Drought decreases streamflow response to precipitation especially in arid regions

Reviewer 3

I found this is an interesting article. I have a few comments detailed below. Minor revision is requested.

- We thank the reviewer for taking time to read our manuscript and we are very pleased that they found the manuscript interesting. The reviewer provides constructive feedback and suggestions, which we will address in the revised manuscript. Below, we summarize the changes we will make in response to these comments. Our responses are shown in blue, the revised text is shown in *italics*, and line numbers mentioned in this response refer to the current version of the manuscript and they are indicated within brackets [xx].

1. Title: I wonder whether the article title chosen by the authors is clear enough. I found it very general and therefore not really convincing on the original results it brings. For example should the annual scale of the analysis be mentioned.

   - We thank the reviewer for the suggestion and we agreed about the importance of adding the temporal scale of the analysis in the title: Drought decreases *yearly* streamflow response to precipitation especially in arid regions

2. Abstract: Are the 2%-3% evolutions significant given all the other uncertainties in data?

   - If the reviewer is questioning the relevance of the findings showing 2–3% influence of NDVI anomalies and drought events from the previous year on the Q-P ratio, we argue that the broader conclusion remains valid despite uncertainties in the data. A relatively small influence suggests that this specific drought type has minimal impact on catchment response. In contrast to the 20–30% changes observed for other drought types, this lower effect may indicate that these catchments are more resilient to changes associated with NDVI. Furthermore, this indicates that the influence of preceding drought events appears to have minimal impact on the yearly Q-P ratio. We will further specify this in the abstract:

     [23-27] Our analysis shows that generally droughts with streamflow or soil moisture anomalies below the 15th percentile lead to around 20% decrease in streamflow sensitivity to precipitation during drought compared to the historical norm. *However, this decrease is reduced to only about 2% one year after the drought, highlighting the generally low influence of preceding drought conditions*. These effects are more pronounced when droughts are longer and more severe.

3. Introduction: The runoff-to-precipitation ratio was heavily analysed in studies based on the Budyko approach. I find it may be useful to more explicitly make a link with the studies which

analysed the sensitivity/elasticity of this approach to various variables and discuss how the proposed study can be linked to these previous works (e.g. Xue et al., 2020)

- We thank the reviewer for this suggestion and for highlighting the work by Xue et al. (2020). In line also with the other reviewers' comments, we agree on the need to better define the yearly Q-P ratio and compare it to other metrics used in the literature (e.g. elasticity). We will add the text below and further check for possible links with the elasticity metric computed through the Budyko Framework by (Creed et al., 2014; Helman et al., 2017; Xue et al., 2020).

  [109] We then computed yearly streamflow-to-precipitation (Q-P) ratio timeseries for each catchment. *This measure represents the annual runoff ratio and is dynamically influenced by climatic and hydrological conditions. By considering an annual timescale, the ratio inherently accounts for evapotranspiration and storage processes within the catchment. However, it is important to note that, first, since the ratio is a lumped representation of these processes, it does not separate individual contributions. Second, in some catchments, storage processes extend beyond a single year, which may influence the annual runoff ratio. This metric differs from other metrics such as elasticity (Anderson et al., 2023; Sankarasubramanian et al., 2001; Zhang et al., 2022). While the annual runoff ratio provides an average measure of how much precipitation contributes to streamflow in a given year, elasticity tells us how streamflow reacts to changes in precipitation (Schaake, 1990).*

4. Section 2.1: I liked the fact that a large data set was used in this study. However I missed a discussion on data quality and possible dependency of results to the type of data used. For example, satellite products are known to be subject to large biases, which are not uniform whatever the regions or conditions. Besides they often show non stationary behaviour over time due to changes in algorithms or data. How these uncertainties may impact results shown in this study? A more detailed description of data used on these aspects would be useful.

   - We agree with the reviewer about the inhomogeneous spatial and temporal performance of global satellite data. In accordance with this, we explored below possible spatial and temporal differences in biases and accordingly we will add these as limitations in the revised manuscript. In particular, we will focus on MSWEP, GRACE and NOAA-NDVI, as these are satellite-based products. In contrast, GSIM relies on observations, and GLEAM soil moisture is modelled data. The limitations of these latter datasets are discussed in Matanó et al. (2024), and we have linked these discussions to our manuscript:
     [97] These datasets and their post-processing are explained in more detail in Table S1 of the Supplementary Information and in Matanó et al. (2024).

