



Data-driven flood classification to assess climate change effects on riverine compound floods in pre-Alpine catchments

Henrique M. D. Goulart^{1,2}, Lily-belle Sweet³, Axel Deijns^{4,5}, Seth Bryant^{6,7,8}, Benjamin Poschlod^{9,10}

¹Climate Adaptation and Disaster Risk Management, Deltares, Delft, the Netherlands

5 ²Institute for Environmental Studies, VU University Amsterdam, Amsterdam, the Netherlands

³Department of Compound Environmental Risks, Helmholtz Centre for Environmental Research, Leipzig, Germany

⁴Royal Museum for Central Africa, Department of Earth Sciences, Tervuren, Belgium

⁵Department of Water and Climate, Vrije Universiteit Brussel, Brussels, Belgium

⁶GFZ Helmholtz Centre for Geosciences, Hydrology Section, Telegrafenberg, 14473 Potsdam, Germany

10 ⁷Institute of Environmental Science and Geography, University of Potsdam, Potsdam, Brandenburg, Germany

⁸University of Wisconsin-Madison, Nelson Institute for Environmental Studies, Madison, WI 53706, U.S.A.

⁹Institute for Global Water Security, Hamburg University of Technology, 21079 Hamburg, Germany

¹⁰Earth and Society Research Hub (ESRAH), Universität Hamburg, 20146 Hamburg, Germany

15 *Correspondence to:* Henrique M. D. Goulart (henrique.goulart@deltares.nl)

Abstract. Flood events are some of the most impactful natural hazards globally, and in most cases, they result from combinations of different hydrometeorological drivers, defined as riverine compound floods. Climate change is projected to alter the frequency and interplay of these drivers, posing a challenge for flood risk assessment. In this study, we develop an unsupervised machine learning approach to identify distinct riverine compound flood types and to classify individual flood events based on hydrometeorological features. These classifications are then used to assess climate change effects on flood risk. We use hydrological large-ensemble simulations in four neighbouring Bavarian pre-Alpine catchments, encompassing historical and future periods. Results project systematic shifts in the frequency and magnitude of flood regimes under warming. The frequency of rainfall-driven and rain-on-snow floods increases with warming, rising by 22% and 8%, respectively, between +1 K and +4 K. Conversely, snowmelt-driven flood frequency declines substantially (approximately 42 % between +1 K and +4 K), consistent with a diminishing role of snow in pre-Alpine flood generation. Frequencies of saturation excess floods, characterised by antecedent wet conditions, show declines of about 10 %. For 100-year return levels, rainfall-driven events show the largest increases in flood magnitude, though with strong variability between catchments (1 % to 48 % between +1 K and +4 K). Conversely, the magnitude of 100-year return-level snowmelt-driven events decreases 10-13 %. Seasonally, pre-Alpine flood risk shifts from a spring, snowmelt-dominated regime towards rainfall-driven flooding throughout the year, with implications for seasonal preparedness, infrastructure design, and forecasting systems. We compare our unsupervised machine learning approach with an established threshold-based classification method, with the two classifications converging for 64 % of events. By identifying which flood types increase or decrease under warming scenarios, our compound flood classification framework supports the development of process-specific adaptation strategies.



1 Introduction

- 35 Riverine flooding causes considerable impacts worldwide, including billions of dollars in economic damages, disruptions to critical infrastructure and services, thousands of fatalities, and the displacement of many more people (Rentschler et al., 2022). Climate change is expected to worsen these impacts (Rogers et al., 2025). Rising temperatures and changing precipitation patterns will likely increase flood frequency and severity in many regions around the world (Huang et al., 2024; Merz et al., 2021; Willkofer et al., 2024).
- 40 Many flood events are not caused by a single extreme driver (i.e., heavy rainfall), but by combinations of drivers that might not be extreme in isolation, which can be defined as riverine compound floods (Berghuijs et al., 2019; Massari et al., 2023, Jiang et al., 2024). In pre-Alpine catchments, a well-documented type of riverine compound floods is rain-on-snow (ROS), which occurs when rainfall on existing snowpack accelerates melt and runoff (Beniston & Stoffel, 2016). These events have caused multiple floods in mountain regions in the United States in the past decades (McCabe et al., 2007; Musselman et al.,
- 45 2018) and are also found to be a dominant flood generating process in the European Alps, pre-Alps, and middle mountain ranges (Berghuijs et al., 2019; Hotovy et al., 2025). Another well-documented riverine compound flood mechanism involves antecedent high soil moisture conditions, where moderate rainfall leads to saturation excess generating potentially severe flooding (Berghuijs et al., 2019; Jiang et al., 2022; Massari et al., 2023), as exemplified by the Bavarian floods in 2013 (Thieken et al., 2022).
- 50 Under climate change, shifts in the drivers and timing of riverine compound floods are already being observed. These include changes in flood seasonality and evidence of a decrease in snowmelt-driven floods alongside an increase in rainfall-driven floods (Jiang et al., 2022), coupled with an intensification of short-duration rainfall events (Haslinger et al., 2025). Future climate projections indicate more extreme rainfall, a continued shift from snowmelt to rainfall dominance in Alpine flood generation, and subsequent changes in the frequency of specific compound event types (Frei et al., 2018). A global analysis of
- 55 ROS projections suggests that ROS events will become more frequent in high-elevation and high-latitude regions, while decreasing in low-elevation zones (Maina & Kumar, 2025).
- However, different catchments respond differently to climate-change-induced shifts in hydrometeorological drivers according to their specific characteristics, including catchment size and shape, topography, soil and geology, land cover, land use, open water bodies, and human management (Musselman et al., 2018; Haslinger et al., 2025; Liu et al., 2022; Stein et al., 2021).
- 60 Hence, the assessment of riverine compound floods relies on different established methods. Common approaches include statistical and empirical analyses (Berghuijs et al., 2019; Jiang et al., 2022), hydro-climatological modelling of drivers (Poschlod et al., 2020a), hydrological modelling (Bonsoms et al., 2024; Staudinger et al., 2025), and event-based reconstructions (Thieken et al., 2022). Assessing flood risk in a changing climate requires both hydrological and climatological perspectives to be considered (Brunner et al., 2021). Recent efforts have been made towards integrated climate-hydrology
- 65 modelling chains to better capture the complex interactions of hydrometeorological drivers under different future climate scenarios (Dottori et al., 2018; Sauer et al., 2021; Willkofer et al., 2024; Zhao et al., 2025).



Classifying flood events into types can improve scientific understanding of the different underlying flood generation processes, and allows researchers to detect and quantify changes in each of these processes (Tarasova et al., 2019). Furthermore, flood classification is relevant for flood risk management, as different flood types require tailored strategies for prevention and adaptation (Corral et al., 2019; Heggli et al., 2022; Lallemand et al., 2021; Rössler et al., 2014). Currently, a variety of classification frameworks are used, each with differing strengths and weaknesses. Tarasova et al. (2019) distinguish between hydroclimatic, hydrological, and hydrograph-based flood classification methodologies. Classification methods can either be tailored to a study area or designed for global application independent from the location. Flood types and corresponding classification criteria can either be derived from the underlying data (Keller et al., 2018) or make use of expert-defined thresholds that are assumed to be globally applicable (Stein et al., 2020). Generally, Tarasova et al. (2019) note that classification methodologies are sensitive to uncertainties or small deviations in the input data. The global flood classification study by Stein et al. (2020) reveals that there is high year-to-year variability in most catchments in flood generating processes. Hence, a sufficient number of flood events is needed for a robust classification, which can be achieved by clustering events from similar catchments or generating long synthetic timeseries of discharge (Turkington et al., 2016).

Different riverine compound flood types exhibit varying sensitivities to climate change, which can alter future risk projections (Brunner et al., 2021). Therefore, quantifying the types of riverine compound floods in a given region and their projected future changes is important for informing effective and climate-adaptive flood risk management policies.

