high-risk, policy-relevant scenarios, we agree that incorporating multiple emission scenario perspectives enhances the robustness and policy relevance of our findings. Accordingly, we now discuss these differences in the Results section (lines 243-252) and Sensitivity Analysis section in the methodology (see lines 1071-1118) to reflect the influence of emissions pathways on compound drought risks.

In the revised Results section (lines 243-252), we now state the following:

“Furthermore, the emergence of unprecedented water stress and scarcity can be dependent on model structure and scenario pathways^{38,39}. To address this, we use data from the CNRM model using two scenarios, SSP3-7.0 and SSP2-4.5. Only this CMIP6 model provided all the necessary variables for our compound DZD indicator. We find that the influence of the scenario on DZD ToFE is region-specific (Fig. S21b-c and f) due to the interaction between regional climate drivers and human water use. Both high (SSP3-7.0) and moderate (SSP2-4.5) scenarios can advance, delay, or have no change on DZD emergence, depending on the region. As a model structure also drives spatial discrepancies (Fig. S21a-b and d-e): CESM2-LE projects broader DZD regions in northern Africa, whereas CNRM highlights some different regions. However, the hot spot regions, the Mediterranean, southern Africa, and North America, are very similar.”

We have added the following sensitivity analysis in the methodology section in lines 1071-1118:

“Finally, to assess the sensitivity of the ToFE of DZD relative to future socioeconomic scenarios, we applied our detection framework to hydro-climatic simulations from CMIP6 CNRM models under the SSP2-4.5 scenario. We utilized the same ensemble members as in the previous CNRM SSP3-7.0 analysis to ensure consistency. The analysis incorporated available water consumption projections from five Global Climate Models (GCMs) from GFDL, HADGEM, IPSL, MIROC, and NORESM under SSP2-RCP4.5. The approach followed the same methodological steps as applied to CESM2-LE (Fig. S1). Specifically, we computed the SPEI48, SRFI48, and SWSI48, and applied the bias correction method, QDM, using ERA5-based reference indices, and subsequently determined the ToFE. All datasets are interpolated to the CNRM atmospheric resolution (1.4° x 1.4°) using the first-order conservative remapping (remapcon) method from the CDO. The results (Fig. S20c) reveal substantial spread among ensemble members under CNRM SSP2-4.5, highlighting pronounced uncertainty in DZD emergence timing throughout the 21st century. Compared to the higher-emission SSP3-7.0 (Fig. S20b), the emergence is delayed and more dispersed, with broader PDFs and later peaks,

suggesting that moderate forcings lead to slower distribution and less certain emergence of water scarcity extremes. When comparing the special pattern of ToFE under CNRM SSP2-4.5 with CESM2-LE SSP3-7.0 (Fig. S21e), results show that high spatial disagreement of 76% of land areas exhibit uncertain DZD emergence, meaning that emergence is detected in only one of the models. Only 9 % of regions show earlier emergence in CESM2-LE SSP3-7.0, while 14% indicate later emergence relative to CNRM SSP2-4.5. By considering the same model, CNRM, under different scenarios, SSP3-7.0 and SSP2-4.5 (Fig. S21f), the uncertainty still dominates but decreases to 43% of the land area, and spatial discrepancies in DZD-prone regions persist across scenarios. Notably, the near-equal split between earlier and later emergence in different regions indicates that scenario choice (SSP3-7.0 vs SSP2-4.5) may affect ToFE more symmetrically but also underscores the spatial heterogeneity of hydrological responses to combined climate and water use stress. The results show that the influence of emission scenarios on DZD ToFE is region-specific, due to the interaction between regional climate drivers and human water use. Under the high-emission scenario (SSP3-7.0), DZD emergence can either advance or be delayed depending on the region. Notably, spatial discrepancies in DZD-prone regions persist across scenarios, with 43% of the land area remaining uncertain between the SSP2-4.5 and SSP3-7.0 scenarios within the CNRM model. However, both scenarios, SSP2-4.5 and SSP3-7.0, agree on DZD emergence across 57 % of the DZD-prone land area. Within this overlap, SSP3-7.0 projects later emergence over 17% of the area and earlier emergence over 18% compared to SSP2-4.5, while 22% of the area shows no change in the ToFE between the two scenarios (Fig. S21f). These findings underscore the role of both scenario and model structures in shaping DZD emergence. Notably, even under high-forcing SSP3-7.0, CESM2-LE may still project later ToFE than CNRM under moderate forcing (SSP2-4.5), pointing to differences in model sensitivity to hydro-climatic stressors. This highlights the importance of multi-model and multi-scenario assessments when evaluating risks associated with extreme emergence and water scarcity. Furthermore, a probabilistic approach such as the FAR requires large ensembles to ensure robust estimates. The relatively small ensemble size of CNRM limits the confidence in scenario-attribution results, underscoring the need for ensemble expansion and multi-model convergence to improve attribution robustness and risk quantification. Given these model differences, CESM2-LE provides output at a higher spatial resolution ($1.25^{\circ} \times 0.9375^{\circ}$) compared to the lower-resolution CNRM model ($1.40625^{\circ} \times 1.40625^{\circ}$). CESM2-LE detects finer-scale features and localized extremes that may be overlooked or underrepresented in the CNRM. Therefore, we have not aggregated events across both CESM2-LE and CNRM, since increasing the CNRM resolution to the resolution of CESM2-LE could introduce spatial biases and distort the representation of extreme events.”

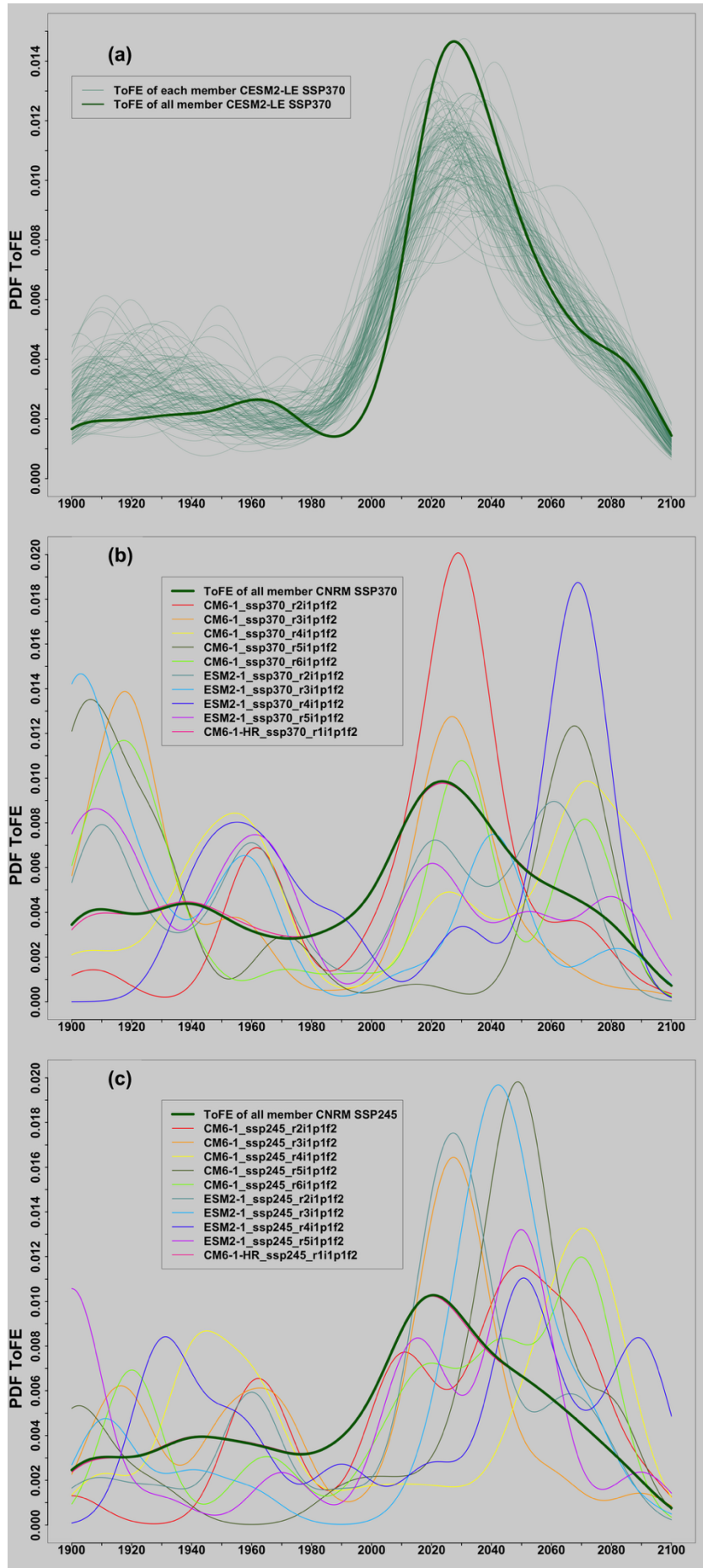


Fig S20: Probability Density Function (PDF) of Time of First Emergence of DZD events, in considering all grid points for each ensemble member across different models and scenarios. (a) ToFE PDFs from CESM2-LE under SSP3.7-0. Thick dark green line represents the PDF of the ToFE based on the sum of all DZD events (as defined in equation 4), while the thin aquamarine lines represent the PDFs of the ToFE for individual ensemble members, based on equation (5) of FAR. (b) ToFE PDFs for different ensemble members from CNRM-CM6-1 and CNRM-ESM2-1 models under SSP3.7-0. (c) Same as (b) but for SSP2.4-5. Colored thin lines represent individual ensemble members distinguished by the CNRM model (as defined in equation 5). The thick dark green line in each panel shows the ToFE based on equation (4). While our primary objective was to emphasize the externally forced signal, hence the use of aggregated events across the ensemble, to assess the internal variability and its influence on our results, we conducted a Time of First Emergence (ToFE) analysis across each ensemble member, to transparently assess the spread and uncertainty within the ensemble. This allows us to examine the spread of emerging timing of Fay Zero Droughts (DZD) and to evaluate the inter-member agreement. We computed the probability density functions (PDFs) of ToFE for each member across all global land covered by DZD. The figure (a) exhibits substantial variability among ensemble members between 1900 and 1990, reflecting high uncertainty during this early period when the anthropogenic signal is still weak relative to internal variability, showing that structural uncertainty arising from the use of a single model remains an important caveat. However, a strong ensemble consensus emerged after 2000, with most members indicating emergence between 2020 and 2030, and increasing agreement toward the end of the 21st century. This coherence across members supports the robustness of our findings in terms of both the timing and magnitude of anthropogenic influence on DZD events. Figure (b) and (c) shows a disagreement between the model in CNRM along all periods, 1900-2100. The dark green line from both models of each panel shows a high density of ToFE between the decades of 2020 and 2030. In terms of the scenario, the emergence under SSP2.4-5 is more delayed and spread out compared to SSP3.7-0. Peaks occur later, and the PDFs are broader compared to Fig. S18b. This suggests that under moderate forcing (SSP2.4-5), DZD emergence is slower and more uncertain. These results highlight the influence of both model structure and emissions scenarios on the DZD emergence.

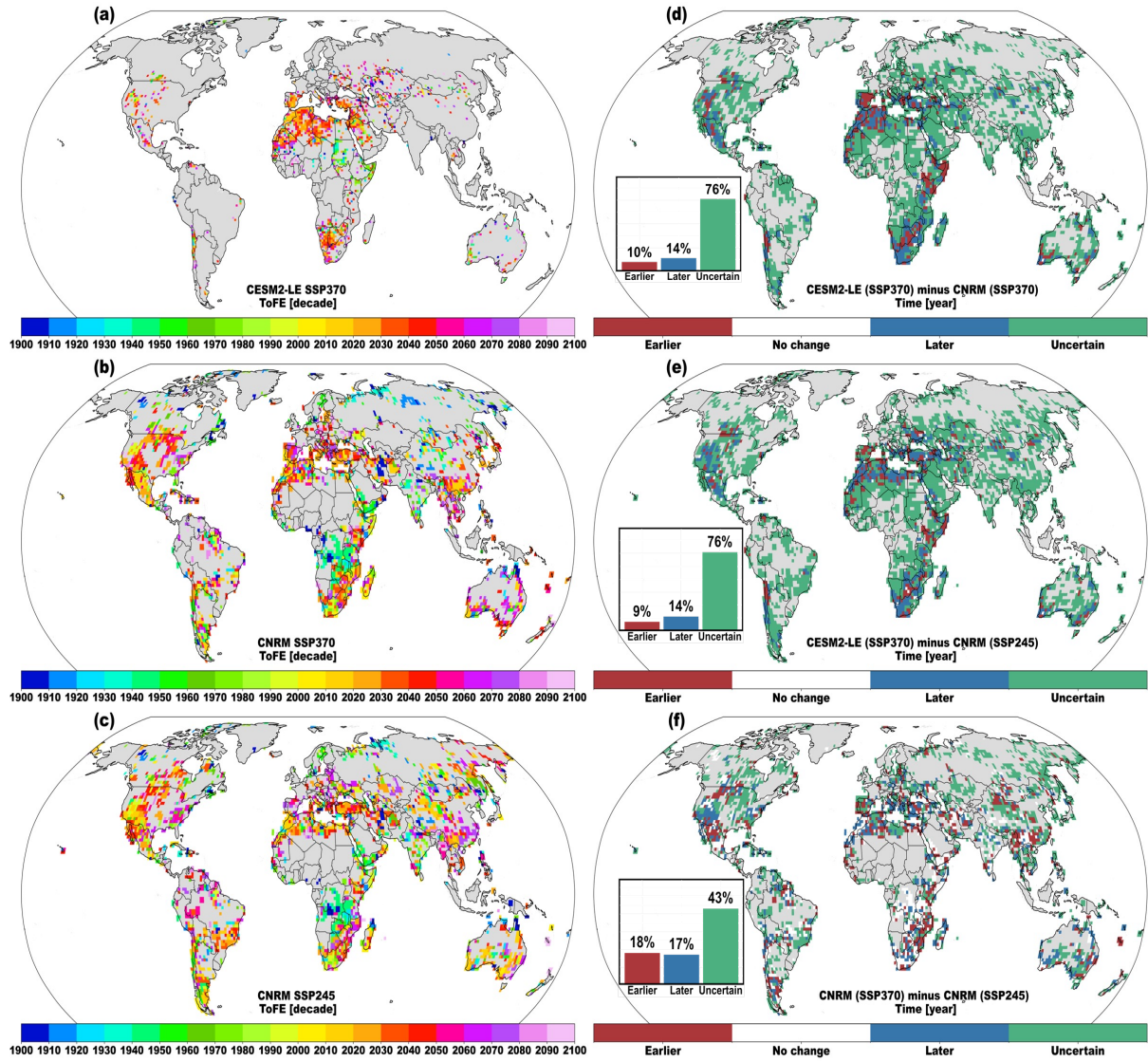


Figure S21: Spatial distribution of the Timing (ToFE) and associated uncertainties of Day Zero Drought (DZD) events across climate models and emission scenarios (CESM2-LE under SSP3-7.0 and CNRM under SSP2-4.5 and SSP3-7.0). Panels (a-c) depict the decadal ToFE of DZD events for each grid cell, calculated as the first decade in which the Fraction of Attributable Risk (FAR) exceeds 0.99, indicating that over 99% of DZD risk is attributable to anthropogenic climate change, based on the cumulative count of DZD events (Equation 4). Results are shown for (a) CESM2-LE under SSP3-7.0, (b) CNRM under SSP3-7.0, and (c) CNRM under SSP2-4.5. Panels (d-f) illustrate inter-model and scenario-based differences in ToFE for grid cells where DZD emergence is detected under those compared cases. Panel (d) represents the difference between CESM2-LE (SSP3-7.0) and CNRM (SSP3-7.0), reflecting structural uncertainty between models. For consistency, ToFE values from CESM2-LE (a) are interpolated to the CNRM resolution to compute the difference between the ToFE between CESM2-LE (SSP3-7.0) and CNRM (SSP3-7.0) as shown in (d) and (e). Panel (e) compares CESM2-LE (SSP3-7.0) and CNRM (SSP2-4.5), highlighting scenario- and model-driven uncertainty. Panel (f) compares CNRM (SSP3-7.0) and CNRM (SSP2-4.5), isolating internal model sensitivity emissions pathways. Inset bar plots in panels (d-f) quantify the proportion of DZD-prone land grid cells experiencing earlier and later emergence, as well as regions with

divergent DZD emergence (uncertain DZD-prone regions). Red and blue shading denote areas where ToFE occurs earlier or later, respectively, in the first model or scenario listed. The green shading indicates regions with inconsistent DZD emergence among the inter-model and scenarios cases (i.e., emergence only occurs in one of the models or scenarios), underscoring uncertainty in projections. The results show that CNRM projects broader emergence in parts of Asia, Australia, and America, while CESM2-LE projects earlier and later emergence across the Mediterranean and Africa. Grey areas indicate locations with no emergence of DZD condition during the analysis period. These results highlight the importance of model structure and emissions scenario in assessing the timing and spatial distribution of DZD emergence.

(2) The bias correction method (Quantile Delta Mapping) is mentioned, but the details of its application are not sufficiently explained. The authors should provide more information on how the bias correction was applied to the hydrological indices and how it affects the results.

Response: We agree that additional detail regarding the bias correction procedure is important for clarity and reproducibility. In our revised manuscript, we have expanded the methods section to provide a more detailed description of the Quantile Delta Mapping (QDM) technique used. The QDM was applied to correct biases in the water stress indices derived from the CESM2-LE simulations, using the corresponding indices derived from the ERA5 reanalysis datasets as the reference, due to a lack of long-term global in-situ observational data.

Specifically, instead of correcting independently the raw climate variables, precipitation temperatures, and river discharge, we applied Quantile Delta Mapping (QDM) directly to the derived water stress indices (SPEI, SRFI, and SWSI) as informed by the findings of Ansari et al. (2023), which demonstrated that bias-correcting multivariate climate indices, particularly standardized indices such as SPEI, is more robust and reliable than correcting the raw input variables. This post-processing approach enhances the accuracy and consistency of drought metrics across regions, especially in studies comparing multiple spatial domains and temporal scales. Each index was treated as a single variable and bias-corrected independently using the QDM method. The correction was performed on a monthly time scale over the reference period between 1979-2022, using ERA5 as the observational reference due to the lack of long-term in-situ observation data at the global scale. This approach ensures that the distributional characteristics of the modelled indices are better aligned with observationally constrained data, while the delta-change component of QDM preserves the projected trends and variability in future simulations. It adjusts only the quantiles rather than transforming the entire distribution, which can help maintain characteristics of extreme values. By applying QDM at the index level, we aimed to correct systematic biases in the characterization of drought and water scarcity conditions, while retaining the climate change signal embedded in the original CESM2-LE outputs. While QDM enhances the accuracy of climate projections for impact assessments, it has certain limitations. The method assumes that the biases identified in the historical data will persist in the future, which may not always be the case due to uncertainty associated with future climate conditions and bias patterns over time. This clarification has been added in the methods section, lines 743-750 of the revised manuscript, as follow:

“Overall, our bias correction method effectively improves the distributional agreement between CESM2-LE and ERA5, while maintaining long-term trends. This provides a more

accurate basis for assessing drought characteristics and their implications for water scarcity under historical and future climate conditions. We have included these clarifications in the Supplementary Material (Fig. S14). As with most bias correction methods, QDM has limitations, as it assumes that model biases are relative to the present reference dataset, which may change in the future. Although this assumption simplifies the correction process, it may not hold under evolving climate conditions.”

To assess the effect of different bias correction strategies, we evaluated both pre- and post-processing approaches. As shown in the supplementary figures, Fig. S14c, post-processing (i.e., bias correction of the indices) better captures the distribution of SPEI from ERA5 (Fig. S14a), while pre-processing (i.e., bias correction of precipitation and temperatures prior to computing indices, Fig. S14d) tends to introduce additional bias, particularly by amplifying wet conditions. These results support the effectiveness of the post-processing approach in preserving the observed statistical properties of the drought indices.

Furthermore, we evaluated the distributional properties of the corrected indices using Q-Q plots, shown in Fig. S14e-j. These plots compare the quantiles of SPEI48 from CESM2-LE, bias-corrected SPEI48, and SPEI48 from ERA5, both at the global mean scale and for a representative grid point (longitude 43.40° and latitude -23.21°). The Q-Q plot revealed that the bias-corrected indices closely follow the normal distribution, especially compared to the raw model output. At the grid level (longitude 43.40° and latitude -23.21°), the correction effectively adjusted the representation of extreme drought conditions and enhanced consistency with observed drought characteristics.

Overall, our bias correction method effectively improves the distributional agreement between CESM2-LE and ERA5 while maintaining long-term trends. This provides a more accurate basis for assessing drought characteristics and their implications for water scarcity under historical and future climate conditions. We provided further discussion of the implications in the Supplementary Material (Fig. S14) have included these clarifications in the revised manuscript (lines 676-750) and have included these clarifications in the revised manuscript (lines 676-750), written as below:

“Bias correction (BC). *In order to minimize the model errors, this study used a bias correction method to reduce model bias. Fig. S1 shows a more detailed structure of the steps in the methods and the processes used in this study. The monthly database from ERA5-Land (1979-2022) was used to calculate ERA5’s SPEI48 and SRFI48, with 1979-2014 as the reference period, which is used as the observational drought indices reference to calibrate the drought indices for each ensemble member of CESM2-LE individually. Although observational sources are the best to achieve the ideal bias correction, we opted for reanalysis products because they consistently assimilate a variety of variables in a physically consistent manner, and it is assumed to be close to observed data. This choice ensures global coverage and temporal completeness, particularly important in data-sparse regions or for long historical records where high-quality observational data are unavailable or inconsistent. The ERA5-Land dataset was found to be a trustworthy reference to calibrate CESM2-LE indices. In order to increase our confidence in future extreme drought projections, we applied the univariate Quantile Delta Mapping (QDM), as Ansari et al.⁹⁹ found it to be more robust for the correction of indices. Fig.*

S14 shows that direct correction (post-processing QDM) of the drought indices as a single variable reduces the bias between ERA's SPEI48 and the ensemble mean of the CESM2-LE's SPEI48 and manages to capture the distribution of SPEI48. In addition, Van de Velde et al.¹⁰⁰ stated that the simpler univariate BC methods are better to use for climate change impact assessment, as the multivariate BC methods failed to handle non-stationary climate conditions. This approach maintains the model-projected climate change signal while simultaneously correcting the distributional biases. The QDM bias correction method, introduced by Cannon et al.¹⁰¹, is a cumulative distribution function (CDF)-based bias correction method designed specifically to reduce the biases between the modeled and observed distribution of drought indices, while preserving the model-projected climate change signal. The additive form of QDM is applied to bias correct the systematic biases in each quantile of the drought indices calculated from the CESM2-LE and CNRM simulations, using the ERA-derived indices as observational references while preserving the model-projected absolute changes across all quantiles of the distribution. The important concept of QDM is its ability to maintain the trend in all the quantiles within the distribution of the climate model output, which is important when future changes are not uniform across the distribution. It is used to quantile detrend the model projections and adjust distributional biases in model projections, ensuring the sensitivity of the underlying climate model without affecting the distribution^{101–103}. The QDM begins by identifying the corresponding quantiles of the observed, model historical (or reference for the calibration), and the model future projection, as a corresponding quantile-based correction derived from the model-observation mapping. Instead of directly fitting the full distribution of the future model, QDM quantifies the change at each quantile between the historical and future period model values at that same quantile level. These changes are then applied to the observed value at the corresponding quantile, retrieved using the inverse CDF of the observed data. This allows distribution biases to be corrected while maintaining quantile-specific climate change signals, thus preserving the sensitivity of the climate model. The univariate bias correction was performed using the QDM method available in the Multivariate Bias Correction (MBC) package in R. For each grid cell, drought indices from each member of the CESM-LE and CNRM are corrected independently, using their quantile location relative to the observed (ERA5) drought indices. Specifically, each value of SPEI48 and SRFI48, computed from each grid cell of every ensemble member of the CESM2-LE and CNRM datasets, within the period 1850-2100, is corrected as a single variable following the direct QDM approach, respectively. To correct the bias in SWSI48, we applied the univariate QDM method to the total water supply (precipitation-evapotranspiration + river discharge) at each grid cell of each ensemble member of CESM2-LE and CNRM, treated as a single aggregated time series rather than bias-correcting each individual component (i.e., precipitation, evapotranspiration, and river discharge). This aggregated variable represents the net variable water and is more relevant for capturing water scarcity as reflected in SWSI48. We could not apply the bias correction of the total water demand (consumption) due to the unavailability of consistent observed sectoral water use data across the historical period at the global scale.

To assess the effect of different bias correction strategies, we evaluated both pre- and post-processing approaches using CESM2-LE under the SSP3-7.0 scenario. As shown in the Supplementary Figures, Figs. S14, post-processing (i.e., direct bias correction of SPEI, Fig.

S14c) better captures the distribution of SPEI from ERA5 (Fig. S14a), while pre-processing (i.e., bias correction of precipitation and temperatures prior to computing the index; Fig. S14d) tends to introduce additional bias, particularly by amplifying wet conditions. These results support the effectiveness of the post-processing approach in preserving the observed statistical properties of the drought indices.

Furthermore, we evaluated the distributional properties of the corrected indices using Q-Q plots, shown in Fig. S14e-j. These plots compared the quantiles of SPEI48 from CESM2-LE (raw and corrected) and ERA5, both at the global mean scale and for a representative grid point (longitude 43.40° and latitude -23.21°). The Q-Q plot revealed that the bias-corrected indices closely follow the normal distribution, especially compared to the raw model output. At the grid level (longitude 43.40° and latitude -23.21°), the correction successfully adjusted for extreme droughts and ensured consistency with observed drought characteristics.

Overall, our bias correction method effectively improves the distributional agreement between CESM2-LE and ERA5, while maintaining long-term trends. This provides a more accurate basis for assessing drought characteristics and their implications for water scarcity under historical and future climate conditions. We have included these clarifications in the Supplementary Material (Fig. S14). As with most bias correction methods, QDM has limitations, as it assumes that model biases are relative to the present reference dataset, which may change in the future. Although this assumption simplifies the correction process, it may not hold under evolving climate conditions.”

References:

- Ansari, R., Casanueva, A., Liaqat, M. U. & Grossi, G. Evaluation of bias correction methods for a multivariate drought index: case study of the Upper Jhelum Basin. *Geosci. Model Dev.* 16, 2055–2076 (2023)

(3) The paper does not adequately address the uncertainties associated with the large-ensemble simulations. While the use of 100 ensemble members is a strength, the authors should discuss the range of variability within the ensemble and how this impacts the robustness of their conclusions.

Response: We agree that addressing ensemble variability is essential for evaluating the robustness of our conclusion. In the revised manuscript, we have expanded our analysis to include comparisons with a structural uncertainty that arises from model differences between CESM2-LE and using simulation from the Centre National de Recherche Météorologiques (CNRM) models under both SSP2-4.5 and SSP3-7.0, sourced from the CMIP6. The new results are presented in the Supplementary Figures S20 and S21, as shown below. We included 10 ensemble members from the CNRM model under SSP2-4.5 and SSP3-7.0, enabling a direct comparison with the CESM2-LE SSP3-7.0 ensembles. This addition allows us to evaluate the sensitivity of DZD relative to different models and climate trajectories.

