We would like to thank both reviewers for the careful review and the very useful comments and questions. **Our detailed replies to reviewer 1 start on this page (Section 1), our detailed replies to reviewer 2 start on page 19 (Section 2).**
Both reviewers ask for additional clarifications and explanations and also for additional user guidance, which we have included. Reviewer 2 points out the paper is quite long and suggests to move the use cases section into the appendix. Since the paper becomes even longer with the additional clarifications, we followed the suggestions of Reviewer 2 and moved the use cases to the appendix. Both reviewers asked for additional guidance on the uncertainty level of the indicators. To address this request and to provide guidance, we introduced three variables classes (L1 = direct, unaltered measurement data, L2 = Data extracted from publicly available, spatially interpolated hydro-meteorological datasets and data subjected to only minimal post-processing, L3 = Variables, indicators, and indices derived by the authors, irrespective of the degree of validation or verification performed. Five tables related to the reliability levels have been added: A table introducing the concept of the reliability levels (Table 1) and tables with an overview of processed variables and suggested reliability levels for hydro-meteorological data and indices derived and presented in Section 4 (Tables 2, 3, 4 and 5). More detailed responses are included below and are highlighted in blue, already implemented changes in the revised manuscript are highlighted in red.

1 Comments reviewer 1

This is a review for ESSD, von Matt et al., 2025: HYD-RESPONSES: daily hydro-meteorological catchment-level time series to analyse HYDrological drought dynamics in RESPONSE to (cumulative) water deficits in Swiss catchments.

The described dataset appears to be of potential use, albeit limited for Switzerland-focused usage. I think the manuscript requires major revisions in terms of structure, motivation for certain choices or clearer descriptions as summarized in the general and the specific comments below.

1.1 General/major comments:

1.1.1 Item 1

(x) The abstract and the introduction, while motivating and describing the dataset, do not lay out the logic of the manuscript. For example, the use cases in sec 6 come a bit as a surprise to the reader.

We added the outline of the paper structure following the revised structure (use cases were moved into the Appendix).

L93–98 (revised version):

The remaining paper is structured as follows: In section 2 the study region and the catchments are presented. Section 3 introduces all datasets used to compile the HYD-RESPONSES dataset. Section 4 elaborates on the processing of hydro- meteorological data. Section 5 is the analogue for the processing and extraction of catchment descriptors. Section 6 finally discusses the dataset and points to potential caveats and cautionary notes while section 7 presents multiple complementary datasets which are valuable in combination with the HYD-RESPONSES dataset. Section 8 provides a concluding summary. Three exemplary use cases to illustrate the nature and potential of the HYD-RESPONSES dataset are provided in Appendix A.

(x) In general, the manuscript would benefit from an additional verification effort, showing that the aggregation procedures work as they are intended. For example, 4.2.1: FOEN uses M7(Q), too, so there would be scope for a comparison.

Thank you for the suggestion. For the M7Q, no aggregation was needed except for a smoothing of the original time series by a 7-day moving average window (using the *zoo* R-package). A scope for comparison might be the Q347 low-flow indicator - but then again - the procedure is following the one of the FOEN based on the same (original) FOEN streamflow time series. Here, we however wanted to ensure catchment intercomparabilty by using a common reference period (1990–2010) among all catchments whereas to my best knowledge - the FOEN uses the entire (homogeneous) time series. Hence, slight differences would be expected. We further added more details on the calculation in Sect. 5.3 (formely 5.2) on L452ff (revised manuscript).

L461–464 (revised version):

The Q347 (Aschwanden, 1992; Aschwanden and Kan, 1999) is a low flow index used as the basis for water abstraction restrictions in Switzerland and corresponds to the daily flow rate exceeded for 347 days per year. The Q347 was derived from the flow duration curve (FDC) by using the *hydroTSM* R-package (Zambrano-Bigiarini, 2020) and corresponds roughly to the 5th streamflow percentile (95th percentile of 365 days ≈ 347, hence Q347).

1.1.2 Item 2. Description of catchments and respective coverage by the datasets (section 2-3, figure 1, 2, 3): Here, I think that a bit more care could be given to a comprehensible presentation:

(x) Section 2 would benefit from clarifications i) that the catchments lie partially outside of CH, ii) whether they are fully disjunct (i.e. there is or there is no hierarchy in the catchments), and iii) that any altitude discussed here is basin average.

We added the following clarifications and additional informations in Section 2:

iii) was addressed on **L105–106** (revised version):

In terms of mean catchment height (elevation), the catchments are distributed relatively equally between 500 and 2500 m a.s.l. with fewer catchments at elevation ranges above 1500 m a.s.l. (see Fig. 2c).

i) and ii) were addressed on **L114–118** (revised version):

Note that 12.5 % (n=23) of the catchments have at least 5 % of catchment area lying outside of the Swiss national borders as the dataset consists of catchments of the entire hydrological Switzerland (catchments that drain in(to) Switzerland). Furthermore, the Swiss streamflow monitoring network is designed such that multiple measurement stations may be located along the same river. As a result, upstream catchments can be nested within larger downstream catchments, leading to hierarchical dependencies.

(x) Then, in section 3.1, there is an explanation why certain stations are not used for the HYD-RESPONSES dataset; some items are self-explanatory, but others are not. Suggest to explain.

We rephrased the reasoning for station inclusion/exclusion and added clarifications on what meaningful means. And yes, the reviewer is absolutely correct that streamflow (Q) is derived from water-level measurements by P-Q relationships. We rephrased the misleading statement for this exclusion criteria. Further, we spelled out what NAWA is (formerly NADUF).

L130–137 (revised version):

Namely stations which provide reliable streamflow (Q) time series and are associated with a physical/natural catchment. Stations have therefore be excluded if they i) only provide water-level information (no Q, 3 stations), ii) are not part of the main streamflow measurement network (e.g., stations from other networks such as the National Surface Water Monitoring Programme (NAWA BAFU, 2023), 4 stations), iii) secondary stations (11 stations), iv) stations with potential return streamflow (= negative Q values, 2 stations), v) Q measured at derivations (2 stations), vi) stations without watershed delineation (i.e., subterranean; 1 station) and vii) uncertainties in time series composition due to displacement and/or temporarily missing Q of contributing stations (4 stations). The complete list of included stations is provided in Tables B6, B7, B8, B9 and B10 in Appendix B.

(x) Section 3.2 starts a bit sloppy, as meteorological variables are indeed provided from multiple sources; suggest to re-phrase or re-organise this description. Which data does MeteoSwiss use for RhiresD in areas outside CH?

We rephrased Section 3.2 by adding an introductory paragraph and made the multiple-source coverage of variables clearer. Measurement networks outside Switzerland are not explicitly mentioned in the MeteoSwiss documentation for RhiresD except for that they origin from weather services in neighbouring countries. The added introductory paragraph is as follows:

L139–141 (revised version):

Hydro-meteorological variables used in this study were compiled from multiple complementary data sources, combining station-based spatial climate analyses, dedicated snow model products, and reanalysis data (Table 1). This multi-source approach allows both comprehensive coverage of relevant variables and comparative analyses between different data products.

(x) The very last sentence of section 3.2 explains that ERA5-Land data are aggregated to daily values, but does not provide details. Is it done in a way that makes respective data comparable to the other sources (TabsD, TminD, TmaxD, RhiresD)?

We added the clarification that indeed the temporal aggregation follows that of the MeteoSwiss data sets and is different for the temperature and precipitation data. To avoid confusion, we however excluded this last sentence in section 3.2 where the original data sources are introduced. We further added a closing sentence referring to the methodological section where this is elaborated in detail (separation of concerns).

The added closing sentence is as follows (**L177** (revised version):

The procedures used to extract time series from all gridded datasets are detailed in Section 4.

(x) Fig 2 is somewhat unmotivated and only referenced in section 6.2.

We agree with reviewer 1 and moved the Figure in the Appendix (now **Figure A4**). We however decided to keep the Figure in the Appendix as part of the extended use cases which were - in the course of the revisions - moved into the Appendix as well. An additional reference was added in Section 4 as the related Figure illustrating the HYD-RESPONSES time series was kept in the main text.

The additional reference was added on **L248–251** (revised version):

Time series of all categories are illustrated in Fig. 6 showing the exceptional drought year 2022 for the example catchment 2034 - Broye, (Payerne, Caserne d'aviation) located in the western Swiss Plateau region (see catchment contours in **Fig. A4**). A detailed analysis of the event year 2022 demonstrating the utility of the time series provided in the HYD-RESPONSES dataset is provided in Sect. A2 in Appendix A.

(x) Section 3.3 does not provide information on coverage outside of CH. This should be clarified. If restricted to CH, is this a problem for catchments with significant portions in neighbouring countries? L344 onwards and the discussion and conclusion sections in principle suggest so.

Thank you for pointing this out. We changed the section as follows:

First, we excluded the swissALTI3D from the list of used datasets, as information on aspect and slope can be retrieved directly via complementary datasets (e.g., the accompanying catchment information provided by the FOEN) which are derived from data that cover all catchments entirely. This was not the case for swissALTI3D. The HYD-RESPONSES dataset on Zenodo (see von Matt et al., 2026) was updated accordingly.

We further completed information on catchment coverage in the last paragraph of the section:

L220–227 (revised version):

Note that the digital soil suitability maps, swissTLM3D hydrography, biogeographic regions of Switzerland as well as information on springs and swallow holes in karst regions are restricted to Swiss national territory. Catchments with a significant area outside of Switzerland should be treated with caution regarding descriptive variables extracted from these datasets (see Sect. 5 for a comprehensive overview on extracted descriptors). The hydrogeological and lithological maps of Switzerland to a large extent also cover areas outside of Switzerland. Only catchments of the Rhine (catchments 2091, 2143, 2288, 2289) and Wiese (catchment 2199) are not entirely covered. However, with a coverage of at least >94%, descriptors extracted from these datasets may still prove valuable for these catchments.

Methodological details on the extraction and preparation of catchment descriptors are presented in Section 5.

(x) Item 3. The information around homogeneity/breakpoints is taken from elsewhere. Still, I think it is important to clearly explain their concepts (L189), because these are not self-explanatory terms. Their usage is also not quite clear. L213: what makes a breakpoint "significant"? Is it an ad hoc definition?

We added more detailed explanations on the methodology and concepts underlying the breakpoint analysis conducted by the FOEN and referred to literature mentioned in the FOEN low-flow methodology guide (BAFU, 2024).

The paragraph now reads as follows:

L208–218 (revised version):

Finally, general information on the gauging stations and streamflow time series (availability and homogeneity) were provided as accompanying (meta-)data by the FOEN. Time series homogeneity was derived by the FOEN using breakpoint tests following the method of Bai and Perron (1998). Breakpoints are identified by partitioning the time series based on the number of potential breakpoints and subsequent modeling of the time series by piecewise linear regression (see Bai and Perron, 1998). The optimal breakpoints are found by minimization of the sum of squared residuals. Resulting breakpoints are indicative to changes in the mean annual 7d mean flow (M7Q) and were further plausibilized by the FOEN based on catchment meta information and known (potentially) relevant anthropogenic influences such as the construction of (reservoir) dams, hydropower and wastewater treatment plants (for more information see BAFU, 2024). General station information includes catchment area, mean height, glaciation percentage, outlet coordinates and streamflow regime type (among others) (see Figs. 1 and 2). Catchment outlines (polygons provided by the FOEN) and catchment outlets (point shapes) are provided in the coordinate system CH1903/LV03 (EPSG:21781).

We further added a reference back to the adjusted paragraph on L213.

L266–270 (revised version):

The length of the time series depends on the dataset that they were derived from (see Table 1 for details). Streamflow time series are provided for three different catchment-specific time periods: (1) the original time series (entire period), (2) the most recent gap-free time-period time series and (3) the most recent homogeneous time series (in case of significant and plausible breakpoints; otherwise equal to the gap-free time series) (see Fig. 3). The breakpoint information is provided by FOEN (see Sect. 3.3).

1.1.3 Item 4. Guidance on how to use the many different quantities in the dataset; the authors have compiled many different indices, deficit manifestions, etc, and their genesis and differences among related ones are explained well enough. However, what is missing is guidance for users which to use for which purpose. Some examples:

(x) L245: Can the authors give context on whether the deficit remaining uncompensated over several years is realistic? They provide an extra quantity of annually reset deficits which indicates that it might not be. An expert user will probably know what to make of it, but less experienced users might be a bit lost.

We added a short discussion.

L309–316 (revised version):

Water-balance based non-standardized drought indices are widely in use in ecohydrological, land-atmosphere interaction research and catchment-memory studies both with and without temporal resets (see e.g., Biegel et al., 2025; Cui et al., 2022; Stocker et al., 2023). Being more strongly tied to the actual physical water availability, non-compensated CWDs may provide valuable information on carry-over effects in multi-year drought contexts and/or long-term shifts in climatic water balance (Stocker, 2021; Fowler et al., 2022; Saft et al., 2015). PCWDs in contrast are based on potential water balance and (absolute) carry-over deficits should hence be treated with caution. CWD and PCWD time series which are annually reset provide complementary year-to-year information, which may better align in contexts of annual low-flow statistics and allows for a year-to-year comparison across years and catchments.

(x) Section 4.4: Which application would require the usage of SPI/SPEI/SMRI, respectively?

We added a short discussion but discussing all possible use cases is beyond the scope of this data paper. In the same context we slightly restructured the first part of Section 4.4 where the individual indices are introduced to match with the discussion at the end. An exemplary application is further presented in form of a composite analysis in Section A3 in Appendix A.

The adjusted presentation of the indices is as follows:

L326–330 (revised version):

The SPI represents deficits driven by precipitation only (derived from P), while the SMRI tracks deficits in liquid water input originating from both rainfall and snowmelt (derived from P+ ΔSWE) accounting for seasonal snowfall and snowmelt dynamics (Staudinger et al., 2014; Baez-Villanueva et al., 2024). The SPEI represents deficits driven by evaporative demand (derived from P-PET) and hence indirectly accounts for temperature effects (Vicente-Serrano et al., 2010; Mwinjuma et al., 2026; Gebrechorkos et al., 2025).

The discussion on the applications of standardized indices reads as follows:

L363–369 (revised version):

SPI, SPEI and SMRI provide complementary (and standardized) information on hydroclimatic variability and drought-related processes facilitating integrated analyses of drought development and propagation and allowing consistent comparisons across catchments, regions and climates (Mwinjuma et al., 2026; Gebrechorkos et al., 2025; Tijdeman et al., 2022). Standardized indices are frequently employed in drought monitoring and early warning systems (DEWS; Tijdeman et al., 2020; Kchouk et al., 2022), drought propagation analysis or as proxy for various storage processes (Haslinger et al., 2014; Cammalleri et al., 2019; Raposo et al., 2023; Peña-Gallardo et al., 2019; Barker et al., 2016). Example use cases for drought event analysis and catchment response patterns are provided in sections A2 and A3 in Appendix A.

(x) Section 4.6: fixed and variable threshold definition.