In this study, we aim to explore climate change effects on flood types in four neighbouring pre-Alpine catchments. Due to the regional climatology, a variety of flood types can occur, including floods driven by short-term rainfall, longer-duration rain events, soil saturation excess, rain-on-snow, and snowmelt. To disentangle how climate change affects the flood-generating processes under local conditions, we propose a compound flood classifier based on an unsupervised machine learning clustering algorithm that categorises flood regimes without predefined flood types and thresholds. We apply the flood classification to a hydrological large ensemble covering 1963–2099 under a high-emission scenario, with 50 realisations equalling almost 7000 years of simulated discharge. The approach is data-driven, and such methods are known to be sensitive to the input data, in which extreme floods are rare and floods of each specific type rarer still. By comparing the flood event classifications obtained using the full dataset for clustering with those obtained using individual ensemble members, we show that our clustering approach is robust to the input dataset and its size. We investigate which flood types arise from the flood-generating processes and their compound occurrence, and how their frequencies and magnitudes change in worlds that are 2 K, 3 K, and 4 K warmer.

2 Study area

For this study, we consider four neighbouring head catchments of the Upper Danube basin in the Alps and pre-Alps, in which the Alpine parts belong to the Northern Limestone Alps. The study area includes the rivers Iller, Lech, Ammer, and Loisach at the gauges Kempten, Füssen, Weilheim, and Schlehdorf, respectively (Fig. 1). While the Iller and Lech are direct tributaries

of the Danube, Loisach and Ammer (via Lake Ammersee; Bueche et al., 2020) contribute to the Isar River, which then flows into the Danube. The four river catchments cover areas from 608 to 1416 km² and an elevation range between 550 m at the Weilheim gauge and over 3000 m at the highest mountain peak of the Lech Alps. In the Alpine areas, bare limestone rock and shallow soils occur, whereas loamy soils and highly permeable gravel deposits are prevalent in the floodplains (Velazquez et al., 2013). Forest dominates the land cover of all catchments (Table 1), with its spatial distribution governed by topography. This results in a north–south gradient, with more forest in the valleys and on the slopes of the southern Alpine regions and elevation defining the tree line. Annual precipitation ranges between 1400 and 1600 mm, with the wet summer season (JJA) contributing more than one-third of annual precipitation. The average annual temperature is between 7 and 8 °C for the Iller, Ammer, and Loisach catchments, while the more Alpine Lech catchment experiences an average annual temperature of 4 °C. These climatological conditions shape the hydrological regimes of the rivers, indicating nivo-pluvial to pluvio-nival regimes (Poschlod et al., 2020b). Winter shows the lowest mean flow, with a minimum in February, while snowmelt induces the highest monthly mean flow in April (Ammer and Loisach) and June (Lech and Iller). Major flooding can occur either in spring due to a combination of snowmelt and heavy rainfall (rain-on-snow) or in summer due to heavy rainfall enhanced by strong orographic lifting (Dobler et al., 2012; Poschlod and Koh, 2024). Hence, the study catchments show flood events governed by a variety of flood-generating processes acting at various timescales and in combination.

Table 1: Areal fraction of land cover of the study area catchments based on CORINE Land Cover 2018 (EEA, 2020).

Land cover	Ammer	Loisach	Iller	Lech
Artificial areas	4 %	4 %	4 %	3 %
Pasture	10 %	36 %	29 %	6 %
Natural grassland	3 %	5 %	23 %	23 %
Forest (broad-leaved)	2 %	6 %	0.7 %	0.4 %
Forest (coniferous)	34 %	35 %	21 %	28 %
Forest (mixed)	11 %	16 %	9 %	6 %
Moors, heathland, wetland	5 %	12 %	4 %	13 %
Bare rock and sparsely vegetated areas	1 %	10 %	5 %	21 %
Open water bodies	2 %	0.3 %	0.8 %	0.4 %

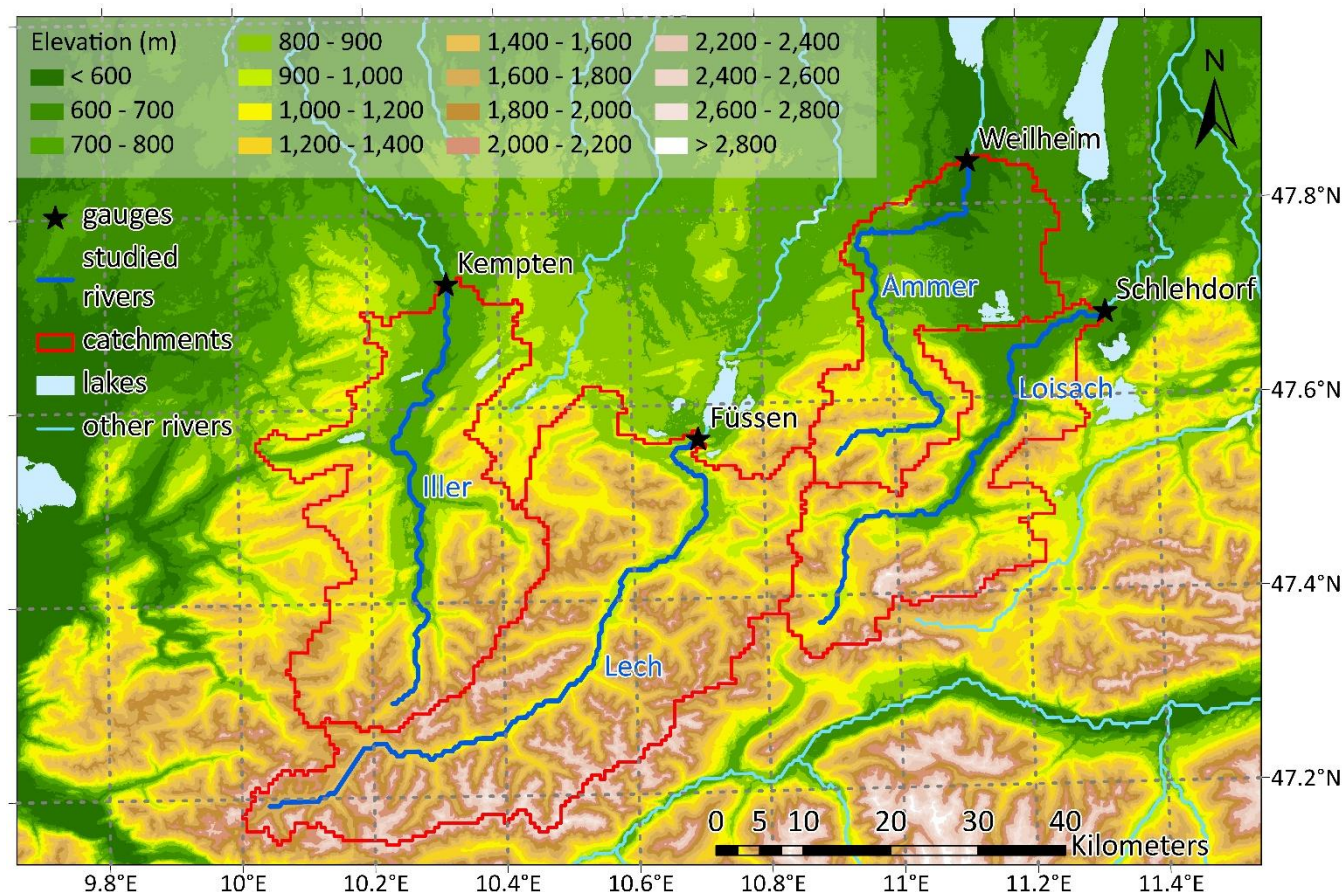


Figure 1: Elevation of the four study catchments in the Alps and pre-Alps. The topography is based on the digital elevation map GLO-30 by Copernicus (ESA, 2025).