We have now included a dedicated discussion on this aspect in the Sensitivity Analysis section, where we address the sensitivity of the ToFE relative to model structure across the CESM2-LE members as shown in lines 999-1025, as written below:

“Fifthly, we look at the sensitivity of the ToFE relative to model structure among the CESM2-LE members. We repeat the analysis, looking at the model uncertainty by looking for the ToFE for each member in CESM2-LE, based on the following formulation of FAR below (equation 5). This allows us to examine the spread of emerging timing of Fay Zero Droughts (DZD) and to evaluate the inter-member agreement as shown in Fig. S20. The result exhibit, Fig. S20a, substantial variability among ensemble members between 1900 and 1990, reflecting high uncertainty during this early period when the anthropogenic signal is still weak relative to internal variability, showing that structural uncertainty arising from the use of a single model remains an important caveat. However, a strong ensemble consensus emerged after 2000, with most members indicating emergence between 2020 and 2030, and increasing agreement toward the end of the 21st century. Individual ensemble members (thin green lines) show very synchronized emergence between 2030-2040. There is a sharp, narrow peak, indicating low ensemble spread and high confidence in ToFE under strong forcing. This coherence across members supports the robustness of our findings in terms of both timing and magnitude of anthropogenic influence on DZD events in CESM2-LE under SSP3-7.0.

$$FAR_i(t) = 1 - \frac{P_{preindustrial,i}}{P_{forcing,i}(t)} \text{ with } \begin{cases} P_{preindustrial,i} = \frac{event_{preindustrial,i}(DZD)}{N_{preindustrial,i}} \\ P_{forcing,i}(t) = \frac{event(t)_{forcing,i}(DZD)}{N_{forcing,i}(t)} \end{cases} \quad (5)$$

Where $P_{preindustrial,i}$ is the probability of the counterfactual for member i , which is the ratio between the summation of the event of the DZD event within the preindustrial period (1850-1899) and the number of samples within the same period ($N_{preindustrial}$). While $P_{forcing,i}(t)$ is the probability of the factual for member i , which is the ratio between the decadal summation of the frequency of the DZD event of the member i during each decade from 1900 to 2100 and the number of samples during the decade ($N_{forcing}(t)$). The ToFE of DZD has been considered as the first decade of FAR greater than 0.99, where a 99% probability of the impact of the acute water scarcity that has emerged can be associated with a human-induced signal after the decade of completion of reservoirs.”

In addition, we evaluate the influence of model structural uncertainty on the ToFE of DZD events across the Centre National de Recherche Météorologiques (CNRM) models (SSP2-4.5 and SSP3-7.0). The discussion can be found in lines 1027- 1069, written as below:

“Sixthly, to evaluate the influence of model structural uncertainty on the ToFE of DZD events, we extended our analysis beyond CESM2-LE by using hydro-climatic data from the Centre National de Recherche Météorologiques (CNRM) models (SSP2-4.5 and SSP3-7.0 with 1.4 x 1.4 degree) from the Coupled Model Intercomparison Project Phase 6 (CMIP6). Specifically, we analysed simulations under the SSP2-4.5 and SSP3-7.0 scenario, including monthly precipitation, minimum and maximum temperature, and river discharge data spanning 1850-2100. Due to the unavailability of water demand projections under SSP3-7.0, we used water consumption estimates from SSP3-RCP6.0 across the five Global Climate Models

(GCMs) from GFDL, HADGEM, IPSL, MIROC, and NORESM, which account for sectoral water use sectors such as domestic, irrigation, industry, electricity, livestock, and mining, capturing socio-economic development water use demand. We applied the same methodology used for CESM2-LE. Computing the three key indicators, the SPEI48, SRFI48, and SWSI48, and applying quantile delta mapping (QDM) bias correction using drought indices ERA5-based references. To ensure methodological consistency and data completeness, we selected 10 ensemble members from the CNRM model that include both atmospheric and river discharge variables across the SSP2-4.5 and SSP3-7.0 scenarios: CM6-1 (r2ilplf2, r3ilplf2, r4ilplf2, r5ilplf2, r6ilplf2), ESM2-1 (r2ilplf2, r3ilplf2, r4ilplf2, r5ilplf2), and CM6-1-HR r1ilplf2. The spatial results (Fig. S21) reveal pronounced inter-model and scenario differences. We use the methods as structured estimates that enable consistent analysis across regions and sectors. The spatial resolution of the datasets is interpolated to the CNRM atmospheric model resolution ($1.4^{\circ} \times 1.4^{\circ}$) using the first-order conservative remapping (remapcon) method from the Climate Data Operator⁷⁸ (CDO). Our results reveal that, compared to CESM2-LE (Fig. S21a), which projects later DZD emergence and a more geographically confined hotspot, especially in the Mediterranean, the United States of America (USA), and Africa, the CNRM models (Fig. S21b-c) show earlier and more widespread emergence. The inter-model comparison (Fig. S21d-e) reveals that CESM2-LE and CNRM disagree on the emergence of DZD in 76% of DZD-prone regions, indicating that emergence is detected in only one of the two models in some areas. Notably, 14% of ToFE show later emergence under CESM2-LE (Fig. S21d), even under the same forcing scenario (SSP3-7.0), suggesting that CESM2-LE is more conservative in detecting later emergence of compound hydrological extremes. However, CESM2-LE and CNRM agree on DZD occurrence across 24 % of the DZD-prone land area, though within this overlap, CESM2-LE projects later emergence over 14% of the area and earlier emergence over 10% compared to CNRM. Moreover, ensemble spread within CNRM (Fig. S20b-c) also illustrates the variability among the models to detect the water scarcity. The PDFs of individual members are more dispersed, with multiple peaks and flatter. The thick green line (representing ToFE derived from equation 4) is broader and flatter, indicating the variability in ToFE across ensemble members, reflecting uncertainty in the timing of DZD emergence across members. This variability emphasized the challenge of detecting a robust probabilistic signal from a limited ensemble size. These findings highlight the critical role of model structural differences in shaping projections of hydrological extremes. Importantly, probabilistic attribution methods, such as the FAR, require large ensemble sizes to confidently characterize forced emergence signals. The relatively small ensemble available for CNRM under SSP3-7.0 limits the reliability of such analysis and reinforces the need for larger and more consistent multi-model ensemble frameworks to assess future water scarcity risks.”

Moreover, we assess the sensitivity of the ToFE of DZD relative to future socioeconomic scenarios, SSP2-4.5 and SSP3-7.0. Please refer to lines 1071-1118 of the revised manuscript for the updated, as follows:

“Finally, to assess the sensitivity of the ToFE of DZD relative to future socioeconomic scenarios, we applied our detection framework to hydro-climatic simulations from CMIP6 CNRM models under the SSP2-4.5 scenario. We utilized the same ensemble members as in the previous CNRM SSP3-7.0 analysis to ensure consistency. The analysis incorporated available

water consumption projections from five Global Climate Models (GCMs) from GFDL, HADGEM, IPSL, MIROC, and NORESM under SSP2-RCP4.5. The approach followed the same methodological steps as applied to CESM2-LE (Fig. S1). Specifically, we computed the SPEI48, SRFI48, and SWSI48, and applied the bias correction method, QDM, using ERA5-based reference indices, and subsequently determined the ToFE. All datasets are interpolated to the CNRM atmospheric resolution ($1.4^{\circ} \times 1.4^{\circ}$) using the first-order conservative remapping (remapcon) method from the CDO. The results (Fig. S20c) reveal substantial spread among ensemble members under CNRM SSP2-4.5, highlighting pronounced uncertainty in DZD emergence timing throughout the 21st century. Compared to the higher-emission SSP3-7.0 (Fig. S20b), the emergence is delayed and more dispersed, with broader PDFs and later peaks, suggesting that moderate forcings lead to slower distribution and less certain emergence of water scarcity extremes. When comparing the special pattern of ToFE under CNRM SSP2-4.5 with CESM2-LE SSP3-7.0 (Fig. S21e), results show that high spatial disagreement of 76% of land areas exhibit uncertain DZD emergence, meaning that emergence is detected in only one of the models. Only 9 % of regions show earlier emergence in CESM2-LE SSP3-7.0, while 14% indicate later emergence relative to CNRM SSP2-4.5. By considering the same model, CNRM, under different scenarios, SSP3-7.0 and SSP2-4.5 (Fig. S21f), the uncertainty still dominates but decreases to 43% of the land area, and spatial discrepancies in DZD-prone regions persist across scenarios. Notably, the near-equal split between earlier and later emergence in different regions indicates that scenario choice (SSP3-7.0 vs SSP2-4.5) may affect ToFE more symmetrically but also underscores the spatial heterogeneity of hydrological responses to combined climate and water use stress. The results show that the influence of emission scenarios on DZD ToFE is region-specific, due to the interaction between regional climate drivers and human water use. Under the high-emission scenario (SSP3-7.0), DZD emergence can either advance or be delayed depending on the region. Notably, spatial discrepancies in DZD-prone regions persist across scenarios, with 43% of the land area remaining uncertain between the SSP2-4.5 and SSP3-7.0 scenarios within the CNRM model. However, both scenarios, SSP2-4.5 and SSP3-7.0, agree on DZD emergence across 57 % of the DZD-prone land area. Within this overlap, SSP3-7.0 projects later emergence over 17% of the area and earlier emergence over 18% compared to SSP2-4.5, while 22% of the area shows no change in the ToFE between the two scenarios (Fig. S21f). These findings underscore the role of both scenario and model structures in shaping DZD emergence. Notably, even under high-forcing SSP3-7.0, CESM2-LE may still project later ToFE than CNRM under moderate forcing (SSP2-4.5), pointing to differences in model sensitivity to hydro-climatic stressors. This highlights the importance of multi-model and multi-scenario assessments when evaluating risks associated with extreme emergence and water scarcity. Furthermore, a probabilistic approach such as the FAR requires large ensembles to ensure robust estimates. The relatively small ensemble size of CNRM limits the confidence in scenario-attribution results, underscoring the need for ensemble expansion and multi-model convergence to improve attribution robustness and risk quantification. Given these model differences, CESM2-LE provides output at a higher spatial resolution ($1.25^{\circ} \times 0.9375^{\circ}$) compared to the lower-resolution CNRM model ($1.40625^{\circ} \times 1.40625^{\circ}$). CESM2-LE detects finer-scale features and localized extremes that may be overlooked or underrepresented in the CNRM. Therefore, we have not aggregated events across

both CESM2-LE and CNRM, since increasing the CNRM resolution to the resolution of CESM2-LE could introduce spatial biases and distort the representation of extreme events.”

While our study leverages the strength of the CESM2-LE, which provides 100 ensemble members, we acknowledge that relying on a single Global Climate Model (GCM) introduces limitations related to structural uncertainty (noted in lines 422-425), written as follows:

“A key limitation of this study is the reliance on a CESM2-LE and a limited number of CNRM simulations for the sensitivity analysis. CESM2-LE provides robust ensemble consistency, suitable for probabilistic analysis, but lacks scenario diversity and structural uncertainties across Earth System Models (ESMs).”

The choice of the methods in summing all Day Zero Drought events across the 100 CESM2-LE members to calculate the Fraction of Attributable Risk (FAR) is to better align with our objective of detecting an externally forced signal. This approach enhances signal clarity by reducing noise and emphasizing the anthropogenic contribution to water scarcity. It also provides a robust estimate of FAR and ToFE by focusing on the central tendency of the emergence signal. Therefore, our choice to focus on CESM2-LE was primarily motivated by its uniquely large ensemble size, which allows us to robustly quantify emergence signals and attribution metrics, such as the Fraction of Attributable Risk (FAR), with higher confidence. Nonetheless, we recognize the value of incorporating multi-model ensembles in future work to further explore structural uncertainty (noted in lines 508-510), written as follows:

“To support such efforts and reduce uncertainty in water scarcity assessment, expanded hydrological simulations across diverse models and emission scenarios are urgently needed.”

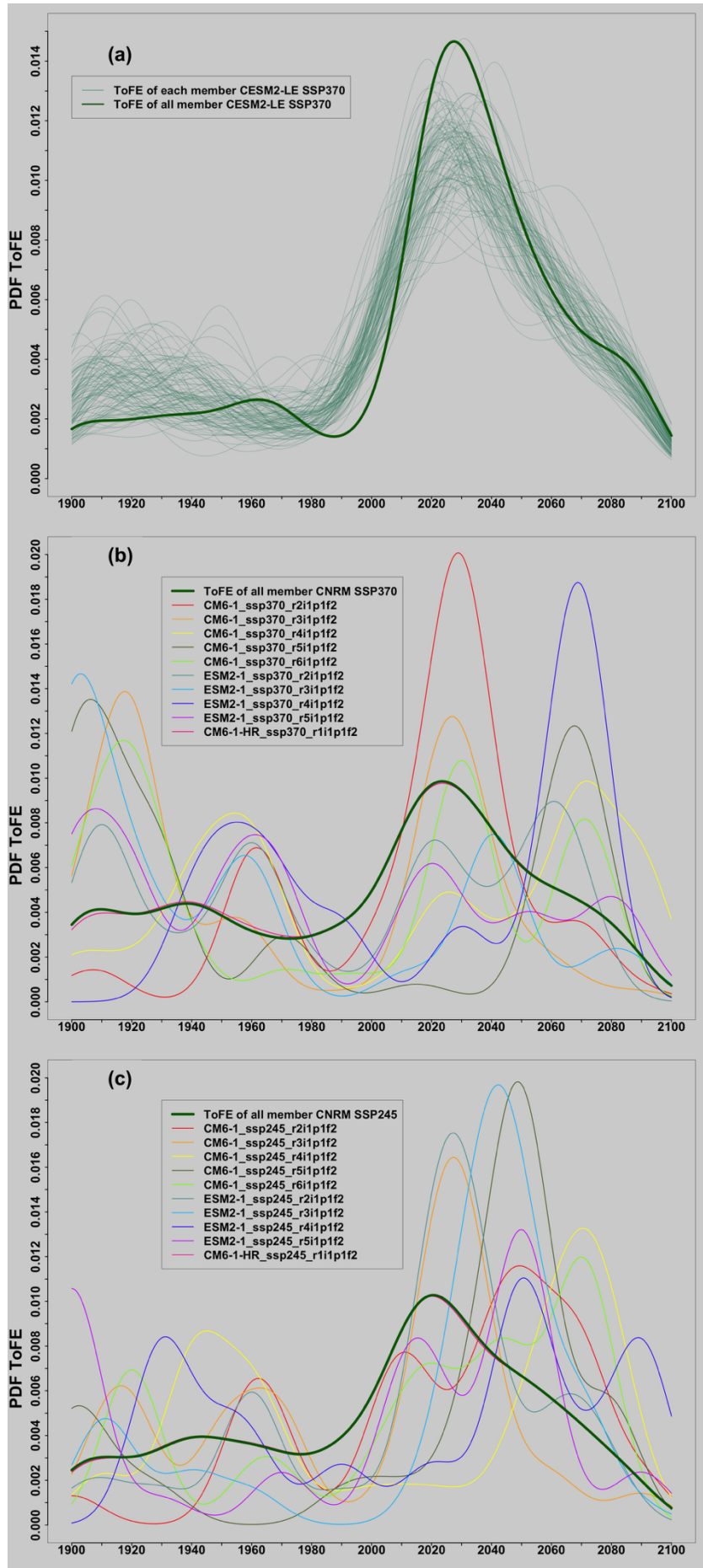


Fig S20: Probability Density Function (PDF) of Time of First Emergence of DZD events, in considering all grid points for each ensemble member across different models and scenarios. (a) ToFE PDFs from CESM2-LE under SSP3.7-0. Thick dark green line represents the PDF of the ToFE based on the sum of all DZD events (as defined in equation 4), while the thin aquamarine lines represent the PDFs of the ToFE for individual ensemble members, based on equation (5) of FAR. (b) ToFE PDFs for different ensemble members from CNRM-CM6-1 and CNRM-ESM2-1 models under SSP3.7-0. (c) Same as (b) but for SSP2.4-5. Colored thin lines represent individual ensemble members distinguished by the CNRM model (as defined in equation 5). The thick dark green line in each panel shows the ToFE based on equation (4). While our primary objective was to emphasize the externally forced signal, hence the use of aggregated events across the ensemble, to assess the internal variability and its influence on our results, we conducted a Time of First Emergence (ToFE) analysis across each ensemble member, to transparently assess the spread and uncertainty within the ensemble. This allows us to examine the spread of emerging timing of Fay Zero Droughts (DZD) and to evaluate the inter-member agreement. We computed the probability density functions (PDFs) of ToFE for each member across all global land covered by DZD. The figure (a) exhibits substantial variability among ensemble members between 1900 and 1990, reflecting high uncertainty during this early period when the anthropogenic signal is still weak relative to internal variability, showing that structural uncertainty arising from the use of a single model remains an important caveat. However, a strong ensemble consensus emerged after 2000, with most members indicating emergence between 2020 and 2030, and increasing agreement toward the end of the 21st century. This coherence across members supports the robustness of our findings in terms of both the timing and magnitude of anthropogenic influence on DZD events. Figure (b) and (c) shows a disagreement between the model in CNRM along all periods, 1900-2100. The dark green line from both models of each panel shows a high density of ToFE between the decades of 2020 and 2030. In terms of the scenario, the emergence under SSP2.4-5 is more delayed and spread out compared to SSP3.7-0. Peaks occur later, and the PDFs are broader compared to Fig. S18b. This suggests that under moderate forcing (SSP2.4-5), DZD emergence is slower and more uncertain. These results highlight the influence of both model structure and emissions scenarios on the DZD emergence.

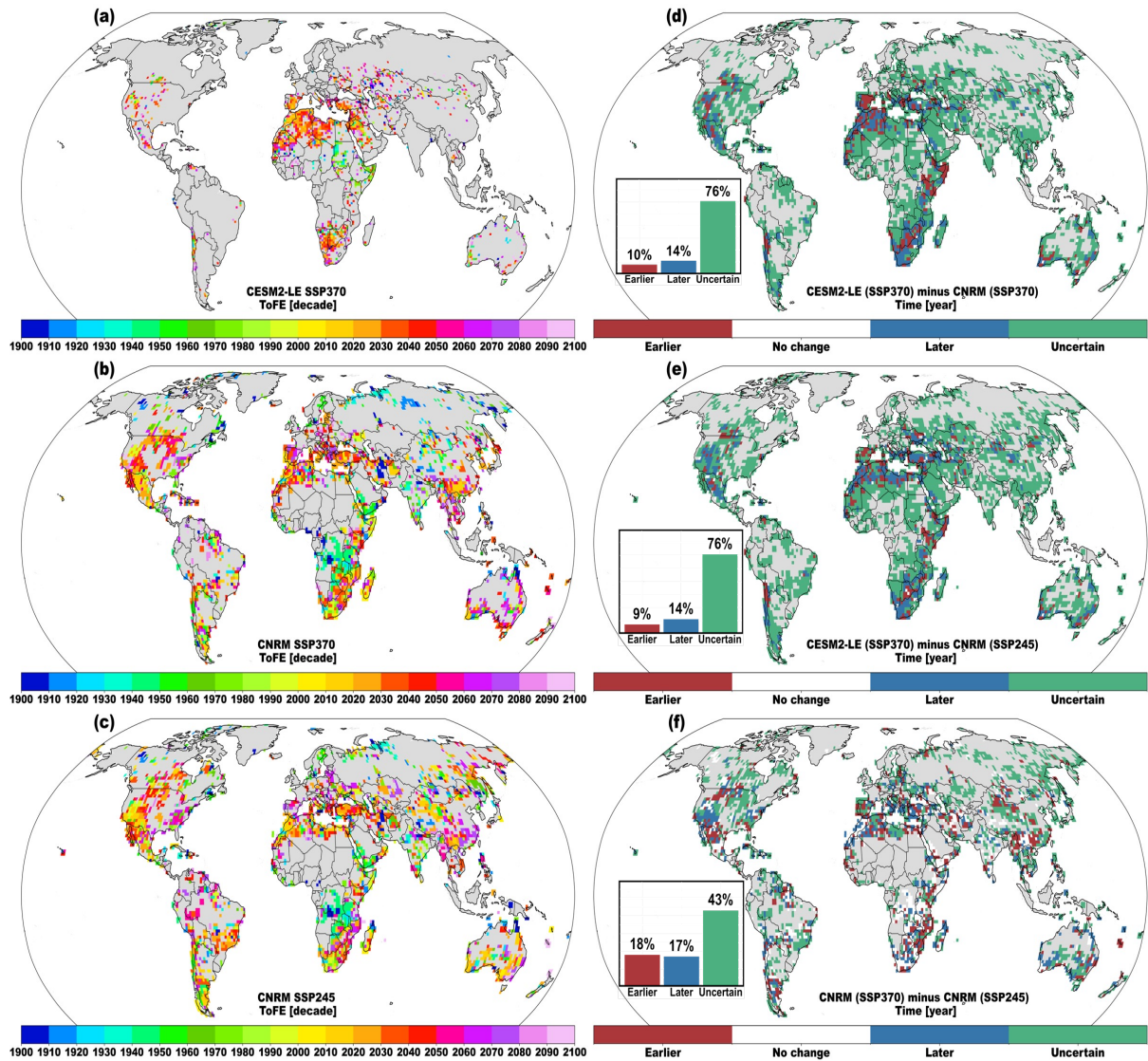


Figure S21: Spatial distribution of the Timing (ToFE) and associated uncertainties of Day Zero Drought (DZD) events across climate models and emission scenarios (CESM2-LE under SSP3-7.0 and CNRM under SSP2-4.5 and SSP3-7.0). Panels (a-c) depict the decadal ToFE of DZD events for each grid cell, calculated as the first decade in which the Fraction of Attributable Risk (FAR) exceeds 0.99, indicating that over 99% of DZD risk is attributable to anthropogenic climate change, based on the cumulative count of DZD events (Equation 4). Results are shown for (a) CESM2-LE under SSP3-7.0, (b) CNRM under SSP3-7.0, and (c) CNRM under SSP2-4.5. Panels (d-f) illustrate inter-model and scenario-based differences in ToFE for grid cells where DZD emergence is detected under those compared cases. Panel (d) represents the difference between CESM2-LE (SSP3-7.0) and CNRM (SSP3-7.0), reflecting structural uncertainty between models. For consistency, ToFE values from CESM2-LE (a) are interpolated to the CNRM resolution to compute the difference between the ToFE between CESM2-LE (SSP3-7.0) and CNRM (SSP3-7.0) as shown in (d) and (e). Panel (e) compares CESM2-LE (SSP3-7.0) and CNRM (SSP2-4.5), highlighting scenario- and model-driven uncertainty. Panel (f) compares CNRM (SSP3-7.0) and CNRM (SSP2-4.5), isolating internal model sensitivity emissions pathways. Inset bar plots in panels (d-f) quantify the proportion of

DZD-prone land grid cells experiencing earlier and later emergence, as well as regions with divergent DZD emergence (uncertain DZD-prone regions). Red and blue shading denote areas where ToFE occurs earlier or later, respectively, in the first model or scenario listed. The green shading indicates regions with inconsistent DZD emergence among the inter-model and scenarios cases (i.e., emergence only occurs in one of the models or scenarios), underscoring uncertainty in projections. The results show that CNRM projects broader emergence in parts of Asia, Australia, and America, while CESM2-LE projects earlier and later emergence across the Mediterranean and Africa. Grey areas indicate locations with no emergence of DZD condition during the analysis period. These results highlight the importance of model structure and emissions scenario in assessing the timing and spatial distribution of DZD emergence.

3 Reservoir Dynamics:

(1) The treatment of reservoir dynamics is a key aspect of the study, but the assumptions made about reservoir operations (e.g., static TRD) are oversimplified. The authors acknowledge this limitation but do not fully explore its implications. A more dynamic approach to modeling reservoir operations, including time-varying management practices, would strengthen the study.

Response: We thank the reviewer for this insightful comment. We appreciate the reviewer's suggestion regarding the incorporation of a more dynamic approach to reservoir operations. Indeed, modelling time-varying management practices and adaptive operational strategies would enhance the realism of water scarcity assessments (as noted in lines 240-242 and 450-454). However respectfully note several key limitations that currently constrain the implementation of such an approach in our study.

Lines 240-242 are written as below:

“These insights underline the need for future work research integrating dynamic reservoir operations and adaptive water management strategies where region-specific data is available.”

Lines 450-454 as follows:

“In the era of ongoing dam construction, time-varying TRD is essential for understanding how reservoir strategies influence water scarcity, but such data are currently unavailable. The interaction between socio-physical drivers and reservoir management is essential for defining compound climate extreme events^{31,66} and assessing DZD impact.”

First, dynamic reservoir modelling requires detailed and region-specific information on reservoir infrastructure characteristics, operational policies, water allocation priorities, and human decision-making frameworks. Unfortunately, such data are scarce and often proprietary, inconsistent, or unavailable across global reservoirs, making it extremely difficult to scale a dynamic approach in a global, ensemble-based framework.

Next, our primary objective is the detection and attribution of anthropogenic climate-driven signals in the emergence of Day Zero Drought (DZD) events using the FAR calculated from the DZD events identified with standardized indices. Adopting a static TRD allows us to focus on the hydroclimatic drivers, while reducing confounding effects variability introduced by human decision-making and adaptive reservoir operations or institutionally driven water

management practices. This simplification enhances comparability and interpretability across regions and time involving climate.

Moreover, the CESM2-LE framework already involves processing large volumes of high-resolution hydrological data across 100 members. Integrating a dynamic reservoir module into 100 members of CESM2-LE at a global scale would not only increase the computational burden significantly but would also create substantial data storage and management challenges on our computing servers, particularly given the temporal resolution and spatial coverage of our simulations. Our framework is already computationally intensive due to the ensemble size, the multi-index drought assessment, and the bias correction of each index of each ensemble, making dynamic modelling of every reservoir infeasible at this stage.

In addition, although the use of a static TRD represents a simplification, it serves as a baseline for assessing vulnerability to acute water scarcity. We acknowledge that reservoir dynamics, such as operational strategies, storage capacity fluctuations, and management interventions, can influence the TRD, meaning that they can influence the duration for a compound drought to dry the reservoir. To partially address this limitation, we conducted sensitivity analyses (lines 224-242 and 971-992). First, we tested whether the inclusion of TRD (as defined in equation 3 for DZD) versus the exclusion of TRD (defining DZD solely as a compound event of $\text{SPEI48} \leq -1.5 \cap \text{SRFI48} \leq -1.5 \cap \text{SWSI48} \leq 0.6$) introduces inconsistencies in the spatial patterns of ToFE. We re-conducted our analysis without accounting for drought duration and TRD to isolate the effect of reservoir influence (now added as supplementary Figure S12). The results show a markedly delayed ToFE in several regions, with FAR greater than 0.99 emerging much later. This delay is primarily due to the fact that events become more common even during the pre-industrial period when reservoir thresholds are not considered, which weakens the contrast between past and future probabilities. In contrast, including TRD and event duration makes these events highly unprecedented, enhancing the detectability of anthropogenic signals. The sensitivity analysis comparing ToFE patterns (Fig. S12) shows that spatial differences are negligible in most regions. The most noticeable delays are confined to the Mediterranean region, where major reservoir constructions were completed mid- to late-20th century (Fig. S6). Second, we explored the potential impact of reservoir behaviour by doubling and quadrupling the TRD, which helps to explore the potential impact of reservoir behaviour, as shown in Fig. S11. Increasing the TRD by up to four times delays the Time of First Emergence (ToFE) in approximately 8% of the regions affected by DZD, particularly in reservoir-dependent areas such as the Mediterranean. This highlights the sensitivity of emergence timing to assumptions about reservoir persistence. These findings underscore that while the TRD used is static, it captures essential dynamic hydrological persistence and reservoir stress.

