How well do hydrological models simulate streamflow extremes and drought-to-flood transitions?

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Abstract. ~~The impacts of floods~~ Flood impacts can be enhanced when they occur shortly after ~~drought. Models can be a useful tool~~ droughts. Hydrological models are useful tools to better understand the underlying processes and mechanisms driving the response of floods occurring in close succession to streamflow drought. However, it is yet unclear how well ~~hydrologic~~ hydrological models capture these compound extreme events and which modeling decisions are most important for high model performance. To address this research gap, we calibrated four conceptual ~~bucket-type~~ bucket-style hydrological models with different structures (GR4J, GR5J, GR6J, and TUW) for 63 catchments located in Chile and Switzerland using different calibration strategies. ~~We tested different configurations of the Kling-Gupta efficiency (KGE) formulation for model calibration to assess their performance in simulating and detecting observed transitions. We~~ Specifically, we assessed the relative importance of different methodological choices in simulating and detecting observed drought-to-flood transitions including model structure, streamflow transformation, and ~~KGE~~ the Kling-Gupta efficiency (KGE) formulation and weights used to calibrate the model parameters. We demonstrate that model performance as expressed by the KGE ~~or NSE~~ does not guarantee a good performance in terms of detecting streamflow extremes and their transitions. ~~Furthermore~~Further, we show that a model's performance with respect to capturing extreme events primarily depends on how well it captures streamflow timing~~(i.e., correlation between observations and simulations) rather than other hydrological signatures or variables such as evapotranspiration or snow water equivalent~~. Our results also highlight that model structure~~and catchment characteristics as well as meteorological forcing~~ , catchment characteristics and meteorological forcings play a key role in the detection of transitions. Specifically, we demonstrate that drought-to-flood transitions are more difficult to capture in semi-arid high-mountain catchments than in humid low-elevation catchments. ~~Finally~~Ultimately, our study provides ~~guidelines~~ insights for further model improvements ~~with respect to~~ to simulate and better understand drought-to-flood transitions ~~, which can support process understanding related to these compound events, identifying~~ and to identify regions prone to this ~~type of event, and contribute to improved risk management – aspects that will enhance preparedness~~hazard.

1 Introduction

Hydrological extreme events such as streamflow droughts and floods are expected to become more frequent, severe, and persistent in a warming climate (e.g., Gu et al., 2023; Asadieh and Krakauer, 2017; Martin, 2018; Tabari et al., 2021)~~, with severe impacts~~. Therefore, severe impacts are expected on infrastructure, agriculture, water supply, and hydropower generation (e.g., McClymont et al., 2020; McMartin et al., 2018; Lehner et al., 2006; Sivakumar, 2011; Wasti et al., 2022), as well as social and political systems (e.g., Doocy et al., 2013; Hurlbert and Gupta, 2017; Kiem and Austin, 2013; Visconti, 2022).

Studies focusing on hydrological extreme events and their impacts often assume temporal and/or spatial independence between them, neglecting that extremes may be multivariate phenomena (Banfi and De Michele, 2022; Brunner, 2023). However, the impacts of floods can be enhanced when they occur during or shortly after a streamflow drought (e.g., Barendrecht et al., 2024; Swain et al., 2018; He and Sheffield, 2020; Rashid and Wahl, 2022). For instance, Handwerger et al. (2019) and Valenzuela et al. (2022) have demonstrated an increase in the occurrence of landslides in California and Chile due to shifts from meteorological drought to intense precipitation. Similarly, Dietze et al. (2022) have shown that the 2018-2020 drought in Europe has enhanced the debris mobilisation during the 2021 flood in the Eifel region of western Germany and Belgium. In 2017, intense precipitation broke the 2012-2016 drought in California and led to severe flooding, the activation of the emergency spillway of the Lake Oroville dam for the first time in its history, and the declaration of emergency (Griffin and Anchukaitis, 2014; Robeson, 2015; Wang et al., 2017). ~~These examples highlight~~ Despite the need to integrate ~~droughts and floods~~ both streamflow extreme events within the same analysis framework (e.g., Ward et al., 2020; Quesada-Montano et al., 2018; Di Baldassarre et al., 2017)~~. Despite this~~, droughts and floods have been mostly studied as independent events. ~~As a result, the occurrence and drivers of~~

As a consequence of a potential intensification of hydrological volatility in a warming climate (Swain et al., 2025), hydrological whiplash, defined as sub-seasonal transitions between hydrological extremes such as droughts and floods (Hammond et al., 2025) , could become more frequent and severe in the future. While the transition from drought to flood can occur within hours or days, the transition to droughts can range from weeks to years, leading to different water management challenges and reaction times for decision-makers (Hammond et al., 2025). Then, due to the inherent asymmetry in spatiotemporal characteristics and underlying drivers, as has been recently shown by Swain et al. (2025) from both meteorological and hydrological perspectives, drought-to-flood transitions ~~are not completely understood (e.g., Matanó et al., 2022, 2024; Brunner, 2023; Götte and Brunner, 2024). Model experiments are needed to explore the sensitivity of flood properties to drought occurrence and characteristics.~~can have more severe impacts than flood-to-drought transitions. Both hydrological droughts and floods are linked to meteorological conditions such as precipitation surplus/deficit or low/high evapotranspiration rates. However, Brunner et al. (2025) have shown that dry-to-wet spells are only weakly associated with drought-to-flood transitions, with a propagation rate of just 10% within a 30-day period, and that wet spells are less likely to lead to floods than dry spells are to cause droughts. Consequently, the occurrence and drivers of these compound events are not yet fully understood (e.g., Matanó et al., 2022, 2024; Brunner, 2023; Götte and Br
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~~Hydrological models are useful tools for studying how streamflow -~~ Process-based hydrological models can provide valuable insights on how streamflow and/or other hydrological fluxes and states ~~-~~ react to variations in ~~different~~ meteorological and environmental inputs ~~. Models enable insight into the mechanisms which drive catchment response to variations, through their representation of hydrological processes~~ (Hrachowitz and Clark, 2017). In recent decades, several efforts have been made to improve ~~hydrological modeling~~ the realism of hydrological models in terms of ~~the representation of~~ spatial variability (e.g., Dembélé et al., 2020), the simulation of low (e.g., Garcia et al., 2017) and ~~high-flows~~ high flows (e.g., Mizukami et al., 2019), or the representation of flood-triggering mechanisms and spatiotemporal coherence (e.g., Brunner et al., 2020, 2021), under current and changing ~~climate~~ climatic conditions (e.g., Fowler et al., 2018). However, modeling hydrological extreme events such as droughts and floods is still ~~very challenging (e.g., Mizukami et al., 2019; Bruno et al., 2024). This can be particularly difficult in contexts where~~ challenging (e.g., Mizukami et al., 2019; Bruno et al., 2024), especially when multiple variables are ~~of interest, e.g. when~~ involved. Such cases include, for example, modeling the dependence between flood peaks and volumes (Brunner and Sikorska-Senoner, 2019)~~or~~ , or modeling the spatial dependence of floods happening in different locations (Brunner et al., 2021). This complexity ~~suggests~~ indicates that capturing consecutive drought-to-flood events might not be trivial either. As model evaluations targeted at compound extremes have not yet been performed, it is still unclear how well hydrological models can~~in fact~~ , in fact, capture drought-to-flood transitions.

Hydrological modeling involves ~~different choices~~ making decisions about model structure (i.e., process ~~representation and parametrization~~representations and parameterizations), spatial discretization, meteorological ~~forcing, and calibration~~ forcings, and parameter estimation approach (e.g., ~~period for~~ calibration/evaluation periods, hydrological target variables or signatures used in objective function), which affect hydrological simulations and whose importance might vary depending on the modeling purpose (e.g., Mendoza et al., 2016; Mizukami et al., 2016; Baez-Villanueva et al., 2021; Guo et al., 2017; Melsen et al., 2019). Previous studies have highlighted that such modeling decisions can substantially influence simulated hydrological extremes and their uncertainties (e.g., Alexander et al., 2023; Melsen and Guse, 2019; Melsen et al., 2019). They have also shown that ~~among these choices,~~ the choice of objective function for model calibration, model structure, and spatial discretization (forcings and domain) are the most influential decisions on modeling outcomes. While these previous studies have focused on analyzing the impacts of modeling decisions on drought and flood attributes (e.g., severity, duration), they have not looked at how these decisions influence event detection, i.e. whether or not ~~the~~ a model can capture extreme events below or above a certain threshold. ~~Furthermore, these previous studies have~~ Moreover, previous work has focused on individual extremes instead of looking at them in a multivariate setting. As such, it is yet unclear how individual modeling decisions might influence the representation of hydrological transitions.

Hydrological modeling often relies on ~~model calibration to define parameters~~ the calibration process to find parameter values that minimize discrepancies between observations and simulations of a target variable (e.g., streamflow). ~~Calibration uses~~ The calibration process requires defining an objective function to measure the similarity between observations and simulations. In general, these objective functions are defined based on "least squares" formulations such as the widely used Nash-Sutcliffe Efficiency (NSE; Nash and Sutcliffe, 1970) and the Kling-Gupta Efficiency (KGE; Gupta et al., 2009). ~~However,~~ Although alternative objective functions have been ~~suggested to improve~~ proposed to enhance the robustness of calibrated parameters ~~. This is especially relevant in the context of a changing climate (e.g., Fowler et al., 2018), and might improve hydrological consistency through metrics that better capture the statistical and dynamic properties of hydrological time series (referred in the literature as hydrological signatures; e.g., Yilmaz et al., 2008; Shafii and Tolson, 2015; McMillan, 2021). While these alternatives are available and concerns regarding the standard options (e.g., Clark et al., 2021; Knoben et al., 2019; Cinkus et al., 2023 have been noted~~and hydrological consistency (e.g., Fowler et al., 2018; Yilmaz et al., 2008; McMillan, 2020), KGE and NSE ~~continue to be~~ remain widely used for model calibration and evaluation (e.g., Klemeš, 1986; Motavita et al., 2019; Seibert et al., 2019; Beven, 2025).

The Kling-Gupta Efficiency (KGE), originally proposed by Gupta et al. (2009), ~~is~~ has been one of the most popular performance metrics used in hydrology ~~. KGE is more widely used than other well-known metrics, such as the NSE, because of its interpretability and the diagnostic power provided, thanks~~ over the last decades. Thanks to the possibility of disaggregating it into its three components ~~, namely~~ — bias, variability, and correlation — KGE provides interpretability and diagnostic power. It has been applied for many modeling purposes, including ~~studies focused on~~ the analysis of streamflow extremes (e.g., Gu et al., 2023; Hirpa et al., 2018). In these studies, despite the lack of objectivity in assessing the model's explanatory power in each catchment (i.e., benchmark; e.g., Knoben, 2024; Seibert et al., 2018), calibrations are considered successful if the KGE performance exceeds a certain threshold during both the calibration and evaluation periods (e.g., KGE > 0.4). This criterion is used as a proxy for how well a model represents streamflow properties such as extreme events (e.g., Lema et al., 2025; Cinkus et al., 2023; Zhao et al., 2025). However, there is often no explicit evaluation of how drought or flood events are represented at the event scale. Thus, the suitability of KGE ~~–~~and alternative formulations (Gupta et al., 2009; Kling et al., 2012; Pool et al., 2018; Tang et al., 2021; Pizarro and Jorquera, 2024) ~~and~~ or adaptations (e.g., transformations and weights; Garcia et al., 2017; Wu et al., 2025; Mizukami et al., 2019) ~~—~~for calibrating models aimed at studying streamflow extreme events ~~, andconsecutive extremes~~ and, in particular, consecutive extremes, has not yet been sufficiently evaluated.

In summary, ~~there exist significant research gaps related to modeling floods which occur in close succession following droughts, that is, drought-to-flood transitions. In particular~~the effectiveness of overall performance metrics - such as KGE - in evaluating the models' ability to capture streamflow extremes has not yet been thoroughly examined. Additionally, it is unclear how different modeling decisions - such as the ~~choice of~~ hydrological model, objective function, and streamflow transformations - affect ~~the simulation of transition events. Furthermore~~drought-to-flood transition simulations. Even more, it remains to be explored which modeling choices are most suitable for capturing these compound hydrological extreme events without compromising hydrological consistency (i.e., representation of different hydrological processes or properties). To address these research gaps, ~~our study aims to~~ we investigate the extent to which hydrological models can represent consecutive drought-to-flood transitions and the impact of model ~~complexity~~ structure and calibration choices on their representation. Specifically, we ~~investigate~~ address the following research questions:

- How suitable is the KGE for calibrating models aimed at jointly simulating streamflow droughts and floods?