120 3 Data

The hydrological large-ensemble simulations (Willkofer et al., 2020, 2024) are generated by driving the Water balance Simulation Model (WaSiM; Schulla, 2021) with climate variables from a single-model initial-condition large ensemble (SMILE). The Canadian Earth System Model version 2 large ensemble (CanESM2-LE; Fyfe et al., 2017), consisting of 50 members, is dynamically downscaled with the Canadian Regional Climate Model version 5 (CRCM5) at 0.11° resolution over Europe (equalling approximately 12 km; Leduc et al., 2019). The climate simulations cover 1955–2099, with the high-emission scenario RCP8.5 starting in 2006. Next, bias adjustment and further statistical downscaling to 500 m resolution are conducted to drive the spatially distributed hydrological model WaSiM at 3-hourly time steps. WaSiM employs process-oriented modules simulating interception, evapotranspiration, snow accumulation, snowmelt, glaciers, soil water storage, and runoff generation (Schulla, 2021). The calibration and validation of the hydrological model are based on a comparison with observed discharge, where Willkofer et al. (2020) follow Moriasi et al. (2007) by applying four performance metrics: the Nash–Sutcliffe efficiency



(NSE), its logarithmic version (logNSE), the Kling–Gupta efficiency (KGE), and the ratio of root mean squared error to standard deviation (RSR). Using this calibration and the driving climate from the 50-member CRCM5-LE, the unique hydro-SMILE WaSiM-LE is generated, for which the ensemble spread can be interpreted as the propagation of internal climate variability to the regional hydrology of the catchments (Deser et al., 2020). Due to the complexity of the full climatological and hydrological modelling chain, we refer the reader to Leduc et al. (2019) for details on climate modelling, Willkofer et al. (2018) for insights into bias correction, and Willkofer et al. (2020) for the calibration and validation of WaSiM. The resulting simulations have been described and successfully applied by Poschlod et al. (2020b) to explore hydrological regimes and by Brunner et al. (2021) and Willkofer et al. (2024) to investigate floods. Furthermore, the four selected neighbouring catchments also serve as a testbed for a statistical deep learning approach to concurrent floods and droughts (Murphy-Barltrop et al., 2026). For the four catchments in this study, the validation metrics indicate satisfactory performance of the modelling chain in capturing discharge characteristics (Table 2).

Table 2: Performance metrics of the validation of the WaSiM setup comparing to discharge observations.

Catchment	NSE	KGE	logNSE	RSR
Ammer (Weilheim)	0.76	0.71	0.79	0.49
Loisach (Schlehdorf)	0.67	0.74	0.74	0.58
Iller (Kempten)	0.76	0.71	0.75	0.49
Lech (Füssen)	0.76	0.86	0.80	0.49

4 Methods

4.1 Flood definition

Flood events are defined using a peaks-over-threshold (POT) approach, where the 5th percentile of the annual maxima for each catchment, pooled over all 50 members and the full simulation period (1963–2099, as 1961–1962 are discarded as hydrological model spin-up), is selected as the operational threshold. A flood event occurs whenever discharge exceeds this threshold. For each continuous exceedance period, the time of peak discharge is designated as the flood occurrence time. To account for the temporal clustering of flood events, exceedances occurring within a five-day period following an initial peak are considered part of the same flood event, with the maximum discharge across the entire period designated as the flood peak. Table 3 shows the discharge threshold for each catchment in this study and corresponding number of identified flood events.



155

Table 3: Catchments, discharge thresholds and the number of identified flood events. Note that the number of floods is based on 137 years $\times$ 50 ensemble members. Hence, on average about three floods per year are identified.

Catchment	Discharge threshold ($\text{m}^3 \text{s}^{-1}$)	Number of flood events
Ammer	68.53	19,507
Loisach	60.21	19,742
Iller	159.54	18,208
Lech	188.57	18,101

4.2 Hydrometeorological and hydrological features

160 The types of floods are defined based on their characteristic hydrometeorological and hydrological conditions. These features are obtained from the WaSiM model, and are mainly divided in precipitation, snow and soil moisture categories (shown in Table 4). They are also selected after confirmation that they are not overrepresented in one of the catchments, to avoid accidentally clustering on catchment characteristics instead of flood-generating processes. Before applying the clustering, all features are normalised using a 0 to 1 scaling to avoid disproportionate weighting of features with larger ranges. To account
 165 for the delay between the triggering process and the flood peak at the outlet of the catchment, we derive the response time of each catchment empirically (Langridge et al., 2020). We identify a subset of very intense rainfall-driven floods with a single discharge peak and assess the time lag between the rainfall peak and discharge peak, yielding response times from 6 hours (Ammer) to 15 hours (Lech).

170

Table 4: Features used for the flood event clustering.

Feature description	Category
Total rainfall in 7 days before response time	Precipitation
Total rainfall in 24 hours before response time	Precipitation
Total snowmelt in 7 days before response time	Snow melt
Soil water increase over 72 hours before response time	Soil moisture



Soil water increase over 5 days before response time	Soil moisture
Ratio of maximum 24h rainfall to total 7-day rainfall before response time	Precipitation
Ratio of 7-day rainfall to total 7-day input (rain + snowmelt) before response time	Precipitation
Ratio of 72-hour rainfall to total 7-day rainfall before response time	Precipitation
Ratio of (72h rain + 24h snowmelt) to total 7-day input before response time	Precipitation and snow melt
Ratio of 24-hour rainfall to total 7-day rainfall before response time	Precipitation
Ratio of 24-hour input (rain + snowmelt) to total 7-day input before response time	Precipitation and snow melt
Ratio of 24-hour snowmelt to total 7-day snowmelt before response time	Snow melt
Ratio of 24-hour rainfall to total 24-hour input (rain + snowmelt) before response time	Rain and snow melt

4.3 Clustering algorithm

To identify flood types, we use the k-means clustering algorithm. It is a widely-used unsupervised machine learning algorithm that partitions observations into k clusters (Likas et al., 2003). The process begins by randomly initialising k cluster centroids and assigning each data point to the nearest centroid. The function calculates the sum of squared Euclidean distances between points and their assigned cluster centroids. The algorithm repeats this process with the objective of reducing the sum of squared distances and until convergence is achieved. The clustering algorithm is applied to all flood events identified in the 50-member ensemble dataset. The optimal number of clusters is determined based on the silhouette and distortion scores (Shahapure, 2020) for k ranging from 3 to 8.

To assess the sensitivity of the clustering approach to the input dataset, we apply the same algorithm separately to repeated subsets of the dataset (corresponding to 1, 2, 5 and 10 members) and compare the classifications for each flood event to those obtained using the full 50-member ensemble.

4.4 Flood classification

The best division of flood categories for the data is achieved for $k = 5$. Upon inspection (Fig. 2), this corresponds to the following flood categories:

- 1) Rainfall-driven floods: These represent flood events where intense rainfall of short to moderate duration is the primary driver, with limited influence from antecedent conditions. They are characterised by high 24-hour antecedent rainfall amounts (median values of 35–50 mm).



- 190 2) Saturation excess (rain): These events occur when catchments are already saturated with water, allowing even less
intense but longer-duration rainfall to cause flooding. They display moderate rainfall amounts (20–30 mm) and lower
snow water equivalent ratios (0.3–0.4).
- 3) Rain-on-snow floods: These are hybrid floods in which rainfall triggers or enhances snowmelt, creating compound
flood events with multiple contributing factors. They show substantial rainfall (30–40 mm) coupled with high snow
195 water equivalent ratios (0.5–0.7), typically within a short to moderate duration.
- 4) Saturation excess (rain and snow): These represent events in which antecedent moisture, combined with some degree
of snowmelt and low to moderate precipitation, creates flood conditions. They exhibit lower rainfall contributions
(15–25 mm) with intermediate snow water equivalent ratios (0.3–0.5).
- 5) Snowmelt-driven floods: These represent temperature-driven events, where accumulated snow melts rapidly,
200 potentially due to warm air masses rather than rainfall. They differ from other types of floods as they show minor
rainfall contribution (<10 mm).