We completed the section with information on the strengths of both fixed and variable percentiles to provide guidance for the user on when to use which type of deficits:

We added the following guidance information:

L392–400 (revised version):

Fixed thresholds (e.g., a constant percentile threshold) are used for critical flow levels that do not change seasonally (e.g., directly linked to physcial/actual low-flow or water scarcity situations) whereas variable thresholds (e.g., seasonally varying percentiles) account for seasonality and changing flow regimes, allowing drought phases and deficits to be identified relative to expected (seasonal) conditions (”anomalies”, Stahl et al., 2020; Van Loon, 2015; Brunner et al., 2019a; von Matt et al., 2024). Hence, variable threshold definitions are often used to analyse seasonally varying streamflow (drought) generating processes or to understand drought propagation mechanisms (Brunner et al., 2023, 2022; Hammond et al., 2022). For the fixed threshold definition, daily M7Q anomalies were derived for events exceeding the Q347 threshold, defined as the daily flow rate exceeded for 347 days per year (i.e., the 347-day exceedance flow, roughly corresponding to the 5th streamflow percentile; see Sect. 5.3).

(x) Section 5.2, L335: two BSI variants.

We added additional information for guidance on the use of the two BSI variants:

L441–448 (revised version):

The first variant is derived based on a ratio between area and basin length (A/L^2) known as form factor (Horton, 1932) and the second variant is based on a ratio between the catchment area and the area of the circle with the smallest radius encircling the entire catchment (A_{catch}/A_{circle}) known as circularity ratio (Miller, 1953). Both indices range from 0 to 1. Both are frequently used (also in combination) as morphometric catchment indicators (see e.g., Das et al., 2022; Pisupati and Ratnakar, 2025). Albeit providing similar information, the form factor is primarily controlled by basin length and hence provides information on catchment elongation, while the circularity ratio is more sensitive to basin shape accounting for complex/irregular shapes resulting in larger areas (for more information on basin shape indices see Das et al., 2022).

1.1.4 Item 5. The manuscript remains sometimes short when in comes to motivating certain choices or methods. For example:

(x) L295: Why are more percentiles provided only for M7Q?

We added some accompanying information on the additional percentiles:

L386–388 (revised version):

For the 7-day average streamflow series (M7Q) we also provide the 2^{nd}, 10^{th} and 15^{th} percentiles which are frequently used in streamflow drought analysis and monitoring (see e.g., Van Loon, 2015; Stahl et al., 2020; Sarailidis et al., 2019; BAFU, 2025).

(x) L309: purpose of "minor pooling"

We added the following information on the purpose of the pooling:

L415–419 (revised version):

A minor pooling of hydrological drought events is introduced by using the 7-day average streamflow (M7Q) time series, which merges closely successing and potentially dependent individual events to one single event as a result of the smoothing of large day-to-day fluctuations (Tallaksen et al., 1997; Tallaksen and Van Lanen, 2004; Hisdal and Tallaksen, 2000; Sarailidis et al., 2019) Streamflow drought events based on both fixed and variable threshold definitions were used for the event shadings in Fig. 6.

I suggest to screen the manuscript for these instances and include respective explanations.

A screening for these instances was done.

1.1.5 Item 6. Figures and references to figures. I think these must be clearly improved:

(x) Figure 2 was mentioned in my item 2 already.

Figure 2 was moved in the Appendix and now corresponds to Figure A4.

(x) I find no reference to Figure 6 (although it might help explain the "phases" question that I put under "specific comments").

We added the Figure reference in Section 4.7. Figure 6 corresponds to Figure 5 in the revised version.

L411 (revised version):

An event starts on the first day values fall below the threshold value and lasts until values exceed the threshold again (see Fig. 5).

(x) Figure 7 should probably specify subfigures as (a) and (b).

We revised Figure 7 accordingly.

(x) Figure 9: Shouldn't the caption specify *streamflow* drought for the pink and green shadings? I think what is missing here is the time series that was used for defining the drought periods. It seems related to panel j but not identical according to the text from L418 onwards. The y-axes should be labeled properly (T2m: [K], SWE: [mm], ...).

We have revised the caption of Figure 9 accordingly. Note however, that due to suggestions of reviewer 2, we moved the exemplary use cases (former section 6) into the Appendix. Figure 9 now corresponds to Figure 6. We added a referential note for panel i) to make the link to streamflow drought events clearer.

The caption to Figure 6 now reads as follows:

Hydro-meteorological time series for the Swiss Plateau catchment 2034 - Broye, Payerne (Caserne d'aviation) for the year 2022. Color shadings in all panels highlight streamflow drought events for two definitions: yearly Q347 (pink, fixed threshold approach) and a moving monthly 15th percentile threshold (green, variable threshold approach). **(a)** Moving monthly anomalies of the 2 m-temperature (T2m), positive anomalies are shown in red and negative anomalies in blue. **(b)** Moving monthly anomalies of the precipitation (P, RhiresD) **(c)** Moving monthly anomalies of the evaporation (ET, ERA5-land). **(d)** Moving monthly anomalies of the soil moisture volume (ESM ERA5-land), soil moisture anomalies are depicted for a near-surface SM-level (black, 0–7 cm) and the deepest level (blue, 100–289 cm) available from ERA5-Land. **(e)** Moving monthly anomalies of the snow water equivalent (SWE SPASS). **(f)** Moving monthly anomalies of the snowmelt (smlt, SPASS). **(g)** SPI colored by aggregation scales from 1- to 24-months. **(h)** SMRI colored by aggregation scales from 1- to 24-months. **(i)** Seven day average streamflow (M7Q) on which streamflow drought events were identified. **(j)** The CQD time series shows the corresponding accumulated M7Q-deficits for both the fixed threshold approach (black) and the variable threshold approach (blue). **(k)** Absolute cumulative water deficit (CWD). **(l)** Potential cumulative water deficit (PCWD). **(m)** Monthly anomalies of the CWD (CWD anomaly). **(n)** Monthly anomalies of the PCWD. Time series of the cumulative water deficits for both absolute values and monthly anomalies are shown for both standard (black, P–E (P_e)) and snowmelt-corrected (blue, P–E+ΔSWE (PsmltSPASS_e)) variants. The same is shown for potential cumulative water deficits which are based on the potential water balance (P–PET (P_pev) and P–PET+ΔSWE (PsmltSPASS_pev)).

(x) Figure 10: not referenced in the main text; the text supposed to discuss the figure mentions "pluvial inferieur", which is not shown in Figure 10, several times around L470. What does the "n" stand for, catchments?

We added references to Figure 10 in section 6.3. We updated the figure caption to clarify what "n" stands for. Note that following suggestions from reviewer 2, the exemplary use cases were moved in the Appendix. In the revised version, Figure 10 now corresponds to Figure A3 in Section A3.

The updated figure caption was complemented by the following clarification:

"n=" refers to the number of catchments with a specific streamflow regime type.
The following references to Figure 10 (now Fig. A3) were made in former Section 6.3 (now A3):

L794–819 (revised version)**:**

Median SPI values are mostly negative across all aggregation time-scales indicating that precipitation conditions co-occuring with streamflow droughts tend to be drier than normal. Several streamflow regimetype-specific response patterns are evident and change across seasons along with contributing streamflow (drought) generating processes.
Glacier melt is the dominant factor for the *a-glaciaire* regime type (Fig A3a–d). Streamflow levels are typically lowest in winter (January–March) as a result of precipitation falling as snow (intermediate storage) and highest in summer due to large contributions of glacier melt (Aschwanden and Weingartner, 1985; Weingartner and Schwanbeck, 2020; Muelchi et al., 2021). Streamflow droughts of strongly glaciated catchments are not associated with moderate drought conditions at any SPI scale. In glacial and nival catchments a shift towards short-term precipitation deficits (SPI-1 to SPI-6) being associated with droughts is present across seasons and drought-generating processes. The transition towards shorter deficit scales emerges in summer for nival regime types (Fig.A3g,k) and in autumn for glacial regime types (Fig. A3d). In pluvial and transitional regime types short-term precipitation deficits (mostly 1- to 3 months) are relevant throughout the year (Fig. A3q–x). Seasonal shifts are also observed for pluvial and transitional regime types with mid- and long-term precipitation deficits becoming more relevant in summer and autumn (Fig. A3t,w–x).
In addition to 3-monthly precipitation deficits, also mid- and long-term deficits become relevant in summer and autumn for (nivo-pluvial) catchments in the Jura region and catchments of the regime type *pluvial inférieur*. Compound moderate droughts are mainly observed for sub-yearly (1- to 9-monthly) scales with most extreme conditions on a 6-monthly scale in the Jura region (especially for nivo-pluvial catchments) and on a (6- to) 9-monthly scale for catchments of the regime type *pluvial inférieur*. In southern Switzerland, precipitation deficits tend to be relevant on longer scales compared to similar regime types north of the Alps. In contrast to nival catchments north of the Alps (*nival alpin*, Fig. A3i–l), droughts in the nival catchments south of the Alps (*nival méridional*, Fig. A3m–p) are associated with substantial precipitation deficits at longer aggregation times (9–24 months). The deficits occur in winter and in summer, but conditions are more extreme in summer (SPI $\approx$ -1.5) on scales longer than 15 months. Further, also 3-monthly precipitation deficits appear to be relevant for streamflow (drought) generation in summer (moderate drought conditions). In spring and autumn, mid- to short-term accumulation scales are more relevant. Interpretations of the differences between the south and north sides of the Alps should however be considered with caution due to the small catchment sample sizes and the spatial proximity of the two *nival méridional* catchments. The observed response patterns may therefore not be representative of nival catchments south of the Alps in general.

1.2 Specific comments:

(x) L23/L89: please introduce CAMELS-CH to the uninformed user not only in section 8 but already at first mention/in the introduction.

We added more contextual information on the CAMELS-CH dataset in both cases.

Abstract (L23) - **L23–25** (revised version):

The dataset is compatible with the recently published ”Catchment Attributes and MEteorology for Large-sample Studies” dataset for hydrological Switzerland (CAMELS-CH) and with additional catchment descriptors provided by the FOEN.

Introduction (L89) - **L89–93** (revised version):

The HYD-RESPONSES dataset can be combined with existing hydro-meteorological time series datasets and catchment descriptors such as CAMELS-CH (Höge et al., 2023), which provides large-sample hydro-meteorological data for hydrologic Switzerland and is the Swiss version of the ”Catchment Attributes and MEteorology for Large-sample Studies” (CAMELS; see e.g., Clerc-Schwarzenbach et al., 2024).

(x) L39/41: do the authors really mean “anthropogenic” in the sense of “caused by humans”? Or is it more about these events impacting the human “sphere” differently? Might also be relevant elsewhere (L375, L390).

We adjusted the formulation in L39/41 and checked other instances to stress that ”anthropogenic” refers to anthropogenic (catchment) disturbances which may alter drought (and) streamflow characteristics (i.e., dams/constructions). Altered characteristics can ultimately also affect the socio-economic impacts (e.g., the human ”sphere”).

We adjusted instances on L39/41 as follows:

L38–46 (revised version):

Individual drought events may differ in their hydro-climatological, hydro-meteorological, hydro-terrestrial and anthropogenic drivers (Mishra and Singh, 2010; Hao and Singh, 2015; Floriancic et al., 2020; Zhou et al., 2021; Massari et al., 2022; Brunner et al., 2023). The consideration of multiple hydro-climatic, hydro-meteorological, hydro-terrestrial and anthropogenic (disturbance) factors is therefore key to understand catchment-specific drought responses and sensitivities and to provide information for drought early warning, preparations, and interventions (e.g., Apurv et al., 2017; Apurv and Cai, 2020; Baez-Villanueva et al., 2024; Brunner et al., 2022, 2021; Ding et al., 2021; Peña-Angulo et al., 2022; Peña-Gallardo et al., 2019; Sutanto and Van Lanen, 2022; Tijdeman et al., 2018; Van Lanen et al., 2013; Savelli et al., 2022; Van Loon and Laaha, 2015; von Matt et al., 2024).

(x) L79: “as a result of non-transformation”, is this simply replicating the statement of “non-standardisation”? If so, recommend to delete.

We deleted the replication.

(x) Caption of Table 1: refer to glossary table in the appendix for variable names?

We added the reference to the glossary table.

(Spatially gridded) Data products used for the time series extraction. Full variable names and associated units are provded in Table B1 (glossary) in Appendix B. Note that the variable short names correspond to the layer/product names in the respective dataset.

(x) L230-233: The causality here is not entirely clear. I am guessing: The reset at sept 1st is a feature of SPASS SWE in order to avoid the “snow tower” feature. This feature leads to large snowmelt values in delta SWE. These large values are mitigated by the described interpolation. If so (or even if not), the chain could be spelled out more clearly.

Thank you for pointing out that the causality was not sufficiently clear in the original description. We agree and have revised the text to clarify that the large negative ΔSWE values around September 1st are not caused by physical snowmelt processes, but are an artifact of the SPASS model setup. Specifically, SPASS resets modeled SWE at the beginning of each snow year (September 1st) to prevent unrealistically large snow accumulation (“snow towers”). When daily changes in SWE (ΔSWE) are computed, this reset produces an artificial negative spike that would otherwise be misinterpreted as extreme snowmelt.
To avoid propagating this known modeling artifact into derived snowfall and snowmelt estimates, ΔSWE values on September 1 were treated as invalid and replaced by linear interpolation using the adjacent days. This correction affects only a single day per year and serves solely to remove a non-physical signal introduced by the model bookkeeping rather than representing a real hydrological process. The manuscript has been revised accordingly to make this causal chain explicit.

The clarified paragraph is now as follows:

L285–290 (revised version):

Note that SWE is reset in the SPASS dataset at the end of every snow year (every September 1st) to avoid unrealistically high accumulation of snow water equivalents (“snow towers”; see Michel et al., 2023). As snowfall and snowmelt were derived from daily differences in SWE (ΔSWE), this reset can result in an artificial large negative ΔSWE value on September 1st that does not represent actual physical snowmelt. To prevent this model artifact from affecting the derived snowmelt time series, ΔSWE values on September 1st were set to missing values and replaced by linear interpolation using the ΔSWE values from the preceding and following days.

(x) L274: 50 implausible/missing values: Is this referring to the time series, or the distribution (i.e., before or after binning)?

We added some additional information on what missing/implausible values is referring to:

L349–353 (revised version):

The distribution was selected among the distributions satisfying the following conditions: (1) the transformed values are not significantly different from a normal distribution for the majority of catchments (p-values> 0.05 for at least 75 % of the catchments), (2) fewer than 5 DOYs flagged and (3) fewer than 50 implausible and/or missing values in the transformed time series (combined consideration of missing values due to flags and unrealistically high/low values).

(x) L282: This means that values are capped at +-3 STD, which could be spelled out here. Can the authors briefly repeat the reasoning for this by Stagge et al. (2015) in this context?

We added the reasoning of Stagge et al. (2015) in this paragraph, specifying implausible values more clearly:

L341–345 (revised version):

Implausible values are defined as values above or below +3 (−3) STD following (Stagge et al., 2015). Estimating more extreme standardized index values from a 30-year climatology requires substantial extrapolation of the fitted distribution and is therefore associated with large uncertainty, particularly given the strong temporal autocorrelation of drought indices. Values beyond 3 correspond to events with return periods far exceeding the length of the reference record and cannot be robustly quantified (Stagge et al., 2015).

(x) L284: Please explain "standard time series".