Lines 224-242 are written as below:

“In addition, reservoir characteristics, specifically the Time for Reservoir to Dry (TRD), play a crucial role in detecting the ToFE of DZD. TRD serves as a proxy for how long a reservoir can sustain water supply under drought conditions when river inflow is the only source of water. The longer it takes for an unprecedented drought to drain water in reservoirs, the later the ToFE will occur, particularly in Mediterranean regions. An increase in TRD, quadrupling the TRD, will affect the ToFE of the 8% of the DZD-prone regions, causing later emergence than in Fig. 2a (Fig. S11, Methods). Therefore, the duration of drier conditions,

combined with rising human water consumption, can dry the reservoirs and trigger severe DZD, including reservoir-dependent regions. However, excluding both drought duration and TRD increases the event occurrence in both historical and future periods and raises their probability. This will delay the human-induced signal ($FAR \geq 0.99$), leading to later ToFE compared to Fig.2, particularly in the Mediterranean regions (Fig.S12). In contrast, DZD emerges earlier in other regions because the probability of future events exceeds the pre-industrial baseline earlier, enabling earlier detection of $FAR \geq 0.99$. Therefore, including the multi-year drought duration and TRD makes these events unprecedented versus pre-industrial conditions, highlighting their importance for understanding the emergence and magnitude of anthropogenic water scarcity and the critical role of reservoirs in water crisis vulnerability. These insights underline the need for future work research integrating dynamic reservoir operations and adaptive water management strategies where region-specific data is available.”

See lines 971-992 of the revised manuscript for the sensitivity analysis of the ToFE relative to the inclusion or exclusion of reservoirs through TRD, as follows:

“Secondly, to assess whether the treatment of grid cells with and without (as defined in equation 3 for DZD) or solely without reservoir (DZD is defined as a compound event of $SPEI48 \leq -1.5 \cap SRFI48 \leq -1.5 \cap SWSI48 \leq 0.6$), introduces inconsistencies in the spatial patterns of ToFE, we conducted a sensitivity analysis comparing ToFE patterns (supplementary Fig.S12). The results reveal that spatial differences are negligible in most regions. The most noticeable delays are confined to the Mediterranean region, where major reservoirs constructions were completed mid- to late-20th century (Fig. S6). As climate change influences the onset of compound events, it is critical for decision-makers to revisit the role of existing water infrastructure in future water security planning. The application of FAR greater than 0.99, combined with localized reservoir adjustment of DZD detection, ensures that the global ToFE pattern represents both high attribution confidence and hydrological realism, without introducing methodological biases between grid cells with and without reservoirs.”

However, we now explicitly clarify the limitations of using static TRD in the revised manuscript, lines 446-455, as follows:

“The GRand database provides valuable reservoir data but lacks information on real-time-varying hydrological dynamic details and includes unverified entries, limiting the number of reservoirs used. Although our study assumes stationary TRD, the static TRD effectively defines the minimum drought duration required to deplete reservoirs below critical storage levels, but it limits the ability to capture the future dynamic reservoir operations during drought. In the era of ongoing dam construction, time-varying TRD is essential for understanding how reservoir strategies influence water scarcity, but such data are currently unavailable. The interaction between socio-physical drivers and reservoir management is essential for defining compound climate extreme events^{31,66} and assessing DZD impact. Despite data limitations, our approach provides a practical and reproducible framework for vulnerability assessment.”

We acknowledge that modelling time-varying management practices and adaptive operational strategies would enhance the realism of water scarcity assessments (as noted in lines 237-242 and 450-455).

Lines 237-242, as follows:

“Therefore, including the multi-year drought duration and TRD makes these events unprecedented versus pre-industrial conditions, highlighting their importance for understanding the emergence and magnitude of anthropogenic water scarcity and the critical role of reservoirs in water crisis vulnerability. These insights underline the need for future work research integrating dynamic reservoir operations and adaptive water management strategies where region-specific data is available.”

Lines 450-455:

“In the era of ongoing dam construction, time-varying TRD is essential for understanding how reservoir strategies influence water scarcity, but such data are currently unavailable. The interaction between socio-physical drivers and reservoir management is essential for defining compound climate extreme events^{31,66} and assessing DZD impact.”

Furthermore, the simplicity of our approach improves the reproducibility of the study, enabling researchers and decision-makers to apply the methodology using local in situ data and region-specific parameters, as we stated in lines 454-455, as follows:

“Despite data limitations, our approach provides a practical and reproducible framework for vulnerability assessment.”

This transparency supports the development of context-aware water management strategies and facilitates broader adoption of the framework in real-world planning and risk assessments. The study highlights the importance of future work to couple hydrological models with dynamic reservoir operation schemes, potentially through global or region-specific case studies and integrated water resources management frameworks.

(2) The paper does not consider the role of groundwater in mitigating water scarcity. Groundwater is a critical resource in many regions (Kuang et al. 2024. The changing nature of groundwater in the global water cycle), and its exclusion from the analysis may lead to an underestimation of water availability during droughts. The authors should discuss this limitation and consider incorporating groundwater data in future work.

Response: We appreciate the reviewer’s thoughtful comment regarding the omission of groundwater. We fully acknowledge that groundwater constitutes a vital component of water supply systems and plays a critical role in mitigating water scarcity, particularly during prolonged droughts. As highlighted by Kuang et al. (2024), climate change and human activities have significantly altered groundwater recharge, discharge, storage, and flow, making subsurface water dynamics more complex and increasingly relevant to global water availability and sustainability. Groundwater extracted from aquifers contributes to river discharge and evapotranspiration, further influencing surface hydrology. However, due to model limitations, the CESM2-LE land component does not simulate dynamic groundwater processes and considers aquifer storage as static, which precludes us from explicitly modelling groundwater variability. The aquifer storage in CESM2-LE does not dynamically respond to climate variability or human extraction. While groundwater is not directly simulated, our use of the SPEI48 metric partially captures long-term hydroclimatic stress and its correlation with

groundwater anomalies (see Fig. S13). Nonetheless, we have acknowledged limitations in the Uncertainty section of the revised manuscript (see lines 430-441) and emphasized the importance of future work to integrate dynamic groundwater components. We agree that incorporating the groundwater process would provide a more comprehensive understanding of water scarcity, and we emphasize this direction as an important avenue for future research (see lines 432-435). The following has been added in the revised manuscript, as follows:

“Moreover, CESM2-LE’s land model assumes static aquifer storage, excluding dynamic groundwater variability. This overlooks the critical role of groundwater as a vital buffer during drought, particularly in groundwater-dependent regions. Groundwater contributes to the global water cycle, influencing river discharge and evapotranspiration, while also being altered by both climate change and human activities⁶². Incorporating dynamic groundwater processes is essential to improve water stress risks assessments. Groundwater is declining globally, leading to dry wells⁶³. Climate change stresses groundwater⁶² through increased use during droughts and reduced natural recharge, potentially worsening the impacts of continued drought⁶⁴. Prolonged rainfall deficits can disrupt the hydrological cycle in a warmer world and can lead to groundwater drought⁶⁵. Despite its important role in water scarcity, global modeled and observed groundwater datasets remain scarce. However, its long-term relationship with atmospheric drought (partially captured by SPEI48; Fig. S13) provides insight into its response to hydroclimatic stress.”

References:

- Kuang et al. The changing nature of groundwater in the global water cycle. Science, 383 (6686), 1234-1239 (2024).

3 Interpretation of Results:

(1) The paper identifies several regions as hotspots for DZD emergence, but the discussion of these results is somewhat superficial. The authors should provide more context on why these regions are particularly vulnerable and how local factors (e.g., population growth, water management practices) contribute to the risk of water scarcity.

Response: In response, we have revised the manuscript to expand our discussion in the results section in lines 188-252, as follows:

*“**Time of First Emergence (ToFE) of DZD.** This study defines ToFE as the first decade in which the Fraction of Attributable Risk (FAR) for DZD exceeds 0.99, indicating a 99% likelihood that human activities caused the onset of these unprecedented compound drought-scarcity events. ToFE is assessed relative to pre-industrial conditions (1850-1899), which serve as the baseline for detecting anthropogenic emergence. The focal hotspot regions affected by unprecedented DZD, with their respective decade of ToFE and the distribution of the ToFE, are shown in Fig. 2. Our results indicate that anthropogenic climate change is projected to trigger the onset and occurrence of DZD, primarily due to severe and persistent compound multi-year hydrological droughts, reservoir depletion, and high-water demand.*

About 14% of the global reservoirs from the Global Reservoir and Dams (GRand) database (Fig.S5, see methods for more information regarding the reservoirs) would dry out

due to a high risk of DZD during their respective ToFE, as shown in Fig. 2a. The 74% of regions covered by DZD are projected to experience an unprecedented water scarcity by 2100. Moreover, almost 35% of those regions are facing the emergence of water scarcity, including their reservoirs, between 2020 and 2030 (Fig. 2b). This will threaten the local freshwater availability in DZD-prone regions (Fig. S7). Declining precipitation and river flows, combined with rising water demand, can dry up the reservoirs and cause water scarcity across sectors, heightening the risks of water, food, or socio-economic insecurity.

The ToFE of DZD is influenced by the severity of the precipitation deficit and increases in evapotranspiration (SPEI48), river drought (SRFI48), and water demand (SWSI48), particularly in Africa (Fig. S10). In parts of Asia and America, increased water consumption can influence the early emergence of DZD compared to other factors. This rise in water consumption is associated with population growth and socio-economic development, encompassing expanded water use across domestic, irrigation, industry, electricity, livestock, and mining sectors. These findings emphasize the importance of jointly considering all four drivers: climate, hydrological supply, event duration, and human demand, since no single factor can fully characterize a compound hydrological extreme event like DZD. Furthermore, the lower the thresholds applied to define the DZD, reflecting more severe and rare events, the later the ToFE will emerge, underscoring the complex relationship between event severity and its anthropogenic emergence (Fig. S10). This compound approach highlights that water scarcity can be triggered by various drivers rather than a single stressor. For instance, a precipitation deficit without strong demand pressure may not induce water scarcity, while excessive demand alone may not trigger a water crisis if demand remains below supply. However, unsustainable consumption driven by population growth and socio-economic development alone can also trigger water scarcity if water use surpasses the available resource. Therefore, the simultaneous occurrence of these factors can lead to the emergence of an unprecedented acute water scarcity.

In addition, reservoir characteristics, specifically the Time for Reservoir to Dry (TRD), play a crucial role in detecting the ToFE of DZD. TRD serves as a proxy for how long a reservoir can sustain water supply under drought conditions when river inflow is the only source of water. The longer it takes for an unprecedented drought to drain water in reservoirs, the later the ToFE will occur, particularly in Mediterranean regions. An increase in TRD, quadrupling the TRD, will affect the ToFE of the 8% of the DZD-prone regions, causing later emergence than in Fig. 2a (Fig. S11, Methods). Therefore, the duration of drier conditions, combined with rising human water consumption, can dry the reservoirs and trigger severe DZD, including reservoir-dependent regions. However, excluding both drought duration and TRD increases the event occurrence in both historical and future periods and raises their probability. This will delay the human-induced signal ($FAR \geq 0.99$), leading to later ToFE compared to Fig. 2, particularly in the Mediterranean regions (Fig. S12). In contrast, DZD emerges earlier in other regions because the probability of future events exceeds the pre-industrial baseline earlier, enabling earlier detection of $FAR \geq 0.99$. Therefore, including the multi-year drought duration and TRD makes these events unprecedented versus pre-industrial conditions, highlighting their importance for understanding the emergence and magnitude of

anthropogenic water scarcity and the critical role of reservoirs in water crisis vulnerability. These insights underline the need for future work research integrating dynamic reservoir operations and adaptive water management strategies where region-specific data is available.

Furthermore, the emergence of unprecedented water stress and scarcity can be dependent on model structure and scenario pathways^{38,39}. To address this, we use data from the CNRM model using two scenarios, SSP3-7.0 and SSP2-4.5. Only this CMIP6 model provided all the necessary variables for our compound DZD indicator. We find that the influence of the scenario on DZD ToFE is region-specific (Fig. S21b-c and f) due to the interaction between regional climate drivers and human water use. Both high (SSP3-7.0) and moderate (SSP2-4.5) scenarios can advance, delay, or have no change on DZD emergence, depending on the region. As a model structure also drives spatial discrepancies (Fig. S21a-b and d-e): CESM2-LE projects broader DZD regions in northern Africa, whereas CNRM highlights some different regions. However, the hot spot regions, the Mediterranean, southern Africa, and North America, are very similar.”

Specifically, we now provide greater context on the vulnerability of these regions by considering key local factors such as the precipitation deficit and increases in evapotranspiration, river drought, and water consumption. In our study, DZD event is defined as the concurrent occurrence of four key hydrological stress indicators: SPEI48 to capture long-term imbalance between precipitation and evapotranspiration which indicate prolonged meteorological drought, SRFI48 to reflect persistent reductions in river flow which captures hydrological drought conditions, the SWSI48 to assess water scarcity through the imbalance between total water supply and total consumption, and TRD to represent the duration required for the compound drought event to exhaust reservoir storage. Each component represents a distinct but interdependent facet of water scarcity, and no single indicator is prioritized over the others. The definitions require that all criteria are simultaneously met.

A DZD event is only identified when all four criteria are simultaneously met, ensuring that detected events reflect not only prolonged and severe drought conditions but also system-wide water scarcity where supply fails to meet demand over a sustained period. This compound-event approach is conservative, as it filters out isolated stress signals and focuses on extreme conditions likely to lead to acute water crises triggered by prolonged drought.

In the study, for a region to face a DZD, it must be susceptible to DZD emergence due to a convergence of climatic and socio-hydrological pressures. These include rainfall deficits and increased evapotranspiration due to warming climates; river flow depletion from reduced river discharge; and important water consumption driven by population growth through water consumption, agriculture, and industrial demand, limited water management capacity, or reservoir storage without sufficient adaptive operations. These local factors exacerbate the impacts of compound hydrological stress, making such regions more prone to DZD events.

This compound framework reflects the reality that drought-driven water scarcity does not arise from a single stressor alone, but rather from the convergence of multiple interacting stressors. For instance, a prolonged precipitation deficit may not lead to a crisis without demand pressure. Similarly, rising water demand may not result in water scarcity even if hydrological conditions remain stable. However, in this study, we assume that the hydrological supply is depleted due to global warming and cannot meet the population's demand. By requiring all

indicators, SPEI48, SRFI48, SWSI48, and TRD, our definition of DZD ensures that no single stressor is overemphasized. Each dimension holds equal importance, and it is their joint occurrence that defines the event. We have provided additional explanation in the Results section in lines 206-223, as follows:

“The ToFE of DZD is influenced by the severity of the precipitation deficit and increases in evapotranspiration (SPEI48), river drought (SRFI48), and water demand (SWSI48), particularly in Africa (Fig. S10). In parts of Asia and America, increased water consumption can influence the early emergence of DZD compared to other factors. This rise in water consumption is associated with population growth and socio-economic development, encompassing expanded water use across domestic, irrigation, industry, electricity, livestock, and mining sectors. These findings emphasize the importance of jointly considering all four drivers: climate, hydrological supply, event duration, and human demand, since no single factor can fully characterize a compound hydrological extreme event like DZD. Furthermore, the lower the thresholds applied to define the DZD, reflecting more severe and rare events, the later the ToFE will emerge, underscoring the complex relationship between event severity and its anthropogenic emergence (Fig. S10). This compound approach highlights that water scarcity can be triggered by various drivers rather than a single stressor. For instance, a precipitation deficit without strong demand pressure may not induce water scarcity, while excessive demand alone may not trigger a water crisis if demand remains below supply. However, unsustainable consumption driven by population growth and socio-economic development alone can also trigger water scarcity if water use surpasses the available resource. Therefore, the simultaneous occurrence of these factors can lead to the emergence of an unprecedented acute water scarcity.”

Moreover, we have clarified the DZD definition accordingly in the methodology section in lines 784-850, written as follows:

“Day zero drought definition. We define “Day zero drought” (DZD) as an acute water scarcity event driven by a compound multi-year hydrological drought, during which water demand exceeds water supply under prolonged drought conditions. DZD occurs due to a critical imbalance between supply and demand, driven both by climate-induced reduction in supply and anthropogenic pressures increasing demand.

In fact, water can be retained in the reservoir through different parts of the hydrological cycle and different resident times (time of water spent in reservoirs) considered similar to TRD. As the river flow contributes to the long-term storage of water in the reservoir, we considered the river discharge to be an appropriate parameter. DZD is the impact of the simultaneous occurrence of a long-term (48-month) critical rainfall deficiency and extreme dearth of water of low-flow river discharge during a prolonged drought in the context of global warming and long duration exceeding the time for the reservoirs to run out of water. This is formalized as follows:

$$\text{DZD occurs if} \tag{3}$$

$$\begin{cases} \text{SPEI48} \leq -1.5 \cap \text{SRFI48} \leq -1.5 \cap \text{SWSI48} \leq 0.6, \text{dur}_{ce} \geq \text{TRD}, \text{if reservoir exists.} \\ \text{SPEI48} \leq -1.5 \cap \text{SRFI48} \leq -1.5 \cap \text{SWSI48} \leq 0.6, \text{if there is no reservoir.} \end{cases}$$

where dur_{ce} is the duration of the compound extreme. The identification of DZD was carried out at each grid cell across each of the 100 members of the CESM2-LE model, offering a comprehensive and probabilistic perspective on future water scarcity risk.

However, global warming is expected to disrupt and intensify the variability of the water cycle²⁴, leading to increasingly frequent and severe fluctuations between excessively wet and dry periods²⁵. Warmer climates are projected to enhance the evapotranspiration, resulting in dry conditions²⁶. Additionally, reductions in precipitation and surface runoff are expected in many regions²⁴, further increasing the likelihood of both climatological and hydrological droughts^{27–30}. Moreover, population growth, economic development, and expansion of modern agriculture drive the rise in water consumption, placing additional pressure on water resources. Therefore, dry conditions driven by anthropogenic climate change and socio-economic development are jointly altering the global balance between water supply and demand, thereby amplifying the risk of DZD. Our concept distinguishes between drought and water scarcity, while also capturing their interaction in driving the DZD event. Drought refers to a reduction in water availability either through decreased precipitation, increased evaporation, or reduced river flow. In contrast, water scarcity arises when water demand exceeds the available water supply. Water Scarcity is often human-driven from anthropogenic pressure, such as population, growth, agricultural expansion, industrial use, and mismanagement of water resources. Water scarcity can occur even in the absence of climate change if water use is unsustainable. In this study, we focused on water scarcity driven by drought, where the reduction of water supply is driven by dry conditions. In this context, the water stress is considered as a result of a compound event due to atmospheric conditions (precipitation and evaporative demand; SPEI48), streamflow conditions (SRFI48), and demand condition (SWSI48) of 48-months occur with important depletion of water supply and increase of water demand; and where the duration of the event is longer than the time of the closest reservoirs to dry (TRD). This study offers a global-scale assessment of DZD emergence and its characteristics, capturing the interactions between climate human-driven factors.

Therefore, DZD is considered as an extreme water scarcity event, characterized by the fact that the water resources available in a region are largely below the limited reservoir's capacity compared to the pre-industrial period. This is attributed to both anthropogenic climate change and an increase in water use. To our knowledge, this study is the first global-scale assessment of the timing of the emergence of Day Zero Drought conditions and its characteristics. DZD is characterized by the concurrent exceedance of critical threshold in four indicators: (i) The standardized Precipitation-Evapotranspiration Index (SPEI48) below minus 1.5 ($SPEI48 \leq -1.5$, exceedance of 1.5 standard deviations, signifying 1.5 standard deviation droughts to classify the extremely dry atmospheric condition, through prolonged deficits in precipitation and increased evapotranspiration, leading to a long-term surface water stress and can significantly influence the change in groundwater (Fig. S13). (ii) The Standardized River Flow Index (SRFI48) below minus 1.5 ($SRFI48 \leq -1.5$, exceedance of 1.5 standard deviation), signifying 1.5 standard deviation droughts, to detect the depletion of river flow conditions, representing the state of the severe drought in river flow during dry periods. (iii) The

Standardized Water Scarcity Index (SWSI48) below 0.6 ($SWSI48 \leq 0.6$) is used to quantify the imbalance between total water supply and demand and to represent the long-term average insufficiency of resources relative to demand during periods of drought, leading to an acute water scarcity. (iv) The duration of the compound event (dur_{ce}) exceeding the estimated time for reservoir depletion (TRD), when reservoirs exist. If no reservoir is present, the DZD is defined by the first three indicators. This framework reflects the reality that water scarcity emerges from the convergence of multiple stressors. Each indicator plays a distinct but interrelated role in defining DZD; therefore, none is weighted as more important than another. Their simultaneous exceedance is necessary to identify a DZD event, filtering out less severe or isolated events. For instance, precipitation deficits alone may not result in a crisis without demand pressure. i.e., in low low-demand case, just as high demand may not lead to scarcity if the supply is still enough. Similarly, even in the absence of climate variability, unsustainable consumption alone can trigger water scarcity if water use surpasses the available resource.”

(2) The societal impacts of DZD are discussed in terms of population exposure, but the paper does not explore the potential economic or ecological consequences in detail. A more thorough discussion of the broader implications of DZD would enhance the paper's relevance to policymakers and stakeholders.

Response: We agree that a more thorough discussion of the broader implications of DZD would enhance the relevance of our findings for policymakers and stakeholders. In response, we have expanded the scope of our discussion to better address the broader implications of DZD. Specifically, we have added a dedicated section on Adaptation pathways and policy implications which outlines strategies for mitigating the risks of DZD and building resilience in vulnerable regions, see lines 403-420, as follows:

“Adaptation pathways and policy implications. The emergence of DZD highlights the urgent need for proactive, integrated water management within policy frameworks to address the compound risks of climate change and unsustainable water use. Climate policy and water security are tightly interconnected in the Sustainable Development Goals (SDGs)^{53,54}, so mitigation and adaptation strategies must align with global targets while fitting regional and community-specific needs for long-term resilience⁵⁵.

Defining DZD events as water scarcity driven by climate change underscores the challenges in sustainable water supply (SDG target 6.1) and efficient water use under stress (SDG target 6.4). Assessing the ToFE of DZD supports early warning signals (SDG target 13.1) and integration of climate adaptation strategies into water management policies (SDG target 13.2). Empowering communities to design local adaptation strategies fosters equitable and context-appropriate responses⁵⁶, through water conservation, crop selection, water storage solutions, and efficient cross-sectors water use, context-specific responses in DZD-prone regions.

Building resilience requires integrating local knowledge, adaptive cooperative management⁵⁷, water governance⁵⁸, and diversified supply strategies, including the re-planning of water reservoirs, desalination, rainwater harvesting, and wastewater recycling.

Climate-resilient infrastructure investments, which have been underfinanced⁵⁹, need to balance conventional and innovative approaches to ensure sustainable water access in drought-prone regions.”

Furthermore, we now separately explore the potential cross-sectoral impact of DZD on the domestic, agricultural, and industrial sectors. This addition underscores the multifaceted and cross-sectoral nature of DZD impacts. We believe this broader framing strengthens the relevance of our findings for informing integrated water management, adaptation planning, and cross-sectoral policy development. The expanded discussion is included in the Discussion section in lines 496-510, as follows:

“DZD, which has threatened Cape Town, is a multifaceted crisis that disproportionately affects low-income communities and exacerbates socio-economic inequalities⁶⁹. It affects the domestic water supply, particularly in urban areas, with cascading effects on public health and societal risk. The impacts of drought vary across regions and sectors, with the least developed countries most vulnerable due to disparities in physical, social, economic, and knowledge-based factors⁷⁰. In agriculture, DZD can reduce crop yields, threaten food security, and impact livestock through water and feed shortages. The need for sustainable irrigation of economically water-scarce cropland is critical to alleviating food insecurity⁷¹. Water-reliant industries and hydropower regions, including mining, can risk operational disruptions, energy shortages, and economic losses. Prolonged drought can degrade freshwater and terrestrial ecosystems, compromising water quality, biodiversity, and long-term ecological resilience. These cross-sectoral impacts underscore the need for integrated potential solutions³⁷ and adaptation strategies with equitable water governance and management⁵⁸ at a regional scale. To support such efforts and reduce uncertainty in water scarcity assessment, expanded hydrological simulations across diverse models and emission scenarios are urgently needed.”

(3) The paper focuses primarily on water quantity, but water scarcity is a multidimensional issue that also includes water quality and environmental flow requirements. The authors should discuss the concept of three-dimensional water scarcity, which integrates water quantity, quality, and environmental flows, as highlighted in recent literature. Incorporating this perspective would provide a more holistic understanding of water scarcity and its implications for ecosystems and human societies.

Response: We agree that water scarcity is a multidimensional issue that encompasses not only water quantity but also water quality and environmental flow requirements (as revised in lines 55-58). In this study, we deliberately focused on replicating a Cape Town-like DZD event, with an emphasis on the quantity dimension, to assess the potential occurrence, timing, and spatial patterns of future DZD events at the global scale, as well as the human exposure under future climate and water use scenarios. We have clarified our study scope in the introduction, focusing on socio-physical water scarcity and human influence, shown in lines 58-71, written as follows:

“This study focuses on socio-physical water scarcity, driven by anthropogenic supply-demand imbalances. However, DZD represents an acute water scarcity triggered by the

simultaneous occurrence of multi-year precipitation deficits, river flow depletion, and high-water demand, leading to a critical depletion of reservoirs. Therefore, DZD is a multi-year compound extreme event that is determined by the concurrent occurrence of several interdependent events¹⁰. A compound extreme event refers to a simultaneous occurrence of multiple extreme events that can have drastic effects on a large scale, far greater than the impact of an individual event^{11,12}. Multi-year meteorological drought, driven by insufficient precipitation and potentially exacerbated by global warming, can lead to hydrological droughts characterized by abnormally low river flows, reducing water availability. Such combined events considerably increase the risk of water scarcity when the available supply is less than the demand. Hence, the simultaneous occurrence of several climate extremes can lead to more severe impacts¹³ on water supply¹⁴ and subsequently on society and ecosystems¹⁵, highlighting the need for integrated drought assessment frameworks that account for compound events.”

While our analysis provides critical insights into the hydrological and demand-driven components of DZD, we acknowledge that it does not explicitly incorporate the concepts of water quality or environmental flows. Thus, we have acknowledged this limitation in the Uncertainty section in lines 442-445, as follows:

“Notwithstanding anthropogenic global warming, population growth and economics remain the major drivers of the water crisis by increasing demand^{27,34}. Our study considers the socio-physical aspects of water security and excludes factors like national water policies, governance, quality, and environmental flow requirements.”

Moreover, we expanded the discussion (see lines 485-487) to emphasize the importance of future research expanding toward a three-dimensional water scarcity framework to capture a more holistic view of water risks. This update is written as below:

“Although this study focuses on socio-physical water scarcity, incorporating water quality and environmental flows, as highlighted by Liu et al.⁹, is critical for a holistic understanding of future water risks.”