- ~~Which KGE formulations, weights, and streamflow transformations are most suitable for simulating drought-to-flood transitions?~~

- ~~To what extent does model structure influence the detection and representation of streamflow~~ Which modeling choices (e.g., model structure, KGE formulation, etc.) are most important for simulating droughts, floods, and their transitions?

- Which are the key hydrological processes that have to be captured by models to ~~well~~ simulate drought-to-flood transitions well?

To address these questions, we ~~first calibrate~~ performed several calibration experiments with four conceptual bucket-type hydrological models (GR4J, GR5J, GR6J, and TUW) ~~for~~ across 63 ~~diverse~~ catchments in Chile and Switzerland. ~~For this calibration experiment~~In our experiments, we tested different configurations of the Kling-Gupta efficiency (KGE) ~~- listed in Table 1 -~~ to assess their performance in simulating and detecting observed transitions. These configurations included five KGE formulations (Table 1), two streamflow transformations (i.e., Q and 1/Q) and their linear combination (i.e., 0.5*KGE(Q)+0.5*KGE(1/Q)), and four different weights applied to the variability term of the KGE (c_2=1,2,4,8). ~~Second, we assess~~ Secondly, we assessed the relative importance of each ~~of these methodological choices for the detection of~~ methodological choice for detecting events and ensuring hydrological consistency. Finally, we ~~explore~~ explored the link between model performance and the representation of different hydrological fluxes and states during transition events.

~~This comprehensive assessment of the influence of different modeling decisions on the accuracy of drought-to-flood transition simulations will enable recommendations on potential future model improvements.~~

2 Study domain and data

The study domain encompasses 24 and 39 near-natural catchments in Chile (CL; Figure 1a) and Switzerland (CH; Figure 1b), respectively. These catchments are selected based on the availability of complete daily streamflow records between 1981 and 2020 for at least 30 years, with a complete year being defined as one in which all months had information for at least 90% of the days. The selected catchments span a wide range of hydroclimatic characteristics (Figure 1c), from energy to water-limited, and different hydrological regimes (Figure 1d), from snowmelt (e.g., p-seasonality < -0.5 and q-seasonality > 0.5) to rainfall-dominated (e.g., p-seasonality < -0.5 and q-seasonality < -0.5). Some catchments are ~~placed~~ positioned above the water limit (i.e., Q/P = 1) or below the energy limit (i.e., Q/P = 1 - 1/(P/PET); Figure 1c), which suggests an underestimation of precipitation – which might require correcting for precipitation undercatch (e.g., Newman et al., 2015; Stisen et al., 2012; Hughes et al., 2021) – or a surplus of streamflow. ~~Consequently, there is a need to adjust the meteorological forcings, e.g. by correcting for precipitation undercatch (e.g., Newman et al., 2015; Stisen et al., 2012; Hughes et al., 2021).~~

The CAMELS Chile (CL; Alvarez-Garreton et al., 2018a) and Switzerland (CH; Höge et al., 2023a) datasets are used to obtain the meteorological forcings, streamflow records, snow water equivalent (SWE) estimates, and catchment ~~outlines for the catchments in the study domain~~boundaries for the study domains. The meteorological forcings of both datasets, CR2Met version 2.5 for Chile (Boisier, 2023) and RhiresD version 2 for Switzerland (MeteoSwiss, 2023), are based on local gridded observation-based products, while SWE products are based on a snow cover model and data assimilation (for more detail refer to Cortés and Margulis, 2017; Magnusson et al., 2014). We prefer these local products over global ones such as ERA5 (Hers-

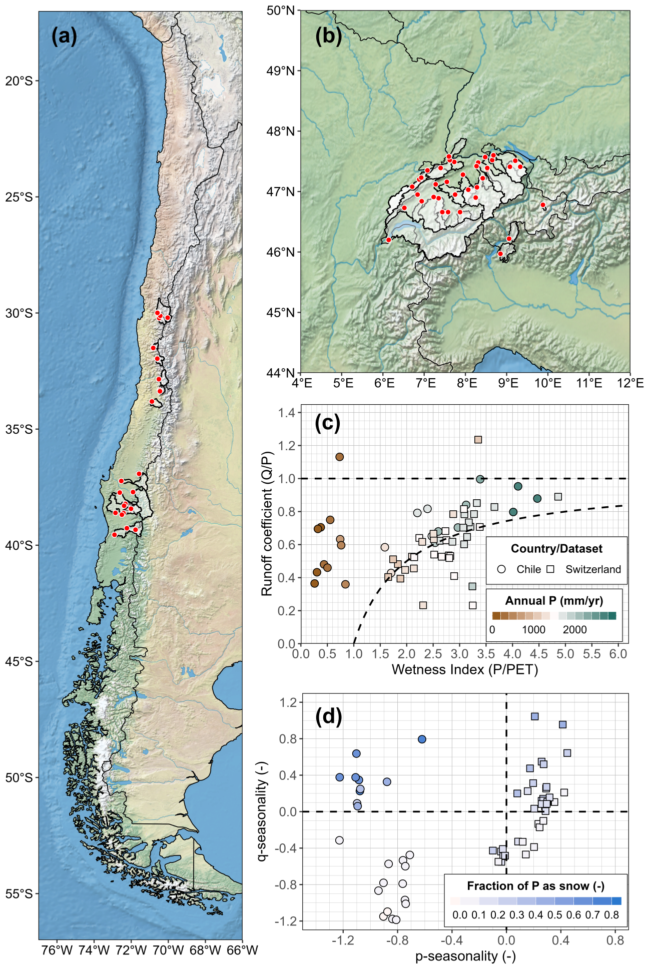


Figure 1. Study domain and hydroclimatic characteristics computed for the period 1981-2020 using data retrieved from CAMELS Chile (CL) and Switzerland (CH). Location of catchments across the study domain in (a) Chile and (b) Switzerland, (c) relationship between wetness index (~~PET/~~P/PET), runoff coefficient (Q/P), and mean annual precipitation, and (d) relationship of seasonality of precipitation and streamflow and fraction of precipitation falling as snow. For p-seasonality and q-seasonality, ~~values near 1~~ positive (~~-1~~negative) ~~suggest strongly~~ values indicate summer (winter) dominated precipitation or streamflow, while values close to zero indicate a uniform distribution across the year.

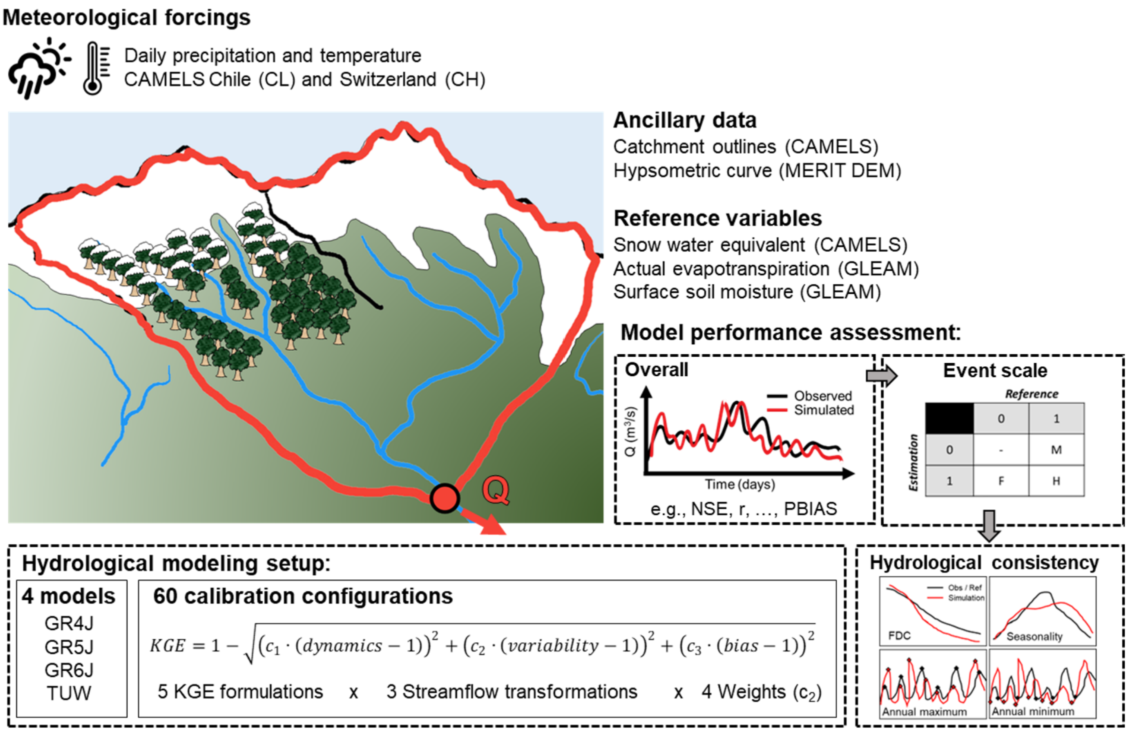
bach et al., 2020) because of their reliance on observations and high ~~spatial resolution~~ horizontal resolutions (approximately 5x5 km^2 for CR2Met and 2x2 km^2 for RhiresD) that ~~allow us to better represent the meteorology~~ enable a better representation of precipitation patterns in the complex topography of our study domain. ~~Furthermore~~Further, these products have been widely used ~~in~~ for hydrological studies in Chile (e.g., Vásquez et al., 2021; Alvarez-Garreton et al., 2021; Araya et al., 2023) and Switzerland (e.g., Peleg et al., 2020; Fatichi et al., 2015; Tuel et al., 2022). Streamflow records available through the CAMELS datasets were acquired from the national agencies in each country (i.e., the General Directorate of Water of Chile - DGA and the Swiss Federal Office for the Environment - FOEN). Additionally, we retrieve time series of actual evapotranspiration (ET) and soil moisture (SM) from the satellite and reanalysis-based GLEAM ~~dataset (Miralles et al., 2011)~~ v3.8a dataset (Miralles et al., 2011), spatially aggregated to the catchment scale. We compute topographic characteristics and hypsometric curves - needed to set up the snow routines - using the catchment outlines from CAMELS and the Multi-Error-Removed Improved-Terrain (MERIT) digital elevation model (Yamazaki et al., 2019).

3 Methodological approach

Our methodological approach is illustrated in Figure 2. Four hydrological models are calibrated with data from the CAMELS datasets and streamflow records, using five different formulations of the Kling-Gupta efficiency (KGE) as objective functions. In addition, we test three streamflow transformations and four different weights applied to the KGE variability term. This calibration ~~exercise~~ experiment results in 60 optimal parameter sets per model and catchment (i.e., 5 KGE x 3 ~~Transformations~~ transformations x 4 ~~Weights). Simulation performance is assessed by comparing observations and model outputs. Specifically, we~~ weights). We evaluate model performance based on (1) general goodness-of-fit metrics (Legates and McCabe Jr., 1999; Althoff and Rodrigues, 2021), (2) ~~for~~ simulation of extreme events and transitions between them, and (3) ~~for~~ hydrological consistency in different processes related to streamflow, snow, evapotranspiration, and soil moisture. ~~Event-specific model performance is evaluated~~ We also assess model performance at the event scale for droughts, floods, and transitions using categorical indices. In this paper, we use the terms ’formulation’ to refer to a specific definition of the KGE (1), ’case’ to refer to the application of KGE weights or flow transformations, and ’configuration’ to mention the combination of a KGE formulation and a case using certain weights and a specific streamflow transformation. ~~In addition~~Further, the cases without weights and/or the linear combination between streamflow without (i.e., Q) and with low-flow transformations (i.e., 1/Q) will be used as a reference for the comparison of the results. To assess the statistical significance of the differences between, e.g., the configurations tested in this study, we applied the Wilcoxon test (Wilcoxon, 1945) at a 5% significance level (further details in Text S3 in the Supplementary Material). The following sections provide a detailed description of the different methodological steps.