When applying the clustering approach to subsets of the dataset from individual ensemble members, the categories obtained
are near-identical in their hydrometeorological characteristics, suggesting that the categories are robust to the input dataset.
For each category, 95–97 % of flood events are classified in the same manner, with the exception of saturation excess (rain
205 and snow), for which 20 % of flood events are categorised differently when input-data subsets are used for clustering, largely
as snowmelt-driven or rain-on-snow events. This behaviour is similar for all catchments and across all flood magnitudes.
Increasing the dataset size results in greater consistency in the classifications. For example, when subsets of five ensemble
members are used, 97–100 % of flood events in each category are identically classified.

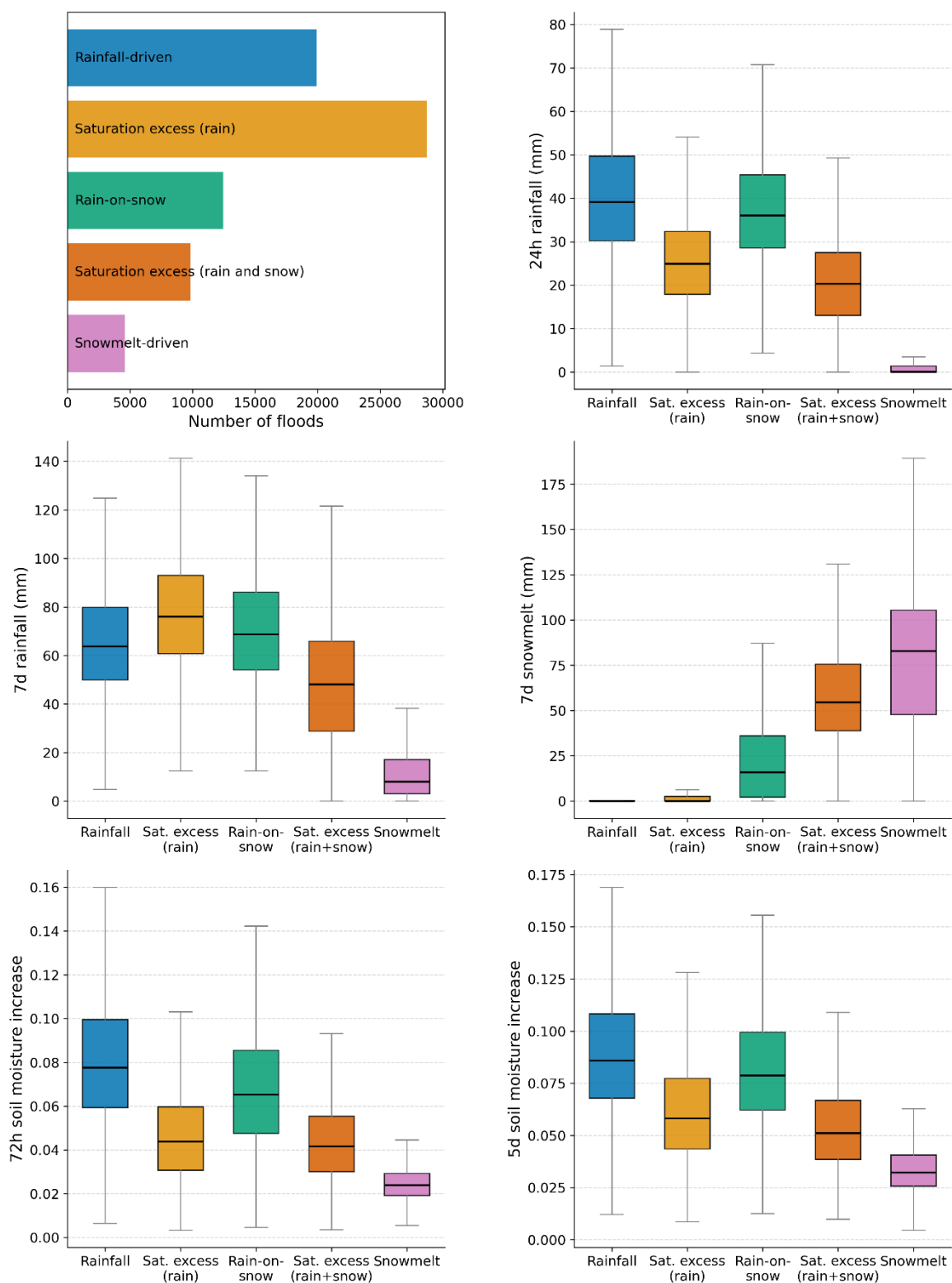




Figure 2: Characteristics of identified flood types. The top-left panel shows the number of flood events assigned to each cluster. The remaining panels show the distributions of key hydrometeorological and hydrological characteristics for each flood type: 24-h rainfall, 7-day rainfall, 7-day snowmelt, and increases in soil moisture over the 72 h and 5 days preceding the flood event. Colours indicate the different flood types (clusters).

4.5 Individual flood events

We demonstrate an individual case of each flood type to clarify the hydrometeorological conditions that trigger different flood types. Rainfall-driven floods (Fig. 3a) have the most direct precipitation–response relationship, in which high-intensity rainfall drives runoff through infiltration excess without meaningful influence from antecedent conditions. Saturation excess floods show the role of high soil moisture in amplifying the effects of rainfall (Fig. 3b) and snowmelt (Fig. 3d), increasing runoff through reduced storage capacity. Rain-on-snow floods (Fig. 3c) demonstrate a different interaction mechanism in which rainfall interacts with the snowpack, increasing snowmelt rates and resulting in higher discharge. Snowmelt floods (Fig. 3e) show events with minimal rainfall contribution and runoff generation dominated by snowmelt as a consequence of radiation and elevated temperatures.