Reference:

- Liu, J., Liu, Q., & Yang, H. (2016). Assessing water scarcity by simultaneously considering environmental flow requirements, water quantity, and water quality. *Ecological Indicators*, 60, 434-441.

4 Figures and Data Presentation:

(1) Some of the figures (e.g., Fig. 1, Fig. 2) are difficult to interpret due to the complexity of the information presented. The authors should consider simplifying these figures or providing additional explanatory text to guide the reader.

Response: We have revised and expanded the captions for Figures 1 and 2 to provide clearer and more detailed explanations of the drought indices (lines 172-186) and Time of First

Emergence (lines 256-270). We believe that the updated captions improve the clarity of the graphical presentation, as shown below:

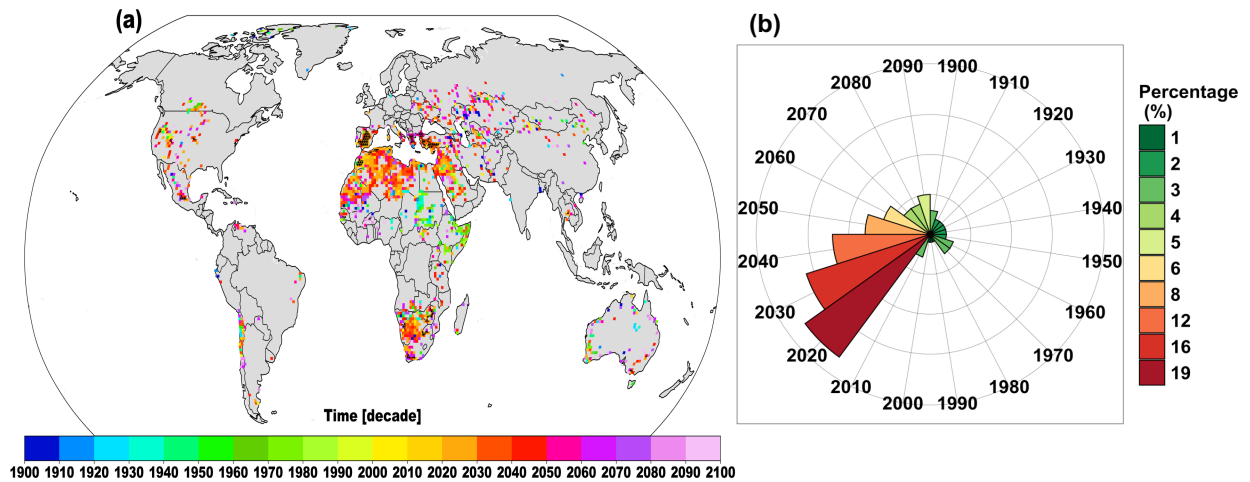


Fig. 2: Time of First Emergence (ToFE) of Day Zero Drought (DZD) event and global hotspot regions based on CESM2-LE ensemble simulations under the SSP3-7.0 scenario. (a) Spatial distribution of the decadal ToFE of DZD events across the globe from 1900 to 2100. Colored shading indicates the first decade during which DZD becomes statistically attributable to anthropogenic climate change, defined as the first decade in which the Fraction of Attributable Risk is greater than 0.99 ($FAR > 0.99$). Gray regions indicate grid cells where no DZD event attributable to anthropogenic climate change is projected to emerge before 2100. For regions with reservoirs, the ToFE is considered to be the first decade after the year of completion (Fig. S6) of their respective reservoirs, when all DZD criteria are simultaneously met. By aligning the emergence timing with the operational onset of water storage infrastructure to reflect the real-world system resilience dynamics. The black stars denote the locations of the reservoirs threatened by DZD emergence. (b) Circular diagram illustrating the temporal distribution of ToFE by decades. The color scale indicates the percentages of grid cells (land areas) experiencing their ToFE distribution in each decade from 1900 to 2100. It provides a temporal overview of how the ToFE is distributed over time and the trends in DZD emergence.

(2) The paper would benefit from a more detailed discussion of the data sources and their limitations. For example, the global reservoir database (GRanD) is used extensively, but the authors do not discuss the potential biases or gaps in this dataset.

Response: We thank the reviewer for highlighting the importance of discussing data sources and their limitations. In response, we have included an Uncertainty section detailing the limitations of the CESM2-LE dataset, CNRM models, Global Reservoir and Dams (GRanD) database, and water consumption downloaded from Khan et al (2023).

Specifically, regarding the GRanD database version 1.3, while it provides expanded attribute coverage and spatial precision, enabling novel global and regional analysis, it also has limitations. These are discussed in lines 446-455 of the revised manuscript, as presented below:

“The GRanD database provides valuable reservoir data but lacks information on real-time-varying hydrological dynamic details and includes unverified entries, limiting the number of reservoirs used. Although our study assumes stationary TRD, the static TRD effectively defines the minimum drought duration required to deplete reservoirs below critical storage levels, but it limits the ability to capture the future dynamic reservoir operations during drought. In the era of ongoing dam construction, time-varying TRD is essential for understanding how reservoir strategies influence water scarcity, but such data are currently unavailable. The interaction between socio-physical drivers and reservoir management is essential for defining compound climate extreme events^{31,66} and assessing DZD impact. Despite data limitations, our approach provides a practical and reproducible framework for vulnerability assessment.”

To assess the Time for Reservoirs to Dry (TRD), we relied on maximum reservoir capacity and observed long-term monthly average discharge data provided in GRanD. However, due to the lack of time-series water level and operational data, our approach assumes static TRD values. We only included reservoirs with verified, good, and fair quality indices, which cover 93% of the dataset, to ensure data reliability. Despite these measures, the absence of detailed temporal data on reservoir water level, minimum capacity, and political decision-making remains a limitation. We also conducted a sensitivity analysis by adjusting the TRD values (doubling and quadrupling) and found only moderate changes in a few regions, suggesting our findings are reasonable under this assumption. Nevertheless, we recognize that a more dynamic representation of TRD, accounting for evolving reservoir management practices and the observed water flow, would enhance the accuracy of our assessment. We have now clarified these points in both the methodology (see lines 545-552 and 752-771) and emphasize a critical need for more reliable data on the precise geographic location of existing reservoirs, as well as temporally resolved information on river inflow and reservoir water level dynamics. Such data are essential for capturing the spatiotemporal variability in reservoir behaviours and understanding their role in the mitigation of water scarcity under climatic and socio-economic conditions, thereby advancing future water scarcity assessments.

Lines 545-552:

“We use the global reservoirs database, which includes information on reservoir location, capacity, and the long-term average discharge (1971-2000) available from the Global Reservoir and Dams (GRanD)⁷³ database. The global reservoir database includes both reservoirs constructed by humans and natural lakes, according to Lehner et al.⁷³. The GRanD database version 1.3 was used due to its highly adaptable geodatabase that offers expanded attribute coverage and spatial precision, making it possible to implement novel regional or global analysis at unprecedented spatial resolution⁷³⁻⁷⁵. We assigned reservoirs to the closest grid point in CESM2-LE to facilitate integration with climate model outputs.”

Lines 752-771:

*“**Time for Reservoirs to Dry (TRD).** An important aspect of drought impacts is the availability of water in reservoirs. The onset of drought conditions and continuing water demand will also affect reservoir water levels. To assess the severity of the drought events, we have to also*

consider the Time for the Reservoir to Dry (TRD) as the ratio of the maximum capacity and the monthly average discharge at reservoir locations, by considering only the reservoirs with verified, good and fair quality index⁷³, which represents 93% of the GRand' reservoirs (Fig. S5).

$$TRD = \frac{\text{maximum capacity of the reservoir}}{\text{monthly average discharge at reservoirs}} \quad (2)$$

For human-made reservoirs, the maximum capacity refers to the maximum value of the storage capacity, and for natural lakes, it is the given lake level by Lehner et al.⁷³. The lack of water level time series in the reservoirs makes it hard to estimate the time scales by which they might run dry. Instead of the available capacity of the reservoir (maximum minus minimum capacity), the maximum capacity was used because it was a readily available parameter for most reservoirs and due to the lack of the points layer of minimum capacity in the GRand database. Moreover, climate change may alter the future operation of reservoirs, so using the maximum capacity is useful for assessing the suitability of water storage strategies. The TRD is similar to the resident time (time of water spent in reservoirs) and can be considered as the duration to take for a drought event to dry the water in the reservoirs if the only source of the water supply of the reservoirs is the depleted river flow during a drought period. This reflects hydrological drought situations in which rivers continue to flow, albeit at diminished levels insufficient to meet water demand, allowing assessment of how long reservoirs can sustain supply under such stress.”

5 Broader Implications and Policy Relevance:

(1) While the paper highlights the need for proactive water management strategies, it does not provide specific recommendations for policymakers. The authors should consider including a section on potential mitigation and adaptation strategies, particularly in regions identified as DZD hotspots.

Response: We have now incorporated a dedicated section on “Adaptation pathways and policy implications” that aligns with the key findings of our DZD analysis. This new section outlines recommendations for policymakers, particularly targeting regions identified as DZD hotspots. The strategies discussed include the integration of adaptive water resources management, diversification of water supply options, demand-side management, and community-led adaptation measures. Furthermore, these strategies are framed within the context of the Sustainable Development Goals (SDGs), highlighting synergies with SDG target 6.1(sustainable water supply), SDG target 6.4 (efficient water use under stress), SDG target 13.1 (early warning and risk reduction), and SDG target 13.2 (integration of climate adaptation strategies into water management policies). This expanded discussion strengthens the policy relevance of our study and provides actionable insights to inform resilience planning and water governance in vulnerable regions. Please refer to lines 403-420, written as follows:

“Adaptation pathways and policy implications. The emergence of DZD highlights the urgent need for proactive, integrated water management within policy frameworks to address the compound risks of climate change and unsustainable water use. Climate policy and water

security are tightly interconnected in the Sustainable Development Goals (SDGs)^{53,54}, so mitigation and adaptation strategies must align with global targets while fitting regional and community-specific needs for long-term resilience⁵⁵.

Defining DZD events as water scarcity driven by climate change underscores the challenges in sustainable water supply (SDG target 6.1) and efficient water use under stress (SDG target 6.4). Assessing the ToFE of DZD supports early warning signals (SDG target 13.1) and integration of climate adaptation strategies into water management policies (SDG target 13.2). Empowering communities to design local adaptation strategies fosters equitable and context-appropriate responses⁵⁶, through water conservation, crop selection, water storage solutions, and efficient cross-sectors water use, context-specific responses in DZD-prone regions.

Building resilience requires integrating local knowledge, adaptive cooperative management⁵⁷, water governance⁵⁸, and diversified supply strategies, including the re-planning of water reservoirs, desalination, rainwater harvesting, and wastewater recycling. Climate-resilient infrastructure investments, which have been underfinanced⁵⁹, need to balance conventional and innovative approaches to ensure sustainable water access in drought-prone regions.”

(2) The paper could also benefit from a discussion of how the findings align with the Sustainable Development Goals (SDGs), particularly SDG 6 (Clean Water and Sanitation). This would help to contextualize the study within the broader framework of global sustainability efforts.

Response: We have added a dedicated section on “Adaptation pathways and policy implications” which explicitly links our study on DZD analysis to global sustainability efforts. In particular, we highlight synergies with SDG target 6.1 (sustainable water supply), SDG target 6.4 (efficient water use under stress), SDG target 13.1 (early warning and risk reduction), and SDG target 13.2 (integration of climate adaptation strategies into water management policies). We emphasize that advancing sustainable water management and climate adaptation strategies is for improving water security and resilience, thereby supporting the achievement of these global sustainability goals. Please refer to lines 403-420, written as follows:

“Adaptation pathways and policy implications. The emergence of DZD highlights the urgent need for proactive, integrated water management within policy frameworks to address the compound risks of climate change and unsustainable water use. Climate policy and water security are tightly interconnected in the Sustainable Development Goals (SDGs)^{53,54}, so mitigation and adaptation strategies must align with global targets while fitting regional and community-specific needs for long-term resilience⁵⁵.

Defining DZD events as water scarcity driven by climate change underscores the challenges in sustainable water supply (SDG target 6.1) and efficient water use under stress (SDG target 6.4). Assessing the ToFE of DZD supports early warning signals (SDG target 13.1) and integration of climate adaptation strategies into water management policies (SDG target 13.2). Empowering communities to design local adaptation strategies fosters equitable and

context-appropriate responses⁵⁶, through water conservation, crop selection, water storage solutions, and efficient cross-sectors water use, context-specific responses in DZD-prone regions.

Building resilience requires integrating local knowledge, adaptive cooperative management⁵⁷, water governance⁵⁸, and diversified supply strategies, including the re-planning of water reservoirs, desalination, rainwater harvesting, and wastewater recycling. Climate-resilient infrastructure investments, which have been underfinanced⁵⁹, need to balance conventional and innovative approaches to ensure sustainable water access in drought-prone regions.”

6 Reevaluate the Critique of the Falkenmark Indicator:

(1) The authors critique the Falkenmark indicator, suggesting that it does not consider demand. However, this is a misinterpretation. The Falkenmark indicator, which measures water availability per capita, inherently incorporates demand through population data, as population is a proxy for water demand. While it is true that per capita water demand varies across countries, the indicator provides a useful high-level assessment of water scarcity. The authors should revise their critique to acknowledge that the Falkenmark indicator does, in fact, consider demand indirectly through population, even if it does not account for sectoral water use or regional variations in consumption patterns.

Response: We appreciate the reviewer’s clarification regarding the Falkenmark indicator and acknowledge that our earlier wording may have unintentionally misrepresented its scope. We agree that the indicator, by measuring water availability per capita, inherently incorporates demand through population data, which serves as a proxy for water demand. However, our intent was to highlight that, while the Falkenmark indicator provides a valuable high-level assessment of water scarcity, it does not explicitly account for sectoral water use or regional variations in consumption patterns, factors that can influence water scarcity, particularly in the context of compound events such as DZD. We have revised our manuscript to accurately reflect the strengths and limitations of the Falkenmark indicator. Please refer to discussion section in lines 476-487, as written below:

“Unlike broader water scarcity metrics like the Falkenmark indicator, used by Liu et al.³⁹, which use per capita water availability and relative population demand, our approach incorporates sector-specific water use and regional imbalance between supply and sectoral consumption (via SWSI) under human-induced climate. Note that SWSI on its own can identify water scarcity driven by high water consumption, but that can occur without climate-caused drought conditions. This distinction is important in the context of our study, as we define DZD as a prolonged anthropogenic drought-driven water scarcity caused by socio-physical factors, including water supply, human-made reservoirs, lakes, and sectoral water consumption. Therefore, it is essential to consider multiple indicators for assessing extreme events⁶⁸, including SPEI48, SRFI48, and SWSI48. Although this study focuses on socio-physical water scarcity, incorporating water quality and environmental flows, as highlighted by Liu et al.⁹, is critical for a holistic understanding of future water risks.”

Reviewer #3 (Remarks to the Author):

Review of Ravinandrasana and Franzke., NCOMMS-25-13170
“The First Emergence of Unprecedented Global Water Scarcity in the Anthropocene”

This study investigates the emergence of water scarcity under global change. This is done with a comprehensive approach that infers water scarcity by considering meteorological, hydrological and demand vs. supply perspectives. The authors find that in future projections calculated with the CESM2 Earth system model, significant water scarcity emerges in the coming decades in some places across the globe. The paper analyzes the timing of the emergence across regions and the affected population. The results furthermore show that the duration and time between water scarcity events can be similar in the future in some regions.

Recommendation:

I think the paper requires major revisions.

The topic of this study is interesting and timely. With ongoing climate change, precipitation and evaporation are changing in many regions, and this can affect river runoff in concert with other changes such as of vegetation or cryosphere dynamics. Moreover, in addition to related changes in freshwater supply, also demand is changing as populations and economies change with time. This study makes an important contribution to understand when and where these changes lead to severe water scarcity. I particularly like the novel, comprehensive approach to characterise water scarcity across meteorological, hydrological and societal domains. This way, I think the manuscript is very relevant and interesting for the readership of Nature Communications.

Response: Thank you for your thoughtful and positive feedback on our manuscript. We appreciate your recognition of the relevance, novelty, and significance of our study on the Day Zero Drought (DZD) events. We have carefully considered your suggestions and have made substantial revisions to improve the clarity and depth of the manuscript. In addition, we have provided a more detailed explanation in the revised manuscript to ensure that all suggestions and comments, including the specific points that you have raised below, are fully and clearly addressed.

In response to your comment on model dependence and scenario uncertainty, we have expanded our analysis to include comparisons with simulations from the Centre National de Recherches Météorologiques (CNRM) models under both SSP2-4.5 and SSP3-7.0 scenarios, sourced from the Coupled Model Intercomparison Project Phase 6 (CMIP6). We now include 10 members from the CNRM model. This addition allows us to evaluate the sensitivity of DZD emergence to differences in model structure and emission scenarios.

More broadly, we have updated the manuscript in the following key points:

- We now explicitly consider uncertainties in the Time of First Emergence (ToFE) of DZD in the results section. Specifically, we address the uncertainties arising from the use different climate model CESM2-LE and CNRM; the focus on surface water; the definition of DZD as a socio-physical water scarcity metric that does not include water quality or

environmental flow requirements; limitations and inaccuracies in the GRand reservoir datasets; and uncertainties in the reconstruction of water consumption data.

- We have dedicated a section on Adaptation pathways and policy implications in the results section to highlight the broader relevance of our findings for policymakers and stakeholders. In particular, we discuss how our study aligns informs progress toward the Sustainable Development Goals (SDGs) targets 6.1, 6.4, 13.1, and 13.2.
- We have extended the study and updated the methodology section, at the same time, made some sensitivity analysis of ToFE. These analyses explore:
 - the sensitivity of using different thresholds of the multi-year compound drought extremes to define DZD,
 - the importance of using reservoirs,
 - the effect of varying the duration of TRD by doubling and quadrupling,
 - the influence of the model structure between the CESM2-LE members and with CNRM models in ToFE,
 - and the sensitivity of ToFE relative to future socioeconomic scenarios (SSP2-4.5 vs SSP3-7.0).

However, before the paper can be published I would ask the authors to consider the concerns described below:

General comments:

(1) While I appreciate the methodological approach used in this study, I think that readers can not understand (and therefore also not appreciate) the results and conclusions with the present main text as this fails to explain most of the key terms and methods used in the analysis. This is a critical shortcoming. I could only follow the results in the main text after reading the full methods section. For example, in line 125 “Our study reveals a co-occurrence...” comes as surprise and it is hard to understand what “co-occurrence” you are referring to. Shortly after, the terms “time of emergence”, “fraction of attributable risk”, and drying out of “global reservoirs” appear without any explanation. In this context, also the “thresholds” in line 156 not clear, and “TRD” in line 159 appears without explanation, and not even the abbreviation is introduced. Finally, also the waiting time as a central concept of Figure 3 appears without introduction in line 174.

Response: We sincerely appreciate your careful reading of our manuscript and your recognition of the methodological approach. We fully understand your concern regarding the clarity of the main text and are grateful for your comments, which have helped us strengthen the clarity and coherence of the manuscript. In response, we have revised the manuscript to ensure that these terms are clearly defined upon first mention, and we have added brief explanations to provide context where needed. Specifically:

- We have clarified the term “co-occurrence” by replacing it with “concurrent occurrence” and expanding the explanation in the revised text lines 59-65, as shown below:

“However, DZD represents an acute water scarcity triggered by the simultaneous occurrence of multi-year precipitation deficits, river flow depletion, and high-water demand, leading to a critical depletion of reservoirs. Therefore, DZD is a multi-year compound extreme event that is determined by the concurrent occurrence of several interdependent events¹⁰. A compound extreme event refers to a simultaneous occurrence of multiple extreme events that can have drastic effects on a large scale, far greater than the impact of an individual event^{11,12}.”

- We have added more explanation for “time of emergence”, “fraction of attributable risk”, in lines 188-192 of the revised manuscript, as follows:

“This study defines ToFE as the first decade in which the Fraction of Attributable Risk (FAR) for DZD exceeds 0.99, indicating a 99% likelihood that human activities caused the onset of these unprecedented compound drought-scarcity events. ToFE is assessed relative to pre-industrial conditions (1850-1899), which serve as the baseline for detecting anthropogenic emergence.”

- We have clarified the meaning of “global reservoirs” in lines 197-199, shown below:

“About 14% of the global reservoirs from the Global Reservoir and Dams (GRand) database (Fig.S5, see methods for more information regarding the reservoirs) would dry out due to a high risk of DZD during their respective ToFE, as shown in Fig. 2a.”

- We have provided a clearer explanation of the “thresholds” in lines 214-216, as follows:

“Furthermore, the lower the thresholds applied to define the DZD, reflecting more severe and rare events, the later the ToFE will emerge, underscoring the complex relationship between event severity and its anthropogenic emergence (Fig. S10).”

- We have explicitly introduced and defined “TRD” in lines 224-226, written as:

“In addition, reservoir characteristics, specifically the Time for Reservoir to Dry (TRD), play a crucial role in detecting the ToFE of DZD. TRD serves as a proxy for how long a reservoir can sustain water supply under drought conditions when river inflow is the only source of water.”

- We have also provided an earlier and clearer introduction of the concept of “waiting time” in lines 272-280, as shown below:

“The recurrence and persistence of compound drought events are critical to understanding future water risk. In this context, we assess the waiting time directly by counting the number of months after the decade of the ToFE until the next event, for all consecutive DZD events until 2100, while the duration is calculated as the number of months a DZD event lasts. Both factors can importantly exacerbate the societal and ecological impact of DZD because its continuity is destructive and costly, especially when the waiting time is short and the duration is long. The duration plays a crucial role in determining the event’s extremeness and affects the exposure and vulnerability of society. Short waiting times between successive events limit the recovery period, thereby amplifying stress on water systems.”

Furthermore, some of these terms and approaches are also used in the abstract (“hydrological compound extremes”, “35%”, “waiting time”) which should instead describe the findings and conclusions more generally to allow readers to follow.

Response: We agree with your comment that the abstract was too technical. In response, we have revised it to present the findings more clearly and generally, making it more accessible to a broader readership. The revised Abstract can be found in lines 9-23 of the manuscript, as follows:

“Access to water is crucial for all aspects of life. Anthropogenic global warming is projected to disrupt the hydrological cycle, leading to water scarcity in many regions. However, which regions and when will experience unprecedented water scarcity is unknown. Here, we estimate the Time of First Emergence of drought-driven water scarcity events, referred to as “Day Zero Drought” (DZD), by analyzing the simultaneous impact of multi-year water supply deficits and high-water consumption. DZD is driven by hydrological compound extremes, where multiple stress factors, including prolonged rainfall deficits, reduced river flow, and increasing water consumption, occur simultaneously to cause acute water scarcity. Using a probabilistic framework and a large ensemble of climate simulations under the SSP3-7.0 scenario, we attribute the timing and likelihood of DZD events to human influence. Our findings indicate that 35% of DZD-prone regions will experience the Time of First Emergence by 2020 and 2030. The emergence of DZD is expected to potentially drain 14% of global reservoirs and to impact urban population most at the 1.5 °C warming level. The length of time between successive DZD events is shorter than the duration of DZD, leading to insufficient recovery periods and exacerbating water scarcity risks. Therefore, more proactive water strategies are urgently needed to avoid severe societal impacts of DZD.”

(2) The results presented here are based on simulations with a single Earth system model, CESM2. I understand that this choice is necessary as the analyses require a large ensemble which is probably not readily available from many Earth system models. At the same time, it is known that trends in precipitation and evapotranspiration, which are key variables for water scarcity projections, differ across projections of different Earth system models (see e.g. Orth et al. 2016, Denissen et al. 2022). I wonder to which extent the CESM ensemble can capture such uncertainty, or whether this only emerges when comparing different models? In any case, the authors should add some discussion about this point in the discussion section.

Response: We sincerely appreciate this insightful comment regarding our reliance on CESM2 large ensemble. Indeed, our study is primarily based on the CESM2-LE because of the need for a large number of realisations to robustly assess the emergence and characteristics of DZD events within a probabilistic framework, such as the Fraction of Attributable Risk (FAR). As the reviewer rightly notes, large ensembles remain rare across Earth System Models, which currently limits the choice of a large ensemble multi-model approach for this compound drought analysis.

We fully agree that structural uncertainties in projections of precipitation and evapotranspiration, which are key drivers of water stress, vary between models, as highlighted by Orth et al. (2016) and Denissen et al. (2022). These differences between models reflect

structural uncertainty, particularly concerning the representation of feedback between the land and the atmosphere, and the hydrological process. Although CESM2-LE captures internal climate variability and allows robust probabilistic assessments within a single model structure (albeit for the SSP3-7.0 scenario only), it does not encompass the structural uncertainties inherent across different models and emission scenarios. Therefore, we have expanded our analysis to include comparisons with simulations from the Centre National de Recherches Météorologiques (CNRM) models under both SSP2-4.5 and SSP3-7.0 scenarios, sourced from the Coupled Model Intercomparison Project Phase 6 (CMIP6).

We have revised the manuscript accordingly to explicitly acknowledge this limitation and cite Orth et al. (2016) and Denissen et al. (2022). The Uncertainty section of the Results section (lines 422-429) and Discussion (508-510) now explicitly discuss this point. Additionally, we have extended the Methodology and added a Sensitivity Analysis section (lines 942-1118) to explore the uncertainty of the Time of First Emergence (ToFE) of DZD more systematically.

To further address this limitation, we extended our analysis in two keys ways:

1. Sensitivity analysis within CESM2-LE. We examined the sensitivity of ToFE to:

- i. thresholds for defining multi-year compound water stress (SPEI48, SRFI48, and SWSI48) (lines 942-969)
- ii. the role of reservoirs assumptions (lines 971-982)
- iii. varying duration for multi-compound drought events to deplete water in the reservoir by doubling and quadrupling the TRD (lines 984-992),
- iv. timescale of the multi-year drought indices (lines 994-997),
- v. and structural uncertainty among the CESM2-LE members (lines 999-1025).

To directly address the concern regarding ensemble variability and to support the robustness of our findings, we computed the Time of First Emergence (ToFE) for each ensemble member (100 members) of CESM2, shown in the figure below (now provided in Supplementary Figure S20). We plot the Probability Density Function (PDF) of ToFE in considering all grid points for each ensemble member. The dark green line represents the PDF of the ToFE based on the ensemble sum of all DZD events (as defined in equation 4), while the aquamarine lines represent the PDFs of the ToFE for individual ensemble members, based on the following formulation of FAR below (as defined in equation 5):

$$FAR_i(t) = 1 - \frac{P_{preindustrial,i}}{P_{forcing,i}(t)} \text{ with } \begin{cases} P_{preindustrial,i} = \frac{event_{preindustrial,i}(DZD)}{N_{preindustrial,i}} \\ P_{forcing,i}(t) = \frac{event(t)_{forcing,i}(DZD)}{N_{forcing,i}(t)} \end{cases}$$

Where $P_{preindustrial,i}$ is the probability of the counterfactual for member i , which is the ratio between the summation of the event of the DZD event within the preindustrial period (1850-1899) and the number of samples within the same period ($N_{preindustrial}$). While $P_{forcing,i}(t)$ is the probability of the factual for member i , which is the ratio between the decadal summation of the frequency of the DZD event of the member i during each decade from 1900 to 2100 and the number of samples during the decade ($N_{forcing}(t)$). The ToFE of DZD has been considered

as the first decade of FAR greater than 0.99, where a 99% probability of the impact of the acute water scarcity that has emerged can be associated with a human-induced signal after the decade of completion of reservoirs.