According to studies that compared satellite precipitation datasets (Gebrechorkos et al., 2024; Mazzoleni et al., 2019), there is no single best-performing precipitation dataset for all regions, and the performance is sensitive to basin characteristics. However, several studies (e.g., (Beck et al., 2017; Satgé et al., 2019) have showed MSWEP's strong spatial performance compared to other datasets, such as ERA5 and CHIRPS, across various global regions. That said, MSWEP tends to perform better in the US, South America, Australia and Europe (Beck et al., 2017, 2019) while exhibiting lower accuracy in Africa (Beck et al., 2017). However, in our study, only a small fraction of stations in Africa passed the quality check, making their contribution to the total dataset minimal. Therefore, spatial biases from MSWEP's performance are likely negligible in the context of our global analysis.

Concerning GRACE: validating the spatial and temporal quality of GRACE data is challenging due to the limited global coverage and the insufficient density of in situ measurements across all hydrological reservoirs (as discussed inSchmidt et al., 2008). However, some studies have attempted regional validation. For example, in South America, GRACE has demonstrated good performance in distinguishing hydrological signals from various reservoirs (Schmidt et al., 2008). Similarly, GRACE have shown strong agreement with local observations in reproducing groundwater storage anomalies at the basin scale in India (Bhanja et al., 2016) and in north America (Wang et al., 2022). In contrast, its performance in Europe has been reported to be lower (Van Loon et al., 2017).

Regarding the transition from GRACE to GRACE Follow-On (GRACE-FO), we note that this did not impact our analysis, as our study covers the period between 1980 and 2016, while GRACE-FO commenced in 2018.

Regarding NOAA-NDVI, we found only regional or country-level studies that validated its spatial reliability. For instance, studies in Australia (Holm et al., 2003) and East Africa (Nicholson et al., 1990) have shown significant performance of the NDVI dataset in capturing vegetation dynamics.

In the manuscript, we will acknowledge the potential uncertainties associated with satellite-derived data:

[567] In addition to differences in temporal scale, satellite datasets also exhibit varying spatial performance. For instance, GRACE has been shown to perform well in North America and India but demonstrates lower accuracy in Europe. Similarly, MSWEP tends to perform better in the U.S. (Beck et al., 2019), Europe, South America and Australia (Beck et al., 2017) while exhibiting lower accuracy in Africa (Beck et al., 2017). However, since our analysis includes only a small fraction of catchments from Africa, potential errors due to lower performance in that region have a limited impact on our global assessment.

5. Section 2.1: I found that Table S1 would be better placed in the main text of the article. This table is important to understand the variety between data used, e.g. in terms of periods available. I was also wondering which quality checks were done on the data used and how gaps in series were processed and accounted for in the models. If all catchments were plotted on a Budyko-type plot, could some specific/outlier behaviours be detected?

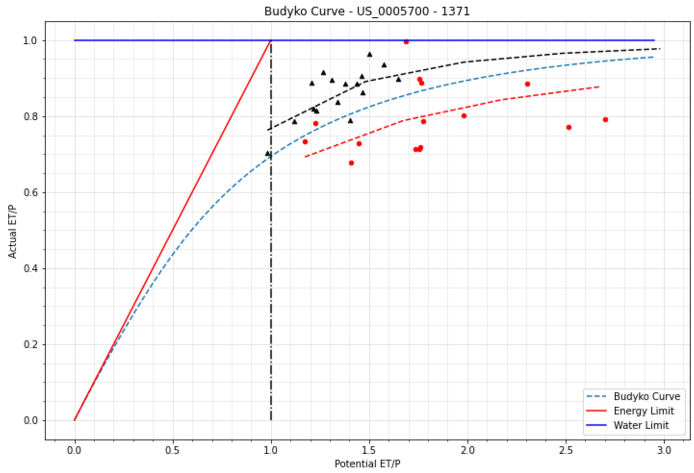
   - We agree with the reviewer's suggestion and will move Table S1 to the main text. Regarding quality checks, we provided additional clarification in Matano et al. (2024) and Supplementary Note 1 of that paper but we will also add some of these clarifications in the main text. Specifically:
     - For streamflow data, we only included stations with high delineation quality for their catchments.
     - We analysed only stations with no missing months within a year and a minimum of 30 years of data.
     - For step-change analysis, stations with more than two years of gaps were excluded.

     [97] These datasets and their post-processing are explained in more detail *in Table 1* and in Matanó et al. (2024). *For instance, for streamflow data, we included only GSIM stations with high delineation quality of their catchments, no missing months within a given year, and a minimum record length of 30 years.*

     [253] To identify shifts in the streamflow response to precipitation from one steady state to another, we carried out a trend analysis in 1107 catchments with non-stationary streamflow-to-precipitation (Q-P) ratio timeseries. *These catchments also have no more than two years of gaps in their streamflow timeseries.*

     Overall, fewer than 2% of the stations analysed had more than three years of total gaps in their time series. The strict criteria applied for data quality resulted in limited data coverage in regions like Asia, Australia, northern and central Africa, and the western United States, as also acknowledge in line 557 of the manuscript.