We rephrased the starting paragraph as follows:

L371–373 (revised version):

Climatologies and anomalies are provided for all time series, including the time series of variables directly extracted from spatially gridded data products with no modifications except for spatial and temporal aggregation where required (see Sect. 4.1), derived indicators (Sect. 4.2), standardized drought indices (Sect. 4.4), and cumulative water deficits (Sect. 4.3 and 4.6).

(x) L299: "Q347" is only introduced in section 5.2; an explanation is necessary at the first instance, I think.

We introduced Q347 in this paragraph but also clarified its derivation in section 5.2:

L299 // **L398–400** (revised version):

For the fixed threshold definition, daily M7Q anomalies were derived for events exceeding the Q347 threshold, defined as the daily flow rate exceeded for 347 days per year (i.e., the 347-day exceedance flow, roughly corresponding to the 5th streamflow percentile; see Sect. 5.3).

In section 5.3 (formerly 5.2) we added following details:

L461–464 (revised version):

The Q347 (Aschwanden, 1992; Aschwanden and Kan, 1999) is a low flow index used as the basis for water abstraction restrictions in Switzerland and corresponds to the daily flow rate exceeded for 347 days per year. The Q347 was derived from the flow duration curve (FDC) by using the *hydroTSM* R-package (Zambrano-Bigiarini, 2020) and corresponds roughly to the 5th streamflow percentile (95th percentile of 365 days ≈ 347, hence Q347).

(x) L305: What constitutes a “phase” as used throughout 4.7? Probably related to Figure 6 (unreferenced, see above). Unless this is clarified, it remains unclear what an “event” is.

We added the reference for Figure 6 in section 4.7 and elaborated more on how the events are defined and represented in the event time series:

L406–419 (revised version):

We define drought events as coherent phases of non-zero deficits for cumulative deficits (CWD, PCWD and CQD) and as negative M7Q-based streamflow anomalies for streamflow droughts. Streamflow drought phases were extracted for the same percentiles and time scales as used for CQDs (see Sect. 4.6), namely for monthly (31 days) and seasonal (91 days) percentiles: 2nd, 5th, 10th, 15th, 25th, 50th (median) and the mean. Streamflow events were also extracted for the fixed (yearly) Q347 threshold (see Sect. 4.6 and 5.3).
An event starts on the first day values fall below the threshold value and lasts until values exceed the threshold again (see Fig. 5). For each variant, the event time series consists of consecutively numbered event phases and information on the event duration since the start (i.e, an event with a duration of 5 days is represented in the time series as: ”1 1 1 1 1” (event phase number), ”1 2 3 4 5” (duration since start)). Additional event characteristics (e.g., lowest value during a phase) can easily be derived by the user in combination with the indicator time series. A minor pooling of hydrological drought events is introduced by using the 7-day average streamflow (M7Q) time series which merges closely successing and potentially dependent individual events to one single event as a result of the smoothing of large day-to-day fluctuations (Tallaksen and Van Lanen, 2004; Hisdal and Tallaksen, 2000; Tallaksen et al., 1997; Sarailidis et al., 2019). Streamflow drought events based on both fixed and variable threshold definitions were used for the event shadings in Fig. 6.

(x) Sub-Headings in section 5: “extraction of catchment descriptors (CD)”, “derivation of other CD”; these seem not very precise. What exactly is the difference between CD in 5.1 and 5.2? Can the header name or the distinction be specified?

We restructured the catchment descriptor section from two to three subsections:

5.1) Field-based descriptors
5.2) Feature-based descriptors
5.3) Time series-based and climatological descriptors

(x) L331: Is competing areal extent of several categories in a catchment the only possible constraint to representativeness? I could imagine that for example the spatial distribution in terms of upstream/downstream/margins could also be a factor.

We agree that competing areal extent of several categories is not the only possible constraint. The review by Tarasova et al. (2024) provides an elusive overview of factors which could be taken account. We pointed out this limitation of overlap-based quantification in the discussion and also in use case ”catchment grouping” in Appendix A1.

Discussion - **L524–528** (revised version):

Field- and feature-based catchment descriptors were aggregated at catchment level via summarization (e.g., karstic sources) or percentage overlaps (see Sect. 5.1). Maximum percentage overlaps with catchment area may however only insufficiently account for spatial differentiation which could enhance the representation of factors most influential to streamflow evolution by accounting for spatial proximity to the stream/river courses (Tarasova et al., 2024; Floriancic et al., 2022).

Appendix A1 - **L713–720** (revised version):

The catchment grouping to biogeographic regions presented here is again based on maximum overlap of catchment area with the specific biogeographic region (see also Fig. 7a). Biogeographic regions are frequently used for grouping catchments into groups of similar streamflow (generation) characteristics and provides usable results (see e.g., Brunner et al., 2019b; Muelchi et al., 2021; von Matt et al., 2024). In specific cases where a categorization into biogeographic regions may not be unambiguous (see Sect. 5.1), categorization may be reconsidered by the user via alternative grouping (e.g. directly on streamflow regime types), alternative categorization approach (other than maximum overlap) or expert judgement. As such the streamflow regime types *nivo-pluvial jurassien* and *pluvial jurassien* could for example be recategorized to the Jura region (see Fig. A2f).

(x) L365: “partly on both monthly and yearly time scales”, this should be specified and motivated.

Thank you for checking this statement. We initially wanted to provide the indices on monthly basis too as to identify seasonal variability in hydro-climatic catchment controls. In the dataset on Zenodo used for the preprint we did however only include yearly information (except for Pardé coefficients). The sentence was adjusted accordingly and reasoning has been added. The provided time series allow the user to derive additional indices on seasonal scale if required.

L476–478 (revised version):

Information on average precipitation, temperature, evaporation, snow water equivalent, streamflow, the fraction of precipitation falling as snow and the runoff fraction (Q/P) are provided on yearly scales for identifying broad climatic (i.e., water balance) and physiographic controls on hydrological behavior.

(x) L383: The authors have provided a short interpretation of Fig 8; I think they should also do this for Figure A1 (which could also be moved from the appendix to the main part?).

Following the recommendation of Reviewer 2 we moved all case study figures - except the former Figure 9 which is kept for time series illustration but not the in-depth case study analysis. Therefore, we did not move Figure A1 to the main part but instead incorporated it in Section A1 (former Section 6.1) where the figure was already referenced. We nevertheless added a short interpretation following your suggestion.

L707–720 (revised version):

Note that whereas catchments smaller than 500 km^2 allow for a more distinct discrimination in streamflow regime types and hence streamflow generating processes, catchments with an area larger than 500 km^2 are influenced by a multitude of streamflow generating and/or storage processes (e.g., groundwater contributions) and are hence provided as *mixed regime (>500 km^2)* type (see Sect.

2). The mixed regime type is the most prevalent among catchments (see Fig. 2 and occurs across all biogeographic regions (Fig. A2) being the most frequent regime type in Western and Eastern Central Alps as well as in the Northern Pre-Alps.
The catchment grouping to biogeographic regions presented here is again based on maximum overlap of catchment area with the specific biogeographic region (see also Fig. 7a). Biogeographic regions are frequently used for grouping catchments into groups of similar streamflow (generation) characteristics and provides usable results (see e.g., Brunner et al., 2019b; Muelchi et al., 2021; von Matt et al., 2024). In specific cases where a categorization into biogeographic regions may not be unambiguous (see Sect. 5.1), categorization may be reconsidered by the user via alternative grouping (e.g. directly on streamflow regime types), alternative categorization approach (other than maximum overlap) or expert judgement. As such the streamflow regime types *nivo-pluvial jurassien* and *pluvial jurassien* could for example be recategorized to the Jura region (see Fig. A2f).

(x) L413: "lacking snowmelt": wouldn't there be more concrete evidence for this somewhere in the HYD-RESPONSES dataset?

Thank you for pointing this out. We added a reference to panels e) and f) of former Figure 9 (Figure 6 in the revised version) which depict the anomalies in monthly SWE and (SWE-derived) snowmelt anomalies.

L747–750 (revised version):

During the variable threshold streamflow droughts in mid-March to April, both SMRI-1 and SMRI-3 reach more negative values than their SPI equivalents, which indicates that lacking snowmelt contributed to the streamflow drought generation (see Fig. 6g,h). Lacking snowmelt as contributing factor is further confirmed by considering the larger and rather persistent negative anomalies in both SWE and snowmelt in the preceeding 1 to 3 months (see Fig. 6e,f).

(x) L424: "Larger CWDs during..." is this a general (climatological) statement? The term "seasonal climatology" and the "(not shown)" addition might indicate this, but I recommend to stress this more clearly.

We rephrased the sentence to clarify the interrelationships between CWDs and climatology.

L761–762 (revised version):

Based on the seasonal climatology of both temperature and evaporation (highest values during summer), larger absolute CWDs are generally expected to occur during the warm season (not shown).

(x) Starting sentence of Section 7: something is not quite right here with the references/model names.

We adjusted the references accordingly and changed the LaTeX-commands from ***citet*** to ***citep***.

1.3 Technical/editorial comments:

We implemented all editorial suggestions.

(x) L9 onwards: inconsistent in naming all MeteoSwiss/SLF parameters, but only ERA5-Land as a whole.

We adjusted the sentence with the mentioned naming inconsistencies by removing the list of extracted hydro-meteorological variables as they are already mentioned earlier in the abstract. We then reformulated the sentence mentioning the different data sources and products without listing individual products or variables when they are part of a larger product (e.g., MeteoSwiss spatial climate analyses).

The sentence now reads as follows:

L7–11 (revised version):

The dataset comprises daily mean streamflow observations obtained from the Federal Office for the Environment (FOEN), complemented by daily hydrometeorological variables aggregated at the catchment scale. Complementary variables are derived from from spatially gridded products provided by MeteoSwiss (Spatial Climate Analyses), the WSL Institute for Snow and Avalanche Research SLF (SPASS), SLF (OSHD), and the European Centre for Medium-Range Weather Forecasts ECMWF (ERA5-Land reanalysis).

(x) L12, “information on precipitation, evaporation-driven and streamflow deficits”, can the authors please re-phrase; something seems not quite right here.

We rephrased this sentence as follows:

L13–14 (revised version):

Deficits related to precipitation, evaporation, and streamflow are quantified using both standardized and non-standardized (drought/deficit) indices.

(x) L93/94: “n=18/94” I think it is misleading as the n refers to streamflow regime types first and then to individual catchments; why not simply include the numbers in prose?

We followed your suggestion and added the numbers in prose.

L100–103 (revised version):

The 184 catchments (Fig. 1) provided in the HYD-RESPONSES dataset span a wide range of catchment areas (0.56–35’878 km^2), glaciation percentages (0–56 %), altitude ranges (467–2937 m a.s.l.) and 18 streamflow regime types (see Fig. 2). A bit more than half of the catchments 51 % (n=94) are small to mid-size with an area of between 10 km^2 and 500 km^2. Only 9 (4 %) catchments are smaller than 10 km^2 and 56 (30.4 %) catchments are larger than 500 km^2.

(x) L203, “variables” should go after “flux”?

We adjusted the first paragraph of section 4.1 to be more precise in terms of variable distinction and conventions used.

L257–262 (revised version):

For this, instantaneous variables and variables representing accumulations or fluxes are distinguished. For instantaneous variables, we provide daily average values. For variables representing accumulations and fluxes, we provide daily sums. Flux variables (mainly precipitation and evapotranspiration) are aggregated using the same temporal convention as RhiresD precipitation sums, i.e., from 06 UTC (day) to 06 UTC (day + 1) (see MeteoSwiss, 2021a). Instantaneous variables and ERA5-Land temperature were averaged from 00 UTC to 00 UTC again following the convention used in equivalent MeteoSwiss products (e.g., TabsD; MeteoSwiss, 2021b).

(x) L264: suggest to unify reference to R packages across the manuscript. E.g., elsewhere it is “cwd R-package”, here it is “SCI-package”.

We unified all package mentions to the following pattern: ***packagename R-package***.

(x) L284: There is a left-over bracket, probably to be closed after “3.2” in L285.

The left-over bracket was deleted.

(x) L293: I suggest to spell out the z score more clearly instead of the “(value-mu)/sigma terminology.

We reformulated the sentence accordingly.

L383–385 (revised version):

Using the moving window climatology, standardized anomalies have been derived by first subtracting the climatological mean (μ) and then dividing by the climatological standard deviation (σ) (also known as *z-scores*).

(x) L308: “event definition”, drop “definition”?

We changed the ”event definition” to ”variant”.

L412–414 (revised version):

For each variant, the event time series consists of consecutively numbered event phases and information on the event duration since the start (i.e, an event with a duration of 5 days is represented in the time series as: ”1 1 1 1 1” (event phase number), ”1 2 3 4 5” (duration since start)).

(x) L362: MAM = march april may as elsewhere? In general, it is not clear what the acronym(s) is/are supposed to say.

We added the acronyms which are related to the two variables mentioned in the sentence and slightly adjusted the commonly used abbreviation ”MAM” for mean annual minimum to MAM_q to avoid confusion with the acronym referring to the seasonal acronym standing for March April May.

The revised sentence reads as follows:

L472—475 (revised version):

The last two indices related to streamflow behaviour are the ”flashiness” or R-B-index (Baker et al., 2004) which represents the ratio of the sum of day-to-day streamflow changes divided by the total streamflow and the flow-stability index which relates the mean annual minimum flows (MAM_q) to the mean annual flow (MQ; MAM_q/MQ).

(x) L383 An other > Another

Adjusted.

(x) L424: “actual” in the sense of “non-anomaly” or in the sense of “non-potential”? Same for L431.

We slightly reformulated both sentences and explanations and also added subfigure references for clarity.

L424 - Adjustments on **L759–761** (revised version):

Similar to the longest streamflow drought phases, also the largest cumulative deficits in water balance (CWD) occurred between May–August 2022 (in terms of both absolute deficits and anomalies, see Fig.6k,m).

L431f - Adjustments on **L766–769** (revised version):

Cumulative deficits in potential water balance (PCWDs, Fig. 6l) are more similar to cumulative streamflow deficits for the variable-threshold definition (CQD, Fig. 6j (blue line)). This reflects the different nature of CWDs and PCWDs. Deficits based on the actual water balance (P-E) are more strongly tied to the actual water availability and hence the individual streamflow (drought) phases (Fig. 6i,k).

(x) L563 and elsewhere: data set or dataset?

Instances were screened and adjusted to ***dataset***

(x) L563: “alsop” typo

Adjusted.

2 Comments reviewer 2

This manuscript presents a comprehensive hydrometeorological dataset that is developed from a range of other, existing, datasets from various sources. This dataset is developed specifically to support assessment of drought and low flow conditions across catchments in Switzerland, and includes time series of a wide range of essential climate variables as well as derived drought indicators (e.g. SPI, SPEI, etc). As this dataset, or rather what I would consider a data collection can support detailed assessment of drought and the drivers of drought (see also use cases presented in the paper), I would think this in line with the scope of the journal.

Overall, the paper is well structured (with comments, see below) and the datasets that have been developed are outlined clearly, including the original data sources and general comments on data quality.

One of the main concerns I have is that the dataset combines various underlying sources, in particular observational datasets and re-analysis datasets and datasets from models. Some attention is given at the start of the discussion on where care should be taken, but this is only discussed for selected variables, particularly related to snow (e.g. SWE), but much less discussed for other variables, for example E and PET (see also comments below). In this sense the discussion is somewhat poorly developed. The first part addresses some of the limitations, but a broader reflection on the quality of the dataset, including derived variables, would add to the depth of assessment of what is presented.