3.1 Streamflow extremes characterization

We detect droughts, floods, and drought-to-flood transitions using the method proposed by Götte and Brunner (2024). This ~~method~~ approach identifies periods of negative streamflow anomalies (i.e., droughts) using a daily varying threshold based on a ~~30 day~~ 30-day rolling percentile of the daily streamflow data, while high streamflow events (i.e., floods) are identified using a fixed threshold based on a percentile of the annual maximum streamflow values. We further require that all drought events have a minimum duration of 30 days, and we merge ~~drought events which have a gap of~~ droughts separated by 15 days or less between them (Van Loon and Van Lanen, 2012; Fleig et al., 2006; Tallaksen et al., 1997) ~~. This is done~~ to limit the detection of minor events.



Meteorological forcings
Daily precipitation and temperature
CAMELS Chile (CL) and Switzerland (CH)
Ancillary data
Catchment outlines (CAMELS)
Hypsometric curve (MERIT DEM)
Reference variables
Snow water equivalent (CAMELS)
Actual evapotranspiration (GLEAM)
Surface soil moisture (GLEAM)
Q
Model performance assessment:
Overall
Observed
Simulated
Q (m³/s)
Time (days)
e.g., NSE, r, ..., PBIAS
Event scale
Reference
Estimation
0
1
-
M
F
H
Hydrological modeling setup:
4 models
GR4J
GR5J
GR6J
TUW
60 calibration configurations
$KGE = 1 - \sqrt{(c_1 \cdot (dynamics - 1))^2 + (c_2 \cdot (variability - 1))^2 + (c_3 \cdot (bias - 1))^2}$
5 KGE formulations x 3 Streamflow transformations x 4 Weights (c_2)
Hydrological consistency
Obs / Ref
Simulation
FDC
Seasonality
Annual maximum
Annual minimum

Figure 2. Overview of the methodological approach. See text for details

Rapid (within 14 days) and seasonal ~~transitions~~ (within 90 days) transitions are defined based on the number of days between the end of the drought to the onset of the flood, ~~as in~~ following Götte and Brunner (2024). The thresholds for droughts ~~and floods (associated with the~~ (30th ~~and 40th~~ percentile of the smoothed daily flow~~and~~) and floods (40th percentile of the annual maxima series~~, respectively~~) were set to ensure roughly one streamflow extreme event of each type (i.e., drought and flood) per year on average for each catchment. This target was set in order to identify a statistically representative number of extreme events~~that results in a statistically representative sample size~~ , comparable to the sample size that would be obtained by the commonly used annual maximum approach (e.g., Meylan et al., 2012). ~~To identify those~~ Considering this definition and the thresholds adopted, we identified one event every four years on average for each catchment. To identify the thresholds that met our criteria, we tested different values (see Figure S1 in the Supplementary Material). Figure 3 ~~shows~~ illustrates the detection of droughts and floods based on the approach adopted for two recorded transitions in two catchments within the study domain.

3.2 Modeling approach

3.2.1 Hydrological models

We use four conceptual bucket-style rainfall-runoff hydrological models: GR4J (Perrin et al., 2003), GR5J ~~(Le Moine, 2008)~~ (Le Moine, 2008; Pushpalatha et al., 2011), GR6J ~~(Pushpalatha et al., 2012)~~(Pushpalatha et al., 2011), all coupled to the snow

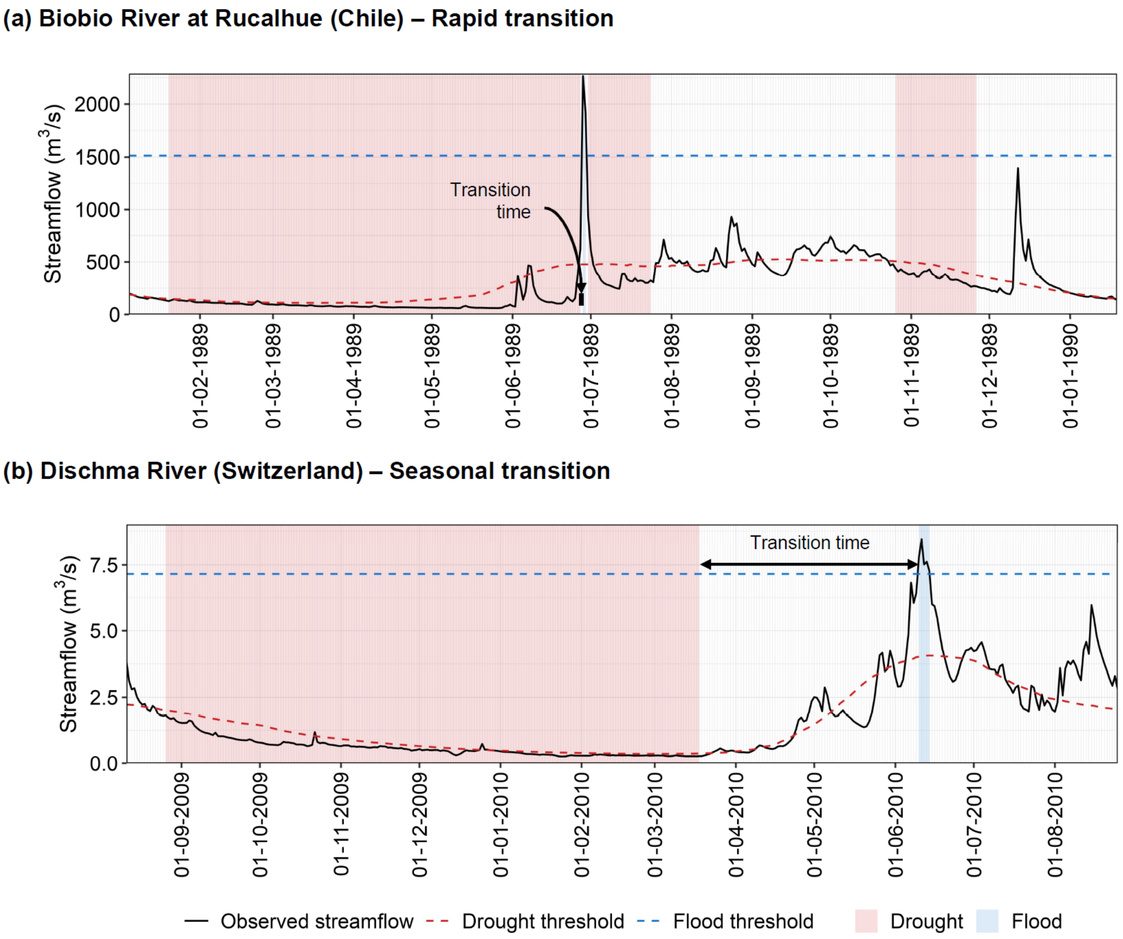


Figure 3. Example of the characterization of streamflow extremes and their transitions for two catchments within the study domain. (a) Biobio River at Rucalhue in Chile, and (b) Dischma River in Switzerland.

accumulation-ablation module CemaNeige (Valéry et al., 2014a, b), and TUWmodel (Parajka et al., 2007), which is based on the HBV model (Bergström and Forsman, 1973). All models have been widely used within the hydrological community during the last decades (Seibert and Bergström, 2022). GR4J, GR5J, and GR6J (with 6, 7, and 8 parameters coupled with CemaNeige, respectively; see Table S1 in the Supplementary Material) were chosen to explore how slight changes in model structure affect simulated streamflow extremes, and the TUW model (with 15 parameters~~) was chosen~~ ; see Table S2 in the Supplementary Material) was selected to explore how more complex models, ~~particularly with respect to~~ in terms of the snow routine and the representation of the processes occurring in the production storage, simulate these phenomena. ~~Such simple bucket-type models have the advantage that they enable studying different processes of the hydrological cycle at a lower computational cost than more complex modelstructures (e.g., Clark et al., 2017; Orth et al., 2015; Poncelet et al., 2017) .~~ To avoid overcompensating for biases in the meteorological forcings, which can be seen in the catchments placed above the water limit or below the energy limit - pointed out in Figure 1c -, two parameters were included in the calibration process in addition to the original setup for each hydrological model. Thus, a multiplicative parameter for precipitation (dP) and an additive parameter for temperature (dT) were included to adjust systematic biases in precipitation and temperature.

The GR4J, GR5J, and GR6J models ~~, which we will refer to collectively~~ - hereafter referred to as GRXJ for simplicity ~~,~~- share the same genealogy, meaning that they are based on the same core structure. These models can be coupled to the snow module CemaNeige, ~~where the precipitation is partitioned between~~ which partitions precipitation into liquid and solid and simulates snow accumulation and melt (rainfall and snowmelt enter ~~to~~ the GRXJ structures). The basic structure of the GRXJ family corresponds to the GR4J model, which includes a parameter for production storage capacity, representing surface processes, and a parameter for routing storage capacity, representing subsurface processes. Additionally, GR4J includes an intercatchment exchange parameter ~~(non-conservative function)~~ and a unit hydrograph parameter that ~~corresponds to~~ represents the delay between precipitation and streamflow. GR5J adds an additional parameter to the GR4J structure to improve the intercatchment exchange function, while GR6J includes a parameter for exponential storage in parallel to the routing storage included in GR4J and GR5J to improve the representation of groundwater processes (i.e., slow runoff).

The TUW model consists of a snow, soil, groundwater (subsurface flow), and a routing routine, similar to the HBV model (Bergström and Forsman, 1973). ~~The~~ One of the major differences between the HBV and TUW models is in the snow routine. The TUW model does not allow for meltwater or rainfall to be retained within the snowpack, nor does it account for the refreezing of liquid water. The snow routine partitions between liquid and solid precipitation and estimates snow accumulation and melt. Rainfall and snowmelt enter the soil routine, where actual evaporation, soil moisture, and recharge are estimated. Then, the recharge flow goes to the groundwater routine, represented by two storages that produce surface runoff and quick flow (upper), and baseflow (lower). The sum of these flows is delayed in the routing routine using a triangular transfer function. Unlike the GRXJ models, which follow a water balance approach to characterize the production storage, TUW estimates evapotranspiration and recharge based on an explicit conceptualization of soil moisture content.

While both CemaNeige and the snow routine implemented in the TUW model follow a degree-day factor approach, there are ~~some differences mainly in~~ differences in (i) the characterization of the precipitation phase (TUW allows the existence of a mixed partition between rain and snow), (ii) the conditions for snowmelt (~~free-parameter in~~ free parameter in the TUW model and set as 0°C for CemaNeige), and (iii) the presence (or ~~not~~absence) of a parameter to correct for snowfall undercatch (not available in CemaNeige). These differences also explain the number of parameters that each of the snow routines has (two and five for CemaNeige and the snow routine in the TUW model, respectively).

Despite their structural differences and conceptualizations (for further details refer to Astagneau et al., 2021b), these models provide simplified representations of some hydrological states, fluxes, and processes at the catchment scale using precipitation (P), mean temperature (T), and potential evapotranspiration (PET) at daily time steps as ~~an input~~inputs. To estimate PET, we use the approach proposed by Oudin et al. (2005), which is based on temperature and ~~includes~~ requires latitude and day of the year as a proxy for extraterrestrial radiation~~for its computation~~. Additionally, as the snow module CemaNeige can be configured in a semi-distributed way, discretizing each catchment into ~~elevation bands of equal area~~ equal-area elevation bands based on the hypsometric curve, we considered 10 elevation bands for all evaluated model structures. To make simulations comparable across model structures, precipitation and temperature for the TUW model were extrapolated following the approach implemented in the GRXJ models through 10 elevation bands, based on the orographic gradients defined by Valéry et al. (2010).