     Regarding the Budyko-type plot, we also conducted this analysis for some catchments. Specifically, we applied the Budyko framework to analyse the catchments that exhibited a step change in the yearly Q-P ratio. We computed the ratio of actual evapotranspiration to precipitation, and the ratio of potential evapotranspiration to precipitation, both before (in black) and after (in red) the change year (see figure below). However, we decided to not include it in this manuscript. Adding this analysis would introduce another layer of results to a study that already implements two methodologies: the mixed-effect panel data model and the step-change analysis. So we decided to leave out this analysis and use it for a follow-up work / future paper.



6. Section 2.1: Could there be any influence of year-splitting on results, especially on the memory to drought conditions? The use of hydrological years make sense, but it will likely split drought events in two parts, i.e. straddling two years. I was also wondering if the hydrological year was determined catchment by catchment or if an homogeneity was sought between catchments in a same region or under similar climate type.

   - We acknowledge the reviewer's concern that splitting drought events across water years could influence the results. While we recognize that drought events are continuous phenomena, we partially addressed this by considering the influence of drought conditions from the preceding year. Aggregating drought events into longer time periods could have reduced the number of events available for analysis, which would have further limited the robustness of our results. Further we have identified water years for each catchment as the 12-month period beginning in the month of the lowest average monthly streamflow (as reported in line 102 of the manuscript). In line with this, we will add to the text:

     [568] *Although drought is a continuum with temporal connectivity between events* (Van Loon et al., 2024)*, our analysis treats droughts as independent events, summarizing their characteristics at a yearly scale to facilitate comparison with the yearly ratio of Q to P. We only partially accounted for drought connectivity by incorporating drought characteristics from the preceding year into our analysis. However, their influence was minimal (less than 5%), with meteorological drought showing a slightly higher influence compared to other drought types.*

7. Section 2.1: Which exponent values were used in the Box-Cox transformation?

   - For the Box-Cox transformation, we used the Python function scipy.stats.boxcox. The exponent value for the transformation, defined as lambda (λ), determines the nature of the transformation. In our case, we set lambda to None, allowing the function to automatically estimate the optimal value of λ that maximizes the log-likelihood function.

8. Section 4: I was not really convinced by several points in the discussion were the authors try to find explanations to the results found. These explanations remain hypotheses and should more clearly be presented as such.

We agree with this point which was also raised by the second reviewer. In the discussion section, our intention was to assess whether our results align with findings from other studies and to explore how these findings have been explained in terms of underlying processes. Upon revisiting the references, we acknowledge that the use of Urgeghe et al., 2010, may indeed be an overextension in this context. As well as the use of Garreaud et al., 2017, so we will delete it. In agreement with the reviewer's comment, we will modify the discussion as following:

> [485] Spatial differences can also be found in the influence of negative NDVI anomalies on the Q-P relationship, *though the overall influence remains small (less than 5%)*. While the response of the Q-P relationship generally increases during negative NDVI anomalies, in arid and semi-arid catchments, this response *slightly* decreases (Figure 2b). This decrease could *partially* be explained by reduced *hydrological* connectivity among bare patches *(Jaeger et al., 2014)* and increased soil evaporation (Guardiola-Claramonte et al. 2011). *However, these processes are highly dependent on the type, timing, and duration of drought, as well as catchment-specific characteristics (Goodwell et al., 2018; Liu et al., 2024), making generalizations challenging. Furthermore, we acknowledge that reduced transpiration, typically associated with negative NDVI anomalies, may also take place (Johnson et al., 2009). The interplay between these processes likely drives the observed variability, underscoring the need for caution when interpreting these results.*

9. Section 4: The catchment memory to past conditions is heavily dependent on geology. Could the authors find a link between their results and geological characteristics?

    - We agree with the reviewer about the important role of geological characteristics in influencing changes in catchment responses to precipitation due to meteorological and hydrological anomalies. In this study, we specifically investigated soil type characteristics, as detailed in lines [233–236] of the manuscript. The results of this analysis are presented in Figure S9 of the Supplementary Information and discussed in lines [389–393]. Our findings indicate for instance that catchment response to precipitation in arid and equatorial sandy catchments is significantly influenced by soil moisture drought, while hydrological drought plays a key role in warm temperate catchments with both clay and sandy soils.

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