This is an important point which we have taken up throughout the paper in particular in the sections describing extracted and derived hydrometeorological indicators. We introduced three suggested reliability levels which we assigned all variables and variable combinations for all hydrometeorological data. We added the reliability classification to the HYD-RESPONSES dataset which is published as version 2 on Zenodo (von Matt et al., 2026). We also complemented the discussion on potential caveats and limitations resulting from variable combinations of different data sources. More detailes are provided in the answers to the specific suggestions.

(x) Perhaps some indicative confidence level on the different datasets and combinations would be useful. I think this should also be added to the metadata provided with the dataset in Zenodo.

Thank you for this suggestion. To provide some guidance for the users of the HYD-RESPONSES dataset, we introduced three variable classes/levels (L1–L3). Level 1 (L1) represents direct, unaltered measurement data and is therefore considered the most reliable. Level 2 (L2) includes data directly extracted from publicly available spatially interpolated hydro-meterological datasets and data subjected to only minimal (post-)processing (e.g., temporal aggregation). Level 3 (L3) comprises all variables, indicators, and indices derived by the authors, irrespective of the degree of validation or verification performed. We added a corresponding overview table for the labels (Table 3, **see attached Table 1**) and provide extensive overview tables for all time series and variants in the Tables B2, B3, B4 and B5 in Appendix B (**corresponding to attached Tables 2, 3, 4 and 5**). These tables provide transparent information on data sources, data processing level and suggested reliability based on levels L1–L3 and were also added to the updated HYD-RESPONSES dataset on Zenodo (see von Matt et al., 2026).

The levels are introduced in Section 4 - **L232–247** (revised version):

Guidance on the reliability of indicators is provided through a three-level classification based on the origin of the underlying data, the extent to which variables rely on (model) assumptions, and the degree of processing applied to derive the hydro-meteorological data, (drought) indices, and events. *Level 1* consists of direct, unaltered measurement data and is therefore considered the most reliable. *Level 2* includes data directly extracted from publicly available spatially interpolated hydro-meterological datasets and data subjected to only minimal (post-)processing (e.g., temporal aggregation). *Level 3* comprises all variables, indicators, and indices derived by the authors, irrespective of the degree of validation or verification performed. For both *Level 2* and *Level 3* data, additional annotations are provided for variables whose derivation is based on a (strong) modeling component. A summary of the classification is provided in Table 3. All extracted and derived variables and their suggested reliability level are listed in the Tables B2, B3, B4 and B5 in Appendix B.

(x) The dataset has been developed specifically for Switzerland, and for application in the Swiss context. It would be interesting to comment on how applicable the methods used/presented here would be applicable in other contexts. Some reflection on how applicable this could be in other contexts/countries, what the requirement are of underlying datasets would be etc. For example, use is made of ERA5-Land, which is of course available globally, but on the other hand the availability of observational data in CH is excellent. In other settings where there is less observational data, more use would then perhaps be made of re-analysis data. However, would this still make "sense"?

This is indeed a very important point which needs to be discussed. We extended the discussion by adding general reflections on the HYD-RESPONSES approach with regard to data (quality) requirements and transferability to other regions/countries where the availability of high-quality station measurements may be limited. We discuss consequences of data availability on application purposes and provide some suggestions and future perspective which may lead to a broader application also in regions/countries where data is more sparse.

We extended the first part of the discussion as follows:

L496–512 (revised version)**:**

Although the dataset was developed for Switzerland, the methodological framework — combining in-situ observations, gridded products, and reanalysis into catchment-scale time series — is transferable, with requirements that scale with data availability. Replication requires four essential components: (1) streamflow observations with defined catchment boundaries, (2) meteorological forcing data (precipitation, temperature), (3) snow information for mountain regions, and (4) static catchment descriptors (e.g., information on soils, geology, topography). While the first component is often limiting, the second component is decisive for the applicability of the dataset on specific use cases. Switzerland can leverage from high-density observational station networks resulting in high-quality spatially gridded hydro-meteorological products (see e.g., MeteoSwiss, 2024). With known biases in mind (especially over complex terrain), ERA5-Land is a viable alternative by providing temporally and physically consistent variables at sufficiently high spatial resolution for comparative catchment studies and machine learning applications aiming for generalizable results in regions where observational networks are less dense (Muñoz-Sabater et al., 2021; Dalla Torre et al., 2024; Scherrer et al., 2023). For local operational drought management or absolute deficit quantification, reliable high-resolution observational products remain however preferable. Several recent developments address observational data limitations, including the Caravan global community dataset (Kratzert et al., 2023), rapidly advancing machine learning-based bias correction methods for downscaling reanalysis products such as ERA5-Land (Menapace et al., 2025; Najafi et al., 2026; Zhang et al., 2025) or advances in developing high-quality remote sensing-based products for soil moisture (e.g. SMAP; see Brocca et al., 2024; An et al., 2025), snow (e.g., ICESat-2 Besso et al., 2024), evaporation (see e.g., Anderson et al., 2024) and terrestrial water storage (e.g., GRACE-FO; Rodell and Reager, 2023).

(x) The use cases that are presented in the paper are interesting and indeed demonstrate the utility of the dataset. On the other hand, they may not be the core of the paper, and the paper is very long One could consider including these in the supplementary material. What could then be interesting is to provide some general reflection on the application of these use cases, and how the HYD-RESPONSES dataset and methods have enabled these analyses, and why that was difficult or not possible prior to the development of this dataset.

We followed your suggestion to move the three use cases from the main part of the data description paper to Appendix A. We extended the discussion with a short discussion on general applications which are enabled by the HYD-RESPONSES dataset. The general discussion frames a variety of applications (as before) but is framed more strongly on what the HYD-RESPONSES dataset enables and why. The applications and strengths are thematically covering the use cases where some of them are illustrated. We did not discuss the use cases in detail to remain consistent with the main part where the use cases are not introduced in detail anymore. The discussion paragraph points the reader to the use cases at the end.

The extended discussion (formerly L481–488) paragraph is now as follows:

L482–495 (revised version)**:**

The HYD-RESPONSES dataset addresses fundamental challenges in hydrological drought analyses by compiling and harmonizing multiple data sources into a coherent catchment-scale framework, enabling multi-variable drought analyses in Switzerland. Drought (deficit) indices derived from two high-resolution snow climatologies for Switzerland (SPASS, OSHD) also allow for in-depth quantitative analyses on the contribution of snow processes to cross-seasonal drought propagation in Alpine catchments (Staudinger et al., 2014, 2017; Brunner et al., 2023). A combined used of standardized indices (SPI, SPEI, SMRI at 1—24 month scales) and non-standardized cumulative deficits (CWD, PCWD, CQD) facilitate multi-scale (drought) deficit and catchment response sensitivity assessments and allows for a concurrent anomaly-based and physically interpretable characterization of drought deficits (Raposo et al., 2023; Van Loon, 2015; Wu et al., 2020; Baez-Villanueva et al., 2024; Stocker et al., 2023). By providing time series for many relevant variables for drought monitoring (precipiation, temperature, evaporation, soil moisture and streamflow; see e.g., WMO and GWP, 2016) at daily temporal resolution, the HYD-RESPONSES dataset may also be used for training machine learning models such as Random Forests (RFs; e.g., Floriancic et al., 2022) or Long Short-Term Memory models (LSTMs; see Kratzert et al., 2018; Lees et al., 2022; Kratzert et al., 2023) which have recently emerged as promising approach for rainfall-runoff modeling (Kratzert et al., 2018, 2019; Lees et al., 2022). Three example applications of the HYD-RESPONSES dataset are illustrated in Sect. A1, A2 and A3 in Appendix A.

2.1 Detailed comments:

(x) Line 98-99: Catchments are described as being at a certain elevation. This seems to be the mean elevation (this is mentioned later). May be useful for comprehension to name that here.

We added the corresponding clarifications in Section 2.

L105–107 (revised version):

In terms of mean catchment height, the catchments are distributed relatively equally between 500 and 2500 m a.s.l. (see Fig. 2c). Only eight catchments are higher than 2500 m a.s.l. and only one catchment is at very low elevation (catchment Wiese, Basel).

(x) Line 116: It may be useful to explain a bit better what “meaningful” means. I understand this is obtained through personal communication, but it is somewhat vague. see below
(x) Line 118: Stations where Q is measure at a water level station. I find this somewhat confusing, as I would presume (and my experience working with FOEN would confirm) that most river stations measure water levels and derive the discharge through a rating curve. Perhaps something else is meant. Please clarify. see below
(x) Line 118: Mention is made of NADUF stations. I am not familiar with what these are. Please provide some explanation.

We rephrased the reasoning for station inclusion/exclusion and added clarifications on what meaningful means. And yes, the reviewer is absolutely correct that streamflow (Q) is derived from water-level measurements by P-Q relationships. We rephrased the misleading statement for this exclusion criteria. Further, we spelled out what NAWA is (formerly NADUF).

L130–137 (revised version):

Namely stations which provide reliable streamflow (Q) time series and are associated with a physical/natural catchment. Stations have therefore be excluded if they i) only provide water-level information (no Q, 3 stations), ii) are not part of the main streamflow measurement network (e.g., stations from other networks such as the National Surface Water Monitoring Programme (NAWA BAFU, 2023), 4 stations), iii) secondary stations (11 stations), iv) stations with potential return streamflow (= negative Q values, 2 stations), v) Q measured at derivations (2 stations), vi) stations without watershed delineation (i.e., subterranean; 1 station) and vii) uncertainties in time series composition due to displacement and/or temporarily missing Q of contributing stations (4 stations). The complete list of included stations is provided in Tables B6, B7, B8, B9 and B10 in Appendix B.

(x) Line 121: list of stations included

A list of all included stations in the HYD-RESPONSES dataset is already provided in the Appendix Tables B6–B10 (formerly A2–A5). Or has the reviewer an other list in mind (list of exclusions)?

(x) Line 124: May be useful to mention what is meant by assembled – I assume that this is compiling the catchment average for these variables.

We restructured Section 3.2 following suggestions from reviewer 1. The introductory paragraph was adjusted following your suggestion.

L139–141 (revised version):

Hydro-meteorological variables used in this study were **compiled** from multiple complementary data sources, combining station-based spatial climate analyses, dedicated snow model products, and reanalysis data (Table 1). This multi-source approach allows both comprehensive coverage of relevant variables and comparative analyses between different data products.

(x) Line 126: I appreciate that the authors use the original names/ids of data depending on the source (e.g. RhiresD, tp). Table A1 provides some explanation which is useful. Perhaps it would be useful to provide in that table something like the WMO standard naming conventions. Would also be clear if the authors mention this strategy in the text, as it may otherwise become somewhat confusing.

Thank you for pointing out the potentially confusing naming based on original (product) layer names. We added a short declaration in Table 1 and also a direct reference to the glossary Table B1 (formerly A1) in Appendix B. In Section 4 we also added some explanatory information on the general variable naming conventions used to minimize confusion in variable naming also with respect to Tables B2–B5 where variables and variable combinations are explicitly listed.

We adjusted the caption of Table 1 as follows:

(Spatially gridded) Data products used for the time series extraction. Full variable names and associated units are provided in Table B1 (glossary) in Appendix B. Note that the variable short names correspond to the original layer/product names in the respective datasets.

We added the following explanations in Section 4:

L240–247 (revised version)**:**

The naming of the unaltered variables directly retrieved from measurement data (streamflow) or extracted from spatially interpolated hydro-meteorological datasets is based on the layer names used in the original input datasets (see variables listed in Table 1 and the glossary provided in Table B1). Derived variables and (standardized) drought indices are named by a suffix representing the type of indicator followed by all contributing variables where ERA5-Land variables are kept in lowercase while variables from other products start with upper-case letters. Naming for derived variables based on the snow products make use of the product name (SPASS) or the combination of product and variable names (OSHD) as identifier for clear distinction. All extracted and derived variables and their suggested reliability level are listed in the Tables B2, B3, B4 and B5 in Appendix B.

(x) Line 139: Mentions is made of the quantile mapping approach being used. It is not so clear to me what the reference is for this bias correction through quantile mapping. Please clarify.

We slightly restructured the part on SPASS and removed the direct mentioning of quantile mapping (which is part of SnowQM):

L153–159 (revised version):

Snow water equivalent (SWE) data were compiled from two independent high-resolution (1×1 km) snow datasets. The primary source is the spatial Snow Climatology for Switzerland (SPASS) developed jointly by MeteoSwiss and SLF (Michel et al., 2023; Marty et al., 2025). This dataset provides modelled and bias-corrected daily SWE for September 1961–September 2022, derived using the SnowQM model based on TabsD and RhiresD. The SnowQM model is presented in detail in Michel et al. (2023). The spatial coverage is restricted to Switzerland. A second snow dataset is derived from the Swiss Operational Snow-Hydrological model system (OSHD), provided by WSL (SLF), which supplies SWE and modelled snowmelt runoff for the period 1998–2022 (Mott, 2023; Mott et al., 2023).

(x) Line 167: I think the word “The” at the start of the sentence needs to be dropped as it is otherwise not clear which digital soil suitability maps are intended as these have not been introduced.

We added ”of Switzerland” to the sentence to make clear that we refer specifically to the maps used in the HYD-RESPONSES dataset which are introduced with this sentence.

L186–190 (revised version):

The digital soil suitability maps of Switzerland provide information on a set of different soil characteristics assessed on 25 different geological and geomorphological units which are further discriminated by different landscape elements depending on aspect, slope and bedrock. The maps were first assessed in 1980 and revised in 2000 (BLW, 2022; Swisstopo, 2020). The different soil characteristics include soil wetness, soil depth, permeability, water storage capacity, nutrient content and skeletal content.

(x) Line 192: Does mean height here imply the mean elevation? Please be consistent.

Yes it does imply mean elevation. We adjusted the phrasing to match the terms used on L98/99 (preprint version).

L215–217 (revised version):

General station information includes catchment area, mean catchment height (elevation), glaciation percentage, outlet coordinates and streamflow regime type (among others) (see Figs. 1 and 2).

(x) Line 205: Check the sentence starting with “For accumulation… “. It is somewhat confusing and may need to be rephrased or elaborated to be clear.

We rephrased the sentence to enhance readability.

L257–259 (revised version):

For this, instantaneous variables and variables representing accumulations or fluxes are distinguished. For instantaneous variables, we provide daily average values. For variables representing accumulations and fluxes, we provide daily sums.

(x) Line 215-216: Limnographs are often mentioned. The word is correct but to my mind not in such common use. It is somewhat a Germanism to my mind. Perhaps use Water level sensor or something similar

We have changed the name to your suggestion from limnograph to ***water level sensor***.

(x) Line 233: Mention is made of interpolation between the day before the end of September and the day after, when SWE is det to zero. Surely the amount of water that melts is the same whether this happens over one or two days – and still unrealistically high, given that when resetting I assume all snow is considered as being melted. Perhaps I am misunderstanding the concept.

We clarified the paragraph as this was also requested/mentioned by reviewer 1.