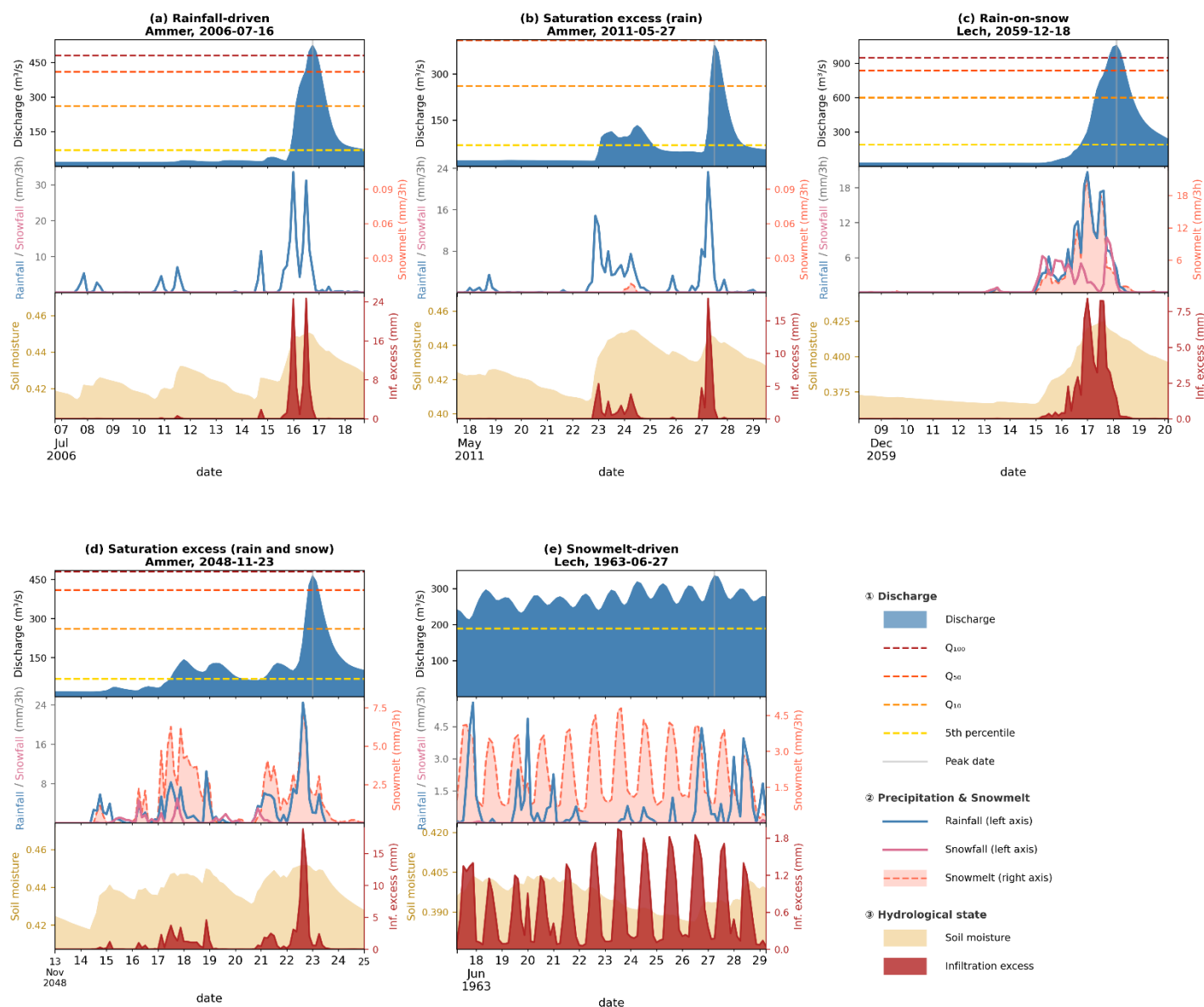


Figure 3: Individual flood events illustrating the processes and temporal behaviour of the five distinct flood types: (a) rainfall-driven, (b) saturation excess (rain), (c) rain-on-snow, (d) saturation excess (rain and snow), (e) snowmelt-driven.



235 4.6 Return level calculation

We calculate 100-year return levels for each flood type by dividing the simulations into 20-year periods with distinct global warming levels of +2 K, +3 K, and +4 K above pre-industrial levels, following Boehnisch et al. (2025). We therefore sample independent flood peaks p above a threshold u as extreme values (Balkema and de Haan, 1974). The exceedances $y = p - u$ are assumed to follow the Generalised Pareto distribution (Davison and Smith, 1990) with the cumulative distribution function

240 Eq. (1):

$$H(y; \xi) = \begin{cases} 1 - (1 + \frac{\xi y}{\beta})^{-\frac{1}{\xi}}, & \xi \neq 0, \beta > 0, y > 0 \\ 1 - \exp\left(\frac{-y}{\beta}\right), & \xi = 0, \beta > 0, y > 0 \end{cases}$$

245 with the scale parameter β and shape parameter ξ governing the spread and tail behaviour of the distribution (Coles, 2001). We assess the goodness of fit with the Anderson-Darling test at the 95 % significance level following Poschlod (2021). The threshold u is iteratively increased until the Anderson-Darling test is passed. Confidence intervals are calculated via parametric bootstrap with 1000 iterations. While Rischmuller et al. (2026) find limited power of the Anderson-Darling test on small sample sizes, we apply the extreme value theory on 20 years $\times$ 50 members, where 100-year events are well within the simulation length yielding robust estimates of rare quantiles.

4.7 Comparison with the flood classification of Stein et al. (2020)

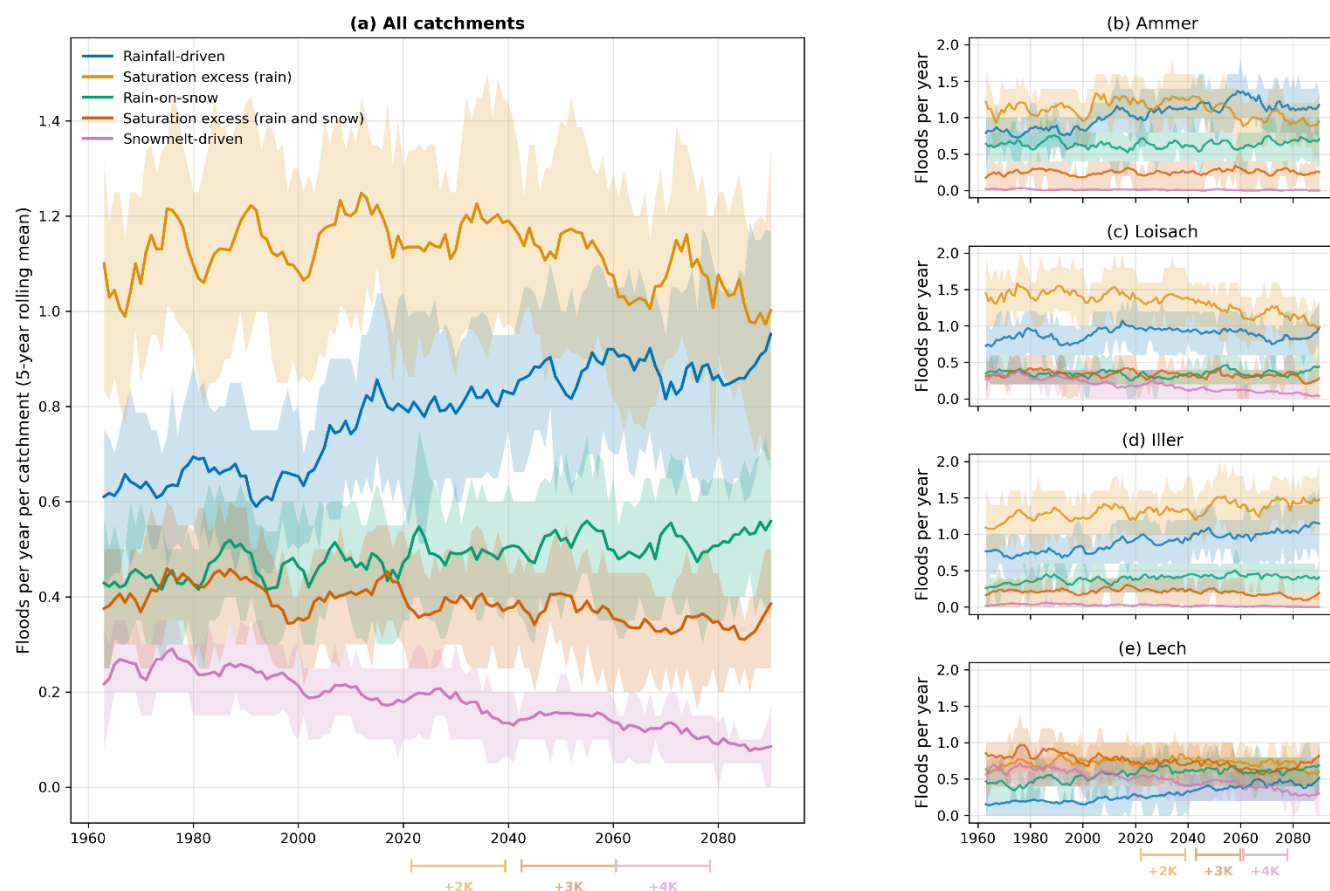
Our flood classification method is compared against the Stein et al. (2020) approach using the same flood events as input data. Stein et al. (2020) propose an event-based flood classification methodology using a decision tree with climate-independent thresholds based on 7-day and single-day precipitation, the soil moisture state and 7-day snowmelt. As the tree builds on percentile thresholds for rainfall and snowmelt as well as ratios of rainfall to snowmelt rather than fixed absolute thresholds, their framework is globally applicable. The classification results in five different hydrometeorological flood generating processes: short rain, long rain, excess rainfall, a combination of rain and snow, and snowmelt. Its application on over 4000 catchments worldwide shows robustness and is evaluated against data from the Dartmouth Flood Observatory (DFO) Global Active Archive of Large Flood Events (Brakenridge, 2018). More details can be found in Stein et al. (2020).