~~In addition to the parameters associated with each hydrological model , two parameters were included in the calibration process to address issues - such as the catchments placed above the water limit or below the energy limit - pointed out in Figure 1c. Thus, a multiplicative parameter for precipitation and an additive parameter for temperature were included to adjust their values.~~

3.2.2 Calibration strategy

~~The parameters of each of the four model structures were~~ The parameters of each model structure, as well as the forcing adjustment parameters introduced, were calibrated using daily streamflow records and the Shuffled Complex Evolution global optimization algorithm (SCE-UA; Duan et al., 1992) ~~on the period between~~ over the period 2000-2020 ~~,~~ (details on the convergence of the optimization algorithm and its configuration in Text S1 in the Supplementary Material). This calibration period was defined to capture the current hydroclimatic conditions in the modeling ~~parameters.~~ setup. Considering the temperature adjustment parameter, potential evapotranspiration was recalculated in each iteration during calibration to ensure consistency between those variables. Different objective functions based on the KGE configuration were used to calibrate each model. In its most general form, the KGE (Eq. (1)) compares simulations to a reference based on three components, i.e. dynamics (e.g., correlation), variability (e.g., standard deviation), and bias (e.g., mean). KGE values range from negative ~~infinite~~ infinity to one, ~~with one corresponding to~~ which is the optimum. How each component is defined depends on which KGE formulation is used. To the best of our knowledge, there exist five such formulations in the literature (Gupta et al., 2009; Kling et al., 2012; Pool et al., 2018; Tang et al., 2021; Pizarro and Jorquera, 2024, more details in Table 1). Additionally, different scaling factors or weights (i.e., c_1, c_2, and c_3 in Eq. (1)) can be used to ~~give~~ put more emphasis to some of the components of the KGE as well as different streamflow transformations to give more weight to specific parts of the flow distribution ~~,~~ (e.g., Thirel et al., 2024; Mizukami et al., 2019). To emphasize low flows, for example, flow can be transformed to the inverse of streamflow (i.e., 1/Q; e.g., Garcia et al., 2017; Wu et al., 2025). Further, linear combinations of the KGE applied to flows without and with transformation (i.e., Q and 1/Q, respectively) have been presented as a useful objective function to find a good compromise between high- and low-flows (e.g., Araya et al., 2023; Knoben et al., 2020; Muñoz-Castro et al., 2023).

$$\text{KGE} = 1 - \sqrt{(c_1 \cdot (\text{dynamics} - 1))^2 + (c_2 \cdot (\text{variability} - 1))^2 + (c_3 \cdot (\text{bias} - 1))^2} \tag{1}$$

For each hydrological model and catchment, 60 different objective functions (OF) are implemented based on the possible combinations of the following methodological ~~decisions~~choices: (i) 5 KGE formulations (Table 1), (ii) 3 streamflow transformation cases (High, Low, High-Low), and (iii) 4 weights applied to the variability term (i.e., in Eq. (1), c_2 = 1, 2, 4, 8). For the low-flow transformation (Low; i.e., using 1/Q), a constant equal to 1% of the mean streamflow is added to the series to avoid zero-flow problems following ~~the recommendations by Pushpalatha et al. (2012)~~recommendations from previous

Table 1. Summary of KGE formulations. In each formulation, the term dynamics stands for the representation of the temporal evolution of the target variable, while the terms variability and bias aim to characterize its distribution.

KGE formulation	Components	Description	Reference
Original (KGE)	**Dynamics:** Pearson correlation coefficient. **Variability:** Ratio between the standard deviation of the simulated and observed values. **Bias:** Ratio between the mean of the simulated and observed values.	Meta-objective function, oriented to quantify the Euclidean distance between the absolute error associated with each component. Proposed to overcome the problems associated with NSE (e.g., observed mean as baseline, formulation, which could lead to large volume balance errors or favor models/parameters sets that underestimate the observed variability).	Gupta et al. (2009)
Modified (KGE_mod1)	**Dynamics:** Pearson correlation coefficient. **Variability:** Ratio between the coefficient of variation of the simulated and observed values. **Bias:** Ratio between the mean of the simulated and observed values.	Modification in the variability component defined in the original formulation (i.e., standard deviation ratio) aimed to ensure that the bias and variability ratios are not cross-correlated.	Kling et al. (2012)
Non-parametric (KGE_np)	**Dynamics:** Spearman’s rank correlation coefficient. **Variability:** Error between all ranked simulated and observed values (i.e., flow duration curve) normalized to remove the volume information and keep only the distribution signal. **Bias:** Ratio between the mean of the simulated and observed values.	Reformulation of the variability and correlation terms in a non-parametric way to address the implicit assumptions of linearity and normality of the data in the original formulation.	Pool et al. (2018)
Modified v2 (KGE_mod2)	**Dynamics:** Pearson correlation coefficient. **Variability:** Ratio between the standard deviation of the simulated and observed values. **Bias:** Ratio between the mean of the simulated minus the observed values and the standard deviation of the observed values.	Modification in the bias component defined in the original formulation aimed to avoid anomalously negative values when the mean value is close to zero.	Tang et al. (2021)
K-Moments (KGE_km)	**Dynamics:** Pearson correlation coefficient. **Variability:** Ratio between the coefficient of variation of the simulated and observed values defined from unbiased estimators of non-central K-moments (alternative formulation for the second moment). **Bias:** Ratio between the mean of the simulated and observed values.	Modification in the variability component defined in the original formulation oriented to make it less sensitive to outliers and non-normal distributions.	Pizarro and Jorquera (2024)

studies (e.g., Pushpalatha et al., 2012; Garcia et al., 2017; Knoben et al., 2020). To facilitate the notation associated with the streamflow transformations tested here, we will refer to the case ’Hi’ (High) when a certain formulation of KGE is applied to untransformed streamflow (i.e., Q), while ’Lo’ (Low) will refer to the case where a low-flow transformation is applied (i.e., 1/Q). ~~To~~ We will refer to the linear combination of both cases (i.e., 0.5*Hi + 0.5*Lo) ~~, we will refer to it as the~~ as ’HiLo’~~case~~.

3.3 Model performance assessment

~~We evaluated model performance with respect to general performance as described by~~

3.3.1 Overall performance and hydrological consistency

To assess our results independently of the KGE configuration across the different calibration experiments tested here, we quantified the overall model performance using the Nash-Sutcliffe Efficiency (NSE; Nash and Sutcliffe, 1970)~~and performance with respect to simulating extreme events as described by the Critical Success Index (CSI). Following~~ , which has become one of the most popular metrics within the hydrological community in the last decades (Melsen et al., 2025). We followed a traditional split-sample test approach (Klemeš, 1986; Beven, 2025) ~~,~~ to assess the model performance ~~is assessed~~ over two time periods defined as (i) calibration (2000-2020), and (ii) evaluation (1985-1999). ~~The following subsections provide a detailed description of how the model's performance was evaluated.~~

3.3.2 ~~Overall performance and hydrological consistency~~

~~To evaluate how different model configurations simulate different hydrological variables, we compute the Nash-Sutcliffe-Efficiency~~ We compute the NSE for different variables, including high- and low-flows (i.e., Q and 1/Q), snow water equivalent (SWE), soil moisture (SM), and actual evapotranspiration (ET). ~~We use the NSE to have a metric easily interpreted and recognized by the hydrological community, that allows us to compare results independently across different configurations adopted for model calibration.~~ To minimize the influence of biases in ET and SM estimates on the estimates of model performance - due, for example, to catchment-scale averaging (e.g., Rouholahnejad Freund et al., 2020) or uncertainties related to the GLEAM algorithm (e.g., Jahromi et al., 2022) - we only ~~consider~~ considered the signal (i.e., timing and variability) associated with these variables rather than their absolute values. Complementarily, we estimate the bias associated with some hydrological signatures derived from the daily streamflow time series (e.g., mean, variance, Q1, Q99). To focus our study on assessing the ability of hydrological models to capture streamflow extreme events and their transitions, these results are presented in Text S2 in the Supplementary Material.

3.3.2 Detection of streamflow extreme events

To assess ~~model performance with respect to the detection of~~ the model's capability to detect streamflow extremes and their transitions, we use the ~~critical success index~~ Critical Success Index (CSI; Eq. (2)), which is formulated based on the number of hits (H; events identified both in the reference/observation and the simulation), misses (M; events only identified in the reference/observation), and false alarm events (F; events identified only in the simulation). The CSI ~~provides a measure of the overall performance of the simulations in terms of detecting observed events and its~~ values vary between zero and one, with one being the optimum. We define hits as simulated events overlapping at least 50% with their observed counterparts. Additionally, for the detection analysis, a tolerance window of 30 and 5 days is defined before the onset and after the end of an observed drought and flood event, respectively. This window allows for considering the differences of gridded meteorological products with reality and how these can affect the timing of the simulated events (i.e., early or late compared to the observed streamflows). In short, we aim to evaluate the models' ability to capture streamflow extremes and their transitions rather than their characteristics (which may be even more restrictive). Therefore, we do not analyse the performance of the model in representing the specific characteristics of each event (e.g., cumulative deficit during the drought period, flow peak, etc.).

$$\mathrm{CSI} = \mathrm{H}/(\mathrm{H} + \mathrm{M} + \mathrm{F}) \tag{2}$$

3.4 Assessment of the relative importance of modeling decisions

To assess the relative importance of ~~each modeling decision~~ modeling decisions on the detection of streamflow extremes and their transitions, we conduct an analysis of variance (ANOVA; Fisher, 1992; Kaufmann and Schering, 2014). The ANOVA ~~allows us to study~~ enables us to examine the relationship between different modeling decisions (e.g. choice of structure and different decisions related to calibration) and quantify their relative importance in explaining the total variance in the target variable (e.g., CSI). Thus, by dividing the total variance into different groups, genuine sources of variation that are not explained by chance can be identified. We assume that the total variance (TV) in the target variable ~~could~~ can be mainly explained by the differences between catchments (CT), hydrological models (HM), KGE formulations (KGEf), streamflow transformations (QTR), and KGE component weights (W). If, for example, weights do not have a significant impact on the detection of streamflow extremes, we would expect a low value for the term "W", that is a lower relative importance (i.e., W/TV) for explaining the total variance with respect to other decisions. Based on this conceptualization and considering a residual term (RS) that groups all the interactions between decisions and the variance that we cannot explain from them, the ANOVA can be expressed as follows:

$$\mathrm{TV} = \mathrm{CT} + \mathrm{HM} + \mathrm{KGEf} + \mathrm{QTR} + \mathrm{W} + \mathrm{RS} \qquad (3)$$

3.5 Identification of important processes in simulating drought-to-flood transitions

To identify the most important processes in simulating drought-to-flood transitions, we ask what explains the accurate detection of events. To address this question, we analyze the relative importance of each model parameter in estimating the CSI through an ANOVA test applied per catchment. This analysis, expressed by Eq. 4, considers the 60 alternative configurations (i.e., parameter sets) available per model and catchment and uses the total variance explained (TV) by each parameter (θ_i; where i = 1, ..., Np, and Np is the number of parameters) as a proxy for the importance of the associated variable/process ~~. In addition, we explore which components of the modeling chain could be improved to better capture transitions. For this, we perform a similar ANOVA analysis, using the bias associated with different hydrological signatures instead of model parameters to estimate their relative importance in explaining the total variance of the CSI. Finally, to identify potential controls on the relative importance of some parameters in our study domain, we compute the Spearman's rank correlation coefficient between the most important parameters and a selection of physiographic and hydroclimatic catchment descriptors.~~ and a residual term (RS). The approach used to analyze the relative importance of the parameters explaining the variance of the CSI may have problems if the parameters do not show enough variation between the different configurations. However, despite the similarities in the configurations used for calibration, almost all the parameters show high variability among the calibrated parameter sets per catchment (see Figure ~~S14~~ S12 in Supplementary Material).

$$\mathrm{TV} = \sum_{i=1}^{Np} \theta_i + \mathrm{RS} \qquad (4)$$

4 Results

The results presented here are based on the simulations with the HiLo (i.e., 0.5*KGE(Q) + 0.5*KGE(1/Q)) configuration, unless specific cases where all 60 configurations per catchment were used (e.g., ANOVA tests). This is considering that our results are consistent with other studies, which have shown that the use of such approaches enables a good compromise in simulating both low and high flows (e.g., Garcia et al., 2017; Thirel et al., 2024; Lema et al., 2025). The results for the alternative streamflow transformations are presented in the Supplementary Material.