The clarified paragraph is now as follows:

L285–290 (revised version):

Note that SWE is reset in the SPASS dataset at the end of every snow year (every September 1^{st}) to avoid unrealistically high accumulation of snow water equivalents ("snow towers"; see Michel et al., 2023). As snowfall and snowmelt were derived from daily differences in SWE (ΔSWE), this reset can result in an artificial large negative ΔSWE value on September 1^{st} that does not represent actual physical snowmelt. To prevent this model artifact from affecting the derived snowmelt time series, ΔSWE values on September 1^{st} were set to missing values and replaced by linear interpolation using the ΔSWE values from the preceding and following days.

(x) Line 239: Also related to the general comment. Here E and PET are derived from observed P (interpolated) and E and PET calculated in ERA5-Land. I am not clear how biases are dealt with, especially in E. If in ERA5-Land the precipitation is strongly biased, then surely E will (climatologically) tend to be too low in catchments that are water limited.

Thank you for your suggestion. We are fully aware of the potential of biases in terms of absolute values for time series related to (potential) water balance which combine one or more independent underlying data sources. As consequence one can not necessarily assume closed water cycles, since - as you point out - ERA5-Land variables are internally consistent but not across datasets. However, given the scarcity of reliable long-term evaporation products, the combination of high-resolution precipitation and snow data (RhiresD, SPASS, OSHD) provides a necessary compromise. The high-resolution precipitation and snow datasets used provide more reliable amounts especially over the Alps. Alternatives for long-term evaporation time series over Switzerland expected to be better suited than ERA5-Land are to our knowledge work-in-progress (see end of complementary data section (Section 7)). We however also provide water balance time series based on ERA5-Land variables only. By adding three reliability levels L1–L3, we further tried to introduce full transparency over the underlying data sources, processing levels with regard to this known limitation. We further also complemented the discussion with a paragraph pointing to these uncertainties and by further discussion also uncertainties related to ERA5-Land (potential) evaporation in general.

The levels are introduced in Section 4 - L232-240 (revised version). We omit replication here as the exact paragraph was already provided above.

The introduced discussion paragraphs reads as follows:

L547–577 (revised version):

Another limitation of the ERA5-Land dataset is the parameterization of subgrid-scale processes and the representation of subsurface storages that affect evapotranspiration (e.g., fixed maximum storage volume assumption; see Muñoz-Sabater et al., 2021). Key processes such as dynamic groundwater-vegetation interactions, irrigation withdrawals, and adaptive rooting strategies are hence not represented and may lead to biases in ET responses (Muñoz-Sabater et al., 2021; Dalla Torre et al., 2024; Wood et al., 2025; Stocker et al., 2023). Although ERA5-Land compares more favorably with in situ soil moisture and ET observations than previous reanalyses (e.g., ERA5), considerable discrepancies remain, especially in dry summers and in regions with heterogeneous land cover (Scherrer et al., 2022; Fluhrer et al., 2025). Given these limitations, drought indicators based on ERA5-Land ET should generally be interpreted with caution. This limitation is further compounded by the fact that the validation of long-term soil moisture and evapotranspiration remains challenging due to the scarcity of consistent observational datasets, particularly at high spatial resolution and over multi-decadal time scales (Hirschi et al., 2020; Yi et al., 2024; Mukherjee et al., 2018). Many state-of-the-art ET products are limited in temporal or spatial extent and can be affected by gaps and cloud contamination (e.g., remote sensing based products; see Yi et al., 2024). ERA5-Land thus remains one of the few datasets providing spatially consistent and continuous long-term ET estimates with sufficiently high spatial resolution over Switzerland.

Additional caution is warranted when using HYD-RESPONSES water balance time series (and indicators derived from them) when they were derived by combining ERA5-Land evapotranspiration with (snow-corrected) precipitation from independent data sources (RhiresD, OSHD, and SPASS). While ERA5-Land variables are internally consistent, the combination with independent data sources may lead to systematic biases in absolute deficit estimates. This limits the interpretability of absolute cumulative deficits but does not invalidate the approach for comparative, process-oriented drought analyses across regions and catchments (e.g., drought propagation, catchment response sensitivities). Relative measures of cumulative deficits, their temporal evolution, and their normalization through ratios (e.g., CWD/PCWD) can still provide valuable insights, even when absolute magnitudes are uncertain. In such contexts, relative anomalies, temporal evolution, and spatial patterns are more informative than absolute deficit magnitudes. Studies have further demonstrated coherent representation of major drought events (e.g., drought years 2003 and 2018) across datasets, which supports the usability of combined indicator time series when known limitations are adequately taken into account (Scherrer et al., 2022; Wood et al., 2025). Note that the HYD-RESPONSES dataset also provides complementary water balance and SPEI time series derived from ERA5-Land variables only providing consistent metrics and opportunity for comparisons among data products. Guidance on the usage and reliability of all HYD-RESPONSES time series products is provided by a classification based on three reliability levels (see Sect. 4 and Table

3). The levels are based on the origin of the underlying data, the extent to which variables rely on (model) assumptions, and the degree of processing applied to derive the hydro-meteorological time series.

(x) Line 246: Here it seems to be suggested that PCWD is calculated using ERA5-Variables. Is that both for P and PET? Please clarify.

Yes, the HYD-RESPONSES dataset also provides water balance time series derived from ERA5-Land variables only. This is the case for PCWDs in this context (i.e., P–E calculated from tp−pev). We added corresponding specifications. An overview over provided time series and underlying processing and data source (combinations) are provided in the added Tables B2–B5 in Appendix B.

L303–304 (revised version):

In some cases (especially for P–PET based only on ERA5-Land variables, i.e., tp−pev), PCWDs are not compensated each year and can persist over multiple years.

(x) Line 255: The word period is used here to indicate the accumulation window for SPI and SPEI. In other sections the word period is used to denote a period in time (e.g. 10 years). Please use words consistently with a defined meaning, as it is otherwise somewhat confusing.

Thank you for pointing out this potentially confusing use of the word period. We screened the manuscript for all instances and changed the wording where applicable. Changes were made in section 4.4 (*Standardized (drought) indices*) which includes Line 255, section 4.5 (*Climatology & Anomalies*) as well as in the conclusions (section 8). Please note that we only highlight changes related to the present suggestion. Revised parts from previous/other suggestions or reviewers are not explicitly highlighted in the extracts below.

Section 4.4 (including Line 255) // **L318–332** (revised version):

Standardized (drought) indices depict the anomaly of a deficit over a fixed retrospective time window (e.g., 1 month). The hydro-meteorological indicator time series is first aggregated over the given window and then transformed to a standard normal distribution by fitting a suitable candidate distribution (Tijdeman et al., 2020; Stagge et al., 2015). Standardized indices therefore provide information on both anomalously dry and wet conditions, which are often defined by thresholds corresponding to standard deviations (STD). As such, values below −1 STD indicate drier than normal conditions (moderate droughts), while values above +1 STD indicate wetter than normal conditions (moderate wetness) (McKee et al., 1993; Tschurr et al., 2020). The HYD-RESPONSES dataset provides daily time series for three standardized (drought) indices: the Standardized Precipitation Index (SPI, McKee et al., 1993), the Snowmelt and Rain Index (SMRI, Staudinger et al., 2014), and the Standardized Precipitation Evaporation Index (SPEI, Vicente-Serrano et al., 2010). The SPI represents deficits driven by precipitation only (derived from P), while the SMRI tracks deficits in liquid water input originating from both rainfall and snowmelt (derived from P+ ΔSWE) accounting for seasonal snowfall and snowmelt dynamics (Staudinger et al., 2014; Baez-Villanueva et al., 2024). The SPEI represents deficits driven by evaporative demand (derived from P-PET) and hence indirectly accounts for temperature effects (Vicente-Serrano et al., 2010; Mwinjuma et al., 2026; Gebrechorkos et al., 2025). Daily time series for all three indices (SPI, SPEI, SMRI) are provided for aggregation windows ranging from 1–24 months (31–730 days). Exemplary SPI and SMRI time series for all aggregation windows are shown in Fig. 6g,h.

Section 4.5 // **L374–375** (revised version):

Both climatologies and anomalies are based on the reference period 1991–2020. The climatology is provided for two variants: i) using moving windows and ii) for fixed time windows.

Conclusions // **L619–622** (revised version):

Additionally, three standardized drought indices (SPI, SPEI, SMRI) for accumulation windows from 1 to 24 months and information on the (non-standardized) cumulative water deficit (CWD), the potential cumulative water deficit (PCWD) and cumulative streamflow deficit (CQD) are provided.

(x) Line 273: mention is made of fewer than five DOYs flagged. I am not sure how these are flagged! Perhaps I missed it. See answer below.
(x) Line 282: I was curious in the derivation of the distributional parameters of the distributions applied in SPI, SPEI and SMRI, if the same period of data was used to derive the parameters of the distribution, or if for each case the whole available time series was used. That could make comparison more difficult.

We extended the section on standardized indices by more comprehensive description of the calculation process and diagnostics provided by the SCI R-package (Gudmundsson and Stagge, 2016). Information on time periods used for fitting distributions were also added as well as clarifications for the distribution evaluation process.

L333–362 (revised version):

All indices were calculated using the *SCI* R-package (Stagge et al., 2015; Gudmundsson and Stagge, 2016) with custom modifications accounting for the daily time series resolution. All candidate distributions provided within the *SCI* R-package (*gamma, genlog, gumbel, lnorm, norm, gev, pe3, weibull*) were tested for suitability. The distributions were fitted for each day of the year (DOY) based on the reference period 1991–2020. This results in a fit for each DOY derived from the same (window of) values for each distribution. Monthly SPI fits (SPI-1) are for example based on the 30 daily values up to the specific DOY for each of the 30 years in the reference period 1991–2020. The suitability of candidate distributions was assessed based on three indicators: the Shapiro-Wilks normality tests (*p*-values; Shapiro and Wilk, 1965), the number of flags returned by the fitting function *fitSCI* (see *SCI* R-package; Gudmundsson and Stagge, 2016), and the number of missing and/or implausible values. Implausible values are defined as values above or below ±3 STD following Stagge et al. (2015). Estimating more extreme standardized index values from a 30-year climatology requires substantial extrapolation of the fitted distribution and is therefore associated with large uncertainty, particularly given the strong temporal autocorrelation of drought indices. Values beyond ±3 correspond to events with return periods far exceeding the length of the reference record and cannot be robustly quantified (see Stagge et al., 2015).
The returned flags in distribution parameter fitting were mainly related to convergence issues (non-convergence) (flag 3, see SCI R-package Gudmundsson and Stagge, 2016). Without a valid fit, the transformation to standardized index values is not possible resulting in missing values on the flagged DOYs in all time series years. As in Staudinger et al. (2014), one best-fitting distribution

(over all DOYs) is chosen for all catchments to allow for catchment comparability. The distribution was selected among the distributions satisfying the following conditions: (1) the transformed values are not significantly different from a normal distribution for the majority of catchments (p-values$>$ 0.05 for at least 75 % of the catchments), (2) fewer than 5 DOYs flagged and (3) fewer than 50 implausible and/or missing values in the transformed time series (combined consideration of missing values due to flags and unrealistically high/low values). The distribution selection procedure is illustrated for the SPEI in Fig. 4. The results of the Shapiro-Wilks tests (p-values) and information on missing/implausible values and flags are also provided in the HYD-RESPONSES dataset and can be used to identify catchments with non-satisfying properties within the overall best-fitting distribution (see Fig. 4). Following Stagge et al. (2015), values of all standardized (drought) indices time series were restricted to the interval [-3, 3] STD.
The *Gamma* distribution was chosen for the SPI for all variables (RhiresD, ERA5-Land), which is consistent with other studies and recommendations of the World Meteorological Organization (WMO) (WMO and GWP, 2016; Stagge et al., 2015; Tschurr et al., 2020; von Matt et al., 2024). The SMRI was fitted by the *genlog* (*lnorm*) distribution for the snow-corrected precipitation series based on SPASS (ERA5-Land and OSHD). For the SPEI, the *genlog* distribution was found to perform best across time scales (see Fig. 4).

(x) Line 292: Mai à May

Adjusted.

(x) Line 336: Length – I guess of the main drainage path -please clarify.

We specified what length means as follows:

L441–444 (revised version)**:**

The first variant is derived based on a ratio between area and basin length (A/L^2) known as form factor (Horton, 1932) and the second variant is based on a ratio between the catchment area and the area of the circle with the smallest radius encircling the entire catchment (A_{catch}/A_{circle}) known as circularity ratio (Miller, 1953).

(x) Line 421: What does HRSg mean – often used but not clarified.

Hrsg. is the german equivalent for editors (Eds.). Only used for publications in german language. We adjusted **Hrsg. to Eds.** also for german sources.

(x) Line 441: Why the 15th percentile – if this is just to illustrate the please state is an arbitrary threshold.

We added the motivation for the choice of that exact percentile in the sentence.

L778–780 (revised version):

Here, we present a composite analysis of median SPI values associated with streamflow droughts defined by the monthly 15$^{\text{th}}$-percentiles of the streamflow which corresponds to the highest of the low-flow percentile used for the Swiss national drought platform (see BAFU, 2025).

(x) Line 490: It may be good to note that ERA5-Reanalysis and ERA5-Land are (to the best of my knowledge) not independent, with ERA5-Land derived from the former by downscaling using features such as elevation etc.

We added this clarification to the corresponding paragraph in the discussion but also in Section 3.2 where the spatially gridded input datasets are introduced.

Section 3.2 - **L171–176** (revised version):

ERA5-Land data are available at hourly resolution for the period 1950—2023 via the Copernicus Climate Data Store (CDS) (`https://cds.climate.copernicus.eu/datasets/reanalysis-era5-land`). ERA5-Land consists of numerical model output from the ECMWF land surface model which itself is driven by downscaled and elevation-corrected meteorological forcing from ERA5 (Muñoz-Sabater et al., 2021). The higher spatial resolution (0.1×0.1°, approximately 9×9 km) results in an enhanced soil moisture representation and river discharge estimations making ERA5-Land more suitable for analyses based on the hydrological cycle than ERA5 (Muñoz-Sabater et al., 2021).

Discussion paragraph (incl. L490) - **L530–535** (revised version):

Several known limitations are further related to the datasets used to compile the HYD-RESPONSES data. ERA5-Land is a state-of-the-art reanalysis product provided at a higher spatial resolution than the standard ERA5 reanalysis (Hersbach et al., 2020; Muñoz-Sabater et al., 2021). The higher spatial resolution results in a better depiction of soil moisture, lakes, river discharge estimations, and the orographic enhancement of precipitation (Muñoz-Sabater et al., 2021). ERA5 and ERA5-Land datasets however share most of the parameterizations as ERA5-Land consists of output of the ECMWF numerical weather prediction model data driven by downscaled and elevation-corrected ERA5 data (Muñoz-Sabater et al., 2021).

(x) Line 499: The discussion that ends here is relevant, as in the dataset several indicators are developed that combine data from different sources - such as the cumulative water deficit, and the snowmelt corrected precipitation datasets. Given that these combine observational and reanalysis data, this may result in different levels of reliability of the derived datasets. I would be curious as to how is this flagged in these derived datasets. In other words, is some flag of degree of confidence set in the meta-data?