5 Results

5.1 Climate change impacts

The simulations show how the frequency of the different flood types evolves over time under the high-emission scenario RCP8.5 (Fig. 4a). Saturation excess (rain) floods across the four catchments maintain the highest frequency (1.17 floods per year at +1 K) but exhibit a slight decline after 2040 (−9 % between +1 K and +4 K). Rainfall-driven floods show a clear increasing trend, particularly between 1980 and 2060, rising by 22 % between +1 K and +4 K, the strongest response of all types. Rain-on-snow floods show a weaker but consistent increase over the period (+8 %). Saturation excess (rain and snow) floods remain relatively stable, with a minor downward trend in recent decades (−11 %). Snowmelt-driven floods occur mainly in the Lech and Loisach catchments, where a decline of approximately 42 % is projected between +1 K and +4 K. At the level of individual catchments (Figs. 4b–e), Ammer is historically dominated by saturation excess (rain), but rainfall-driven floods increase with global warming (+25 %) and exceed saturation excess (−16 %) as the main driver after 2040. Iller has a balanced distribution between saturation excess and rainfall-driven floods, with both increasing in frequency under global warming (+6 % and +25 %, respectively). Due to the relatively strong influence of snow dynamics, Lech has historically had the most even distribution of flood types. However, saturation excess (rain and snow) and snowmelt-driven floods clearly decrease over time (−20 % and −35 %), whereas rainfall-driven and rain-on-snow floods increase in frequency (+110 % and +10 %, the rainfall-driven increase starting from a low base of 0.21 events per year). Loisach has the highest share of saturation excess (rain) floods, which remain the primary flood mechanism over time despite declining (−19 %). Snowmelt-driven floods show a clear decrease in frequency (−56 %), while the remaining flood types remain mostly stable (−4 to −6 %).



280 **Figure 4: Main panel: Frequency of flood types in the 50-member ensemble over time for all catchments. Right panels: same as main panel, but for each individual catchment. Lines represent ensemble rolling means, and shaded envelopes indicate interquartile range. Colours denote the different types of floods. Bottom axes indicate time windows corresponding to global warming levels.**

Concerning seasonality changes among the different flood types, our results show a consistent advance in the timing of snow-influenced floods under warming (Fig. 5), although the magnitude of this shift varies across flood types and catchments. The
 285 clearest signal is found for snowmelt-driven floods, for which the median timing moves from late spring towards earlier spring, typically by about 3–6 weeks in Ammer, Iller, and Loisach, while the shift is smaller in Lech. Rain-on-snow and saturation excess (rain and snow) floods also tend to occur earlier, but with broader and partly overlapping seasonal distributions, indicating that the change is not a uniform displacement in all catchments. In contrast, rainfall-driven and saturation excess
 290 (rain) floods remain centred in summer, with a slight tendency to occur earlier in the year under warming conditions.

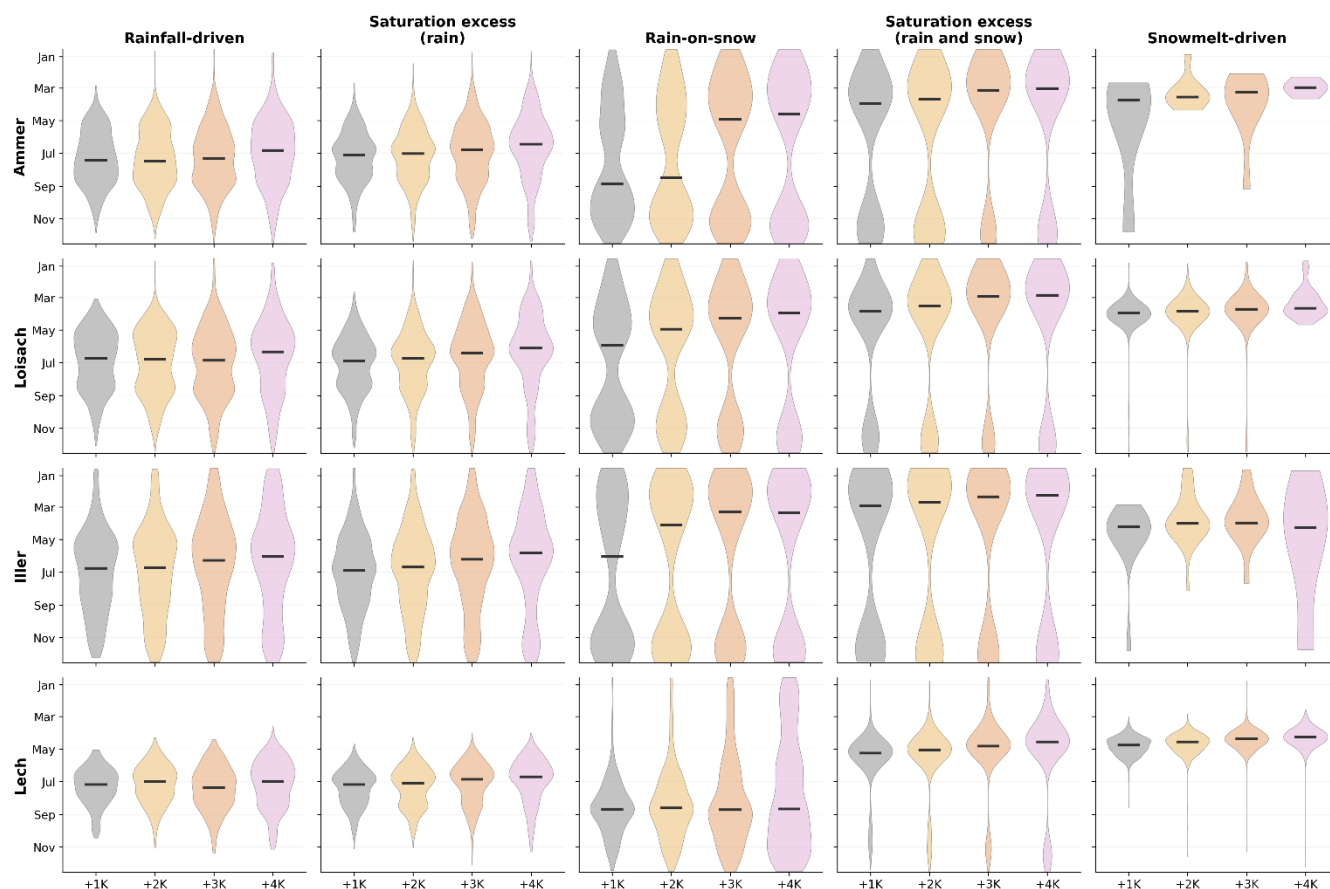


Figure 5: Seasonality changes of the five flood types under global warming levels of +1K, +2K, +3K, and +4K for the four catchments (Ammer, Loisach, Iller, and Lech).

295 To determine the effects of climate change on extreme floods, we examine 100-year return levels under different warming levels across flood types (Fig. 6). The largest percentage increases in flood magnitude occur for rainfall-driven events, for which the median response in the Lech catchment reaches nearly +50 % under the +4 K scenario, with upper bounds exceeding +70 %. However, response sensitivity across warming levels varies by catchment, with Loisach showing minimal change under +4 K (+1 %) compared with lower warming levels (+6 % at both +2 K and +3 K), and Ammer peaking at +3 K (+24 %) rather than +4 K (+13 %), indicating that flood magnitudes do not scale linearly with warming. Saturation excess (rain) events show consistent positive trends across catchments with higher warming, with median increases reaching 18–22 % in Iller and Lech at +4 K, and more moderate increases in Loisach (+9 %) and Ammer (+8 %). Rain-on-snow events also show substantial increases in Iller (+29 %) and Lech, although the highest response in Lech occurs under +3 K (approximately 34 % median increase) rather than +4 K (approximately 26 %), and Ammer shows no change (+3 %). For saturation excess (rain and snow) events, responses are highly catchment-dependent, with Ammer and Loisach showing substantial increases under +4 K

300

305



(median changes of approximately 26 % and 19 %, respectively), whereas Iller and Lech display minor overall changes (+5 % and +4 %). Finally, snowmelt-driven events in Loisach and Lech decline substantially at higher warming levels, with median decreases of approximately 10–13 % under the +4 K scenario; in Ammer and Iller, snowmelt floods are too rare to support a return-level estimate.