4.1 Suitability of KGE for calibrating models aimed at simulating drought-to-flood transitions

~~Model performance described by general performance metrics such as KGE during calibration and evaluation is often used as a proxy for how well a model represents streamflow properties such as extreme events. To explore how valid this assumption is, i.e. how closely~~ To illustrate how closely the general model performance described by the KGE is linked to ~~its capability of representing~~ the capability of detecting extreme events, we compare the ~~performance of the model during the calibration and evaluation period based on the objective function defined for calibration~~ objective function value retrieved for one of our calibration configurations - the original KGE formulation configured with unweighted HiLo (i.e., c_2 = 1 and HiLo = 0.5*KGE(Q) + 0.5*KGE(1/Q)), which is later used as a reference - with the performance in detecting droughts, floods and their transitions based on the ~~critical success index (CSI ;~~ CSI (Figure 4). Our comparison clearly shows that ~~while~~ model performance varies across catchments and model structures for both the KGE and CSI. While the overall performance described by the KGE can potentially be ~~a useful~~ used as a proxy for a model's performance in capturing droughts for some catchments (e.g., ~~CSI~~ points close to the optimal values for both KGE and CSI, i.e., 1, and CSI ranges from 0.23 to 0.79 for GR4J and from 0.21 to 0.74 for TUW), it is not ~~for~~ generalizable to floods and transitions ~~. A~~ or to all the models tested here. Therefore, a high KGE does not necessarily imply a high CSI for these two types of events. ~~Model performance varies across catchments and different model structures both for KGE and CSI (Figure 4). For droughts and transitions (panels a.1-b.1 and a.3-b.3, respectively), GR4J and TUW show comparable results both in terms of the median KGE (e.g., 0.85 and 0.80 in evaluation) and CSI (e.g., 0.59 and 0.51 for droughts) as well as their variability (error bars), but the model performance decreases when GR5J and GR6J are analyzed. For floods (i.e., panels a.2 and b.2), the GR4J outperforms the other models tested both in terms of general performance (median KGE is 0.06-0.11 and 0.04-0.18 larger than in other models for calibration and evaluation period respectively) and the detection of extreme events (median CSI is 0.03-0.13 larger than in other models depending on the type of event).~~

While KGE is not necessarily a good proxy for how well a model captures extreme events (especially floods and transitions), some specific KGE formulations might be better suited for this task than others. Next, we ~~therefore~~ evaluate to what extent different adjustments in the 'basic' configuration used for the ~~analyses~~ analysis presented above can (or cannot) improve the performance in detecting streamflow extreme events and, particularly, drought-to-flood transitions.

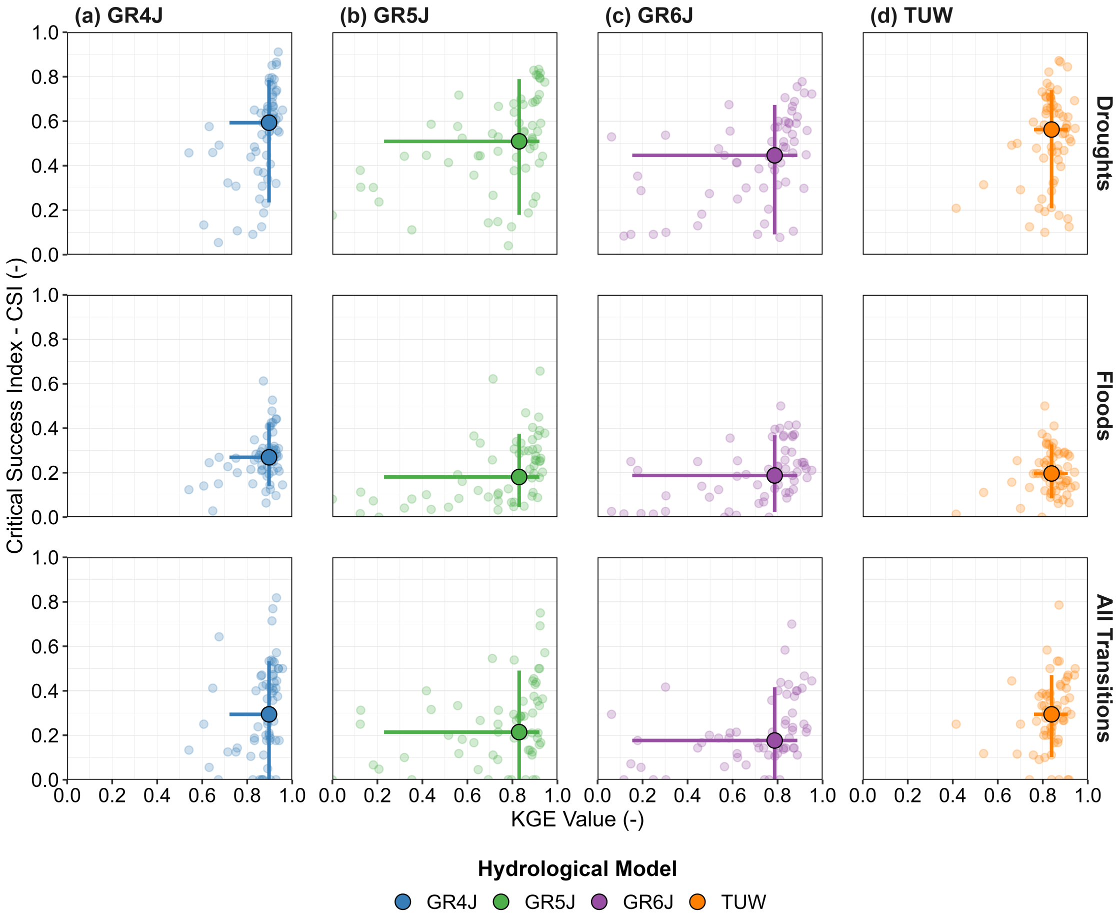


Figure 4. Comparison between the Kling-Gupta Efficiency (KGE) for the ~~(a)~~ calibration ~~and (b) evaluation~~ period and the Critical Success Index (CSI) for ~~(1)~~ droughts, ~~(2)~~ floods, and ~~(3)~~ transitions, based on the simulations with the models (a) GR4J, (b) GR5J, (c) GR6J, and (d) TUW calibrated with the unweighted ~~HiLo~~ original KGE formulation as the objective function. ~~CSI is calculated for the whole period (i.e., equal values for both the calibration and evaluation).~~ The ~~error~~ dispersion bars are associated with the 10th and 90th percentiles across catchments, while the central shape is associated with the 50th percentile. Circles with transparency show results for each catchment. For both KGE and CSI, the optimal value is 1.

4.2 Impacts of KGE configurations on drought-to-flood transition simulations

4.2.1 ~~KGE weights~~

To assess the added value of ~~applying~~ the application of weights to the variability term of the KGE as well as the use of different KGE formulations for detecting independent extreme events and their transitions~~in terms of the critical success index (CSI), we compute the difference between the non-weighted case (reference) and the application of three different weights~~

~~(alternative cases) for each KGE formulation and streamflow transformation (Figure 5 a~~ , Figure 5 shows - for the GR4J model ~~). This comparison shows that, in general, the use of weights does not consistently improve the ability of the models to detect streamflow extreme events or transitions between them (median difference is centered around 0). While there are some catchments where the introduction of weights improves model performance (catchments with negative differences), there are as many catchments where the introduction of weights decreases performance (catchments with positive differences). Figure 5b provides the same comparison but uses as a reference an unweighted HiLo configuration, showing similar results (i.e., no consistent improvements and median centered around zero) . However, there are some differences between different streamflow transformations and weights in the representation of floods (panel 2 in Figure 5b), with the unweighted HiLo being better in approximately 75% of cases compared to the weighted low-flow transformation. This finding generalizes to the other three model structures (see Figures S3 andS4 in the Supplementary Material).~~

as an example - the differences in CSI between the unweighted original KGE (reference) and alternative cases (e.g., weights and/or KGE formulations).These results highlight that, in the context of a large-sample study, ~~the use of weights for the~~ weighting the variability term of the KGE ~~is not beneficial as it~~ does not consistently ~~improve the model 's~~ enhance model performance in detecting streamflow extremes and their transitions ~~, and its usefulness will depend on the characteristics of the study domain (see Figures S5 in the Supplementary Material). Additionally, our results show that, for the task of modelling drought to flood transitions, an objective function which puts equal weight on high- and low flows (i.e. HiLo) improves model performance as floods are much better captured in this configuration than in configurations which rely on low-flow transformations (i.e., Lo) and equally well represented as in the configuration without transformation (i.e., Hi).~~

~~Difference in the CSI for GR4J simulations using model calibrations with no weights (reference) versus different weights (alternative) for (1) droughts, (2) floods, and (3) transitions. In (a), each alternative is compared with its unweighted analog, while in (b) the reference includes the HiLo transformation. Values above (below) 0 indicate better (worse) performance of the reference compared to the alternative.~~

4.2.1 ~~Streamflow transformation~~

~~Considering the HiLo (i.e., 0.5*KGE(Q) + 0.5*KGE(1/Q)) configuration as a reference (see Figures S6-S8 in the Suplementary Material for more details about its overall suitability), we assess the role of streamflow transformation on model performance for simulating high and low flows, snow water equivalent, actual evapotranspiration, and soil moisture (Figure ??a for the GR4J model as an example). We find that a transformation which puts equal weight on high- and low flows has the best performance on average, independently of the KGE formulation adopted for the calibration (different colors) and independent of the variable used for the evaluation (different columns). In particular, the results for high- and low flows (i.e., NSE(Q) and NSE(1/Q), respectively) highlight the added value of HiLo compared to transformations focusing on high and low flows individually. Between 50-90% of catchments profit from the HiLo transformation depending on the model and objective function used for calibration. HiLo improves the performance in simulating low (high) flows in comparison to using only high (low) streamflow transformations during model calibration without compromising the model's ability to adequately represent the opposite flow type (~~median difference is centered around 0 ~~for NSE(Q)-Hi and NSE(1/Q)-Lo). For the other variables,~~

~~besides better performance on average, the added value of HiLo compared to the transformations focusing on high and low flows only is less clear. Additionally, there exists substantial variability among catchments. These findings again generalize to the other model structures tested (Figures S9a~~ in both cases) and ~~S10a in Supplementary material) .~~

4.2.1 ~~KGE formulation~~

~~Figure ??b compares - for the GR4J model as an example - the unweighted HiLo case for all the different KGE formulations against the original KGE formulation (i.e., Gupta et al., 2009) as a benchmark. We find that using a modified KGE formulation, rather than the original, does not substantially improve model performance for either of the variables evaluated (i.e., Q, 1/Q, SWE, ET, and SM). However, there also exists substantial variability across catchments. Some catchments show an improvement in model performance when using alternative KGE formulations while others show a decrease in model performance. A small difference in the performance achieved through disparate formulations may be found in the high-flow representation (i.e., NSE(Q)), for which the original KGE provides slightly better values on average than the alternatives.Similarly, for SWE, ET, and SM, the added value of the original KGE formulation compared to the alternatives is less clear.~~ may even be detrimental.In short, the ~~differences in NSE between model formulations are close to zero, and the changes which do occur are not systematic or consistent. This suggests that the~~ use of weights and the choice of the KGE formulation ~~does~~ do not play a dominant role in the overall performance of the model over the study domain, and its usefulness will depend on the characteristics of the study domain and the model structure (see Figures S6 in the Supplementary Material). These findings are consistent across other model structures tested (Figures ~~S9b and S10b~~ S4-S11 in Supplementary material).

~~Difference in the NSE for GR4J simulations of different hydrological variables in the evaluation period obtained with different KGE configurations. In (a), each alternative configuration is compared to its unweighted HiLo analog, while in (b) the reference represents the original KGE formulation. Values higher (lower) than 0 represent a better (worse) performance of the reference compared to the alternative in simulating high-flows (NSE(Q), first column), low-flows (NSE(1/Q), second column), snow water equivalent (NSE(SWE), third column), actual evapotranspiration (NSE(ET), fourth column), and surface soil moisture (NSE(SM), fifth column).~~

4.3 Importance of model structure

Our results show that the detection of ~~low-flow anomalies~~ droughts is typically more reliable than ~~high-flow~~ flood and transition detection (Figure 6). However, there are substantial differences in the detection rate depending on the hydrological model structure used for simulating extreme events. GR4J ~~overall has the best model performance independently~~ yields the overall best performance regardless of the KGE formulation chosen for calibration (median CSI values across KGE formulations around 0.58, 0.26, and 0.31 for droughts, floods, and transitions, respectively). The performance of the GR5J and GR6J models decreases compared to GR4J (changes between 0.05 and 0.13 depending on the model and type of extreme event). This suggests that increasing model complexity decreases rather than increases model performance in detecting streamflow extreme events. However, these decreases in performance cannot be directly attributed to increases in the ~~complexity of the model~~ number of parameters because the TUW model shows comparable results to GR4J despite its ~~more complex~~ structure (median CSI values