Thank you very much for this suggestion. We agree that caveats and potential limitations of combining variables from different data sources must be discussed in more detail and corresponding guidance provided in the dataset itself. Revisions for several earlier suggestions already tackle the suggestion and in combination serve to provide an extended guidance for the user with regard to the reliability of different variable and variable combinations used to derive hydrometeorological data and indicators. This includes the introduction of three reliability levels and accompanying tables (which is also provided in the updated version of the HYD-RESPONSES dataset). Further, also the discussion section was extended to provide a detailed discussion on reliability and consequences of variable combinations from different data sources.

NOTE: As these extensive changes are declared already included as part of previous suggestions we do not replicate them here.

(x) Table 3: I am not sure if Zenodo can be considered a provider – is this not more a repository?

We changed the wording where applicable.

(x) Line 563: also

Changed.

(x) Figure 4: “complete” is mentioned – I guess this is the same as full. Nice to be consistent.

Changed.

(x) Figure 5: The label NAs/Implausible should be described as to what it means (one can guess of course – but best to be clear).

We changed the legend title of Figure 5 (Figure 4 in the revised version) from *NAs/Implausible* to *Missing/Implausible*. Further explanation on missing and implausible values for standardized (drought) indices were added in the text according to suggestions from reviewer 1 referring to L274. We replicated the answer given to reviewer 1 below.

The following additional information related to missing/implausible values were added:

L349–353 (revised version):

The distribution was selected among the distributions satisfying the following conditions: (1) the transformed values are not significantly different from a normal distribution for the majority of catchments (p-values$>$ 0.05 for at least 75 % of the catchments), (2) fewer than 5 DOYs flagged and (3) fewer than 50 implausible and/or missing values in the transformed time series (combined consideration of missing values due to flags and unrealistically high/low values).

3 Tables introduced in the revised manuscript version

Table 1: Three-level reliability classification used for hydro-meteorological data in the HYD-RESPONSES dataset.

Level	**Description**
Level 1 (L1)	Direct, unaltered measurement data. These data are considered the most reliable, as they are not subject to interpolation, modeling assumptions, or additional processing.
Level 2 (L2)	Data extracted from publicly available, spatially interpolated hydro-meteorological datasets and data subjected to only minimal post-processing, such as temporal aggregation. Variables whose derivation relies on strong underlying (modeling) assumptions are explicitly annotated.
Level 3 (L3)	Variables, indicators, and indices derived by the authors, irrespective of the degree of validation or verification performed. Variables whose derivation relies on strong underlying (modeling) assumptions are explicitly annotated.

Table 2: Information on the underlying processing and reliability of basic and derived time series variables.

	Type	Level	Data source	Processing	Temporal resolution	Modeling component	Variables
Sect. 4.1	Streamflow	L1	Streamflow measurements (Q-Meas.)	–	daily mean	–	Q
	Precipitation	L2	Spatial climate analyses (SCA)	catchment average	daily total (sum)	–	RhiresD
	Sunshine Duration	L2		catchment average	daily relative (%)	–	SrelD
	Temperature	L2		catchment average	daily mean	–	TabsD, TmaxD, TminD
	Snow	L2	SPASS	catchment average	daily mean	yes	SWECLQMD
	Snow	L2	OSHD	catchment average	daily mean	yes	swee
		L2		catchment average	daily total (sum)	yes	romc
	Various	L2	ERA5-Land	catchment average, daily mean	daily mean	–	t2m
		L2		catchment average, daily mean	daily mean	strong	pev, sd, ssr, swvl1, swvl2, swvl3, swvl4
		L2					
		L2		catchment average, daily total (sum)	daily total (sum)	–	tp
		L2		catchment average, daily total (sum)	daily total (sum)	strong	ro, smlt, sro, e
Sect. 4.2	Streamflow	L1	Q-Meas.	7-day average (centered)	daily	–	M7Q
		L3	ERA5-Land			strong	ro7Q
	Snow-related	L2	SCA, OSHD	P + Snowmelt	daily	yes	P_SMLT_OSHDromc
		L2	SCA, OSHD	P + ΔSWE	daily	yes	P_SMLT_OSHDswe
		L2	SCA, SPASS	P + ΔSWE	daily	yes	P_SMLT_SPASS
		L2	OSHD	ΔSWE	daily	yes	SWE_diff_OSHD
		L2	SPASS	ΔSWE	daily	yes	SWE_diff_SPASS
		L2	OSHD	ΔSWE > 0	daily	yes	SWE_posdiff_OSHD
		L2	SPASS	ΔSWE > 0	daily	yes	SWE_posdiff_SPASS
		L3	ERA5-Land	P + Snowmelt	daily	strong	tp_smlt
	Water balance	L3	SCA, ERA5-Land	P - E	daily	strong	P_e
		L3	SCA, ERA5-Land	P - PET	daily	strong	P_pev
		L3	SCA, OSHD, ERA5-Land	P + Snowmelt - E	daily	strong	PsmltOSHDromc_e
		L3	SCA, OSHD, ERA5-Land	P + Snowmelt - PET	daily	strong	PsmltOSHDromc_pev
		L3	SCA, OSHD, ERA5-Land	P + ΔSWE - E	daily	strong	PsmltOSHDswe_e
		L3	SCA, OSHD, ERA5-Land	P + ΔSWE - PET	daily	strong	PsmltOSHDswe_pev
		L3	SCA, SPASS, ERA5-Land	P + ΔSWE - E	daily	strong	PsmltSPASS_e
		L3	SCA, SPASS, ERA5-Land	P + ΔSWE - PET	daily	strong	PsmltSPASS_pev
		L3	ERA5-Land	P - E	daily	strong	tp_e
		L3	ERA5-Land	P - PET	daily	strong	tp_pev
		L3	ERA5-Land	P + Snowmelt - E	daily	strong	tpsmlt_e
		L3	ERA5-Land	P + Snowmelt - PET	daily	strong	tpsmlt_pev

Table 3: Information on the underlying processing and reliability of standardized (drought) indices and cumulative deficit time series.

	Type	**Level**	**Data source**	**Processing**	**Temporal resolution**	**Distributions**	**Index Aggregation** (months)	**Modeling component**	**Variables**
Sect. 4.4	SPI	L3	SCA	fitted transformation	daily	gamma	1 - 24	yes	RhiresD
		L3	ERA5-Land	fitted transformation	daily	gamma	1 - 24	yes	tp
	SPEI	L3	SCA, ERA5-Land	fitted transformation	daily	genlog	1 – 24	strong	P_pev
		L3	ERA5-Land	fitted transformation	daily	genlog	1 – 24	strong	tp_pev
	SMRI	L3	SCA, SPASS	fitted transformation	daily	genlog	1 – 24	yes	P_SMLT_SPASS
		L3	SCA, OSHD	fitted transformation	daily	lnorm	1 – 24	yes	P_SMLT_OSHDromc
		L3	SCA, OSHD	fitted transformation	daily	lnorm	1 – 24	yes	P_SMLT_OSHDswe
		L3	ERA5-Land	fitted transformation	daily	lnorm	1 – 24	strong	tp_smlt

	Type	**Level**	**Data source**	**Processing**	**Temporal resolution**	**Variants**	**Threshold-level**	**Modeling component**	**Variables**
Sect. 4.3	CWD	L3	SCA, ERA5-Land	cumulative sum of negative threshold deviations	daily	multi-year,yearly	P - E < 0	strong	P_e
		L3	SCA, OSHD, ERA5-Land		daily	multi-year,yearly	P - E < 0	strong	PsmltOSHDromc_e
		L3	SCA, OSHD, ERA5-Land		daily	multi-year,yearly	P - E < 0	strong	PsmltOSHDswe_e
		L3	SCA, SPASS, ERA5-Land		daily	multi-year,yearly	P - E < 0	strong	PsmltSPASS_e
		L3	ERA5-Land		daily	multi-year,yearly	P - E < 0	strong	tp_e
		L3	ERA5-Land		daily	multi-year,yearly	P - E < 0	strong	tpsmlt_e
	PCWD	L3	SCA, ERA5-Land	cumulative sum of negative threshold deviations	daily	multi-year,yearly	P - PET < 0	strong	P_pev
		L3	SCA, OSHD, ERA5-Land		daily	multi-year,yearly	P - PET < 0	strong	PsmltOSHDromc_pev
		L3	SCA, OSHD, ERA5-Land		daily	multi-year,yearly	P - PET < 0	strong	PsmltOSHDswe_pev
		L3	SCA, SPASS, ERA5-Land		daily	multi-year,yearly	P - PET < 0	strong	PsmltSPASS_pev
		L3	ERA5-Land		daily	multi-year,yearly	P - PET < 0	strong	tp_pev
		L3	ERA5-Land		daily	multi-year,yearly	P - PET < 0	strong	tpsmlt_pev
Sect. 4.6	CQD	L2	Q-Meas.	cumulative sum of negative threshold deviations	daily	multi-year,yearly	**monthly/seasonal:** 2nd, 5th, 10th, 15th, 25th, 50th (median), mean **yearly:** Q347	–	M7Q

Table 4: Information on the underlying processing and reliability of climatology and anomaly time series.

	Type	**Level**	**Processing**	**Temporal resolution**	**Variant**	**Statistics**	**Window / Anomaly-Scale**	**Variables**
Sect. 4.5	climatology	L1–L2	statistical summary	monthly seasonal extended season yearly	regular	min, q05, q25, med, mean, q75, q95, max, sd, sum	–	Sect. 4.1
	climatology	L1–L3	statistical summary	monthly seasonal extended season yearly	regular	min, q05, q25, med, mean, q75, q95, max, sd, sum	–	Sect. 4.2
	climatology	L2–L3	statistical summary	monthly seasonal extended season yearly	regular	min, q05, q25, med, mean, q75, q95, max, sd, sum	–	Sect. 4.3
	climatology	L2	statistical summary	monthly seasonal extended season yearly	regular	min, q05, q25, med, mean, q75, q95, max, sd, sum	–	Sect. 4.6
	climatology	L1–L2	statistical summary	daily	window	min, q05, q25, med, mean, q75, q95, max, sd, sum	no window (daily) 31 days (monthly) 91 days (seasonal)	Sect. 4.1
	climatology	L1–L3	statistical summary	daily	window	min, q05, q25, med, mean, q75, q95, max, sd, sum	no window (daily) 31 days (monthly) 91 days (seasonal)	Sect. 4.2
	climatology	L2–L3	statistical summary	daily	window	min, q05, q25, med, mean, q75, q95, max, sd, sum	no window (daily) 31 days (monthly) 91 days (seasonal)	Sect. 4.3
	climatology	L2	statistical summary	daily	window	min, q05, q25, med, mean, q75, q95, max, sd, sum	no window (daily) 31 days (monthly) 91 days (seasonal)	Sect. 4.6
	anomalies	L1–L2	z-scores	daily	window	(value - mean) / sd	no window (daily) 31 days (monthly) 91 days (seasonal)	Sect. 4.1
	anomalies	L1–L3	z-scores	daily	window	(value - mean) / sd	no window (daily) 31 days (monthly) 91 days (seasonal)	Sect. 4.2
	anomalies	L2–L3	z-scores	daily	window	(value - mean) / sd	no window (daily) 31 days (monthly) 91 days (seasonal)	Sect. 4.3
	anomalies	L2	z-scores	daily	window	(value - mean) / sd	no window (daily) 31 days (monthly) 91 days (seasonal)	Sect. 4.6

Table 5: Information on the underlying processing and reliability of event time series.

	Type	Level	Data source	Processing	Temporal resolution	Threshold-level	Variables
Sect. 4.7	Cumulative water deficits	L3	Sect. 4.3	deficit > 0	daily	–	Sect. 4.3
	Cumulative streamflow deficits	L2	Sect. 4.6	deficit > 0	daily	–	Sect. 4.6
	Streamflow droughts	L2	FOEN	M7Q < threshold-level	daily	**monthly/seasonal:** 2nd, 5th, 10th, 15th, 25th, 50th (median), mean **yearly:** Q347	Sect. 4.7

References

An, H., Ouyang, C., and Chen, X.: Real-time estimation of SMAP soil moisture in mountainous areas and its impact on rainfall-runoff simulation, Journal of Hydrology, 660, 133 487, https://doi.org/10.1016/j.jhydrol.2025.133487, 2025.

Anderson, M. C., Kustas, W. P., Norman, J. M., Diak, G. T., Hain, C. R., Gao, F., Yang, Y., Knipper, K. R., Xue, J., Yang, Y., Crow, W. T., Holmes, T. R. H., Nieto, H., Guzinski, R., Otkin, J. A., Mecikalski, J. R., Cammalleri, C., Torres-Rua, A. T., Zhan, X., Fang, L., Colaizzi, P. D., and Agam, N.: A brief history of the thermal IR-based Two-Source Energy Balance (TSEB) model – diagnosing evapotranspiration from plant to global scales, Agricultural and Forest Meteorology, 350, 109 951, https://doi.org/10.1016/j.agrformet.2024.109951, 2024.

Apurv, T. and Cai, X.: Drought Propagation in Contiguous U.S. Watersheds: A Process-Based Understanding of the Role of Climate and Watershed Properties, Water Resources Research, 56, e2020WR027 755, https://doi.org/10.1029/2020WR027755, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1029/2020WR027755, 2020.

Apurv, T., Sivapalan, M., and Cai, X.: Understanding the Role of Climate Characteristics in Drought Propagation, Water Resources Research, 53, 9304–9329, https://doi.org/10.1002/2017WR021445, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/2017WR021445, 2017.

Aschwanden, H.: Die Niedrigwasserabflussmenge Q347 – Bestimmung und Abschätzung in alpinen schweizerischen Einzugsgebieten., Tech. Rep. 18, Bern, 1992.

Aschwanden, H. and Kan, C.: Die Abflussmenge Q347 – eine Standortbestimmung., Tech. Rep. 27, Bern, 1999.

Aschwanden, H. and Weingartner, R.: Die Abflussregimes der Schweiz., Tech. Rep. 65, Geographisches Institut der Universität Bern (GIUB), Bern, URL `https://boris.unibe.ch/133660/`, 1985.

Baez-Villanueva, O. M., Zambrano-Bigiarini, M., Miralles, D. G., Beck, H. E., Siegmund, J. F., Alvarez-Garreton, C., Verbist, K., Garreaud, R., Boisier, J. P., and Galleguillos, M.: On the timescale of drought indices for monitoring streamflow drought considering catchment hydrological regimes, Hydrology and Earth System Sciences, 28, 1415–1439, https://doi.org/10.5194/hess-28-1415-2024, publisher: Copernicus GmbH, 2024.

BAFU: Nationale Beobachtung Oberflächengewässerqualität (NAWA), URL `https://www.bafu.admin.ch/bafu/de/home/themen/thema-wasser/wasser--daten--indikatoren-und-karten/wasser--messnetze/nationale-beobachtung-oberflaechengewaesserqualitaet--nawa-.html`, 2023.

BAFU: Stationsbericht Niederigwasserstatistik - Leitfaden, URL `https://www.bafu.admin.ch/dam/bafu/de/dokumente/hydrologie/fachinfo-daten/leitfaden-stationsberichte-niedrigwasserstatistik-bafu.pdf.download.pdf/leitfaden-stationsberichte-niedrigwasserstatistik-bafu.pdf`, 2024.

BAFU: Der kombinierte Trockenheitsindex - Nationale Trockenheitsplattform, URL `https://www.trockenheit.admin.ch/de/trockenheit/trockenheitsindex`, 2025.