The results (Fig. S20a) exhibit substantial variability among ensemble members between 1900 and 1990, reflecting high uncertainty during this early period when the anthropogenic signal is still weak relative to internal variability, showing that structural uncertainty arising from the use of a single model remains an important caveat. The result indicates a strong agreement across members, with the highest density of emergence concentrated between 2020 and 2030. Agreement increases over time, particularly by the end of the 21st century, underscoring the robustness of the signal under CESM2-LE. This ensemble-based approach provides a meaningful and reliable estimation of FAR and ToFE, and we now explicitly discuss its limitations in the context of model dependency and structural uncertainty, see lines 422-429 and 999-1025.

2. Cross-model and scenario comparison using CNRM models:

We have extended our analysis to include comparisons with simulations from the Centre National de Recherches Météorologiques (CNRM) models under both SSP2-4.5 and SSP3-7.0 scenarios, sourced from the Coupled Model Intercomparison Project Phase 6 (CMIP6). This allowed us to explore structural uncertainty and scenario sensitivity for DZD emergence (Supplementary Figures S20 and S21). We selected 10 ensemble members from CNRM members that include both atmospheric and river discharge variables across SSP2-4.5 and SSP3-7.0 scenarios: CM6-1 (r2ilp1f2, r3ilp1f2, r4ilp1f2, r5ilp1f2, r6ilp1f2), ESM2-1 (r2ilp1f2, r3ilp1f2, r4ilp1f2, r5ilp1f2), and CM6-1-HR r1ilp1f2 (see Methodology and Sensitivity Analysis, lines 1027-1118). This choice was driven by the limitations in river discharge datasets, as CNRM was the only model that provided more ensemble members with both atmospheric and river discharge variables. Furthermore, probabilistic attribution methods such as the FAR require large ensemble sizes to confidently characterize forced emergence signals. The limited ensemble size available for CNRM under SSP3-7.0 limits the reliability of such analysis and emphasizes the need for larger and more consistent multi-model ensemble frameworks to assess future water scarcity risks.

Results show that model structure influences projections of ToFE, with spatial patterns and ToFE varying across CESM2-LE and CNRM ensembles under the same scenario SSP3-7.0 (Figs. S20a-b and S21a-b, d; see lines 1027-1069). The Probability Density Functions of DZD ToFE of individual members (ToFE derived from equation 5) exhibit greater dispersion and multiple flattened peaks across ensemble members (Figs. S20b-c). The thick green line (ToFE derived from equation 4, aggregated event) is broader and flatter, indicating considerable variability in ToFE across ensemble members and highlighting the uncertainty in the timing of DZD emergence across members. This variability emphasized the challenge of detecting a robust probabilistic signal from a limited ensemble size.

Comparing the spatial pattern of DZD ToFE between CESM2-LE and CNRM, we found that approximately 76% of the land fraction is classified as uncertain with respect to future DZD emergence, illustrating substantial inter-model disagreement in the DZD-prone

region in the model (now provided in Supplementary Figure S21). Models structure contributes to spatial discrepancies (Fig. S21a-b and d-e), with CESM2-LE projects broader DZD emergence in northern Africa, whereas CNRM highlights different regions. Notably, 14% of ToFE show later emergence under CESM2-LE (Fig. S21d), even under the same forcing scenario (SSP3-7.0), suggesting that CESM2-LE is more conservative in detecting later emergence of compound hydrological extremes. However, CESM2-LE and CNRM agree on DZD occurrence across 24 % of the DZD-prone land area, though within this overlap, CESM2-LE projects later emergence over 14% of the area and earlier emergence over 10% compared to CNRM. Moreover, ensemble spread within CNRM (Fig. S20b-c) also illustrates the variability among the models to detect the water scarcity. The PDFs of individual members are more dispersed, with multiple peaks and flatter. The thick green line (representing ToFE derived from equation 4) is broader and flatter, indicating the variability in ToFE across ensemble members, reflecting uncertainty in the timing of DZD emergence across members. This variability emphasized the challenge of detecting a robust probabilistic signal from a limited ensemble size.

We also assessed scenario sensitivity by comparing SSP2-4.5 and SSP3-7.0. Results show that the influence of emission scenarios on DZD ToFE is region-specific (Fig. S20b-c and f), due to the interaction between regional climate drivers and human water use. High-emission (SSP3-7.0) can either advance or delay DZD emergence. Notably, spatial discrepancies in DZD-prone regions persist across scenarios. When comparing the spatial pattern of ToFE under CNRM SSP2-4.5 with CESM2-LE SSP3-7.0 (Fig. S21e), results show that high spatial disagreement of 76% of land areas exhibit uncertain DZD emergence, meaning that emergence is detected in only one of the models. Only 9 % of regions show earlier emergence in CESM2-LE SSP3-7.0, while 14% indicate later emergence relative to CNRM SSP2-4.5. By considering the same model, CNRM, under different scenarios, SSP3-7.0 and SSP2-4.5 (Fig. S21f), the uncertainty still dominates but decreases to 43% of the land area, and spatial discrepancies in DZD-prone regions persist across scenarios. Notably, the near-equal split between earlier and later emergence in different regions indicates that scenario choice (SSP3-7.0 vs SSP2-4.5) may affect ToFE more symmetrically but also underscores the spatial heterogeneity of hydrological responses to combined climate and water use stress. The results show that the influence of emission scenarios on DZD ToFE is region-specific, due to the interaction between regional climate drivers and human water use. Under the high-emission scenario (SSP3-7.0), DZD emergence can either advance or be delayed depending on the region.

The extended Sensitivity Analysis section on the Time of First Emergence (ToFE) of DZD can be found in lines 942-1118 of the revised manuscript and is written as follows:

Sensitivity Analysis. *We tested the sensitivity of ToFE to six factors. Firstly, the threshold for defining the multi-year compound drought can influence the detection of DZD. Therefore, to test the robustness of the DZD definition, we performed a sensitivity analysis using different thresholds for SPEI48, SRFI48, and SWSI48 (Fig. S10). First, we modified the SPEI48 threshold to be below -2 and kept SRFI48 below -1.5 and SWSI48 below 0.6 (Fig. S10a and S10i). The ToFE emerges later than in Fig. 2a, particularly in Africa, where ToFE is sensitive to SPEI, i.e., to the decreasing precipitation and increasing evapotranspiration. Next, we*

slightly changed SRFI48 to be below -1.6, SPEI48 to be below -2, and kept SWSI48 below 0.6 (Fig. S10b and S10j). The ToFE remains almost the same, and the ToFE emerges later by increasing the severity of SRFI to be below -2 (Fig. S10c and S10k), particularly in the northern part of Africa. Then, as we continued to modify SRFI48 so that it is less than -1 (Fig. S10d and S10l), the ToFE becomes earlier than Fig. 2a, mostly in the northern part of Africa. The ToFE is sensitive to the severity of the streamflow drought in Africa. After that, we repeated the same analysis, but considering SWSI48 of less than 1 and SPEI48 of less than -2 below and SRFI48 below -1.5 (Fig. S10e and S10m); while SRFI48 below 1.6 for Fig. S10f and S10n. The results show that ToFE is more likely to start earlier than Fig. 2a in a few regions, meaning that ToFE is more likely to be sensitive to streamflow depletion (SRFI48) and increased water consumption (SWSI48). In the latter case, we kept SPEI48 below -1.5 and SRFI48 below -2 with SWSI48 below 1 for Fig. S10g and S10o; and SWSI48 below 0.6 for Fig. S10h and S10p. The results show the sensitivity of the ToFE to SRFI48 and SWSI48; and the ToFE emerges later than Fig. 2a in Africa but earlier in other regions. Therefore, we can conclude that the ToFE of DZD is more sensitive to the severity of decreasing precipitation and increased evapotranspiration (SPEI48), the river flow drought (SRFI48) and increased water demand (SWSI48), particularly in Africa, while increasing water consumption solely have an impact on the early emergence of ToFE in some parts of Asia and America, compared to the other factor. The SRFI and SWSI are more closely related to the actual availability of river flow and water use, respectively. When water demand rises, the available water supply (e.g., river flow, even if unaffected by precipitation) becomes insufficient to meet demand, triggering drought-like conditions (or water scarcity) in terms of availability.

Secondly, to assess whether the treatment of grid cells with and without (as defined in equation 3 for DZD) or solely without reservoir (DZD is defined as a compound event of $SPEI48 \leq -1.5 \cap SRFI48 \leq -1.5 \cap SWSI48 \leq 0.6$), introduces inconsistencies in the spatial patterns of ToFE, we conducted a sensitivity analysis comparing ToFE patterns (supplementary Fig. S12). The results reveal that spatial differences are negligible in most regions. The most noticeable delays are confined to the Mediterranean region, where major reservoirs constructions were completed mid- to late-20th century (Fig. S6). As climate change influences the onset of compound events, it is critical for decision-makers to revisit the role of existing water infrastructure in future water security planning. The application of FAR greater than 0.99, combined with localized reservoir adjustment of DZD detection, ensures that the global ToFE pattern represents both high attribution confidence and hydrological realism, without introducing methodological biases between grid cells with and without reservoirs.

Thirdly, the estimation of the TRD may influence the ToFE of DZD. The TRD is considered as the duration to take for a multi-compound drought event to dry the water in the reservoirs if the only source of the water supply of the reservoirs is river flow during a drought period. Our approach seems to be reasonable, and we also checked the sensitivity of our assumption by doubling and quadrupling the TRD time scale (Fig. S11). The results show that only a few regions have a small change of one decade with increased TRD. However, the TRD

is also influenced by various socio-economic factors, such as water demand and the socio-economic sectoral usage, which we address using the Standardized Water Scarcity Index (SWSI48). It is important to note that political decisions regarding management were not included in this modeling approach.

Fourthly, we have looked at the sensitivity of the time scale by considering the 36- and 60-month time scales (Figs. S15 and S16) of long-duration compound events for SPEI, SRFI, and SWSI. Only a few regions, located almost entirely in Africa, show changes in ToFE using a 36 or 60-month timescale of extreme events as shown in Fig. S17.

Fifthly, we look at the sensitivity of the ToFE relative to model structure across the CESM2-LE members. We repeat the analysis, looking at the model uncertainty by looking for the ToFE for each member in CESM2-LE, based on the following formulation of FAR below (equation 5). This allows us to examine the spread of emerging timing of Fay Zero Droughts (DZD) and to evaluate the inter-member agreement as shown in Fig. S20. The result exhibit, Fig. S20a, substantial variability among ensemble members between 1900 and 1990, reflecting high uncertainty during this early period when the anthropogenic signal is still weak relative to internal variability, showing that structural uncertainty arising from the use of a single model remains an important caveat. However, a strong ensemble consensus emerged after 2000, with most members indicating emergence between 2020 and 2030, and increasing agreement toward the end of the 21st century. Individual ensemble members (thin green lines) show very synchronized emergence between 2030-2040. There is a sharp, narrow peak, indicating low ensemble spread and high confidence in ToFE under strong forcing. This coherence across members supports the robustness of our findings in terms of both timing and magnitude of anthropogenic influence on DZD events in CESM2-LE under SSP3-7.0.

$$FAR_i(t) = 1 - \frac{P_{preindustrial,i}}{P_{forcing,i}(t)} \text{ with } \begin{cases} P_{preindustrial,i} = \frac{event_{preindustrial,i}(DZD)}{N_{preindustrial,i}} \\ P_{forcing,i}(t) = \frac{event(t)_{forcing,i}(DZD)}{N_{forcing,i}(t)} \end{cases} \quad (5)$$

Where $P_{preindustrial,i}$ is the probability of the counterfactual for member i , which is the ratio between the summation of the event of the DZD event within the preindustrial period (1850-1899) and the number of samples within the same period ($N_{preindustrial}$). While $P_{forcing,i}(t)$ is the probability of the factual for member i , which is the ratio between the decadal summation of the frequency of the DZD event of the member i during each decade from 1900 to 2100 and the number of samples during the decade ($N_{forcing}(t)$). The ToFE of DZD has been considered as the first decade of FAR greater than 0.99, where a 99% probability of the impact of the acute water scarcity that has emerged can be associated with a human-induced signal after the decade of completion of reservoirs.

Sixthly, to evaluate the influence of model structural uncertainty on the ToFE of DZD events, we extended our analysis beyond CESM2-LE by using hydro-climatic data from the Centre National de Recherche Météorologiques (CNRM) models (SSP2-4.5 and SSP3-7.0 with 1.4×1.4 degree) from the Coupled Model Intercomparison Project Phase 6 (CMIP6). Specifically, we analysed simulations under the SSP2-4.5 and SSP3-7.0 scenario, including monthly precipitation, minimum and maximum temperature, and river discharge data spanning 1850-2100. Due to the unavailability of water demand projections under SSP3-7.0, we used water consumption estimates from SSP3-RCP6.0 across the five Global Climate Models (GCMs) from GFDL, HADGEM, IPSL, MIROC, and NORESM, which account for sectoral water use sectors such as domestic, irrigation, industry, electricity, livestock, and mining, capturing socio-economic development water use demand. We applied the same methodology used for CESM2-LE. Computing the three key indicators, the SPEI48, SRFI48, and SWSI48, and applying quantile delta mapping (QDM) bias correction using drought indices ERA5-based references. To ensure methodological consistency and data completeness, we selected 10 ensemble members from the CNRM model that include both atmospheric and river discharge variables across the SSP2-4.5 and SSP3-7.0 scenarios: CM6-1 (r2i1p1f2, r3i1p1f2, r4i1p1f2, r5i1p1f2, r6i1p1f2), ESM2-1 (r2i1p1f2, r3i1p1f2, r4i1p1f2, r5i1p1f2), and CM6-1-HR r1i1p1f2. The spatial results (Fig. S21) reveal pronounced inter-model and scenario differences. We use the methods as structured estimates that enable consistent analysis across regions and sectors. The spatial resolution of the datasets is interpolated to the CNRM atmospheric model resolution ($1.4^\circ \times 1.4^\circ$) using the first-order conservative remapping (remapcon) method from the Climate Data Operator⁷⁸ (CDO). Our results reveal that, compared to CESM2-LE (Fig. S21a), which projects later DZD emergence and a more geographically confined hotspot, especially in the Mediterranean, the United States of America (USA), and Africa, the CNRM models (Fig. S21b-c) show earlier and more widespread emergence. The inter-model comparison (Fig. S21d-e) reveals that CESM2-LE and CNRM disagree on the emergence of DZD in 76% of DZD-prone regions, indicating that emergence is detected in only one of the two models in some areas. Notably, 14% of ToFE show later emergence under CESM2-LE (Fig. S21d), even under the same forcing scenario (SSP3-7.0), suggesting that CESM2-LE is more conservative in detecting later emergence of compound hydrological extremes. However, CESM2-LE and CNRM agree on DZD occurrence across 24 % of the DZD-prone land area, though within this overlap, CESM2-LE projects later emergence over 14% of the area and earlier emergence over 10% compared to CNRM. Moreover, ensemble spread within CNRM (Fig. S20b-c) also illustrates the variability among the models to detect the water scarcity. The PDFs of individual members are more dispersed, with multiple peaks and flatter. The thick green line (representing ToFE derived from equation 4) is broader and flatter, indicating the variability in ToFE across ensemble members, reflecting uncertainty in the timing of DZD emergence across members. This variability emphasized the challenge of detecting a robust probabilistic signal from a limited ensemble size. These findings highlight the critical role of model structural differences in shaping projections of hydrological extremes. Importantly, probabilistic attribution methods, such as the FAR, require large ensemble sizes to confidently characterize forced emergence signals. The relatively small ensemble available for CNRM

under SSP3-7.0 limits the reliability of such analysis and reinforces the need for larger and more consistent multi-model ensemble frameworks to assess future water scarcity risks.

Finally, to assess the sensitivity of the ToFE of DZD relative to future socioeconomic scenarios, we applied our detection framework to hydro-climatic simulations from CMIP6 CNRM models under the SSP2-4.5 scenario. We utilized the same ensemble members as in the previous CNRM SSP3-7.0 analysis to ensure consistency. The analysis incorporated available water consumption projections from five Global Climate Models (GCMs) from GFDL, HADGEM, IPSL, MIROC, and NORESM under SSP2-RCP4.5. The approach followed the same methodological steps as applied to CESM2-LE (Fig. S1). Specifically, we computed the SPEI48, SRFI48, and SWSI48, and applied the bias correction method, QDM, using ERA5-based reference indices, and subsequently determined the ToFE. All datasets are interpolated to the CNRM atmospheric resolution ($1.4^{\circ} \times 1.4^{\circ}$) using the first-order conservative remapping (remapcon) method from the CDO. The results (Fig. S20c) reveal substantial spread among ensemble members under CNRM SSP2-4.5, highlighting pronounced uncertainty in DZD emergence timing throughout the 21st century. Compared to the higher-emission SSP3-7.0 (Fig. S20b), the emergence is delayed and more dispersed, with broader PDFs and later peaks, suggesting that moderate forcings lead to slower distribution and less certain emergence of water scarcity extremes. When comparing the spatial pattern of ToFE under CNRM SSP2-4.5 with CESM2-LE SSP3-7.0 (Fig. S21e), results show that high spatial disagreement of 76% of land areas exhibit uncertain DZD emergence, meaning that emergence is detected in only one of the models. Only 9 % of regions show earlier emergence in CESM2-LE SSP3-7.0, while 14% indicate later emergence relative to CNRM SSP2-4.5. By considering the same model, CNRM, under different scenarios, SSP3-7.0 and SSP2-4.5 (Fig. S21f), the uncertainty still dominates but decreases to 43% of the land area, and spatial discrepancies in DZD-prone regions persist across scenarios. Notably, the near-equal split between earlier and later emergence in different regions indicates that scenario choice (SSP3-7.0 vs SSP2-4.5) may affect ToFE more symmetrically but also underscores the spatial heterogeneity of hydrological responses to combined climate and water use stress. The results show that the influence of emission scenarios on DZD ToFE is region-specific, due to the interaction between regional climate drivers and human water use. Under the high-emission scenario (SSP3-7.0), DZD emergence can either advance or be delayed depending on the region. Notably, spatial discrepancies in DZD-prone regions persist across scenarios, with 43% of the land area remaining uncertain between the SSP2-4.5 and SSP3-7.0 scenarios within the CNRM model. However, both scenarios, SSP2-4.5 and SSP3-7.0, agree on DZD emergence across 57 % of the DZD-prone land area. Within this overlap, SSP3-7.0 projects later emergence over 17% of the area and earlier emergence over 18% compared to SSP2-4.5, while 22% of the area shows no change in the ToFE between the two scenarios (Fig. S21f). These findings underscore the role of both scenario and model structures in shaping DZD emergence. Notably, even under high-forcing SSP3-7.0, CESM2-LE may still project later ToFE than CNRM under moderate forcing (SSP2-4.5), pointing to differences in model sensitivity to hydro-climatic stressors. This highlights the importance of multi-model and multi-scenario assessments when evaluating risks associated with extreme emergence and water scarcity. Furthermore, a probabilistic approach such as the

FAR requires large ensembles to ensure robust estimates. The relatively small ensemble size of CNRM limits the confidence in scenario-attribution results, underscoring the need for ensemble expansion and multi-model convergence to improve attribution robustness and risk quantification. Given these model differences, CESM2-LE provides output at a higher spatial resolution ($1.25^{\circ} \times 0.9375^{\circ}$) compared to the lower-resolution CNRM model ($1.40625^{\circ} \times 1.40625^{\circ}$). CESM2-LE detects finer-scale features and localized extremes that may be overlooked or underrepresented in the CNRM. Therefore, we have not aggregated events across both CESM2-LE and CNRM, since increasing the CNRM resolution to the resolution of CESM2-LE could introduce spatial biases and distort the representation of extreme events.”

Finally, CESM2-LE is particularly valuable for event attribution studies, using the Fraction of Attributable Risk (FAR), as it provides a large number of simulations under both historical and climate scenarios. The spread across the ensemble members (100 members) captures internal climate variability, which enables a more accurate quantification of uncertainty in event attribution. This ensemble structure allows for a robust separation of the human-induced attribution from natural climate variability, an essential requirement for FAR calculations, particularly for rare events such as DZD. At the same time, we fully acknowledge that CESM2-LE does not capture the structural and scenario-related uncertainties inherent in multi-model projections. Our inclusion of CNRM results explicitly addresses this limitation and highlights the importance of model dependency in projections of DZD emergence. We now address these limitations in the Uncertainty section of the revised manuscript (lines 422-429) along with their implications for our findings, detailed below:

“A key limitation of this study is the reliance on a CESM2-LE and a limited number of CNRM simulations for the sensitivity analysis. CESM2-LE provides robust ensemble consistency, suitable for probabilistic analysis, but lacks scenario diversity and structural uncertainties across Earth System Models (ESMs). Conversely, the CNRM model includes more scenarios but has fewer ensemble members and lower spatial resolution, limiting its ability to capture localized extremes. These limitations underrepresent inter-model variability in drought drivers, including precipitation and evapotranspiration, whose trends may vary among ESMs^{60,61}, limiting our uncertainty assessment.”

Moreover, we recommend that future research incorporate broader multi-model and scenario comparisons, as noted in the Discussion section, (lines 508-510), as follows:

“To support such efforts and reduce uncertainty in water scarcity assessment, expanded hydrological simulations across diverse models and emission scenarios are urgently needed.”

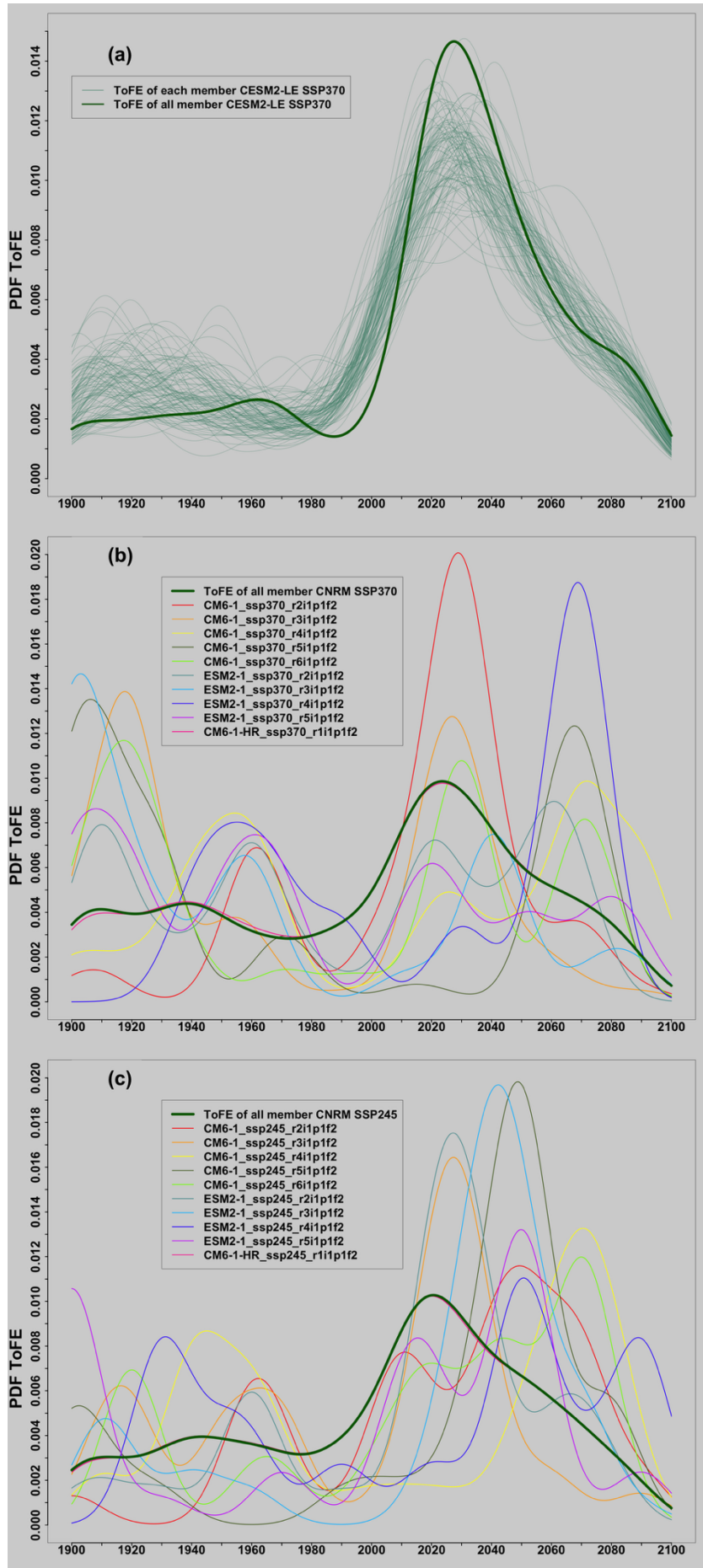


Fig S20: Probability Density Function (PDF) of Time of First Emergence of DZD events, in considering all grid points for each ensemble member across different models and scenarios. (a) ToFE PDFs from CESM2-LE under SSP3.7-0. Thick dark green line represents the PDF of the ToFE based on the sum of all DZD events (as defined in equation 4), while the thin aquamarine lines represent the PDFs of the ToFE for individual ensemble members, based on equation (5) of FAR. (b) ToFE PDFs for different ensemble members from CNRM-CM6-1 and CNRM-ESM2-1 models under SSP3.7-0. (c) Same as (b) but for SSP2.4-5. Colored thin lines represent individual ensemble members distinguished by the CNRM model (as defined in equation 5). The thick dark green line in each panel shows the ToFE based on equation (4). While our primary objective was to emphasize the externally forced signal, hence the use of aggregated events across the ensemble, to assess the internal variability and its influence on our results, we conducted a Time of First Emergence (ToFE) analysis across each ensemble member, to transparently assess the spread and uncertainty within the ensemble. This allows us to examine the spread of emerging timing of Fay Zero Droughts (DZD) and to evaluate the inter-member agreement. We computed the probability density functions (PDFs) of ToFE for each member across all global land covered by DZD. The figure (a) exhibits substantial variability among ensemble members between 1900 and 1990, reflecting high uncertainty during this early period when the anthropogenic signal is still weak relative to internal variability, showing that structural uncertainty arising from the use of a single model remains an important caveat. However, a strong ensemble consensus emerged after 2000, with most members indicating emergence between 2020 and 2030, and increasing agreement toward the end of the 21st century. This coherence across members supports the robustness of our findings in terms of both the timing and magnitude of anthropogenic influence on DZD events. Figure (b) and (c) shows a disagreement between the model in CNRM along all periods, 1900-2100. The dark green line from both models of each panel shows a high density of ToFE between the decades of 2020 and 2030. In terms of the scenario, the emergence under SSP2.4-5 is more delayed and spread out compared to SSP3.7-0. Peaks occur later, and the PDFs are broader compared to Fig. S18b. This suggests that under moderate forcing (SSP2.4-5), DZD emergence is slower and more uncertain. These results highlight the influence of both model structure and emissions scenarios on the DZD emergence.