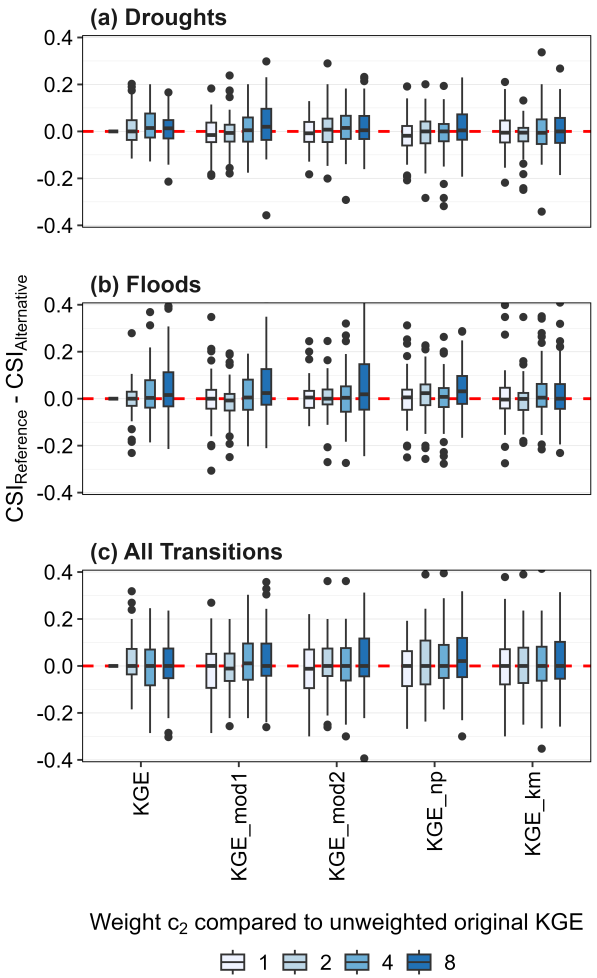


Figure 5. Difference in the CSI for GR4J simulations using model calibrations with no weights and the original KGE (reference) versus different weights and KGE formulations (alternative) for (a) droughts, (b) floods, and (c) transitions. Values above (below) 0 indicate better (worse) performance of the reference compared to the alternative. Each boxplot displays the information of 63 values (i.e., one per catchment).

across KGE formulations around 0.56, 0.19, and 0.28 for droughts, floods, and transitions, respectively). If model structures are compared for Switzerland and Chile (see Figure S7 in Supplementary Material), the same conclusions can be drawn in terms of model performance, with comparable results between GR4J and TUW and lower performance of the GR5J and GR6J models. However, the detection of extreme events is more challenging in catchments located in Chile compared to those located in Switzerland, with differences in the median CSI between countries being around 0.23, 0.02, and 0.13 for droughts, floods, and drought-to-flood transitions, respectively~~(see Figure S11 in Supplementary Material)~~. In summary, the GR4J and TUW models seem to be the models best suited for simulating droughts and floods among the models considered in this study.

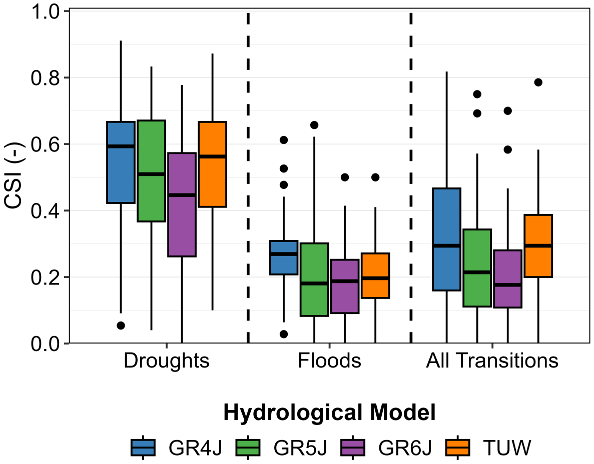


Figure 6. Critical Success Index (CSI) for (a) droughts, (b) floods, and (c) drought-to-flood transitions, based on the simulations with GR4J, GR5J, GR6J, and TUW (different colors) calibrated with ~~different~~ the unweighted HiLo original KGE ~~formulations~~ formulation as the objective ~~functions~~ function. Each boxplot displays the information of 63 values (~~different colors~~i.e., one per catchment).

Different model structures can result in similar streamflow simulations even though they represent hydrological fluxes and states in different ways. To illustrate this, we compare simulated fluxes obtained for an observed seasonal drought-to-flood transition in the Dischma river in Switzerland across the four hydrological models (Figure 7). While three out of four models capture the transition event successfully (GR6J fails in capturing its timing) and show similar temporal patterns of ET, snowmelt, and SWE, the contribution of baseflow (presented as a percentage of total runoff) and soil moisture ~~varies~~ vary strongly among them. Consequently, the analysis of the drivers associated with such transition events will vary depending on which model structure is analyzed. Although there is a high agreement between the models ~~for~~ in terms of the detection of the event in this example case (i.e., 3 out of 4), this is not necessarily the case for all ~~the~~ events and catchments ~~catchment~~ (Figure 4).

4.4 Relative importance of different modeling decisions

~~Consistent~~ In agreement with our earlier findings (Figure 6), the results of the ANOVA ~~analysis~~ show that the most important modeling decision is the choice of a suitable model structure, followed by the choice of the streamflow transformation, and the differences between catchments (Figure 8). In contrast, the choices of KGE formulation and weights do not have a strong impact on the performance ~~of~~ in simulating streamflow extremes. The relative importance of the methodological choices is similar when analyzing other categorical indices~~such as~~, such as the probability of detection~~(POD)~~, false alarm ratio~~(FAR)~~, and frequency of bias (~~fbias), as well as the model performance in simulating high and low flows, SWE, ET, and SM, as evaluated by NSE (see Figure S12 in~~ see Figure S8 in the Supplementary Material). For rapid transitions, the difference between catchments is more important for explaining the CSI values than it is for seasonal transitions. This difference indicates

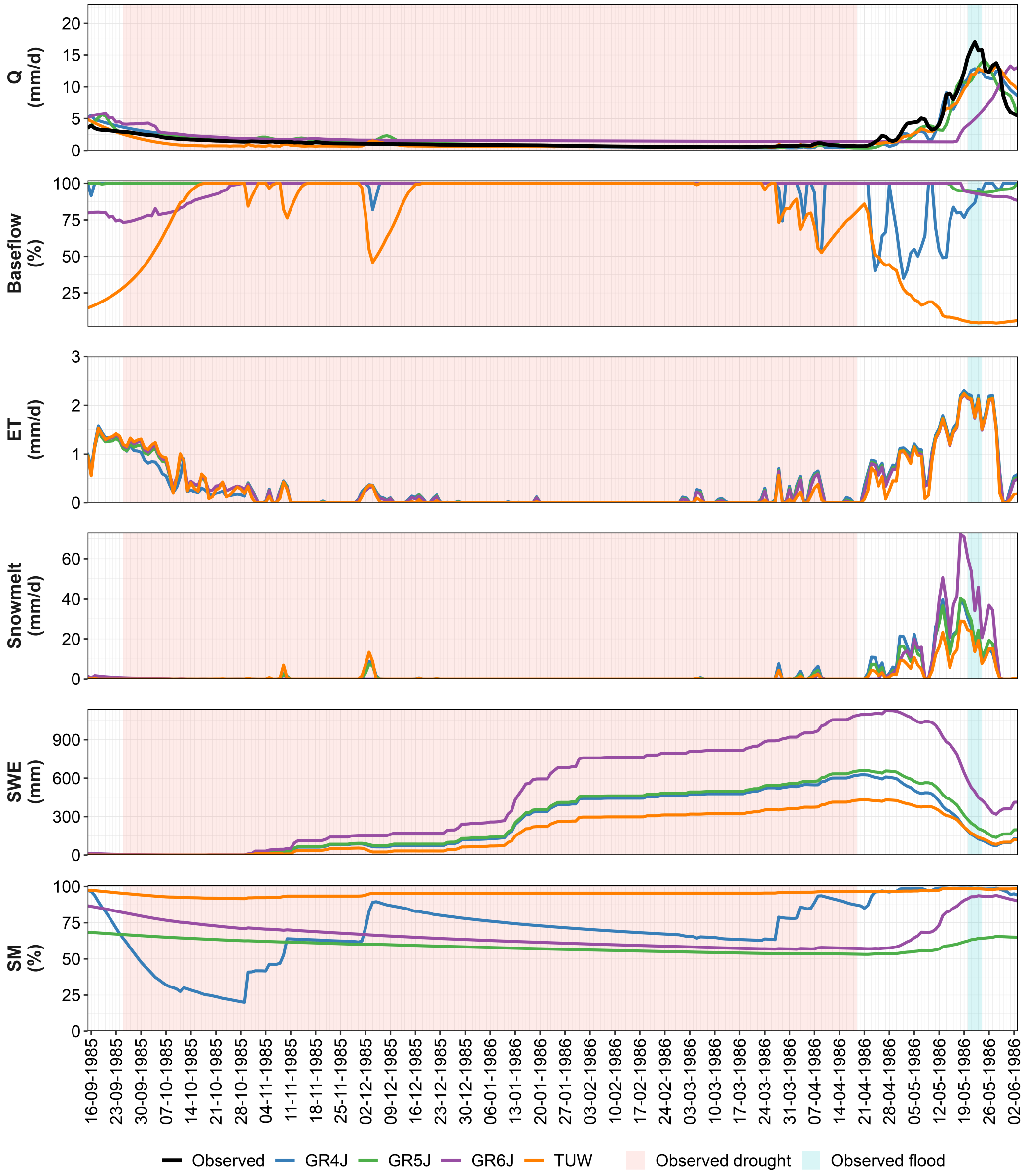


Figure 7. Example of how different hydrological fluxes and states are simulated for an observed drought-to-flood transition in the Dischma river (Switzerland) with the GR4J, GR5J, GR6J, and TUW hydrological models calibrated with the unweighted HiLo original KGE formulation.

that the detection of rapid transition events ~~may depend on the~~ depends even more strongly on catchment attributes (e.g., mean elevation, streamflow regime, etc.).

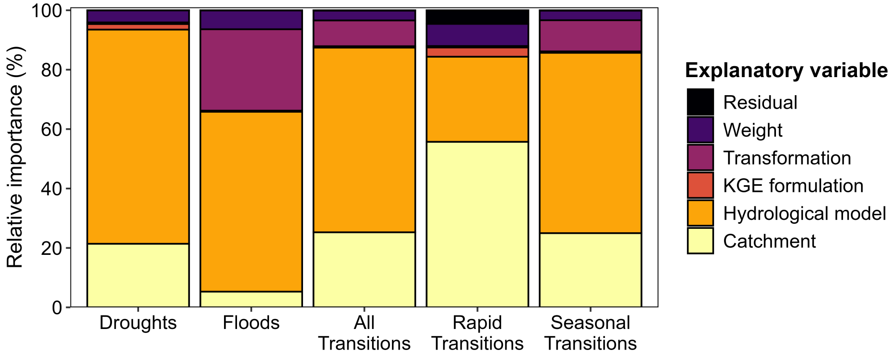


Figure 8. Results of the analysis of variance (ANOVA) applied to the Critical Success Index (CSI) for droughts, floods, all ~~drought-flood~~ drought-to-flood transitions (i.e., rapid and seasonal), rapid transitions (<14 days), and seasonal transitions (<90 days).

4.5 Model performance depends on catchment characteristics

~~Model performance in simulating extreme hydrological events and their transitions depends on catchment characteristics (Figure 9). To identify catchments where model performance is better compared to others, we~~ We explore the relationship between model performance and catchment characteristics using Spearman's rank correlation coefficient. ~~For this~~ To this end, we focus on the CSI obtained for the different types of extreme events of interest (droughts, floods, and transitions) generated with the GR4J and TUW models calibrated with the unweighted ~~Hilo~~ HiLo original KGE formulation (Figure 9).

Our results show that ~~drought-to-flood transitions~~ a model's capability in simulating extreme hydrological events and their transitions depends on catchment characteristics (Figure 9). Drought-to-flood transitions are more difficult to capture in semi-arid (negative correlation between aridity index and CSI), high-mountain (negative correlation between mean elevation and CSI), and flashy (negative correlation between the slope of the flow duration curve and CSI) catchments than in humid low-elevation catchments with high streamflow elasticity to precipitation. This result is generalizable to the other models and the different KGE formulations tested (see Figure ~~S13~~ S9 in the Supplementary Material).