Bai, J. and Perron, P.: Estimating and Testing Linear Models with Multiple Structural Changes, Econometrica, 66, 47–78, https://doi.org/10.2307/2998540, publisher: [Wiley, Econometric Society], 1998.

Baker, D. B., Richards, R. P., Loftus, T. T., and Kramer, J. W.: A New Flashiness Index: Characteristics and Applications to Midwestern Rivers and Streams, JAWRA Journal of the American Water Resources Association, 40, 503–522, https://doi.org/10.1111/j.1752-1688.2004.tb01046.x, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1752-1688.2004.tb01046.x, 2004.

Barker, L. J., Hannaford, J., Chiverton, A., and Svensson, C.: From meteorological to hydrological drought using standardised indicators, Hydrology and Earth System Sciences, 20, 2483–2505, https://doi.org/10.5194/hess-20-2483-2016, publisher: Copernicus GmbH, 2016.

Besso, H., Shean, D., and Lundquist, J. D.: Mountain snow depth retrievals from customized processing of ICESat-2 satellite laser altimetry, Remote Sensing of Environment, 300, 113 843, https://doi.org/10.1016/j.rse.2023.113843, 2024.

Biegel, S., Schindler, K., and Stocker, B. D.: Unrecognised water limitation is a main source of uncertainty for models of terrestrial photosynthesis, Biogeosciences, 22, 7455–7481, https://doi.org/10.5194/bg-22-7455-2025, publisher: Copernicus GmbH, 2025.

BLW, B. f. L.: Bodeneignungskarte der Schweiz, URL `https://www.blw.admin.ch/blw/de/home/politik/datenmanagement/geografisches-informationssystem-gis/bodeneignungskarte.html`, 2022.

Brocca, L., Gaona, J., Bavera, D., Fioravanti, G., Puca, S., Ciabatta, L., Filippucci, P., Mosaffa, H., Esposito, G., Roberto, N., Dari, J., Vreugdenhil, M., and Wagner, W.: Exploring the actual spatial resolution of 1 km satellite soil moisture products, Science of The Total Environment, 945, 174 087, https://doi.org/10.1016/j.scitotenv.2024.174087, 2024.

Brunner, M. I., Björnsen Gurung, A., Zappa, M., Zekollari, H., Farinotti, D., and Stähli, M.: Present and future water scarcity in Switzerland: Potential for alleviation through reservoirs and lakes, Science of The Total Environment, 666, 1033–1047, https://doi.org/10.1016/j.scitotenv.2019.02.169, 2019a.

Brunner, M. I., Farinotti, D., Zekollari, H., Huss, M., and Zappa, M.: Future shifts in extreme flow regimes in Alpine regions, Hydrology and Earth System Sciences, 23, 4471–4489, https://doi.org/10.5194/hess-23-4471-2019, publisher: Copernicus GmbH, 2019b.

Brunner, M. I., Slater, L., Tallaksen, L. M., and Clark, M.: Challenges in modeling and predicting floods and droughts: A review, WIREs Water, 8, e1520, https://doi.org/10.1002/wat2.1520, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/wat2.1520, 2021.

Brunner, M. I., Van Loon, A. F., and Stahl, K.: Moderate and Severe Hydrological Droughts in Europe Differ in Their Hydrometeorological Drivers, Water Resources Research, 58, e2022WR032 871, https://doi.org/10.1029/2022WR032871, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1029/2022WR032871, 2022.

Brunner, M. I., Götte, J., Schlemper, C., and Van Loon, A. F.: Hydrological Drought Generation Processes and Severity Are Changing in the Alps, Geophysical Research Letters, 50, e2022GL101 776, https://doi.org/10.1029/2022GL101776, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1029/2022GL101776, 2023.

Cammalleri, C., Barbosa, P., and Vogt, J. V.: Analysing the Relationship between Multiple-Timescale SPI and GRACE Terrestrial Water Storage in the Framework of Drought Monitoring, Water, 11, 1672, https://doi.org/10.3390/w11081672, number: 8 Publisher: Multidisciplinary Digital Publishing Institute, 2019.

Clerc-Schwarzenbach, F., Selleri, G., Neri, M., Toth, E., van Meerveld, I., and Seibert, J.: Large-sample hydrology – a few camels or a whole caravan?, Hydrology and Earth System Sciences, 28, 4219–4237, https://doi.org/10.5194/hess-28-4219-2024, publisher: Copernicus GmbH, 2024.

Cui, G., Ma, Q., and Bales, R.: Assessing multi-year-drought vulnerability in dense Mediterranean-climate forests using water-balance-based indicators, Journal of Hydrology, 606, 127 431, https://doi.org/10.1016/j.jhydrol.2022.127431, 2022.

Dalla Torre, D., Di Marco, N., Menapace, A., Avesani, D., Righetti, M., and Majone, B.: Suitability of ERA5-Land reanalysis dataset for hydrological modelling in the Alpine region, Journal of Hydrology: Regional Studies, 52, 101 718, https://doi.org/10.1016/j.ejrh.2024.101718, 2024.

Das, B. C., Islam, A., and Sarkar, B.: Drainage Basin Shape Indices to Understanding Channel Hydraulics, Water Resour Manage, 36, 2523–2547, https://doi.org/10.1007/s11269-022-03121-4, 2022.

Ding, Y., Gong, X., Xing, Z., Cai, H., Zhou, Z., Zhang, D., Sun, P., and Shi, H.: Attribution of meteorological, hydrological and agricultural drought propagation in different climatic regions of China, Agricultural Water Management, 255, 106 996, https://doi.org/10.1016/j.agwat.2021.106996, 2021.

Floriancic, M. G., Berghuijs, W. R., Jonas, T., Kirchner, J. W., and Molnar, P.: Effects of climate anomalies on warm-season low flows in Switzerland, Hydrology and Earth System Sciences, 24, 5423–5438, https://doi.org/10.5194/hess-24-5423-2020, publisher: Copernicus GmbH, 2020.

Floriancic, M. G., Spies, D., van Meerveld, I. H. J., and Molnar, P.: A multi-scale study of the dominant catchment characteristics impacting low-flow metrics, Hydrological Processes, 36, e14 462, https://doi.org/10.1002/hyp.14462, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/hyp.14462, 2022.

Fluhrer, A., Baur, M. J., Piles, M., Bayat, B., Rahmati, M., Chaparro, D., Dubois, C., Hellwig, F. M., Montzka, C., Kübert, A., Mueller, M. M., Augscheller, I., Jonard, F., Schellenberg, K., and Jagdhuber, T.: Assessing evapotranspiration dynamics across central Europe in the context of land–atmosphere drivers, Biogeosciences, 22, 3721–3746, https://doi.org/10.5194/bg-22-3721-2025, publisher: Copernicus GmbH, 2025.

Fowler, K., Peel, M., Saft, M., Nathan, R., Horne, A., Wilby, R., McCutcheon, C., and Peterson, T.: Hydrological Shifts Threaten Water Resources, Water Resources Research, 58, e2021WR031 210, https://doi.org/10.1029/2021WR031210, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1029/2021WR031210, 2022.

Gebrechorkos, S. H., Sheffield, J., Vicente-Serrano, S. M., Funk, C., Miralles, D. G., Peng, J., Dyer, E., Talib, J., Beck, H. E., Singer, M. B., and Dadson, S. J.: Warming accelerates global drought severity, Nature, 642, 628–635, https://doi.org/10.1038/s41586-025-09047-2, publisher: Nature Publishing Group, 2025.

Gudmundsson, L. and Stagge, J. H.: SCI: Standardized Climate Indices such as SPI, SRI or SPEIR package version 1.0-2., 2016.

Hammond, J. C., Simeone, C., Hecht, J. S., Hodgkins, G. A., Lombard, M., McCabe, G., Wolock, D., Wieczorek, M., Olson, C., Caldwell, T., Dudley, R., and Price, A. N.: Going Beyond Low Flows: Streamflow Drought Deficit and Duration Illuminate Distinct Spatiotemporal Drought Patterns and Trends in the U.S. During the Last Century, Water Resources Research, 58, e2022WR031 930, https://doi.org/10.1029/2022WR031930, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1029/2022WR031930, 2022.

Hao, Z. and Singh, V. P.: Drought characterization from a multivariate perspective: A review, Journal of Hydrology, 527, 668–678, https://doi.org/10.1016/j.jhydrol.2015.05.031, 2015.

Haslinger, K., Koffler, D., Schöner, W., and Laaha, G.: Exploring the link between meteorological drought and streamflow: Effects of climate-catchment interaction, Water Resources Research, 50, 2468–2487, https://doi.org/10.1002/2013WR015051, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/2013WR015051, 2014.

Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., Simmons, A., Soci, C., Abdalla, S., Abellan, X., Balsamo, G., Bechtold, P., Biavati, G., Bidlot, J., Bonavita, M., De Chiara, G., Dahlgren, P., Dee, D., Diamantakis, M., Dragani, R., Flemming, J., Forbes, R., Fuentes, M., Geer, A., Haimberger, L., Healy, S., Hogan, R. J., Hólm, E., Janisková, M., Keeley, S., Laloyaux, P., Lopez, P., Lupu, C., Radnoti, G., de Rosnay, P., Rozum, I., Vamborg, F., Villaume, S., and Thépaut, J.-N.: The ERA5 global reanalysis, Quarterly Journal of the Royal Meteorological Society, 146, 1999–2049, https://doi.org/10.1002/qj.3803, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/qj.3803, 2020.

Hirschi, M., Davin, E. L., Schwingshackl, C., Wartenburger, R., Meier, R., Gudmundsson, L., and Seneviratne, S. I.: Soil moisture and evapotranspiration, Report, ETH Zurich, https://doi.org/10.3929/ethz-b-000389455, accepted: 2020-06-05T07:44:43Z, 2020.

Hisdal, H. and Tallaksen, L. M.: Drought event definition. Technical Report to the ARIDE project No. 6. Department of Geophysics, University of Oslo., Tech. rep., 2000.

Horton, R. E.: Drainage-basin characteristics, Eos, Transactions American Geophysical Union, 13, 350–361, https://doi.org/10.1029/TR013i001p00350, _eprint: https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1029/TR013i001p00350, 1932.

Höge, M., Kauzlaric, M., Siber, R., Schönenberger, U., Horton, P., Schwanbeck, J., Floriancic, M. G., Viviroli, D., Wilhelm, S., Sikorska-Senoner, A. E., Addor, N., Brunner, M., Pool, S., Zappa, M., and Fenicia, F.: CAMELS-CH: hydro-meteorological time series and landscape attributes for 331 catchments in hydrologic Switzerland, Earth System Science Data, 15, 5755–5784, https://doi.org/10.5194/essd-15-5755-2023, publisher: Copernicus GmbH, 2023.

Kchouk, S., Melsen, L. A., Walker, D. W., and van Oel, P. R.: A geography of drought indices: mismatch between indicators of drought and its impacts on water and food securities, Natural Hazards and Earth System Sciences, 22, 323–344, https://doi.org/10.5194/nhess-22-323-2022, publisher: Copernicus GmbH, 2022.

Kratzert, F., Klotz, D., Brenner, C., Schulz, K., and Herrnegger, M.: Rainfall–runoff modelling using Long Short-Term Memory (LSTM) networks, Hydrology and Earth System Sciences, 22, 6005–6022, https://doi.org/10.5194/hess-22-6005-2018, publisher: Copernicus GmbH, 2018.

Kratzert, F., Klotz, D., Shalev, G., Klambauer, G., Hochreiter, S., and Nearing, G.: Towards learning universal, regional, and local hydrological behaviors via machine learning applied to large-sample datasets, Hydrology and Earth System Sciences, 23, 5089–5110, https://doi.org/10.5194/hess-23-5089-2019, publisher: Copernicus GmbH, 2019.

Kratzert, F., Nearing, G., Addor, N., Erickson, T., Gauch, M., Gilon, O., Gudmundsson, L., Hassidim, A., Klotz, D., Nevo, S., Shalev, G., and Matias, Y.: Caravan - A global community dataset for large-sample hydrology, Sci Data, 10, 61, https://doi.org/10.1038/s41597-023-01975-w, publisher: Nature Publishing Group, 2023.

Lees, T., Reece, S., Kratzert, F., Klotz, D., Gauch, M., De Bruijn, J., Kumar Sahu, R., Greve, P., Slater, L., and Dadson, S. J.: Hydrological concept formation inside long short-term memory (LSTM) networks, Hydrology and Earth System Sciences, 26, 3079–3101, https://doi.org/10.5194/hess-26-3079-2022, publisher: Copernicus GmbH, 2022.

Marty, C., Michel, A., Jonas, T., Steijn, C., Muelchi, R., and Kotlarski, S.: SPASS – new gridded climatological snow datasets for Switzerland: Potential and limitations, EGUsphere, pp. 1–21, https://doi.org/10.5194/egusphere-2025-413, publisher: Copernicus GmbH, 2025.

Massari, C., Avanzi, F., Bruno, G., Gabellani, S., Penna, D., and Camici, S.: Evaporation enhancement drives the European water-budget deficit during multi-year droughts, Hydrology and Earth System Sciences, 26, 1527–1543, https://doi.org/10.5194/hess-26-1527-2022, publisher: Copernicus GmbH, 2022.

McKee, T., Doesken, N., and Kleist, J.: THE RELATIONSHIP OF DROUGHT FREQUENCY AND DURATION TO TIME SCALES, Eight conference on applied climatology, 17-22 January 1993, Anaheim, California, URL `https://www.semanticscholar.org/paper/THE-RELATIONSHIP-OF-DROUGHT-FREQUENCY-AND-DURATION-McKee-Doesken/c3f7136d6cb726b295eb34565a8270177c57f40f`, 1993.

Menapace, A., Dhawan, P., Dalla Torre, D., Kaffas, K., Crespi, A., Larcher, M., Righetti, M., and Cannon, A. J.: Review of bias correction methods for climate model outputs in hydrology, Journal of Hydrology, 660, 133 213, https://doi.org/10.1016/j.jhydrol.2025.133213, 2025.

MeteoSwiss: Daily Precipitation (final analysis): RhiresD, URL `https://www.meteoswiss.admin.ch/dam/jcr:4f51f0f1-0fe3-48b5-9de0-15666327e63c/ProdDoc_RhiresD.pdf`, 2021a.

MeteoSwiss: Daily Mean, Minimum and Maximum Temperature: TabsD, TminD, TmaxD, URL `https://www.meteoswiss.admin.ch/dam/jcr:818a4d17-cb0c-4e8b-92c6-1a1bdf5348b7/ProdDoc_TabsD.pdf`, 2021b.

MeteoSwiss: Spatial Climate Analyses - MeteoSwiss, URL `https://www.meteoswiss.admin.ch/climate/the-climate-of-switzerland/spatial-climate-analyses.html`, 2024.

Michel, A., Aschauer, J., Jonas, T., Gubler, S., Kotlarski, S., and Marty, C.: SnowQM 1.0: A fast R Package for bias-correcting spatial fields of snow water equivalent using quantile mapping, Geoscientific Model Development Discussions, pp. 1–28, https://doi.org/10.5194/gmd-2022-298, publisher: Copernicus GmbH, 2023.