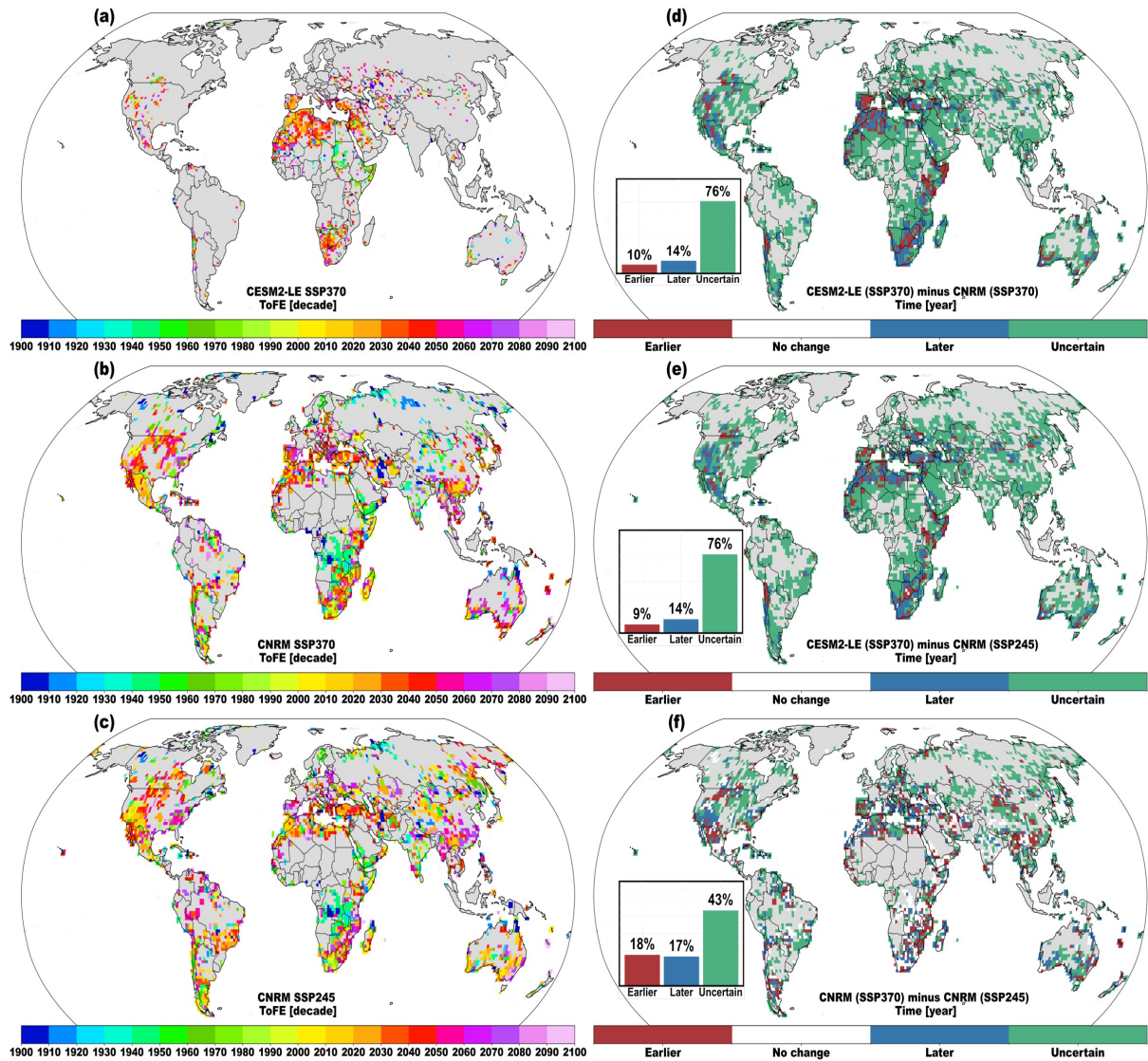


Figure S21: Spatial distribution of the Timing (ToFE) and associated uncertainties of Day Zero Drought (DZD) events across climate models and emission scenarios (CESM2-LE under SSP3-7.0 and CNRM under SSP2-4.5 and SSP3-7.0). Panels (a-c) depict the decadal ToFE of DZD events for each grid cell, calculated as the first decade in which the Fraction of Attributable Risk (FAR) exceeds 0.99, indicating that over 99% of DZD risk is attributable to anthropogenic climate change, based on the cumulative count of DZD events (Equation 4). Results are shown for (a) CESM2-LE under SSP3-7.0, (b) CNRM under SSP3-7.0, and (c) CNRM under SSP2-4.5. Panels (d-f) illustrate inter-model and scenario-based differences in ToFE for grid cells where DZD emergence is detected under those compared cases. Panel (d) represents the difference between CESM2-LE (SSP3-7.0) and CNRM (SSP3-7.0), reflecting structural uncertainty between models. For consistency, ToFE values from CESM2-LE (a) are interpolated to the CNRM resolution to compute the difference between the ToFE between CESM2-LE (SSP3-7.0) and CNRM (SSP3-7.0) as shown in (d) and (e). Panel (e) compares CESM2-LE (SSP3-7.0) and CNRM (SSP2-4.5), highlighting scenario- and model-driven uncertainty. Panel (f) compares CNRM (SSP3-7.0) and CNRM (SSP2-4.5), isolating internal model sensitivity emissions pathways. Inset bar plots in panels (d-f) quantify the proportion of

DZD-prone land grid cells experiencing earlier and later emergence, as well as regions with divergent DZD emergence (uncertain DZD-prone regions). Red and blue shading denote areas where ToFE occurs earlier or later, respectively, in the first model or scenario listed. The green shading indicates regions with inconsistent DZD emergence among the inter-model and scenarios cases (i.e., emergence only occurs in one of the models or scenarios), underscoring uncertainty in projections. The results show that CNRM projects broader emergence in parts of Asia, Australia, and America, while CESM2-LE projects earlier and later emergence across the Mediterranean and Africa. Grey areas indicate locations with no emergence of DZD condition during the analysis period. These results highlight the importance of model structure and emissions scenario in assessing the timing and spatial distribution of DZD emergence.

(3) I like the idea of analysing waiting times and durations of water scarcity events in Figure 3. At the same time, the comparison PDFs in the present Figure 3 does not allow to infer explicitly where and how often durations actually exceed waiting times. To me it seems that this aspect is most critical in terms of impacts and for informing future adaptation strategies, and therefore I would recommend revising Figure 3 to highlight this more explicitly.

Response: We thank the reviewer for highlighting the importance of spatially explicit exceedance analysis. We agree that highlighting where and how often DZD durations exceed waiting times is critical for understanding impacts and for informing effective adaptation strategies.

In response to this valuable suggestion, we have revised Fig. 3 and added a new panel (Panel c) to more explicitly represent the frequency of extreme DZD events, defined as cases where the duration exceeds the waiting time. The updated panel now shows the spatial distribution of frequency (%) of such events across all grid cells. In addition, we have included a circular inset histogram summarizing the proportion of affected land areas, thereby offering a more intuitive view of regional vulnerability across the frequency of extreme prolonged DZD.

The revised result can be found in lines 313-324, as follows:

“To identify where DZD events will be most severe, Fig. 3c shows the DZD-prone regions and their frequency, defined as a case where DZD event duration exceeds its waiting time, indicating short recovery periods and prolonged impact. Almost 47% of the global high-risk regions will experience extreme DZD events with a frequency between 20% and 30%. Around 12% of the DZD-prone regions have a frequency of extreme prolonged DZD events above 50%, indicating that almost half of the events have longer durations than waiting times, suggesting frequent and severe water crisis conditions with substantial socio-economic impacts. Regions with high water demand and strained reservoirs, such as the Mediterranean, exhibit both high frequency and long durations of extreme DZD. In these areas, the compounded effects of hydro-climatic stress and human demands intensify the severity and persistence of DZD, exposing heightened vulnerability to water crises and limiting recovery capacity.”

In addition, we clarified the methodology section (DZD characteristics: waiting time and duration, lines 910-933), to explain the methodology of the frequency of extreme DZD

events and the relevance of this metric for identifying priority regions for resilience planning against prolonged water crisis, as follows:

“DZD characteristics: waiting time and duration. While the ToFE is an important measure of global warming impacts, its true impact is measured by how long these events last and how soon they will re-occur once they have emerged for the first time. The length of time of a DZD event is defined as the DZD duration, while the waiting time is identified as the time elapsed between the end of the previous event and the start of the next consecutive DZD event, as illustrated in Fig. S8. To quantify these characteristics, we calculate the DZD duration and waiting time at each grid cell globally across the CESM2-LE for all ensemble members. We calculate the waiting time directly by counting the number of months after the decade of the ToFE under anthropogenic influence until the next event, for all consecutive DZD events until 2100, while the duration is calculated by length of a DZD event once it occurs.

In addition, we assess the frequency of extreme DZD conditions, characterized by events that are both frequent and prolonged. Specifically, for each grid point and each ensemble member of CESM2-LE, we identify all DZD events occurring between the decade of ToFE and the year 2100. We then count the number of DZD event where its duration exceeds the waiting time, i.e., cases where the DZD event persists longer than the recovery period before the next event. These counts are aggregated at each grid across all 100 members of CESM2-LE within the ToFE and 2100. The frequency of extreme DZD conditions is computed at each grid cell as the ratio of the sum of these events to the total DZD events across all members of CESM2-LE within the ToFE and 2100 period. This spatially explicit frequency is then mapped globally (Fig. 3c) to highlight regions most vulnerable to sustained and recurrent DZD conditions.

For each DZD-prone region shown in central spatial map of Fig.3, we then average the values across all grids located within the regions. To characterize the statistical distribution of these metrics, we fit probability density functions (PDFs) to the distributions of DZD duration and waiting time.”

This addition emphasizes the locations and intensity of the most impactful compound drought situations leading to water scarcity. We have also updated the figure 3 caption in lines 332-349, as below:

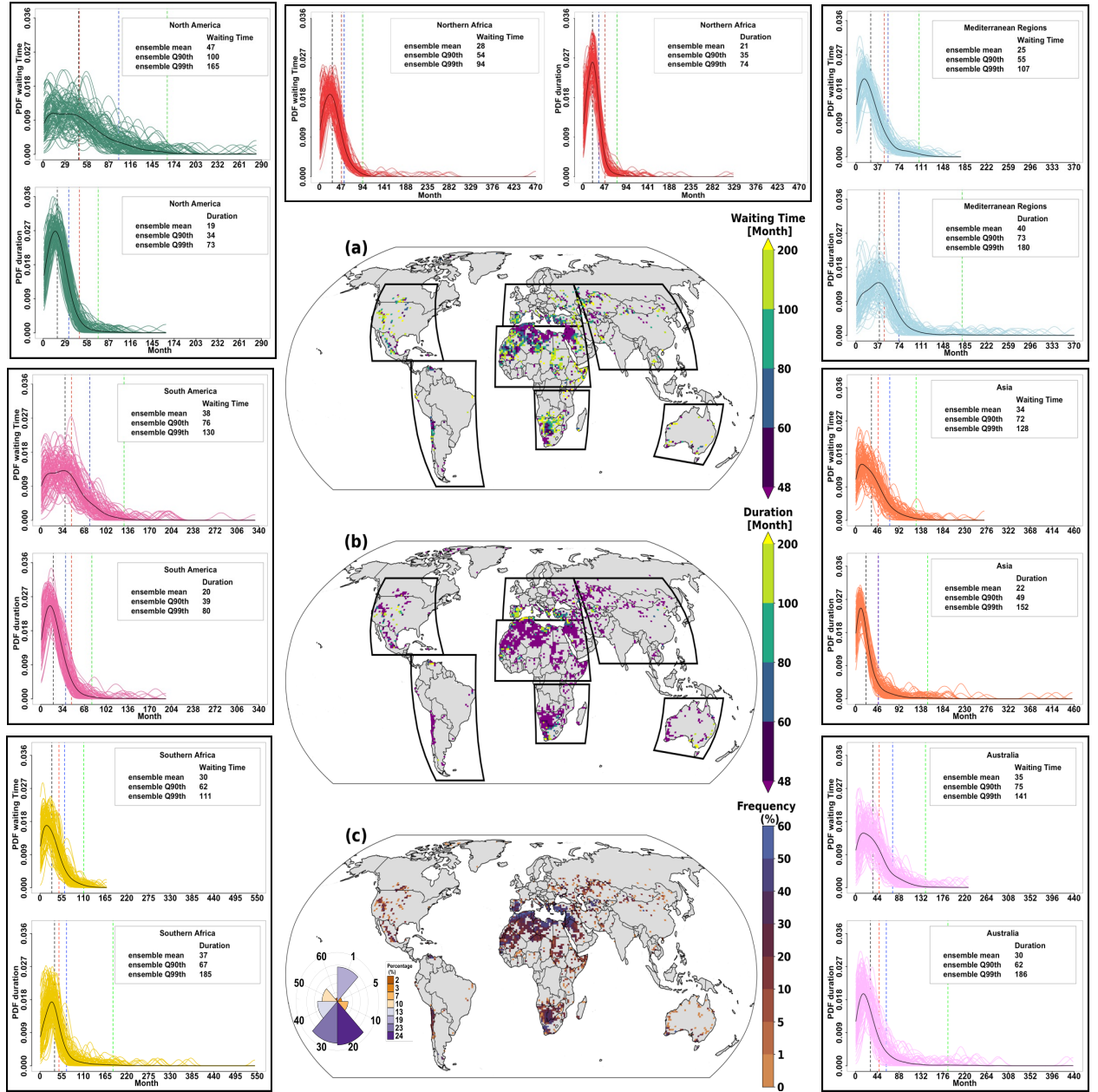


Fig. 3: Characteristics of Day Zero Drought (DZD) events in terms of waiting time and duration, based on CESM2-LE simulations under the SSP3-7.0 scenario. The central spatial map shows the spatial distribution of the ensemble-mean waiting time (a) and duration (b) of DZD events, respectively, following the Time of First Emergence (ToFE) at each grid point of DZD-prone regions across the globe. Panel (c) represents the spatial distribution of the frequency (%) of extreme DZD events, defined as those where the event duration exceeds the waiting time, indicating prolonged water scarcity impact and short recovery period. The accompanying inset circular diagram of panel (c) illustrates the distribution of these events, with the color scale indicating the proportion (percentages) of grid cells experiencing such conditions. This visualization highlights where and how frequently extreme DZD conditions with long duration and short waiting time emerge. The surrounding paired panels depict the Probability Density Function (PDF) of waiting time and duration for DZD events across seven

DZD-prone regions. Colored lines represent the PDF of each ensemble of 100 CESM2-LE, while the black line is the ensemble mean of the respective PDF. The vertical dashed lines mark the ensemble mean (black), 90th percentile (blue), and 99th percentile (green) for each region. The red dashed line represents the monthly scale of the compound extreme event, which is 48 months. The period considered for each grid point started from the month after each decade of their respective ToFE and continued until 2100.

Specific comments:

line 62: I think this is not always the case; the simultaneous occurrence of several climate extremes **can** lead to more severe impacts

Response: Our intention was not to suggest that compound extremes always result in more impacts, but rather to highlight that their simultaneous occurrence can increase risks. To clarify, we have revised the sentence, in lines 68-71, to read:

“Hence, the simultaneous occurrence of several climate extremes can lead to more severe impacts¹³ on water supply¹⁴ and subsequently on society and ecosystems¹⁵, highlighting the need for integrated drought assessment frameworks that account for compound events.”

line 66: “global warming disrupts the water cycle”, this statement is too strong and too general, and comes without explanation and references; a similar statement should be corrected in lines 494-496

Response: We have revised the sentence to provide a more precise statement, supported by appropriate references, as written below (lines 81-85):

“On a global level, future climate projections indicate that global warming is expected to disrupt and intensify the water cycle variability²⁴, leading to more severe wet-dry fluctuation periods²⁵, enhancing evapotranspiration²⁶, and reducing precipitation and surface runoff²⁴ in many regions. These changes are expected to increase the likelihood of both climatological and hydrological water stress²⁷⁻³⁰. ”

In addition, we have updated the corresponding statement in the Methodology section to provide a clearer explanation and proper references, as written below (see lines 802-806):

“However, global warming is expected to disrupt and intensify the variability of the water cycle²⁴, leading to increasingly frequent and severe fluctuations between excessively wet and dry periods²⁵. Warmer climates are projected to enhance the evapotranspiration, resulting in dry conditions²⁶. Additionally, reductions in precipitation and surface runoff are expected in many regions²⁴, further increasing the likelihood of both climatological and hydrological droughts²⁷⁻³⁰. ”

References:

- 24. Douville, H., K. Raghavan, J. Renwick, R.P. Allan, P.A. Arias, M. Barlow, R. Cerezo-Mota, A. Cherchi, T.Y. Gan, J. Gergis, D. Jiang, A. Khan, W. Pokam Mba, D. Rosenfeld, J. Tierney, and O. Zolina, & Intergovernmental Panel On Climate Change (Ipcc). Water Cycle Changes. In Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. (Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 2021). doi:10.1017/9781009157896.010.
- 25. Yoon, J.-H. et al. Increasing water cycle extremes in California and in relation to ENSO cycle under global warming. Nat. Commun. 6, 8657 (2015).
- 26. Dai, A., Zhao, T. & Chen, J. Climate Change and Drought: a Precipitation and Evaporation Perspective. Curr. Clim. Change Rep. 4, 301–312 (2018).
- 27. Vörösmarty, C. J., Green, P., Salisbury, J. & Lammers, R. B. Global Water Resources: Vulnerability from Climate Change and Population Growth. Science 289, 284–288 (2000).
- 28. Dai, A. Drought under global warming: a review. WIREs Clim. Change 2, 45–65 (2011).
- 29. Dai, A. Increasing drought under global warming in observations and models. Nat. Clim. Change 3, 52–58 (2013).
- 30. Vicente-Serrano, S. M. et al. Global characterization of hydrological and meteorological droughts under future climate change: The importance of timescales, vegetation-CO₂ feedbacks and changes to distribution functions. Int. J. Climatol. 40, 2557–2567 (2020).

line 74: What did these studies find, and how does this study move beyond them?

Response: We have revised the manuscript to clearly summarize the key findings of the cited studies and explicitly state how our study advances beyond them. We now highlight that while a few studies have examined the Time of First Emergence (ToFE) of extreme events, such as unprecedented low river discharge and water scarcity under anthropogenic climate change, important gaps remain. In particular, Liu et al. (2024) estimated the ToFE of water scarcity using a per-capita water availability threshold; however, the compound role of hydrological drought and human water demand in shaping the ToFE of water scarcity has not been fully addressed. Our study advances this field by explicitly analysing the compound dynamics of climate-driven water stress and anthropogenic water use, and by providing a more integrated perspective on the emergence of Day Zero Drought. We define DZD as drought-driven water scarcity arising from an imbalance between the water supply (reduced by drought) and water consumption. Please find the updated in lines 91-99, shown as below:

“To the best of our knowledge, few studies have assessed the Time of First Emergence (ToFE) of extreme events such as unprecedented hydrological drought³⁸ and water scarcity³⁹, under human-induced climate change. For instance, Liu et al.³⁹ estimated the ToFE of water scarcity and its potential disappearance based on a per-capita water availability metric. However, the ToFE of water scarcity driven by the compound effects of hydrological drought and socio-economic growth remains limited. Here, water scarcity arises when freshwater demand exceeds the available supply, including reservoir storage, under compound drought conditions.

Reservoirs are essential for managing local water availability and assessing the severity of water scarcity under climate change⁴⁰.”

line 94: I know that this is a widely used index and agree that it fits well in this study, but It should be clarified that potential evapotranspiration is less relevant for the water cycle than actual evapotranspiration

Response: We have revised the manuscript to clarify that while the SPEI is widely used indicator of atmospheric water demand through Potential Evapotranspiration (PET), PET does not account for actual water losses from the land surface. Actual evapotranspiration (AET) better represents terrestrial water availability. However, PET-based drought indices remain suitable for detecting climate-driven drought in long-term, large-scale studies due to their broader data availability and standardized formulation. This clarification has been added in lines 127-134, written as:

“We define drought-driven water scarcity as a compound extreme event characterized by the concurrent exceedance of thresholds of four indicators: the 48-month Standardized Precipitation Evapotranspiration Index (SPEI48), the Standardized River Flow Index (SRFI48), and the Standardized Water Scarcity Index (SWSI48) (Fig. 1). Although SPEI is widely used for capturing atmospheric water demand through Potential Evapotranspiration (PET), it does not reflect actual water losses from the land surface, which actual evapotranspiration better represents. Nonetheless, PET-based indices remain suitable for detecting climate-driven drought in long-term, large-scale studies due to their broader data availability and methodology.”

In addition, we update the statement in the methodology in lines 603-608, as follows:

“This study uses the SPEI to quantify and classify drought severity due to its capacity to reflect the change in water deficiency. The index does not account for actual water losses from the land surface but considers potential evapotranspiration (PET), a significant factor⁸⁷ in the future risk of extreme drought⁸³, making it more robust in categorizing drought and detecting its onset and evolution in the context of global warming⁸⁸ due to its contribution to the interaction of land-atmosphere conditions and drought⁸⁷.”

line 100 & Figure 1: it should be explained that SPEI48 refers to SPEI at 48-month time scale (similar for the other indices)

Response: We have clarified that SPEI48, SRFI48, and SWSI48 refer to indices calculated at a 48-month timescale in the section introducing these variables (lines 127-130), as follow:

“We define drought-driven water scarcity as a compound extreme event characterized by the concurrent exceedance of thresholds of four indicators: the 48-month Standardized Precipitation Evapotranspiration Index (SPEI48), the Standardized River Flow Index (SRFI48), and the Standardized Water Scarcity Index (SWSI48) (Fig. 1).”

Moreover, to further enhance the clarity, we have revised the corresponding sentence to explicitly emphasize the 48-month scale and ensured consistency between the main text and the Figure 1 captions (lines 172-186), as below:

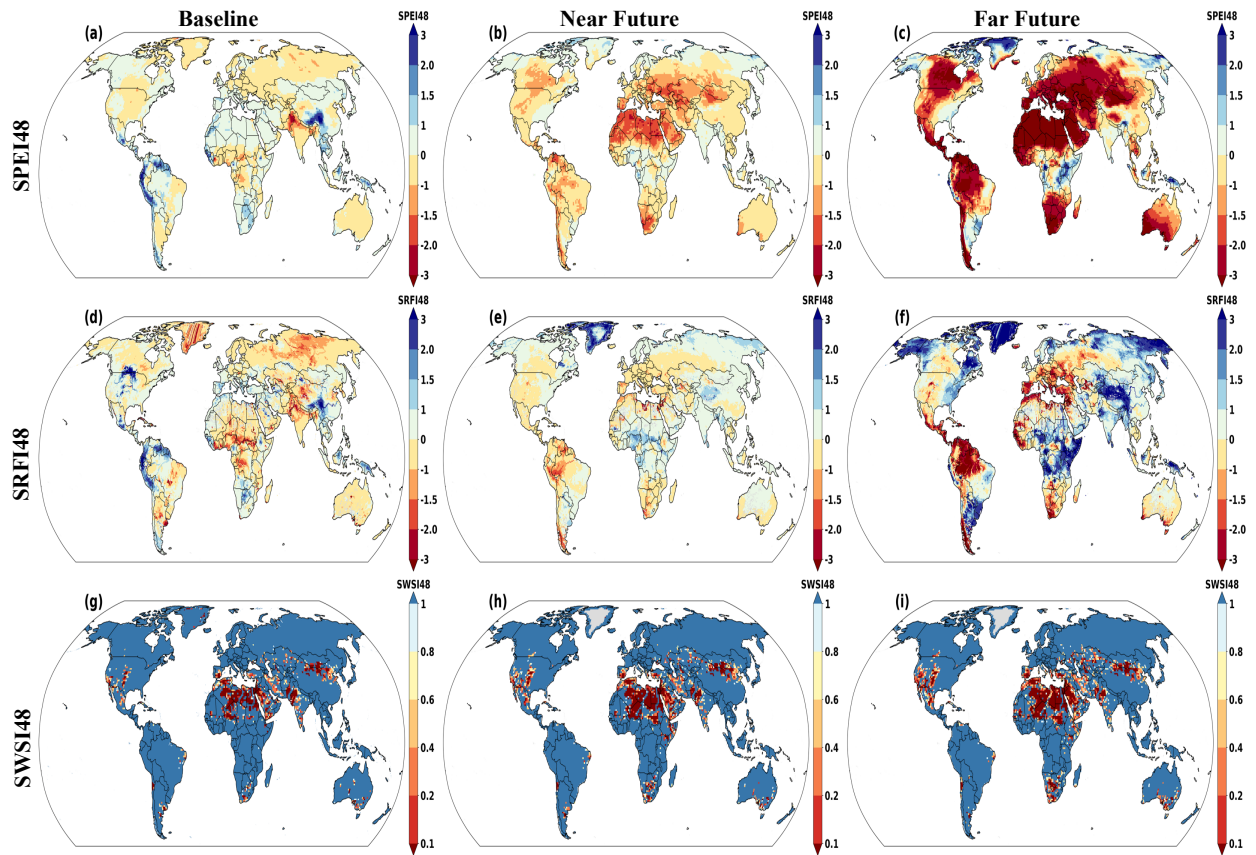


Fig. 1: Ensemble mean of drought-related and water scarcity indices at a 48-month timescale across three time periods based on CESM2-LE simulations. The first column panel shows the ensemble mean of water stress for the pre-industrial period (1850-1899), which is considered as the baseline period, the second column panel for the near future (2020-2050), and the third column panel for the far future (2070-2100). The top row (a, b, c) presents the Standardized Precipitation-Evapotranspiration Index (SPEI48), indicating long-term climatic water balance at a 48-month timescale. The middle row (d, e, f) shows the Standardized River Flow Index (SRFI48), capturing hydrological drought conditions at a 48-month timescale. The bottom row (g, h, i) depicts the Standardized Water Scarcity Index (SWSI48), reflecting the ratio of total water supply to total water consumption at a 48-month timescale. Each panel represents the ensemble mean, illustrating the spatial pattern and severity of compound water stress indicators over time. Negative values of SPEI48 and SRFI48 indicate increasingly dry conditions, while lower SWSI48 values (i.e., supply-to-demand ratios below normal) signal intensifying water scarcity driven by growing demand. Together, these projections reveal areas at high risk of compound, long-term water stress under future climate and socio-economic scenarios.

line 135: It should be made clear that the time of emergence refers to pre-industrial conditions

as a reference. This is a valid approach. Nevertheless, in the discussion section it should be explained that this perspective could provide limited information for future planning and adaptation measures because current infrastructures are not designed for pre-industrial conditions but rather for conditions prevailing during the previous decades.

Response: We have clarified in the revised manuscript that the Time of First Emergence (ToFE) is assessed relative to pre-industrial conditions (1850-1899) as the baseline, as now explicitly stated in the Results section (lines 190-192), as follows:

“ToFE is assessed relative to pre-industrial conditions (1850-1899), which serve as the baseline for detecting anthropogenic emergence.”