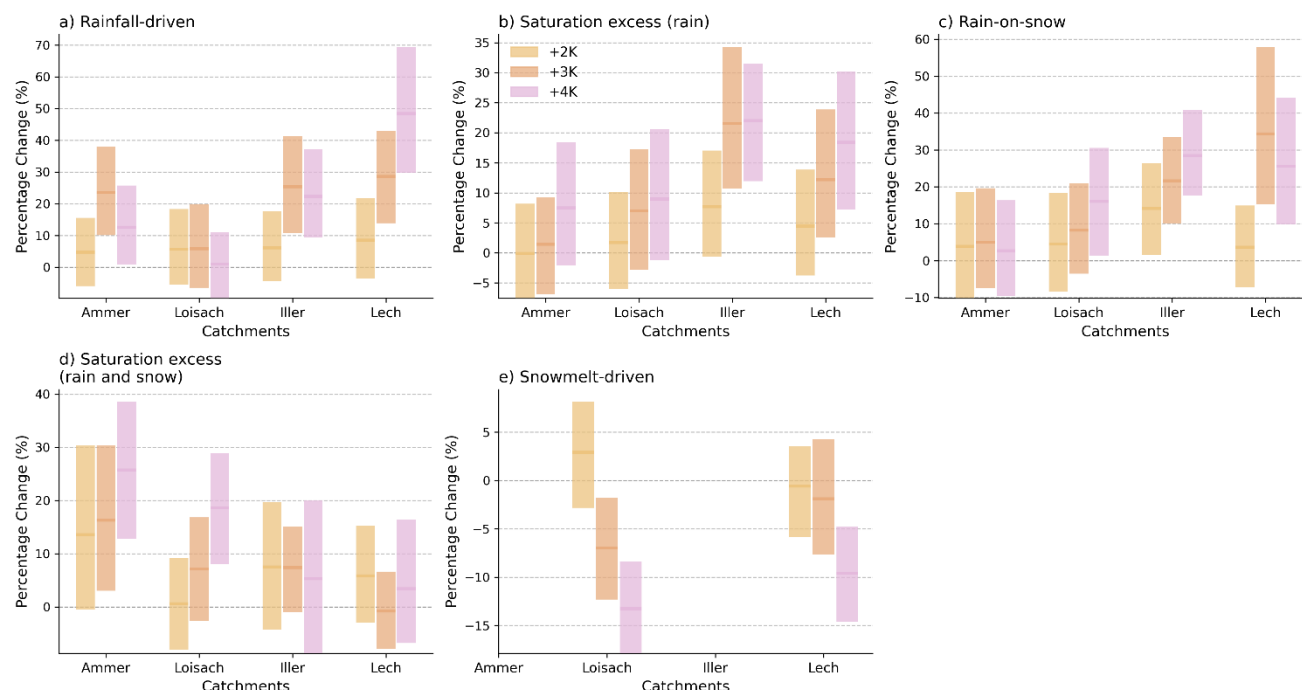


Figure 6: Percentage changes in 100-year return-level flood magnitudes across the four catchments (Ammer, Loisach, Iller, and Lech) under different global warming scenarios (+2 K, +3 K, and +4 K) compared with a present-day (+1 K) global warming level. Each panel describes a flood-event type: (a) rainfall-driven, (b) saturation excess (rain), (c) rain-on-snow, (d) saturation excess (rain and snow), and (e) snowmelt-driven. The transparent areas denote 95 % confidence intervals derived from the parametric bootstrap of the 100-year return levels.

5.2 Clustering comparison

Our clustering method is compared to the method by Stein et al. (2020; Fig. 7). The Stein method classifies the same flood events into five flood-generating processes plus a residual "other" class, with the following distribution: short rain (19.2 %), excess rain (9.7 %), long rain (40.4 %), rain/snow (16.2 %), snowmelt (13.0 %), and other (1.6 %). Given the differences in both methods in number of flood categories and how they are determined, we consider roughly equivalent flood categories as: rainfall-driven category to short rain and excess rain (Stein); saturation excess (rain) to long rain and excess rain (Stein); rain-on-snow and saturation excess (rain and snow) to rain/snow (Stein); and snowmelt-driven to snowmelt (Stein). Overall, the two methods agree for 64.3 % of all flood events (Table A1). Saturation excess (rain) and long rain (Stein) events converge on 65.1 % of cases. Short rain (Stein) events match rainfall-driven events in 62.8 % of cases, whereas excess rain (a category absent in our approach) matches 34.5 %. Our method identifies two snow-related categories whereas Stein uses one. Rain/snow



(Stein) matches 55.4 % of saturation excess (rain and snow) and 33.2 % of rain-on-snow events, totalling almost 90 % of convergence. Snowmelt events show a 78.6 % convergence across both methods.

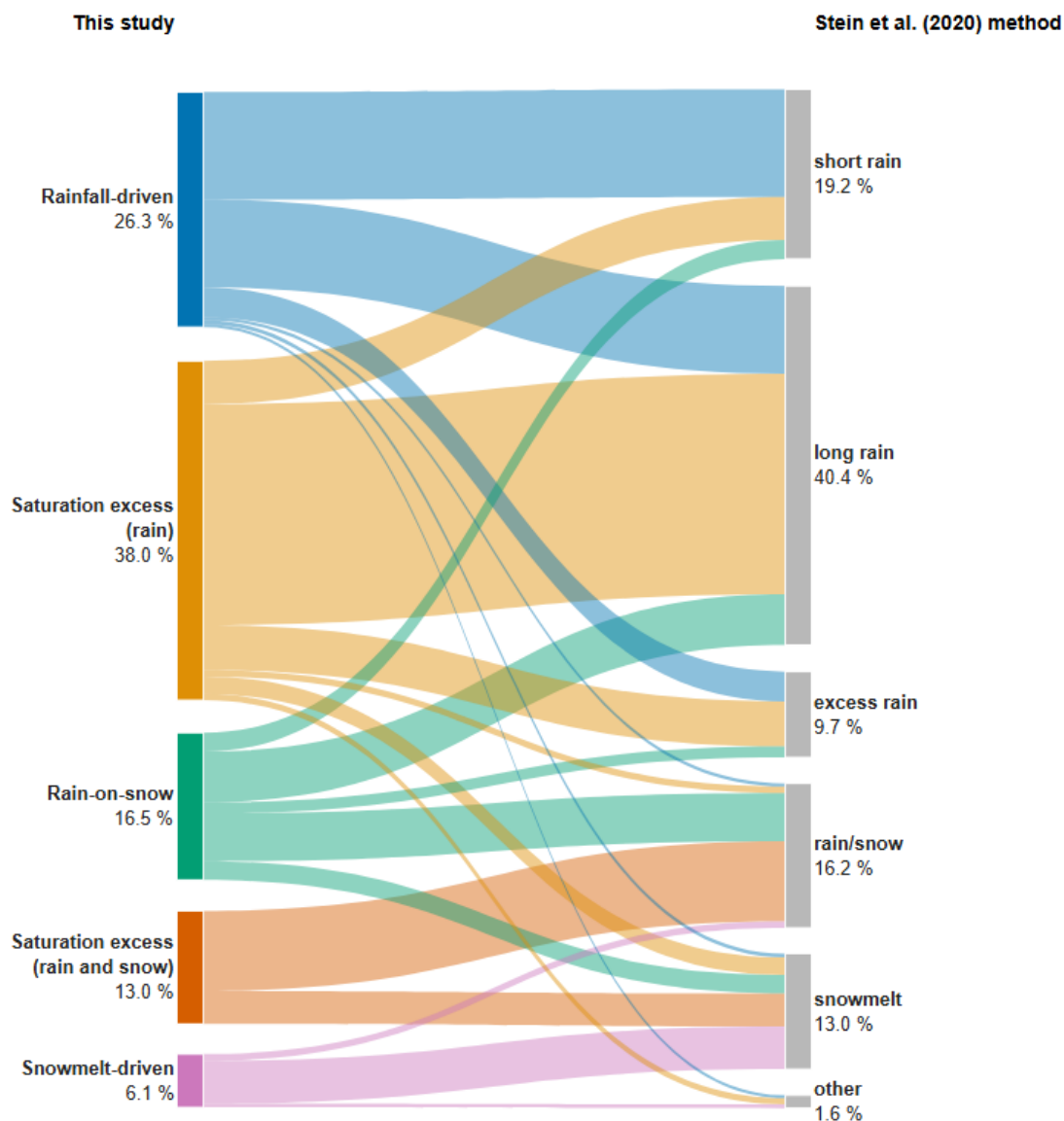


Figure 7: Sankey diagram illustrating the floods classifications between this study and the method by Stein et al. (2020).