Miller, V. C.: A quantitative geomorphic study of drainage basin characteristics in the Clinch Mountain Area, Virginia and Tennessee. New York: Columbia University, Office of Naval Research Project NR 389 - 042, Technical Report No. 3., Project NR 389 - 042, Technical Report 3, Columbia University, Office of Naval Research, New York, URL `https://apps.dtic.mil/sti/citations/tr/AD0057755`, 1953.

Mishra, A. K. and Singh, V. P.: A review of drought concepts, Journal of Hydrology, 391, 202–216, https://doi.org/10.1016/j.jhydrol.2010.07.012, 2010.

Mott, R.: Climatological snow data since 1998, OSHD. EnviDat. https://www.doi.org/10.16904/envidat.401., 2023.

Mott, R., Winstral, A., Cluzet, B., Helbig, N., Magnusson, J., Mazzotti, G., Quéno, L., Schirmer, M., Webster, C., and Jonas, T.: Operational snow-hydrological modeling for Switzerland, Front. Earth Sci., 11, https://doi.org/10.3389/feart.2023.1228158, publisher: Frontiers, 2023.

Muelchi, R., Rössler, O., Schwanbeck, J., Weingartner, R., and Martius, O.: River runoff in Switzerland in a changing climate – runoff regime changes and their time of emergence, Hydrology and Earth System Sciences, 25, 3071–3086, https://doi.org/10.5194/hess-25-3071-2021, publisher: Copernicus GmbH, 2021.

Mukherjee, S., Mishra, A., and Trenberth, K. E.: Climate Change and Drought: a Perspective on Drought Indices, Curr Clim Change Rep, 4, 145–163, https://doi.org/10.1007/s40641-018-0098-x, 2018.

Muñoz-Sabater, J., Dutra, E., Agustí-Panareda, A., Albergel, C., Arduini, G., Balsamo, G., Boussetta, S., Choulga, M., Harrigan, S., Hersbach, H., Martens, B., Miralles, D. G., Piles, M., Rodríguez-Fernández, N. J., Zsoter, E., Buontempo, C., and Thépaut, J.-N.: ERA5-Land: a state-of-the-art global reanalysis dataset for land applications, Earth System Science Data, 13, 4349–4383, https://doi.org/10.5194/essd-13-4349-2021, publisher: Copernicus GmbH, 2021.

Mwinjuma, M., Wang, R., Mtupili, M., and Twaha, M.: Comparisons of SPI and SPEI in capturing drought dynamics: A Global assessment across arid and humid regions, Atmospheric Research, 329, 108 475, https://doi.org/10.1016/j.atmosres.2025.108475, 2026.

Najafi, H., Lagerwall, G. L., Obeysekera, J., and Liu, J.: Machine Learning in Climate Downscaling: A Critical Review of Methodologies, Physical Consistency, and Operational Applications, Water, 18, 271, https://doi.org/10.3390/w18020271, publisher: Multidisciplinary Digital Publishing Institute, 2026.

Peña-Angulo, D., Vicente-Serrano, S. M., Domínguez-Castro, F., Lorenzo-Lacruz, J., Murphy, C., Hannaford, J., Allan, R. P., Tramblay, Y., Reig-Gracia, F., and El Kenawy, A.:

The Complex and Spatially Diverse Patterns of Hydrological Droughts Across Europe, Water Resources Research, 58, e2022WR031 976, https://doi.org/10.1029/2022WR031976, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1029/2022WR031976, 2022.

Peña-Gallardo, M., Vicente-Serrano, S. M., Hannaford, J., Lorenzo-Lacruz, J., Svoboda, M., Domínguez-Castro, F., Maneta, M., Tomas-Burguera, M., and Kenawy, A. E.: Complex influences of meteorological drought time-scales on hydrological droughts in natural basins of the contiguous Unites States, Journal of Hydrology, 568, 611–625, https://doi.org/10.1016/j.jhydrol.2018.11.026, 2019.

Pisupati, S. L. and Ratnakar, P.: Morphometric analysis and prioritization of sub-watersheds in the Gosthani River Basin of southern India using PCA-WSM and geospatial techniques, Journal of Water and Climate Change, 16, 2006–2031, https://doi.org/10.2166/wcc.2025.727, 2025.

Raposo, V. d. M. B., Costa, V. A. F., and Rodrigues, A. F.: A review of recent developments on drought characterization, propagation, and influential factors, Science of The Total Environment, 898, 165 550, https://doi.org/10.1016/j.scitotenv.2023.165550, 2023.

Rodell, M. and Reager, J. T.: Water cycle science enabled by the GRACE and GRACE-FO satellite missions, Nat Water, 1, 47–59, https://doi.org/10.1038/s44221-022-00005-0, publisher: Nature Publishing Group, 2023.

Saft, M., Western, A. W., Zhang, L., Peel, M. C., and Potter, N. J.: The influence of multiyear drought on the annual rainfall-runoff relationship: An Australian perspective, Water Resources Research, 51, 2444–2463, https://doi.org/10.1002/2014WR015348, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/2014WR015348, 2015.

Sarailidis, G., Vasiliades, L., and Loukas, A.: Analysis of streamflow droughts using fixed and variable thresholds, Hydrological Processes, 33, 414–431, https://doi.org/10.1002/hyp.13336, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/hyp.13336, 2019.

Savelli, E., Rusca, M., Cloke, H., and Di Baldassarre, G.: Drought and society: Scientific progress, blind spots, and future prospects, WIREs Climate Change, 13, e761, https://doi.org/10.1002/wcc.761, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/wcc.761, 2022.

Scherrer, S. C., Hirschi, M., Spirig, C., Maurer, F., and Kotlarski, S.: Trends and drivers of recent summer drying in Switzerland, Environ. Res. Commun., https://doi.org/10.1088/2515-7620/ac4fb9, 2022.

Scherrer, S. C., Göldi, M., Gubler, S., Steger, C. R., and Kotlarski, S.: Towards a spatial snow climatology for Switzerland: Comparison and validation of existing datasets, Meteorologische Zeitschrift, https://doi.org/10.1127/metz/2023/1210, publisher: Schweizerbart'sche Verlagsbuchhandlung, 2023.

Shapiro, S. S. and Wilk, M. B.: An Analysis of Variance Test for Normality (Complete Samples), Biometrika, 52, 591–611, https://doi.org/10.2307/2333709, publisher: [Oxford University Press, Biometrika Trust], 1965.

Stagge, J. H., Tallaksen, L. M., Gudmundsson, L., Van Loon, A. F., and Stahl, K.: Candidate Distributions for Climatological Drought Indices (SPI and SPEI), International Journal of Climatology, 35, 4027–4040, https://doi.org/10.1002/joc.4267, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/joc.4267, 2015.

Stahl, K., Vidal, J.-P., Hannaford, J., Tijdeman, E., Laaha, G., Gauster, T., and Tallaksen, L. M.: The challenges of hydrological drought definition, quantification and communication: an interdisciplinary perspective, in: Proceedings of IAHS, vol. 383, pp. 291–295, Copernicus GmbH, https://doi.org/10.5194/piahs-383-291-2020, iSSN: 2199-8981, 2020.

Staudinger, M., Stahl, K., and Seibert, J.: A drought index accounting for snow, Water Resources Research, 50, 7861–7872, https://doi.org/10.1002/2013WR015143, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/2013WR015143, 2014.

Staudinger, M., Stoelzle, M., Seeger, S., Seibert, J., Weiler, M., and Stahl, K.: Catchment water storage variation with elevation, Hydrological Processes, 31, 2000–2015, https://doi.org/10.1002/hyp.11158, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/hyp.11158, 2017.

Stocker, B. D.: cwd v1.0: R package for cumulative water deficit calculation (v1.0). Zenodo. https://doi.org/10.5281/zenodo.5359053, 2021.

Stocker, B. D., Tumber-Dávila, S. J., Konings, A. G., Anderson, M. C., Hain, C., and Jackson, R. B.: Global patterns of water storage in the rooting zones of vegetation, Nat. Geosci., 16, 250–256, https://doi.org/10.1038/s41561-023-01125-2, number: 3 Publisher: Nature Publishing Group, 2023.

Sutanto, S. J. and Van Lanen, H. A. J.: Catchment memory explains hydrological drought forecast performance, Sci Rep, 12, 2689, https://doi.org/10.1038/s41598-022-06553-5, number: 1 Publisher: Nature Publishing Group, 2022.

Swisstopo: Bodeneignungskarte der Schweiz, URL `https://www.bfs.admin.ch/bfs/de/home/dienstleistungen/geostat/geodaten-bundesstatistik/boden-nutzung-bedeckung-eignung/abgeleitete-und-andere-daten/bodeneignungskarte-schweiz.html`, 2020.

Tallaksen, L. M. and Van Lanen, H. A. J., eds.: Hydrological drought: processes and estimation methods for streamflow and groundwater., no. 48 in Developments in Water Science, Elsevier Science B.V., Amsterdam, the Netherlands, 2004.

Tallaksen, L. M., Madsen, H., and Clausen, B.: On the definition and modelling of streamflow drought duration and deficit volume, Hydrological Sciences Journal, 42, 15–33, https://doi.org/10.1080/02626669709492003, publisher: Taylor & Francis _eprint: https://doi.org/10.1080/02626669709492003, 1997.

Tarasova, L., Gnann, S., Yang, S., Hartmann, A., and Wagener, T.: Catchment characterization: Current descriptors, knowledge gaps and future opportunities, Earth-Science Reviews, 252, 104 739, https://doi.org/10.1016/j.earscirev.2024.104739, 2024.

Tijdeman, E., Barker, L. J., Svoboda, M. D., and Stahl, K.: Natural and Human Influences on the Link Between Meteorological and Hydrological Drought Indices for a Large Set of Catchments in the Contiguous United States, Water Resources Research, 54, 6005–6023, https://doi.org/10.1029/2017WR022412, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1029/2017WR022412, 2018.

Tijdeman, E., Stahl, K., and Tallaksen, L. M.: Drought Characteristics Derived Based on the Standardized Streamflow Index: A Large Sample Comparison for Parametric and Nonparametric Methods, Water Resources Research, 56, e2019WR026 315, https://doi.org/10.1029/2019WR026315, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1029/2019WR026315, 2020.

Tijdeman, E., Blauhut, V., Stoelzle, M., Menzel, L., and Stahl, K.: Different drought types and the spatial variability in their hazard, impact, and propagation characteristics, Natural Hazards and Earth System Sciences, 22, 2099–2116, https://doi.org/10.5194/nhess-22-2099-2022, publisher: Copernicus GmbH, 2022.

Tschurr, F., Feigenwinter, I., Fischer, A. M., and Kotlarski, S.: Climate Scenarios and Agricultural Indices: A Case Study for Switzerland, Atmosphere, 11, 535, https://doi.org/10.3390/atmos11050535, number: 5 Publisher: Multidisciplinary Digital Publishing Institute, 2020.

Van Lanen, H. a. J., Wanders, N., Tallaksen, L. M., and Van Loon, A. F.: Hydrological drought across the world: impact of climate and physical catchment structure, Hydrology and Earth System Sciences, 17, 1715–1732, https://doi.org/10.5194/hess-17-1715-2013, publisher: Copernicus GmbH, 2013.

Van Loon, A. F.: Hydrological drought explained, WIREs Water, 2, 359–392, https://doi.org/10.1002/wat2.1085, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/wat2.1085, 2015.

Van Loon, A. F. and Laaha, G.: Hydrological drought severity explained by climate and catchment characteristics, Journal of Hydrology, 526, 3–14, https://doi.org/10.1016/j.jhydrol.2014.10.059, 2015.

Vicente-Serrano, S. M., Beguería, S., and López-Moreno, J. I.: A Multiscalar Drought Index Sensitive to Global Warming: The Standardized Precipitation Evapotranspiration Index, Journal of Climate, 23, 1696–1718, https://doi.org/10.1175/2009JCLI2909.1, publisher: American Meteorological Society Section: Journal of Climate, 2010.

von Matt, C. N., Muelchi, R., Gudmundsson, L., and Martius, O.: Compound droughts under climate change in Switzerland, Natural Hazards and Earth System Sciences, 24, 1975–2001, https://doi.org/10.5194/nhess-24-1975-2024, publisher: Copernicus GmbH, 2024.

von Matt, C. N., Martius, O., and Stocker, B.: HYD-RESPONSES: High-resolution daily catchment-level time series for relevant hydro-meteorological variables, (water) deficit accumulation and streamflow droughts for Switzerland, https://doi.org/10.5281/zenodo.15748821, 2026.

Weingartner, R. and Schwanbeck, J.: Veränderung der Niedrigwasserabflüsse und der kleinsten saisonalen Abflüsse in der Schweiz im Zeitraum 1961 – 2018. Im Auftrag des Bundesamts für Umwelt (BAFU), Bern, Schweiz, 41 S., Tech. rep., Bern, Schweiz, 2020.

WMO and GWP: Handbook of Drought Indicators and Indices (M. Svoboda and B. A. Fuchs). Integrated Drought Management Programme (IDMP), Integrated Drought Management Tools and Guidelines Series 2. Geneva., 2016.

Wood, R. R., Janzing, J., van Hamel, A., Götte, J., Schumacher, D. L., and Brunner, M. I.: Comparison of high-resolution climate reanalysis datasets for hydro-climatic impact studies, Hydrology and Earth System Sciences, 29, 4153–4178, https://doi.org/10.5194/hess-29-4153-2025, publisher: Copernicus GmbH, 2025.

Wu, J., Chen, X., Love, C. A., Yao, H., Chen, X., and AghaKouchak, A.: Determination of water required to recover from hydrological drought: Perspective from drought propagation and non-standardized indices, Journal of Hydrology, 590, 125 227, https://doi.org/10.1016/j.jhydrol.2020.125227, 2020.

Yi, K., Senay, G. B., Fisher, J. B., Wang, L., Suvočarev, K., Chu, H., Moore, G. W., Novick, K. A., Barnes, M. L., Keenan, T. F., Mallick, K., Luo, X., Missik, J. E. C., Delwiche, K. B., Nelson, J. A., Good, S. P., Xiao, X., Kannenberg, S. A., Ahmadi, A., Wang, T., Bohrer, G., Litvak, M. E., Reed, D. E., Oishi, A. C., Torn, M. S., and Baldocchi, D.: Challenges and Future Directions in Quantifying Terrestrial Evapotranspiration, Water Resources Research, 60, e2024WR037 622, https://doi.org/10.1029/2024WR037622, _eprint: https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1029/2024WR037622, 2024.

Zambrano-Bigiarini, M.: hydroTSM: Time Series Management, Analysis and Interpolation for Hydrological ModellingR package version 0.6-0. URL https://github.com/hzambran/hydroTSM. DOI:10.5281/zenodo.839864., 2020.

Zhang, L., Yan, Z., Huang, K., and Zhang, W.: Evaluation and statistical bias correction of ERA5-Land meteorological variables for a humid river basin in Southwest China, Sci Rep, 15, 41 101, https://doi.org/10.1038/s41598-025-24942-4, publisher: Nature Publishing Group, 2025.

Zhou, Z., Shi, H., Fu, Q., Ding, Y., Li, T., and Liu, S.: Investigating the Propagation From Meteorological to Hydrological Drought by Introducing the Nonlinear Dependence With Directed Information Transfer Index, Water Resources Research, 57, e2021WR030 028, https://doi.org/10.1029/2021WR030028, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1029/2021WR030028, 2021.