In the Discussion, we further acknowledge that while this baseline is appropriate for attributing anthropogenic signals, it may offer limited practical relevance for future planning, since existing infrastructure is designed for more recent climatic conditions. We have incorporated this clarification into the Discussion section (lines 488-495), written as:

“Using the FAR method, we found that the contribution of human-induced climate change to DZD increases throughout the 21st century (Fig. S9). Identifying ToFE with a very high attribution confidence ($FAR \geq 0.99$) of human-induced signal relative to the pre-industrial period (1850-1899) provides robust scientific attribution, but it offers limited practical guidance for planning and adaptation, since most water infrastructure and management systems were designed based on the late 20th-century (Fig. S6) climatic conditions rather than pre-industrial norms. Regions with $FAR < 0.99$ (Fig. S19) may still face DZD in the future, but with weaker anthropogenic attribution.”

line 137: not clear what you mean with “drive a DZD”

Response: The sentence has been revised for clarity. The revision clarifies that the emergence of DZD is primarily attributed to anthropogenic forcing as indicated by FAR values exceeding 0.99. These updates are reflected in the revised text (lines 188-196), read as:

“This study defines ToFE as the first decade in which the Fraction of Attributable Risk (FAR) for DZD exceeds 0.99, indicating a 99% likelihood that human activities caused the onset of these unprecedented compound drought-scarcity events. ToFE is assessed relative to pre-industrial conditions (1850-1899), which serve as the baseline for detecting anthropogenic emergence. The focal hotspot regions affected by unprecedented DZD, with their respective decade of ToFE and the distribution of the ToFE, are shown in Fig. 2. Our results indicate that anthropogenic climate change is projected to trigger the onset and occurrence of DZD, primarily due to severe and persistent compound multi-year hydrological droughts, reservoir depletion, and high-water demand.”

line 154: This seems to be the first supplementary figure that is referred to in the main text; make sure the numbering of the supplementary figures matches their appearance in the main text. In addition make sure to refer to, and explain, all supplementary figures in the main text.

Response: We have carefully revised the manuscript to ensure that all supplementary figures are numbered correctly and that their numbering in the supplementary figures matches their appearance in the main text. In addition, we have also updated the manuscript to clearly refer to and explain each supplementary figure in the manuscript.

lines 168/169: While I appreciate the consideration of reservoirs, I feel it would be needed to provide some analysis about potential inconsistencies in the spatial patterns that the different treatment of grid cells with reservoirs vs. grid cells without reservoirs may introduce.

Response: We appreciate the comment regarding the potential inconsistencies introduced by the different treatment of grid cells with and without reservoirs. To evaluate this, we performed a sensitivity analysis comparing the ToFE calculated with and without the reservoir-based adjustment, shown below (now presented in supplementary Figure S12). The results show that accounting for the reservoirs affects the ToFE of DZD, with only localized effects, such as delayed ToFE in parts of the Mediterranean, while a few isolated regions show minor advances. This indicates that the influence of the reservoir is localized and does not systematically bias global spatial patterns of ToFE. Importantly, the FAR-based filter (FAR greater than 0.99) is applied uniformly to all grid cells, regardless of reservoir presence, ensuring that both reservoir-affected and unaffected areas are included only when the forced signal of DZD emergence is statistically robust. Thus, the use of FAR greater than 0.99 complements the reservoir adjustment by enhancing the attribution confidence, and the combined approach minimizes methodological bias. We have clarified this point in the revised manuscript (lines 230-242), in Fig. S12 (below), and included this analysis in the Sensitivity analysis (lines 971-982) of the methodology section to ensure transparency and robustness of our findings.

The result section (lines 230-242) states:

“Therefore, the duration of drier conditions, combined with rising human water consumption, can dry the reservoirs and trigger severe DZD, including reservoir-dependent regions. However, excluding both drought duration and TRD increases the event occurrence in both historical and future periods and raises their probability. This will delay the human-induced signal ($FAR \geq 0.99$), leading to later ToFE compared to Fig.2, particularly in the Mediterranean regions (Fig.S12). In contrast, DZD emerges earlier in other regions because the probability of future events exceeds the pre-industrial baseline earlier, enabling earlier detection of $FAR \geq 0.99$. Therefore, including the multi-year drought duration and TRD makes these events unprecedented versus pre-industrial conditions, highlighting their importance for understanding the emergence and magnitude of anthropogenic water scarcity and the critical role of reservoirs in water crisis vulnerability. These insights underline the need for future work research integrating dynamic reservoir operations and adaptive water management strategies where region-specific data is available.”

The corresponding sensitivity analysis (lines 971-982) reads as follows:

“Secondly, to assess whether the treatment of grid cells with and without (as defined in equation 3 for DZD) or solely without reservoir (DZD is defined as a compound event of

$SPEI48 \leq -1.5 \cap SRFI48 \leq -1.5 \cap SWSI48 \leq 0.6$), introduces inconsistencies in the spatial patterns of ToFE, we conducted a sensitivity analysis comparing ToFE patterns (supplementary Fig.S12). The results reveal that spatial differences are negligible in most regions. The most noticeable delays are confined to the Mediterranean region, where major reservoirs constructions were completed mid- to late-20th century (Fig. S6). As climate change influences the onset of compound events, it is critical for decision-makers to revisit the role of existing water infrastructure in future water security planning. The application of FAR greater than 0.99, combined with localized reservoir adjustment of DZD detection, ensures that the global ToFE pattern represents both high attribution confidence and hydrological realism, without introducing methodological biases between grid cells with and without reservoirs.”

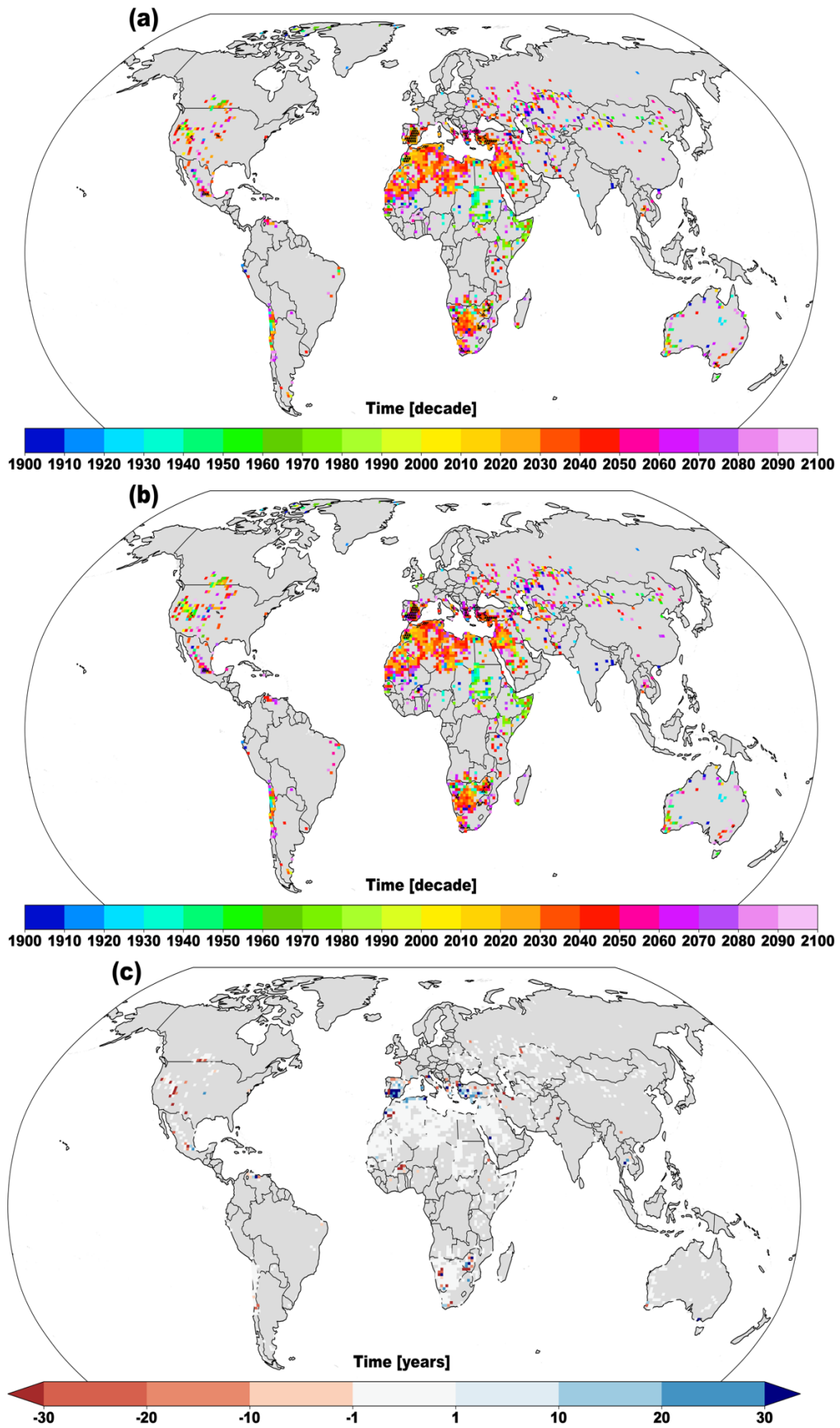


Fig. S12: Sensitivity of the Time of the First Emergence (ToFE) of DZD to reservoir adjustment. (a) shows the ToFE with and without reservoirs combined, where the ToFE is set to the first

decade following the completion year of each reservoir (same as Fig. 2a and DZD is defined with the equation (3) in the manuscript, i.e., DZD occurs when $SPEI48 \leq -1.5 \cap SRFI48 \leq -1.5 \cap SWSI48 \leq 0.6, dur_{ce} \geq TRD$, if reservoir exists and $SPEI48 \leq -1.5 \cap SRFI48 \leq -1.5 \cap SWSI48 \leq 0.6$, if there is no reservoir. (b) represents the ToFE of DZD without considering the reservoir, i.e., without considering the duration of the compound event and the TRD, i.e. $SPEI48 \leq -1.5 \cap SRFI48 \leq -1.5 \cap SWSI48 \leq 0.6$, when there is no reservoir. Where all grid cells follow the same DZD indicators thresholds criteria. (c) represents the difference between the ToFE of (b) and (a), expressed in years. The results show minimal differences across most regions. The ToFE without reservoir is delayed than the figure (a) due to the late emergence of the strong anthropogenic signal of FAR greater than 0.99, mostly in Mediterranean regions. While a few scattered isolated areas show slight advances. This indicates that the influence of the reservoir is localized and does not systematically bias global spatial patterns of ToFE.

line 171 and Figure 2: percentage of what?

Response: The figure caption and corresponding text have been revised to clarify that the percentages in the circular diagram refer to the proportion of global land grid cells experiencing their Time of First Emergence (ToFE) of DZD within each decade. This clarification is now reflected in the revised caption for Figure 2 (lines 267-270). Please find below the updated figure 2 and its caption:

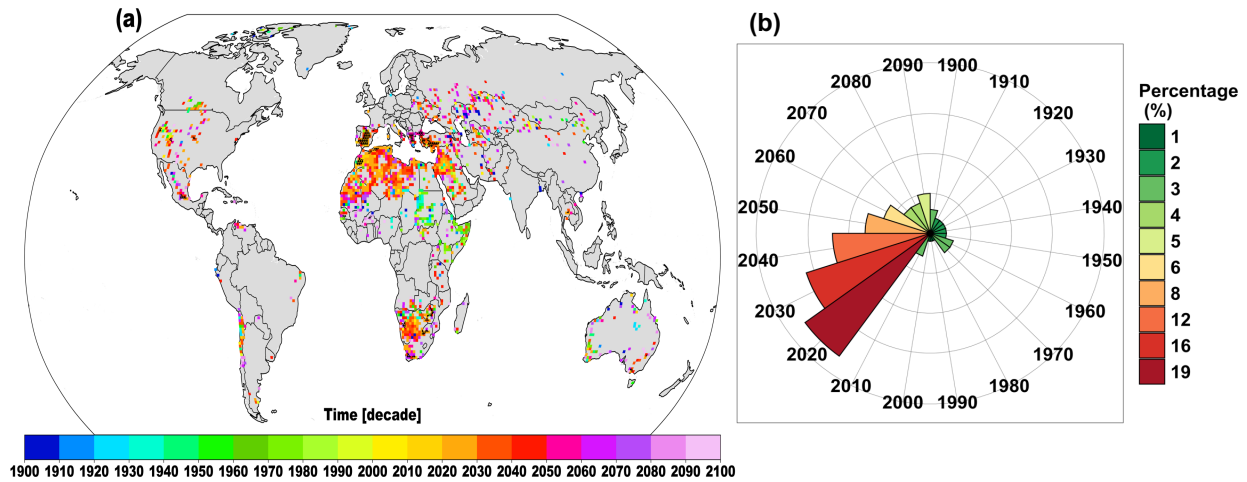


Fig. 2: Time of First Emergence (ToFE) of Day Zero Drought (DZD) event and global hotspot regions based on CESM2-LE ensemble simulations under the SSP3-7.0 scenario. (a) Spatial distribution of the decadal ToFE of DZD events across the globe from 1900 to 2100. Colored shading indicates the first decade during which DZD becomes statistically attributable to anthropogenic climate change, defined as the first decade in which the Fraction of Attributable Risk is greater than 0.99 ($FAR > 0.99$). Gray regions indicate grid cells where no DZD event attributable to anthropogenic climate change is projected to emerge before 2100. For regions with reservoirs, the ToFE is considered to be the first decade after the year of completion (Fig. S6) of their respective reservoirs, when all DZD criteria are simultaneously met. By aligning the emergence timing with the operational onset of water storage infrastructure to reflect the real-world system resilience dynamics. The black stars denote the locations of the reservoirs

threatened by DZD emergence. (b) Circular diagram illustrating the temporal distribution of ToFE by decades. The color scale indicates the percentages of grid cells (land areas) experiencing their ToFE distribution in each decade from 1900 to 2100. It provides a temporal overview of how the ToFE is distributed over time and the trends in DZD emergence.

line 179: abbreviation PDF not introduced

Response: The abbreviation “PDF”, Probability Density Function, has now been introduced in lines 281-283 of the revised manuscript, which read as:

“The spatial distribution and the Probability Density Functions (PDFs) of DZD duration and waiting time across hotspot regions reveal distinct regional variations in the magnitudes and the distribution (Fig. 3).”

line 195: is water retention capacity changing over time in CESM2?

Response: We apologize for the confusion and lack of clarity. We have revised the manuscript to clarify that “water retention capacity” refers to the volume of water that reservoirs can retain under drought conditions. This clarification is now reflected in lines 295-302, as follows:

“Altered precipitation and river flow patterns can prolong the dry conditions and reduce the volume of inflows to freshwater systems, exacerbating water shortages. Increased evapotranspiration and water consumption deplete water sources (water available in rivers, lakes, and reservoirs) more quickly and prolong DZD duration. The volume of water that reservoirs can retain will decrease due to prolonged periods of stress caused by both climate change and human activities. As ecosystems are weakened and less capable of retaining water, even brief periods of rainfall may be insufficient to end a drought or replenish water supplies, limiting the recovery period before the next DZD event.”

line 236: related *to* the baseline period

Response: The phrase (see lines 366-368) has been updated to: *“The Paris climate goals are expressed in terms of global warming levels (GWL), making it essential to assess the societal impact of DZD related to the warming level at the ToFE of DZD relative to the baseline period.”*

line 243: rephrase to “total population of 488 million”

Response: We have revised the sentence (see lines 374-377) to read: *“Hitting the mark of 1.5 °C represents the maximum of the exposed population (Fig. 4e), with a total population of 488 million, which can be decomposed into 322 million of urban and 166 million of rural population, suggesting the urgent need to limit warming at most 1.5°C.”*

lines 334/335: are maximum and minimum temperatures calculated from daily or hourly data?

Response: We have clarified in the manuscript that the maximum and minimum temperatures as well as the total precipitation, from CESM2-LE and ECMWF Reanalysis v5 (ERA5-Land) dataset are calculated from daily data. This clarification has been updated in lines 526-528, as follows: *“We use monthly mean data, derived from daily data, including average temperature, maximum temperature, minimum temperature, and total precipitation from CESM2-LE.”*

line 419: evapotranspiration is not a water resource

Response: We appreciate the reviewer for the helpful observation and apologize for the earlier misstatement. We agree that evapotranspiration is not a water resource. The manuscript has been revised to clarify this point (see lines 648-650) by defining: *“The total water supply is estimated as the sum of surface water resources, including river flow and the net water balance (precipitation minus evapotranspiration), representing the available freshwater availability.”*

lines 431-343: I find this quite relevant, and would suggest to move it to the main text.

Response: We appreciate the reviewer’s suggestion to move this section to the main text. However, to ensure a consistent structure and address all reviewer comments and recommendations, we dedicated a Sensitivity Analysis section in the methodology to present all sensitivity tests related to the ToFE, including the analysis of time scale sensitivity (lines 994-997). This placement maintains the focus of the main text while providing a detailed exploration of time scale effects for interested readers.

Lines 994-997 read as follows:

“Fourthly, we have looked at the sensitivity of the time scale by considering the 36- and 60-month time scales (Figs. S15 and S16) of long-duration compound events for SPEI, SRFI, and SWSI. Only a few regions, located almost entirely in Africa, show changes in ToFE using a 36 or 60-month timescale of extreme events as shown in Fig. S17.”

line 451: How and why are trends removed and reintroduced?

Response: We apologize for any confusion or lack of clarity in the original manuscript. To provide further clarification, we have revised the Bias correction section to provide a more explicit and detailed explanation. This revision ensures that the methodology is clearly articulated and aligns with the overall objectives of the study. The updated content can be found in lines 676-735 of the revised manuscript, written as:

*“**Bias correction (BC).** In order to minimize the model errors, this study used a bias correction method to reduce model bias. Fig. S1 shows a more detailed structure of the steps in the methods and the processes used in this study. The monthly database from ERA5-Land (1979-2022) was used to calculate ERA5’s SPEI48 and SRFI48, with 1979-2014 as the reference period, which is used as the observational drought indices reference to calibrate the drought indices for each ensemble member of CESM2-LE individually. Although observational sources are the best to achieve the ideal bias correction, we opted for reanalysis products because they consistently assimilate a variety of variables in a physically consistent manner, and it is assumed to be close to observed data. This choice ensures global coverage and temporal completeness, particularly important in data-sparse regions or for long historical records where high-quality observational data are unavailable or inconsistent. The ERA5-Land dataset was found to be a trustworthy reference to calibrate CESM2-LE indices. In order to increase our confidence in future extreme drought projections, we applied the univariate Quantile Delta Mapping (QDM), as Ansari et al.⁹⁹ found it to be more robust for the correction of indices. Fig. S14 shows that direct correction (post-processing QDM) of the drought indices as a single variable reduces the bias between ERA’s SPEI48 and the ensemble mean of the CESM2-LE’s*

SPEI48 and manages to capture the distribution of SPEI48. In addition, Van de Velde et al.¹⁰⁰ stated that the simpler univariate BC methods are better to use for climate change impact assessment, as the multivariate BC methods failed to handle non-stationary climate conditions. This approach maintains the model-projected climate change signal while simultaneously correcting the distributional biases. The QDM bias correction method, introduced by Cannon et al.¹⁰¹, is a cumulative distribution function (CDF)-based bias correction method designed specifically to reduce the biases between the modeled and observed distribution of drought indices, while preserving the model-projected climate change signal. The additive form of QDM is applied to bias correct the systematic biases in each quantile of the drought indices calculated from the CESM2-LE and CNRM simulations, using the ERA-derived indices as observational references while preserving the model-projected absolute changes across all quantiles of the distribution. The important concept of QDM is its ability to maintain the trend in all the quantiles within the distribution of the climate model output, which is important when future changes are not uniform across the distribution. It is used to quantile detrend the model projections and adjust distributional biases in model projections, ensuring the sensitivity of the underlying climate model without affecting the distribution^{101–103}. The QDM begins by identifying the corresponding quantiles of the observed, model historical (or reference for the calibration), and the model future projection, as a corresponding quantile-based correction derived from the model-observation mapping. Instead of directly fitting the full distribution of the future model, QDM quantifies the change at each quantile between the historical and future period model values at that same quantile level. These changes are then applied to the observed value at the corresponding quantile, retrieved using the inverse CDF of the observed data. This allows distribution biases to be corrected while maintaining quantile-specific climate change signals, thus preserving the sensitivity of the climate model. The univariate bias correction was performed using the QDM method available in the Multivariate Bias Correction (MBC) package in R. For each grid cell, drought indices from each member of the CESM-LE and CNRM are corrected independently, using their quantile location relative to the observed (ERA5) drought indices. Specifically, each value of SPEI48 and SRFI48, computed from each grid cell of every ensemble member of the CESM2-LE and CNRM datasets, within the period 1850-2100, is corrected as a single variable following the direct QDM approach, respectively. To correct the bias in SWSI48, we applied the univariate QDM method to the total water supply (precipitation-evapotranspiration + river discharge) at each grid cell of each ensemble member of CESM2-LE and CNRM, treated as a single aggregated time series rather than bias-correcting each individual component (i.e., precipitation, evapotranspiration, and river discharge). This aggregated variable represents the net variable water and is more relevant for capturing water scarcity as reflected in SWSI48. We could not apply the bias correction of the total water demand (consumption) due to the unavailability of consistent observed sectoral water use data across the historical period at the global scale.

To assess the effect of different bias correction strategies, we evaluated both pre- and post-processing approaches using CESM2-LE under the SSP3-7.0 scenario. As shown in the Supplementary Figures, Figs. S14, post-processing (i.e., direct bias correction of SPEI, Fig. S14c) better captures the distribution of SPEI from ERA5 (Fig. S14a), while pre-processing (i.e., bias correction of precipitation and temperatures prior to computing the index; Fig. S14d)

tends to introduce additional bias, particularly by amplifying wet conditions. These results support the effectiveness of the post-processing approach in preserving the observed statistical properties of the drought indices.”

To reduce systematic biases in the modeled drought indices while preserving the climate change signal, we applied the univariate Quantile Delta Mapping (QDM) method (Cannon et al. 2015). This approach corrects distributional biases in the model series relative to observation, while preserving model-projected absolute changes across all quantiles. QDM operates in two main steps: first, future model outputs are detrended by quantile and bias corrected to observations by quantile mapping; second, model-projected relative changes in quantiles are superimposed on the bias-corrected model outputs.

We applied the additive form (describe below) of QDM independently for each grid point and ensemble member of CESM2-LE to correct SPEI48, SRFI48, and SWSI48 using the same indices calculated from ERA5-Land as the reference observational dataset. This method allows us to preserve the future change signal in quantiles simulated by the model.

The following explanation closely follows the description provided in Cannon et al. 2015.

“This process begins by computing the non-exceedance probability of a model-projected variable $x_{m,p}$ at a time t , based on the time-dependent Cumulative Distribution Function (CDF) of the model-projected series $x_{m,p}$:

The non-exceedance probability of a model projected variable $x_{m,p}$ at a time t is

$$\tau_{m,p}(t) = F_{m,p}^{(t)}[x_{m,p}(t)], \quad \tau_{m,p}(t) \in \{0,1\}$$

We then retrieve the corresponding modelled $\tau_{m,p}$ quantile in the historical period using the inverse CDF: $F_{m,h}^{-1}[\tau_{m,p}(t)]$.

The absolute change in quantiles between the historical and future periods is calculated as:

$$\begin{aligned} \Delta_m(t) &= F_{m,p}^{(t)-1}[\tau_{m,p}(t)] - F_{m,h}^{-1}[\tau_{m,p}(t)] \\ &= x_{m,p}(t) - F_{m,h}^{-1}[\tau_{m,p}(t)] \end{aligned}$$

Next, the modelled $\tau_{m,p}$ quantile at time t is bias corrected by applying the inverse CDF estimated from observed (drought indices computed from ERA5 datasets, for our study) values $x_{o,h}$ over the historical period:

$$\hat{x}_{o:m,h:p}(t) = F_{o,h}^{-1}[\tau_{m,p}(t)].$$

Finally, the bias-corrected future projection at time t is given by adding the change signal in quantiles $\Delta_m(t)$ to this historical bias-corrected value:

$$\hat{x}_{m,p}(t) = \hat{x}_{o:m,h:p}(t) + \Delta_m(t)$$

Detrending by quantile and then quantile mapping means that $\hat{x}_{o:m,h:p}$ takes on the statistical characteristics of the historical observations; this is where biases between the modelled and observed quantiles are corrected. Adding the bias-corrected series Δ_m reintroduces the

projected climate change signal; this is where absolute change in modelled quantiles is preserved.”

Reference:

- Cannon, A. J., Sobie, S. R. & Murdock, T. Q. Bias Correction of GCM Precipitation by Quantile Mapping: How Well Do Methods Preserve Changes in Quantiles and Extremes? J. Clim. 28, 6938–6959 (2015)

line 455: please explain “as a single value”

Response: In this context, “as a single value” means that the total water supply variable, calculated as an aggregated variable (total water supply = Precipitation - Evapotranspiration + river discharge), was treated as one combined time series during the bias correction process. This approach was chosen to directly adjust the combined water availability to ensure a signal relevant for SWSI48, rather than correcting each individual component separately. We have clarified this in the revised manuscript (see lines 720-727), as follows:

“To correct the bias in SWSI48, we applied the univariate QDM method to the total water supply (precipitation-evapotranspiration + river discharge) at each grid cell of each ensemble member of CESM2-LE and CNRM, treated as a single aggregated time series rather than bias-correcting each individual component (i.e., precipitation, evapotranspiration, and river discharge). This aggregated variable represents the net variable water and is more relevant for capturing water scarcity as reflected in SWSI48. We could not apply the bias correction of the total water demand (consumption) due to the unavailability of consistent observed sectoral water use data across the historical period at the global scale.”

lines 473/474: isn’t it the duration to dry out the reservoir if there is *no* river water input, not if river water input continues to be the (only) source

Response: The intent was to describe the Time for Reservoir to Dry (TRD) under drought conditions, assuming that depleted river inflow remains the only active source of water supply during the drought event. Specifically, TRD refers to the duration over which the available reservoir storage would be exhausted under persistently low river inflow, in the absence of rainfall. This approach reflects realistic drought scenarios in many regions where rivers, while not immediately drying up, have drastically decreased flow that eventually becomes insufficient to meet water demand, leading to total depletion of both reservoir storage and river inflow. Updated in lines 766-771 and read as:

“The TRD is similar to the resident time (time of water spent in reservoirs) and can be considered as the duration to take for a drought event to dry the water in the reservoirs if the only source of the water supply of the reservoirs is the depleted river flow during a drought period. This reflects hydrological drought situations in which rivers continue to flow, albeit at diminished levels insufficient to meet water demand, allowing assessment of how long reservoirs can sustain supply under such stress.”

line 537: “ex”?