4.6 Linking model performance to hydrological processes during streamflow extremes

We ~~perform~~ conduct an ANOVA test to analyze the relative importance of different model parameters ~~for the detection of~~ in detecting streamflow extremes and ~~transitions between them~~ their transitions (Figure 10; ~~for~~ the extended version ~~see Figure S15~~ with rapid and seasonal transitions is presented in Figure S13 in the Supplementary Material). Here, we show that some model parameters are relatively more important than others (e.g., X4 for floods in GRXJ models), but that the relative importance of a given parameter can vary substantially across catchments. All ~~of the tested~~ the hydrological models show a high importance of the parameters aimed to adjust the forcings (i.e., dP and dT for all the models as well as SCF in TUW model, which seeks to correct for the snow undercatch), highlighting the need for adequate forcing to improve the estimation of extreme hydrological events. For the GRXJ models, ~~parameters~~ X3 (routing store capacity) and X4 (unit hydrograph

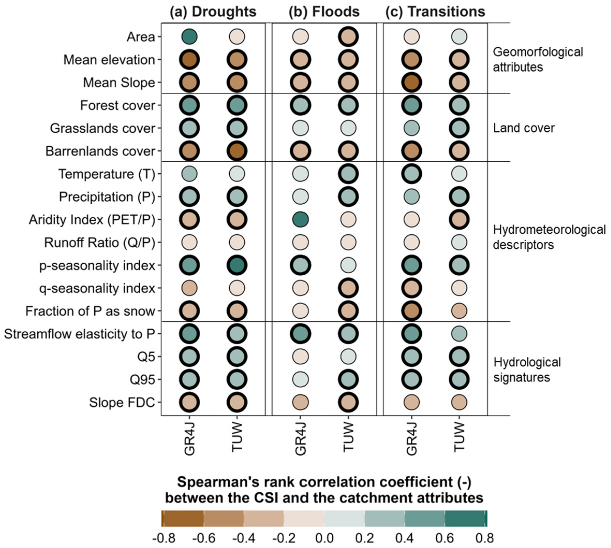


Figure 9. Spearman's rank correlation coefficient between different catchment attributes and the CSI for (a) droughts, (b) floods, and (c) drought-to-flood transitions, based on the simulations with GR4J and TUW calibrated using the unweighted HiLo original KGE formulation as the objective function. The circles with thick outlines indicate statistically significant correlation coefficients at a the 5% significance level.

time constant) are more important in the simulation of low and high flow compared to the rest of the parameters, which is accentuated even more when more complexity is added to the base structure ~~is made more complex~~ (i.e., GR6J). In the TUW model, which has more parameters than the GRXJ structures, the relative importance of each ~~of the parameters is more equal~~ parameter is more uniform, and their relative importance is low, except for the parameter k0 (storage coefficient for very fast response)~~during floods. Additionally, we compare the relative importance of biases in hydrological signatures in the detectionof streamflow extremes and their transitions to identify key processes to be captured to better simulate them, finding that model performance is mainly driven by an adequate representation of streamflow timing (Figure S16 in the Supplementary Material).~~ , which becomes more important for flood detection.

~~The relative importance of the parameters changes depending on the type of streamflow extreme (Figure 10). We select the most important parameters in each model to explore their relationship with some physiographic and hydroclimatic catchment descriptors (see Figure S17 in the Supplementary Material). For the GRXJ models we considered CN2 (degree-day melt coefficient), X3 (routing store capacity), and X4 (unit hydrograph time constant), and for the TUW model DDF (degree-day factor), k0 (storage coefficient for very fast response), and bmax (maximum base of the triangular transfer function). Our results show that while topographic characteristics (i.e., area, mean elevation, slope) show more correlation with the relative importance of snow and river routing parameters for floods, runoff routing parameters become less important during rapid transitions depending on land cover and seasonality. In addition, snow and runoff routing parameters play a key role during seasonal transitions.~~

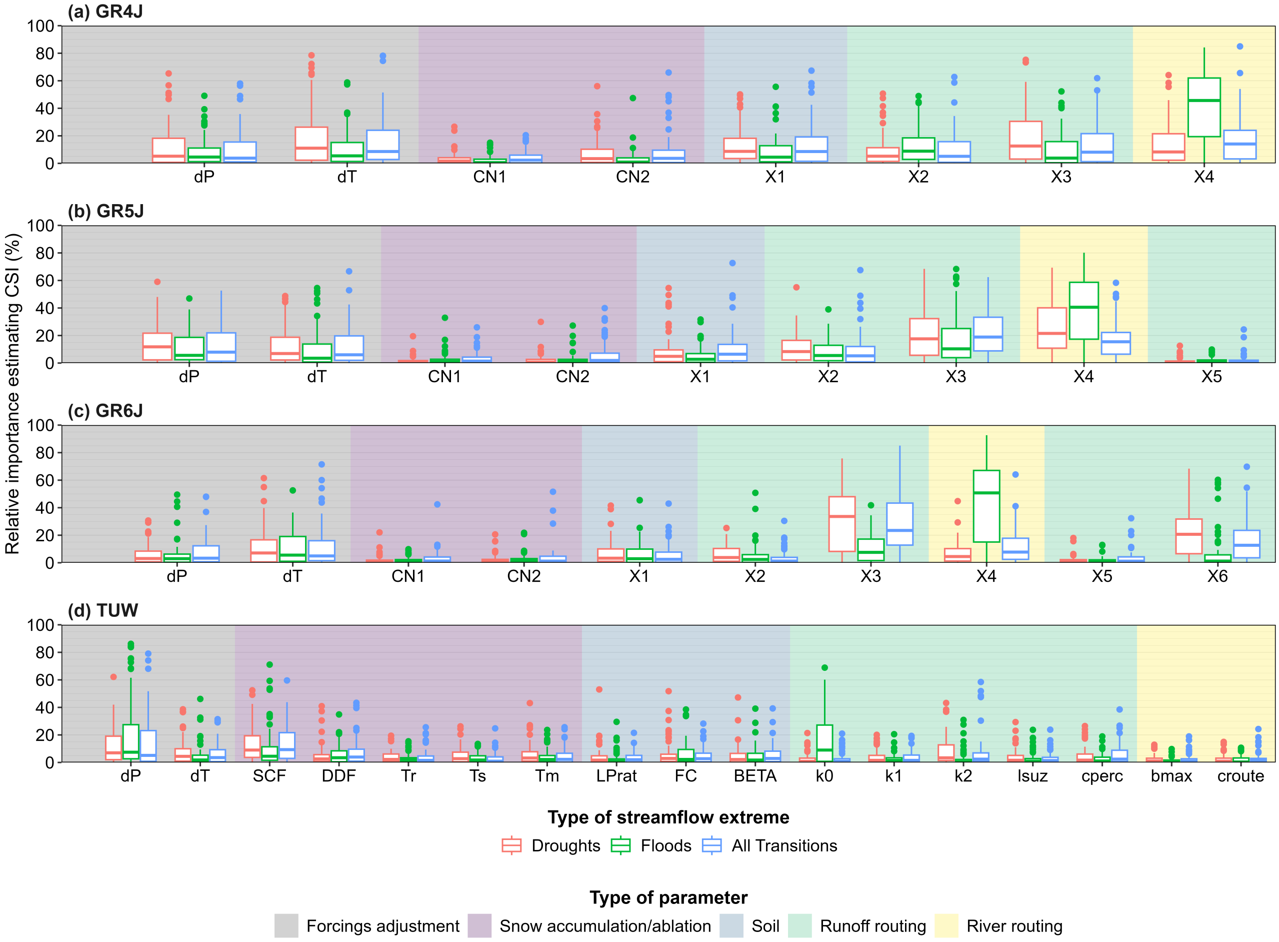


Figure 10. Relative importance of parameters for explaining the Critical Success Index (CSI) for models (a) GR4J, (b) GR5J, (c) GR6J, and (d) TUW based on the results of an analysis of variance (ANOVA).

5 Discussion

5.1 Simulation of compounding streamflow extreme events

We find that the hydrological models tested are better at detecting droughts (median CSI across catchments and KGE formulations: 0.45-0.58 depending on the model) than floods (median CSI across catchments and KGE formulations: 0.15-0.26 depending on the model), and their performance in detecting drought-to-flood transitions is closely related to the performance in detecting floods (Figure 4). This difference in drought and flood simulation performance can be attributed to the different timescales ~~during which~~ associated with these two types of extreme events~~develop~~: while droughts vary in duration from months to years (or decades), floods develop, and may also subside, in a matter of hours or days. This is consistent with the poor performance of all the models tested in capturing rapid transitions (i.e., occurring within 14 days; median CSI equal to zero when rapid and seasonal transitions are analyzed separately; not shown). Moreover, only in ~~thirteen~~ 13 basins - based on different configurations - we obtained CSI values greater than zero for rapid transitions (Table ~~S2~~ S4 in Supplementary Material). Our ~~analysis highlights~~ analyses highlight that these fast processes are rather difficult to capture in conceptual ~~models, even when they have been calibrated.~~ rainfall-runoff models.

5.2 Good general performance does not imply that extremes are well detected

Our results highlight that a good general model performance ~~as e.g. described by the~~ in terms of KGE does not necessarily imply a good performance in detecting streamflow extremes. Even models with ~~high KGEvalues (~~KGE$>$ 0.6 ~~)~~ struggle to capture extreme events, in particular floods and transitions from droughts to floods (Figure 4). These findings are aligned with previous studies ~~which discussed~~ discussing the potential of KGE to represent high-flow values or capture flashy dynamics (e.g., Astagneau et al., 2022; Brunner et al., 2021; Mathevet et al., 2020). For instance, Astagneau et al. (2021a) demonstrated that the relationship between KGE values and ~~model performance in terms~~ a model’s capability of simulating summer floods is weak. Similarly, Bruno et al. (2024) ~~have shown thatduring extreme low-flows~~ showed that, during extreme low-flow conditions, model performance is usually lower than during normal flow conditions. Spieler and Schütze (2024) showed that ~~by focusing on basic catchment-scale behaviors,~~ the KGE lacks the capacity to provide information about detailed processes, leading to gaps between model accuracy (i.e., how well a model matches simulations with observations) and adequacy (i.e., how well a model captures key processes and behaviors of the observed system). These findings suggest that the traditional evaluation of hydrological models through goodness-of-fit metrics such as KGE or NSE must be accompanied by an explicit examination of their capability to simulate and detect streamflow extreme events, e.g. by using metrics such as the CSI.

5.3 The importance of different modeling decisions for simulating streamflow extremes and their transitions

Our results show that model structure is the most important modeling decision for capturing extreme events and their transitions (Figure 8), which is consistent with previous studies focused on the independent analysis of extreme events (e.g., Alexander et al., 2023; Me
. Among the structures tested, the GR4J model ~~is the one that shows the~~ provided the best performance both for the simulation of independent extreme events and for transitions (Figure 6). The TUW model shows similar results but with a lower flood detection performance (median CSI between KGE formulations of 0.19 compared to 0.26 for GR4J). These deficiencies in flood simulation performance translate to deficiencies in capturing drought-to-flood transitions (Figure 4 and Figure 6). The lack of an explicit structural component that allows for the simulation of floods that occur under dry conditions with low soil moisture could explain the poor performance associated with this type of compound event. Astagneau et al. (2022) highlighted that conditioning the storages and fluxes of a lumped conceptual hourly-timestep model on rainfall intensities could benefit model performance in catchments with a fast response to precipitation (i.e., flashy-catchments). For droughts, van Kempen et al. (2021) have shown that the magnitudes of the low-flow events are significantly affected by alterations in the architecture of the upper and lower storages, which is consistent with the changes in performance among the GRXJ models, where small structural modifications lead to important changes in the detection of these events.~~van Kempen et al. (2021) have shown~~

~~that multiple hydrological processes significantly affect the magnitude of high- and low-flow events, which implies that the model structure is an important source of uncertainty. This supports our findings, which show that in the context of studying streamflow extreme events, the choice of hydrological model is the most important decision (Figure 8).~~

We demonstrated that the capability to identify streamflow extreme events and their transitions in simulations is model-dependent. However, the change in performance in detecting extreme events does not necessarily depend on the number of parameters or model complexity. We obtained similar performances between GR4J and TUW despite their structural differences (Figure 6), unlike GR5J and GR6J, whose performance declines in comparison with GR4J. ~~Thus, how hydrological models represent the interactions, flows and states in the hydrological cycle (i.e., model parametrization) could be influencing their performance (e.g., Knoben et al., 2020; Beven and Chappell, 2021; van Kempen et al., 2021).~~ Several studies have highlighted that including a more detailed representation of hydrological processes in models does not necessarily imply better performance (e.g., Orth et al., 2015; Valéry et al., 2014a). This is because more ~~detailed~~ realistic representations require more detailed information to characterize the system of interest ~~, which is not necessarily always available at high quality~~ (e.g., land cover maps, distributed forcings, high-resolution digital terrain model, soil properties~~, etc.).~~), which is not always available. Recently, Santos et al. (2025) found that models with varying complexity can lead to similar robustness issues~~. Consequently, beyond the complexity of the selected modeling structure, understanding the extent to which these are useful for studying the phenomenon of interest is key, suggesting the~~ , stressing the need to improve strategies for ~~identifying~~ diagnosing the suitability of ~~a given structure~~ model structures to improve the understanding of specific processes (e.g., Spieler and Schütze, 2024; Knoben et al., 2020).