Response: We apologize for the oversight. The term “ex” was mistakenly used in place of “e.g.” and has now been corrected to appropriately indicate an illustrative example (see lines 967-969), which read as:

“When water demand rises, the available water supply (e.g., river flow, even if unaffected by precipitation) becomes insufficient to meet demand, triggering drought-like conditions (or water scarcity) in terms of availability.”

lines 540-550: this should be moved to the beginning of the section

Response: Thank you for the helpful suggestion. We agree that moving this content to the beginning of the section improves the clarity and logical flow of the text. We have revised the manuscript accordingly and this content now appears in lines 789-800 as follows:

“In fact, water can be retained in the reservoir through different parts of the hydrological cycle and different resident times (time of water spent in reservoirs) considered similar to TRD. As the river flow contributes to the long-term storage of water in the reservoir, we considered the river discharge to be an appropriate parameter. DZD is the impact of the simultaneous occurrence of a long-term (48-month) critical rainfall deficiency and extreme dearth of water of low-flow river discharge during a prolonged drought in the context of global warming and long duration exceeding the time for the reservoirs to run out of water. This is formalized as follows:

$$DZD \text{ occurs if} \quad (3)$$

$$\begin{cases} SPEI48 \leq -1.5 \cap SRFI48 \leq -1.5 \cap SWSI48 \leq 0.6, dur_{ce} \geq TRD, \text{ if reservoir exists.} \\ SPEI48 \leq -1.5 \cap SRFI48 \leq -1.5 \cap SWSI48 \leq 0.6, \text{ if there is no reservoir.} \end{cases}$$

where dur_{ce} is the duration of the compound extreme. The identification of DZD was carried out at each grid cell across each of the 100 members of the CESM2-LE model, offering a comprehensive and probabilistic perspective on future water scarcity risk.”

line 602-605: I do not understand this

Response: We have revised the text to more clearly describe how DZD characteristics, specifically duration and waiting time, are calculated and analysed. The revised version now provides a more structured and transparent description of the method to assess these DZD characteristics. We have rewritten the sentence in lines 910-933, as:

“DZD characteristics: waiting time and duration. *While the ToFE is an important measure of global warming impacts, its true impact is measured by how long these events last and how soon they will re-occur once they have emerged for the first time. The length of time of a DZD event is defined as the DZD duration, while the waiting time is identified as the time elapsed between the end of the previous event and the start of the next consecutive DZD event, as illustrated in Fig. S8. To quantify these characteristics, we calculate the DZD duration and waiting time at each grid cell globally across the CESM2-LE for all ensemble members. We calculate the waiting time directly by counting the number of months after the decade of the*

ToFE under anthropogenic influence until the next event, for all consecutive DZD events until 2100, while the duration is calculated by length of a DZD event once it occurs.

In addition, we assess the frequency of extreme DZD conditions, characterized by events that are both frequent and prolonged. Specifically, for each grid point and each ensemble member of CESM2-LE, we identify all DZD events occurring between the decade of ToFE and the year 2100. We then count the number of DZD event where its duration exceeds the waiting time, i.e., cases where the DZD event persists longer than the recovery period before the next event. These counts are aggregated at each grid across all 100 members of CESM2-LE within the ToFE and 2100. The frequency of extreme DZD conditions is computed at each grid cell as the ratio of the sum of these events to the total DZD events across all members of CESM2-LE within the ToFE and 2100 period. This spatially explicit frequency is then mapped globally (Fig. 3c) to highlight regions most vulnerable to sustained and recurrent DZD conditions.

For each DZD-prone region shown in central spatial map of Fig.3, we then average the values across all grids located within the regions. To characterize the statistical distribution of these metrics, we fit probability density functions (PDFs) to the distributions of DZD duration and waiting time.”

Figures 1 and 2:

It feels a bit inconsistent that the time periods considered in Figure 1 do not include 2020, which turns out to be relevant in Figure 2.

Response: We have revised Figure 1 to consider the 2020-2050 period as the near-future window. This update enhances coherence across the figures and ensures that key periods relevant to analysis, particularly those highlighting the emergence of DZD, are presented consistently throughout the manuscript. Please find the updated Figure 1 and corresponding caption in lines 171-186, as below:

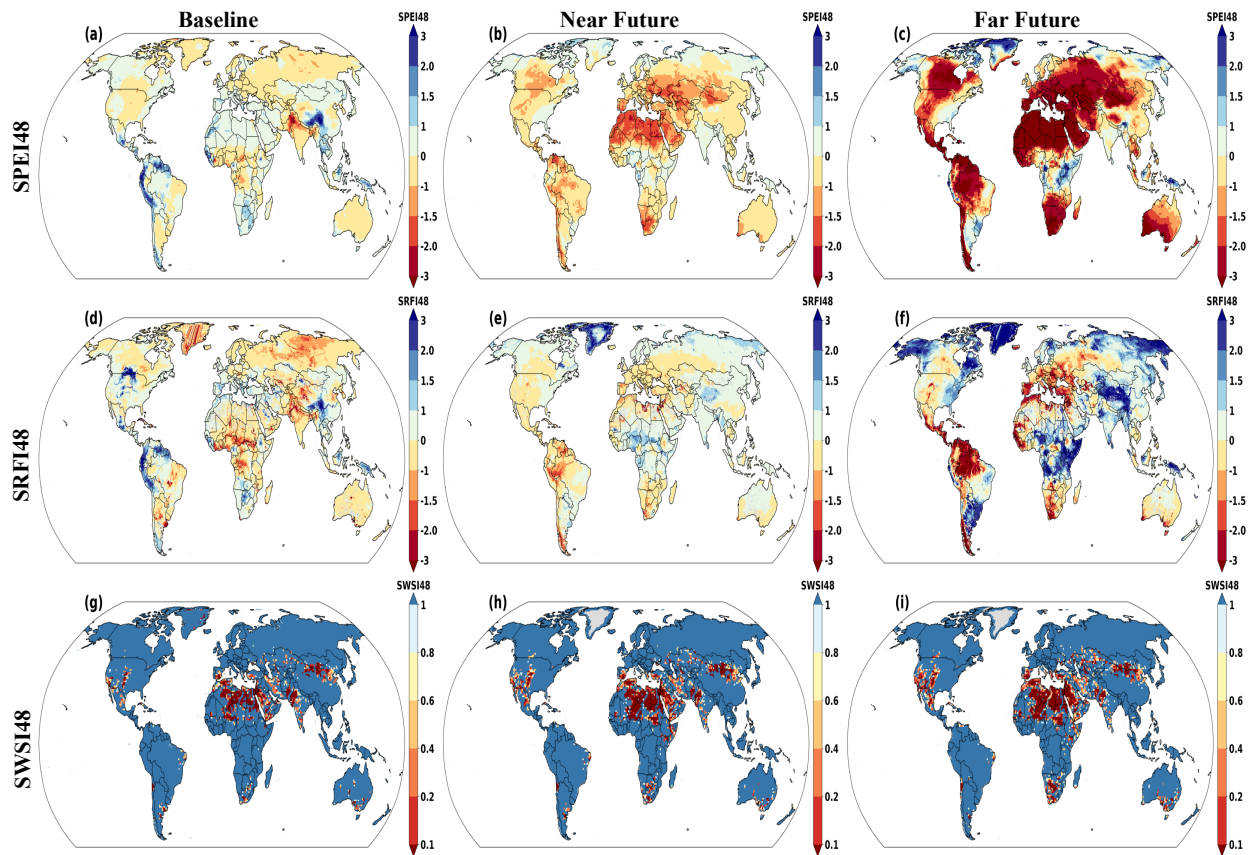


Fig. 1: Ensemble mean of drought-related and water scarcity indices at a 48-month timescale across three time periods based on CESM2-LE simulations. The first column panel shows the ensemble mean of water stress for the pre-industrial period (1850-1899), which is considered as the baseline period, the second column panel for the near future (2020-2050), and the third column panel for the far future (2070-2100). The top row (a, b, c) presents the Standardized Precipitation-Evapotranspiration Index (SPEI48), indicating long-term climatic water balance at a 48-month timescale. The middle row (d, e, f) shows the Standardized River Flow Index (SRFI48), capturing hydrological drought conditions at a 48-month timescale. The bottom row (g, h, i) depicts the Standardized Water Scarcity Index (SWSI48), reflecting the ratio of total water supply to total water consumption at a 48-month timescale. Each panel represents the ensemble mean, illustrating the spatial pattern and severity of compound water stress indicators over time. Negative values of SPEI48 and SRFI48 indicate increasingly dry conditions, while lower SWSI48 values (i.e., supply-to-demand ratios below normal) signal intensifying water scarcity driven by growing demand. Together, these projections reveal areas at high risk of compound, long-term water stress under future climate and socio-economic scenarios.

Figure 2 and 4:

Figures 2b and 4c are similar but quite distant from each other in the flow of arguments.

Response: We understand your observation regarding the similarity between Fig. 2b and Fig. 4c, and we appreciate your suggestions to enhance the flow of the argument. However, we

believe it is important to keep these figures separate to maintain clarity, as they address distinct aspects of the DZD analysis.

Figure 2 focuses on illustrating the Time of First Emergence (ToFE) of DZD events, showing these events first emerge in relation to anthropogenic climate change. Specifically, Figure 2b provides a circular diagram that depicts the temporal distribution of the ToFE by decades, highlighting the percentage of grid cells (land areas) experiencing their first DZD event in each decade from 1900 to 2100. The diagram offers a temporal overview of the progression of DZD events, demonstrating the trends in their emergence over time. Thus, the Fig. 2b shows when and how rapidly DZD events are emerging across the globe.

In contrast, Figure 4 focuses on the impact of DZD on populations, specifically the exposure of rural, urban, and total populations to DZD events at the time of their emergence. Fig. 4c provides a circular diagram that illustrates the exposure of rural, urban, and total populations to DZD at the ToFE, spanning from 1900 to 2100. Thus, Fig. 4c emphasizes the relative contributions of rural, urban, and total populations to overall exposure and highlights disparities in vulnerability across time.

We believe that presenting these figures in separate sections allows for a clear and distinct presentation of both the timing (Figure 2) and the impacts on populations (Figure 4) of DZD events. The current arrangement of the figures in the manuscript follows a logical progression moving from the underlying drivers of DZD (Figure 1) to the emergence of DZD events (Figure 2), their characteristics (Figure 3), and ultimately the impacts of DZD on human populations (Figure 4). This structure provides a clear and cohesive flow, guiding the reader from foundational factors of DZD to its concrete effects on populations. We hope this explanation clarifies the reasoning behind the current figure placement and addresses your concern. We respectfully suggest retaining the current figure placement.

References:

- Orth, R., J. Zscheischler, and S.I. Seneviratne, Record dry summer in 2015 challenges precipitation projections in Central Europe, *Sci. Rep.* 6, 28334, doi: 10.1038/srep28334 (2016).
- Denissen, J.M.C., A.J. Teuling, A.J. Pitman, S. Koirala, M. Migliavacca, W. Li, M. Reichstein, A.J. Winkler, C. Zhan, and R. Orth, Widespread shift from ecosystem energy to water limitation with climate change, *Nature Climate Change*, 12, 677–684, doi: 10.1038/s41558-022-01403-8 (2022).

Response: We thank you for providing these valuable references. They have helped improve the clarity and the context of our study and are now appropriately cited in the manuscript (references 60 and 61), as noted (see lines 427-429) in the manuscript:

“These limitations underrepresent inter-model variability in drought drivers, including precipitation and evapotranspiration, whose trends may vary among ESMs^{60,61}, limiting our uncertainty assessment.”

REVIEWER COMMENTS AND RESPONSE

Reviewer #1 (Remarks to the Author):

The authors did a great and careful job in revising their manuscript. I am happy with their responses and now I can recommend the manuscript for publications.

Response: We thank the reviewer for carefully evaluating our revised manuscript. We are grateful for the positive feedback and are pleased to know the reviewer considers our revised manuscript to be suitable for publication in Nature Communications. We also greatly appreciate your valuable time and support throughout the review process.

Reviewer #3 (Remarks to the Author):

Second Review of Ravinandrasana et al., manuscript number NCOMMS-25-13170A
“The First Emergence of Unprecedented Global Water Scarcity in the Anthropocene”

I appreciate the efforts made by the authors to address my and the other reviewers' comments which have improved the paper. After a few more refinements and expansions the paper is ready for publication in my opinion:

Response: We are grateful for the reviewer's careful consideration and for providing a positive evaluation. We are glad that our revisions successfully improved the study and would like to thank the reviewer for the encouraging remarks and supportive recommendation.

Regarding changes made in response to main comment (1) from my previous review: I appreciate the clarifications in the revised manuscript. However, still many of the key concepts are introduced quite late (after 1/3-1/2 of the entire manuscript) such that readers can not fully understand and appreciate the motivation, approach and first results of the study. For example, FAR is mentioned in lines 109/110 without further explanation where readers can not understand what is attributed and why.

Furthermore, in this context I also suggest to move the first two paragraphs of the results section to the end of the previous section as this text is about methods rather than results.

Response: We appreciate the reviewer's thoughtful comment and recognition of the improvements made in our previous revision. In response to the concern regarding the late introduction of key concepts, we have carefully revised the manuscript to enhance clarity and ensure that readers can better understand the motivation, methodological framework, and results of our study.

Specifically:

- We now provide an earlier and clearer explanation of the Fraction of Attributable Risk (FAR) within the methodological context of our study. This addition clarifies that the increased risk of DZD events is attributed to human influence and explains why FAR is a suitable framework for this study. The revised manuscript now includes the following clarification (see lines 124-128):

“We evaluate the global ToFE of prolonged drought-driven water scarcity, such as DZD, using a novel method based on the Fraction of Attributable Risk (FAR) of the joint probability of compound extremes, incorporating reservoir and lake levels. We apply the FAR to quantify the increase in the likelihood of DZD events due to human-induced climate change, attributing the risk to the anthropogenic forcing.”

- We have moved the first two paragraphs of the results section into the introduction section to improve the logical flow of the manuscript. The relocated content has been integrated appropriately in lines 108-123.
- We have revised the introduction to ensure that the motivation and objectives are clearly presented. This includes the following lines: lines 87-90 and lines 128-131:

Lines 87-90: *“Anthropogenic climate change contributed to DZD^{36,37} and is expected to increase its future likelihood³³. However, global-scale assessments of the emergence and attribution of DZD-like events under global warming remain limited. Understanding where and when such compound events will emerge is crucial for local and global water security strategies.”*

Lines 128-131: *“Our study focuses on DZD as an acute water scarcity event due to a long period of unprecedented compound extreme events in water supply shortage and rising demand under a warming climate. Our goal is to identify i) When and where anthropogenic DZD first emerges? ii) How long will events last? and iii) How many people will be exposed to DZD?”*

These changes aim to improve the manuscript, helping readers better understand the motivation, methodology of this study.

Regarding changes made in response to main comment (2) from my previous review: I appreciate the inclusion of data of a second Earth system model which is very relevant to assess the reliability and (un)certainty of the main conclusions of the study. I disagree with the authors that detected hot spot regions are “very similar” between both models (lines 251/252). I feel that the maps in Fig. S21 are substantially different with e.g. new hot spot regions in South America or Australia detected in the CNRM model but not in the CESM model. On a related aspect: it would be great to also reproduce Figure 2b in Figure S21, and not only Figure 2a as presently done.

Response: We thank the reviewer for the continued thoughtful feedback and valuable suggestions. We acknowledge the concern regarding regional differences between the CESM2-LE and CNRM models and have revised the manuscript text to reflect this more accurately. Specifically, we have removed the previous statement that hotspot regions “are very similar”. We apologise for any confusion caused by our earlier wording. Our intended meaning was to highlight general consistency in certain regions, such as the Mediterranean, parts of southern Africa, and North America, where both models identify key DZD hotspot emergence. However, we fully agree that there are notable regional discrepancies, particularly in South America and Australia, which are highlighted in the CNRM model but not in CESM2-LE. We now explicitly

acknowledge these differences in the revised manuscript and provide a more balanced interpretation. This revision is reflected in lines 251-255, as follows:

“Model structure also drives spatial discrepancies (Fig. S21a-b and d-e): CESM2-LE projects broader DZD regions in northern Africa, while CNRM highlights other regions such as South America and Australia. Nonetheless, both models consistently identify the Mediterranean, parts of southern Africa, and North America as key emerging hotspots.”

In response to the reviewer’s additional suggestion, we have also updated Figure S21 to include the equivalent of Figure 2b, specifically, adding a circular diagram illustrating the temporal distribution of ToFE by decades for SSP2-4.5 and SSP3-7.0 of the CNRM model, alongside the previously shown map (Fig. S21). In addition, we have added the following explanatory sentence to the revised manuscript in the Results section (see lines 246-248) and Sensitivity Analysis section (see lines 1050-1053):

Lines 246-248: *“Both scenarios project that 51% of DZD-affected regions will face unprecedented water scarcity by 2100, with 22% experiencing emergence as early as 2020-2030 (Fig. S21b-c).”*

Lines 1050-1053: *“The spatial patterns (Fig. S21) reveal pronounced inter-model and scenario differences. Results from the CNRM model indicate that, under both SSP2-4.5 and SSP3-7.0 scenarios, 51% of DZD-affected regions are projected to face unprecedented water scarcity by 2100, with 22% experiencing emergence as early as 2020-2030 (Fig. S21b-c).”*

These additions provide a more comprehensive comparison of both ToFE between CESM2-LE and CNRM models, thereby strengthening the assessment of model robustness and uncertainty. Please find the updated Figure S21 below.

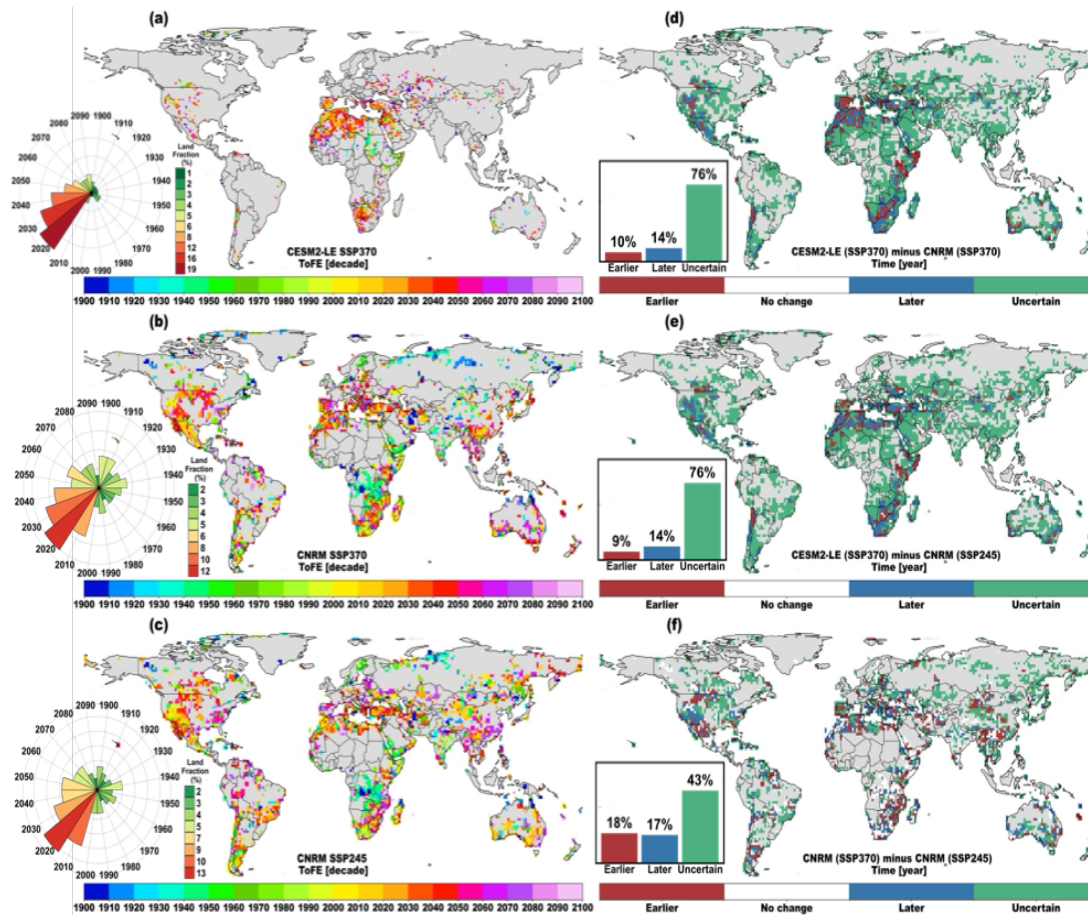


Figure S21: Spatial distribution of the Timing (ToFE) and associated uncertainties of Day Zero Drought (DZD) events across climate models and emission scenarios (CESM2-LE under SSP3-7.0 and CNRM under SSP2-4.5 and SSP3-7.0). Panels (a-c) depict the decadal ToFE of DZD events for each grid cell, calculated as the first decade in which the Fraction of Attributable Risk (FAR) exceeds 0.99, indicating that over 99% of DZD risk is attributable to anthropogenic climate change, based on the cumulative count of DZD events (Equation 4). Results are shown for (a) CESM2-LE under SSP3-7.0, (b) CNRM under SSP3-7.0, and (c) CNRM under SSP2-4.5. The inset circular diagram in panel (a-c) illustrates the global distribution of DZD-prone land grid cells by decade. These diagrams show how the ToFE of DZD is distributed across time, highlighting periods of concentrated emergence and allowing for comparison across models and scenarios. The color scale represents the percentages of grid cells (land areas) experiencing their ToFE in each decade from 1900 to 2100, providing a temporal overview of global DZD emergence trends. Panels (d-f) illustrate inter-model and scenario-based differences in ToFE for grid cells where DZD emergence is detected under those compared cases. Panel (d) represents the difference between CESM2-LE (SSP3-7.0) and CNRM (SSP3-7.0), reflecting structural uncertainty between models. For consistency, ToFE values from CESM2-LE (a) are interpolated to the CNRM resolution to compute the difference between the ToFE between CESM2-LE (SSP3-7.0) and CNRM (SSP3-7.0) as shown in (d) and (e). Panel (e) compares CESM2-LE (SSP3-7.0) and CNRM (SSP2-4.5), highlighting scenario- and model-driven uncertainty. Panel (f) compares CNRM (SSP3-7.0) and CNRM (SSP2-4.5), isolating internal model sensitivity emissions pathways. Inset bar plots in panels (d-f) quantify the proportion of DZD-prone land grid cells experiencing earlier and later emergence, as well

as regions with divergent DZD emergence (uncertain DZD-prone regions). Red and blue shading denote areas where ToFE occurs earlier or later, respectively, in the first model or scenario listed. The green shading indicates regions with inconsistent DZD emergence among the inter-model and scenarios cases (i.e., emergence only occurs in one of the models or scenarios), underscoring uncertainty in projections. The results show that CNRM projects broader emergence in parts of Asia, Australia, and America, while CESM2-LE projects earlier and later emergence across the Mediterranean and Africa. Grey areas indicate locations with no emergence of the DZD condition during the analysis period. These results highlight the importance of model structure and emissions scenario in assessing the timing and spatial distribution of DZD emergence.

More generally, this important uncertainty needs to be better reflected in the abstract which so far does not include this information and instead provides seemingly accurate numbers (35%, 14%) which may be (very) different in other Earth system models. This issue is very relevant as the abstract will be read by people from outside the field including practitioners and policy-makers such that special care is necessary to also communicate the existing uncertainty to them.

Response: We agree that communicating model uncertainty in the abstract is essential, particularly for readers outside the field, such as practitioners and policy-makers.

Accordingly, we have revised the abstract (see lines 9-25) to explicitly acknowledge uncertainties arising from model differences and scenario pathways. This revision ensures that the abstract presents the importance of our findings while ensuring transparency about their uncertainties for a broader audience. The updated abstract is as follows:

“Access to water is crucial for all aspects of life. Anthropogenic global warming is projected to disrupt the hydrological cycle, leading to water scarcity in many regions. However, which regions and when will experience unprecedented water scarcity is unknown. Here, we estimate the Time of First Emergence (ToFE) of drought-driven water scarcity events, referred to as “Day Zero Drought” (DZD), by analysing the simultaneous impact of multi-year water supply deficits and high-water consumption. DZD is driven by hydrological compound extremes, where multiple stress factors, including prolonged rainfall deficits, reduced river flow, and increasing water consumption, occur simultaneously to cause acute water scarcity. Using a probabilistic framework and a large ensemble of climate simulations, we attribute the timing and likelihood of DZD events to human influence. Results indicate that many regions, along with their reservoir, may face a high risk of DZD by 2020 and 2030. While the ToFE and the DZD-prone region are subject to uncertainty related to models and scenario pathways, consistent hotspots include the Mediterranean, southern Africa, and parts of North America. The emergence of DZD is expected to impact urban population most at the 1.5 °C warming level. The length of time between successive DZD events is shorter than the duration of DZD, leading to insufficient recovery periods and exacerbating water scarcity risks. Therefore, more proactive water strategies are urgently needed to avoid severe societal impacts of DZD.”

Other specific comments:

lines 245/246: Please add information on the source of the CMIP6 model data. I suggest to use the Earth System Grid Federation (ESGF) public data repository, <https://aims2.llnl.gov/search/?project=CMIP6/>. Maybe you can find the required data from more models there, incase you have not yet checked it?

Response: We acknowledge the reviewer's helpful suggestion. We have now specified in the revised manuscript (see lines 1138-1140) that the Centre National de Recherches Météorologiques (CNRM) model data used in our study are publicly available via the Earth System Grid Federation (ESGF) data repository (<https://aims2.llnl.gov/search/?project=CMIP6/>). We also explored the availability of the required variables across multiple CMIP6 models on ESGF. However, CNRM was the only one that provided both multiple ensemble members and the full set of variables needed to compute our compound DZD indicator, consistently available across the historical period and both SSP2-45 and SSP3-7.0 future scenarios. This enables the application of our probabilistic framework. To ensure methodological consistency and data completeness, we selected 10 ensemble members from the CNRM model that include both atmospheric and river discharge variables across historical and both SSP2-45 and SSP3-7.0 future scenarios: CM6-1 (r2ilplf2, r3ilplf2, r4ilplf2, r5ilplf2, r6ilplf2), ESM2-1 (r2ilplf2, r3ilplf2, r4ilplf2, r5ilplf2), and CM6-1-HR r1ilplf2. This selection is described in the Methods (see lines 536-546) and the Sensitivity Analysis section of the revised manuscript (see lines 1042-1046), as follows:

Lines 536-546: *“To assess the sensitivity of our results to model structure and emission scenarios, we also include simulations from the Centre National de Recherches Météorologiques (CNRM) model under both SSP3-7.0 and SSP2-4.5 scenarios. For consistency, we analyse 10 ensemble members available for each scenario and consider the same hydroclimatic variables as used with CESM2-LE. Due to the coarser spatial resolution and limited ensemble size of the CNRM simulations relative to CESM2-LE, the CNRM model is used exclusively for sensitivity analysis of the event emergence time. The CESM2-LE large ensemble enables us to compute probabilistic estimates of the ToFE, duration, and waiting time of extreme events. Our 100-member CESM2 large ensemble provides enough data to robustly estimate extreme event statistics. Only CESM2-LE and CNRM provide the variables necessary for our analysis, so other large ensemble simulations cannot be used in our study.”*

Lines 1042-1046: *“To ensure methodological consistency and data completeness, we selected 10 ensemble members from the CNRM model that include both atmospheric and river discharge variables across historical and both SSP2-45 and SSP3-7.0 future scenarios: CM6-1 (r2ilplf2, r3ilplf2, r4ilplf2, r5ilplf2, r6ilplf2), ESM2-1 (r2ilplf2, r3ilplf2, r4ilplf2, r5ilplf2), and CM6-1-HR r1ilplf2.”*

There is a typo in the caption of Figure S7, CES2-LE should be CESM2-LE.

Response: We have corrected the typo accordingly in the caption of Figure S7 in the revised version.

I do not wish to remain anonymous - Rene Orth.

Response: We sincerely thank Rene Orth for the constructive feedback and for choosing to disclose his identity. We greatly appreciate the valuable comments, which have improved the clarity and robustness of our manuscript. We have acknowledged Dr R. Orth by name in the manuscript (see lines 1152-1154).