~~Compared to~~ The results presented here show that the choice of ~~model structure, the choice of~~ objective function is ~~less important~~ relatively less important compared to the choice of model structure (Figure 8). However, model performance can be optimized both in terms of general performance (NSE) and the representation of extreme events (CSI) under (a) the application of equal weights to all components of the KGE (Figure 5) and (b) the application of a streamflow transformation that focuses on both high and low flows (Figure ~~??a~~S6 and S7 in the Supplementary Material). Our comparison also highlights that the potential benefit from adjusting these choices (e.g., using other weights or other transformations) varies widely between catchments (Figure 5). This is in line with the findings of Mizukami et al. (2019), who found that the influence of weights on model performance depends on model structure and ~~catchments~~ catchment characteristics. While none of the tested modifications in the objective function consistently ~~improves~~ improve the simulation of streamflow extremes across all catchments in the study domain, some of the alternative KGE formulations could improve the simulation of certain variables. ~~For example, KGE_np (Pool et al., 2018) shows median differences close to zero when both NSE(Q) and NSE(1/Q) are assessed independently of the flow transformation applied. Its performance highlights the ability of this formulation to capture the distribution of flows, which can be directly attributed to its non-parametric conceptualization.~~

~~The meteorological forcing used to simulate streamflow extreme events can also have a major impact on the model's performance (Figure 10). Our results show a high importance of the parameters aimed to adjust the forcings~~ Given the relative importance shown by the forcing adjustment parameters (i.e., dP and dT for all the models as well as SCF in TUW model, which seeks to correct the snow undercatch~~)~~ ; Figure 10), the meteorological forcings can also have a major impact for detecting streamflow extremes and their transitions. ~~Obtaining reliable meteorological forcing has been highlighted as one of the key challenges in hydrological modeling studies (e.g., Brunner, 2023; Döll et al., 2016).~~ Several studies have shown that errors in meteorological forcing ~~data have a~~ are a key challenge in hydrological modeling (e.g., Brunner, 2023; Döll et al., 2016) due to, e.g., their large influence on the simulation of snow processes (e.g., Tang et al., 2023; Günther et al., 2019)~~because of their influence on the precipitation phase (Harder and Pomeroy, 2014)~~, or significant impacts on the partitioning between evaporation and runoff (e.g., Nasonova et al., 2011). ~~These previous studies and our findings suggest that~~ Here, we attempt to reduce this effect by (1) utilizing local meteorological products over global ones, based on the evidence that these may enhance hydrological modeling (e.g., Clerc-Schwarzenbach et al., 2024), and (2) incorporating adjustment factors to account for potential systematic biases associated with them (e.g., Hughes, 2024; Probst and Mauser, 2022). However, introducing forcing adjustment factors could compensate for some model deficiencies by modifying the inputs (e.g., Tang et al., 2023, 2025) . This is somehow reflected by the high dispersion of forcing adjustment factors within each configuration (Figure S11 in the Supplementary Material). Therefore, an improvement in the spatiotemporal representation of precipitation and temperature, as well as of the potential interactions between these variables, could contribute to ~~improving the representation of compounding~~ improved representations of compound streamflow extreme events in hydrological models.

5.4 Limitations and recommendations for future work

Our model ~~and methods intercomparison~~ calibration experiments focused on the simulation of extreme streamflow events, which required the choice of specific event definitions. Here, we ~~have~~ defined hydrological droughts and floods using ~~threshold based-approaches. The thresholds have been~~ threshold-based approaches, and the thresholds were adjusted in a way to identify, on average, one event per year and catchment. ~~This~~ Because this methodological choice does, to a certain degree~~influence~~, affect the outcomes of the comparison~~. To describe this influence~~, we tested different thresholds for defining streamflow extreme events. The results of this sensitivity analysis ~~show that the use of more relaxed~~ indicate that using more flexible thresholds to define droughts (i.e., higher percentiles) can ~~improve the performance of the models in detecting such events~~enhance the detection of these events, as more instances are identified, and they tend to be less severe compared to more restrictive thresholds. However, we did not find such an effect for floods and transitions, for which we ~~find~~ obtained similar model performances ~~independently~~ regardless of the thresholds used (see Figure S2 in Supplementary Material). The improvement in drought detection when the threshold is relaxed can be explained by the ~~observation~~ fact that models generally struggle ~~more with more extreme events~~ during more extreme hydrological drought periods (e.g., Bruno et al., 2024), which are relatively less ~~numerous~~ frequent if the threshold is ~~lowered.~~ raised. Similar results are obtained when the overlap window used to identify the hits is modified (Figure S3). While our study shows that ~~threshold choice~~ the choice of threshold does not substantially affect model performance in terms of transition events, the method used to define streamflow extreme events can have a major impact on the characteristics of the transition events identified.

To support our analysis, we tested four bucket-type hydrological models ~~widely~~ used within the hydrological modeling community (Addor and Melsen, 2019). Even though these models are at the lower end in terms of model complexity (Hrachowitz and Clark, 2017), and three of them share the same core structure, they allowed us to perform a comprehensive analysis of different model structures at a lower computational cost than when using models with more complex structures (e.g., Clark et al., 2017; Orth et al., 2015; Poncelet et al., 2017). Furthermore, previous studies ~~and our study have~~ have also shown that more complexity does not necessarily imply better performance (Figure 6; e.g., Li et al., 2015; Merz et al., 2022). These models have been calibrated based on daily streamflow records, assuming that the numerical convergence of the optimization algorithm ensures (to some extent) a successful calibration process (see Text S1 in the Supplementary Material). However, it is important to acknowledge that potential compensations for biases in meteorological forcings or model deficiencies can make the "optimal" parameter sets less identifiable (e.g., Clark and Vrugt, 2006; Vrugt et al., 2005; Beven, 2025). Here, we explore the (dis)agreement between the optimal parameters for each configuration (Figure S12 in the Supplementary Material), showing overall agreement indices of around 0.5 (i.e., the parameters have a range of variation of approximately 50% of the parameter space). This highlights the need to incorporate, for example, hydrological variables such as SWE or ET, to (i) complement model assessment, (ii) better define the parameter exploration range (Figure S10 in the Supplementary Material), and (iii) lead to parameter sets that ensure reliability and fidelity in representing hydrological processes.

Our results provide ~~some insights on which~~ insights on possible avenues of future research that could benefit drought-to-flood transitions modeling~~:~~, which include: (1) exploring the use of modular platforms and a multi-model ensemble approach to quantify model uncertainty and identify more suitable model structures (e.g., Saavedra et al., 2022); (2) improving our understanding of the role of the spatial variability of precipitation for accurate flood simulations (e.g., Macdonald et al., 2025; Astagneau et al., 2022); (3) assessing the benefits of model runs at a subdaily timestep (e.g., hourly); and (4) exploring alternative data-driven modeling approaches such as long short-term memory (LSTM) networks ~~(e.g., Frame et al., 2022; Anshuka et al., 2022)~~ (e.g., Frame et al., 2022; Acuña Espinoza et al., 2025; Kratzert et al., 2018). Additionally, exploring relationships between the occurrence or characteristics (e.g., duration, severity) of this type of hydrological extreme events and some large-scale climate patterns (Garreaud et al., 2020; Marengo and Espinoza, 2016; Sun et al., 2016; De Luca et al., 2020) could improve their predictability.

6 Conclusions

We performed a ~~methods and models~~ modeling intercomparison study to (i) explore to what extent hydrological models can simulate drought-to-flood ~~transition~~ transitions and (ii) identify suitable modeling choices aimed at capturing these compound extreme events. For this intercomparison, we calibrated four conceptual bucket-type hydrological models (GR4J, GR5J, GR6J, and TUW) for 63 catchments in Chile and Switzerland using 60 different configurations of the Kling-Gupta Efficiency (KGE) as objective functions, based on five KGE formulations, four scaling factors, and three streamflow transformations. Based on the results of this intercomparison, we draw the following conclusions:

1. ~~Drought events are better captured by hydrological models than flood events. As a consequence, a model's capability in detecting transitions from drought-to-flood events mainly depends on how well it captures flood events. In addition, model performance with respect to capturing all three event types varies widely between catchments.~~

2. A satisfactory general model performance, as expressed by the KGE~~or NSE ,~~, does not guarantee a good performance in terms of detecting streamflow extremes and their transitions. While KGE can serve as a rough proxy for low-flow performance, it cannot for high-flows and drought-to-flood transitions. Consequently, assessments of the suitability of hydrological models for simulating extreme events and their transitions should be complemented with metrics describing extreme event detection performance such as the critical success index (CSI).

3. The most important modeling decision when it comes to simulating floods, droughts, and their transitions is the choice of a suitable model structure. Here, we demonstrate that the GR4J and TUW models have similar performance - with GR4J being slightly better at detecting floods and transitions - and adding model complexity by increasing the number of parameters does not necessarily improve the representation of extreme events.

4. In contrast, the choice of the objective function and its exact configuration are less important. The choice of a suitable streamflow transformation can improve the simulation of extreme events to a certain degree. Specifically, a joint focus on high and low flows by equally weighting the two streamflow transformations in the objective function (referred to as HiLo in our analysis) can improve model performance without compromising its ability to capture streamflow extremes. However, the choice of the exact KGE formulation and the use of weights for the variability term of the KGE do not substantially affect the simulation of extreme events and the direction of this effect depends on the catchment.

5. ~~The model parameters targeted at adjusting the meteorological forcing are relatively more important than other parameters in explaining the CSI variations. This highlights the need for adequate meteorological forcing data that adequately represent the spatiotemporal properties of precipitation and temperature.~~

6. A model's performance in simulating streamflow extremes and transitions primarily depends on how well it captures streamflow timing rather than other hydrological signatures or variables such as evapotranspiration or snow water equivalent.

7. Drought-to-flood transitions are more difficult to capture in semi-arid, high-mountain, and flashy catchments than in humid low-elevation catchments.

This ~~methods and model~~ methodological intercomparison highlights that simulating streamflow extremes and their transitions is not a trivial modeling task and continued research is needed to improve model performance. The results of this intercomparison study suggest that time is best invested when focusing on improving model structures rather than calibration procedures. Specifically, hydrological model development should focus on improving the representation of processes and components associated with the temporal dynamics of discharge, such as routing or the soil response to intense snowmelt and rainfall. ~~In addition~~Additionally, the strong link between model performance and parameters aimed at correcting precipitation inputs suggests that the representation of extreme events could also be improved by investing in the quality of meteorological forcing datasets. Investments in improving the simulation of extreme events and their transitions are crucial because hydrological models can not only support process understanding related to compounding streamflow extremes, but also can be used to forecast such events at short time scales ~~,~~ and to project future changes in the ~~occurrences~~ occurrence of drought-to-flood transitions~~– applications that are strongly needed~~. Such applications are critical to ensure society's preparedness for these ~~impactful~~ types of hydrometeorological extreme events.

Code and data availability. The R-scripts and data used to produce the results shown in this paper - such as parameter sets used to generate the simulations and performance metrics - are publicly available through Zenodo (Muñoz-Castro et al., 2025, https://doi.org/10.5281/zenodo.14803501). CAMELS-CL (Alvarez-Garreton et al., 2018a) is available at PANGAEA (Alvarez-Garreton et al., 2018b) and https://camels.cr2.cl/ while CAMELS-CH (Höge et al., 2023a) at Zenodo (Höge et al., 2023b). The GLEAM3.8a dataset (Miralles et al., 2011) is available upon request at https://www.gleam.eu/.

Author contributions. EMC, BJA, and MIB conceptualized and designed the study. EMC conducted all the model simulations, analysis of results, and created the figures. All authors contributed to discussing the methodology and results and to reviewing and editing the manuscript.

Competing interests. One of the co-authors is a member of the editorial board of Hydrology and Earth System Sciences (HESS).

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