6 Discussion and conclusion

This study explores the climate change effects on flood types in four pre-Alpine catchments. To this end, we develop a data-driven, unsupervised machine learning approach to identify and classify different types of riverine compound floods in these catchments.

The clustering algorithm detects physically interpretable flood categories that align with known pre-Alpine flood-generating processes (Berghuijs et al., 2019; Jiang et al., 2022; Tarasova et al., 2023), and the large ensemble allows us to confirm that these classifications are highly robust to the input dataset. Our approach shows 64 % convergence with the Stein et al. (2020) framework. Among the differences, our method distinguishes two distinct snow-influenced compound flood types, saturation excess (rain and snow) and rain-on-snow, which are largely grouped into a single "rain/snow" category in the Stein et al. (2020) method. Furthermore, we find that these two flood categories are affected differently by a warming climate in terms of their frequency (Fig. 4), seasonality (Fig. 5), and extreme intensity (Fig. 6). This demonstrates the capacity of the data-driven approach to capture local and regional nuances in flood generation that may be missed by threshold-based classification approaches. Because the two snow-related types respond differently to warming (Figs. 4–6), classification schemes that merge them can mask divergent trajectories of compound flood risk in transition regions such as the pre-Alps.

Our findings indicate that warming increases rainfall-driven and rain-on-snow floods across most catchments, while reducing saturation excess (rain and snow) and snowmelt-driven events. Moreover, extreme flood risk (100-year return level) is expected to increase considerably for rainfall-driven and rain-on-snow floods (by up to 50 % under 4 K warming in some catchments), while snowmelt-driven 100-year floods decrease by up to 13 %. The shift from snow-dominated to rainfall-dominated flooding due to climate change is also identified in other studies (Brunner et al., 2019; Hanus et al., 2021; Willkofer et al., 2024; Niu et al., 2025). Vormoor et al. (2016) found precipitation to have an increasing role in flood generation in Norway between 1962 and 2012, while the role of snowmelt decreased over the same period. Ombadi et al. (2023) project that the risk of extreme rainfall events in mountainous regions will increase as the fraction of snow decreases due to climate change. The implication of higher precipitation–snow ratios is a higher magnitude of floods (Davenport et al., 2020). For rain-on-snow specifically, Hotovy et al. (2025) conducted a perturbation experiment with warming in the range of 0–4 °C and precipitation in the range of 80–120 %. They found that rain-on-snow events in Central European middle mountain ranges and the European Alps show a broad range of alterations in a warmer climate. While warming leads to a lower contribution of rain-on-snow events to total runoff in the Czech Republic and Switzerland, this effect can be offset by wetter perturbations with 110 % and 120 % annual precipitation. Furthermore, they diagnosed that the frequency of rain-on-snow events depends on the elevation of the respective catchments. However, they did not investigate the magnitude of rare flood events. In areas with persistent snow cover, rain-on-snow flood risk is projected to increase due to the shift from snowfall to rainfall (Musselman et al., 2018). While our results support this trend, the projected rate of increase in rain-on-snow flood risk is higher at +3 K than at +4 K for the Lech catchment. This nonlinear response reflects diminishing snowpack availability, with +4 K warming representing an inflection point at which rain-on-snow flood risk starts to diminish (Beniston et al., 2016; Musselman et al., 2018). For the Ammer



365 catchment, which has the lowest mean elevation of the four study catchments at 800 m above sea level, no significant change in ROS flood intensity is diagnosed. The seasonality shifts observed here in snow-influenced catchments are consistent with projected changes reported for similar Alpine catchments (Köplin et al., 2014).

The pre-Alpine region is a hydro-climatological transition zone, exhibiting high heterogeneity in catchment responses to warming (Poschlod et al., 2020b). As snow cover diminishes, flood generation mechanisms become increasingly catchment-specific, driven by localised interactions between precipitation intensity and soil moisture states (Massari et al., 2023; Staudinger et al., 2025). While effective for global or large-scale assessments, threshold-based classification frameworks may miss the continuous evolution of compound drivers observed in our study. This is specifically true for transition regimes like pre-Alpine (Vormoor et al., 2015). Our unsupervised approach defines flood typologies directly from the studied data. This allows for the identification of shifts and particularities in flood generation from certain regions, providing a more robust basis for adaptation planning in complex topographies.

The hydro-SMILE simulations rely on a single climate model (CanESM2-LE downscaled with CRCM5) and hydrological model, which means that our results do not account for the structural model uncertainties across different climate and hydrological models. While the CRCM5-LE still covers a wide range of climatic change as represented by the multi-model EURO-CORDEX ensemble (Leduc et al., 2019, von Trentini et al., 2019), future multi-model ensemble studies could provide a more comprehensive picture of the plausible range of future changes. Extreme events are typically underrepresented in model simulations (Schewe et al., 2019). While large ensembles can help mitigate this limitation (Willkofer et al. 2024), alternative approaches, including storylines, historical investigations of past extremes and the UNSEEN approach, offer additional insights in dealing with (future) extreme events (Kelder et al., 2025, Goulart et al., 2024, Thompson et al., 2017). A further limitation stems from classification as an approach in itself. Non-fuzzy classification methods impose discrete boundaries on what is in reality a continuum of compound flood-generating processes, so that events lying between two flood types are assigned to a single event type. Using large ensembles allows us to assess the robustness of our classification approach to the input dataset used, and we find that the obtained categories, and the resulting projections in flood magnitude under climate change, are highly consistent with those obtained when using single ensemble members only. When using observation data, assessing the robustness of this approach would be highly challenging. Furthermore, we select the hydrometeorological features to use for clustering based on domain knowledge and the labelling of the clusters as flood types ultimately relies on expert interpretation based on post-hoc analysis of the characteristics of the flood events in each cluster. Using alternative features, clustering algorithms or labelling could shift individual events between types, although we expect the catchment-scale frequency and seasonality signals reported here to be robust to such choices.

The results of this study have practical implications for flood risk management. There are multiple water reservoirs and dams in the European Alps, which serve several objectives in the region, including flood protection, hydroelectric power generation, and water supply. The projected changes in the seasonality of different flood types can inform reservoir management, while the projected changes in flood magnitude show the need to adapt the dimensions of flood-protection measures. More generally,

the increase in future flood risk due to climate change suggests that investment in civil protection and preparedness will be required for optimal performance (Kellner et al., 2021).

400 Understanding the changes in risk per flood type (i.e. rainfall-driven and rain-on-snow) can inform adaptation efforts, such as the type of early warning system to be used (Green et al., 2025), and the operational changes needed in water resources to continuously meet their multiple objectives (Herman et al., 2020). By disentangling flood types, we also identify earlier seasonal flood projections in catchments where snow-related flood processes are important, which is also relevant for flood preparedness (Vormoor et al., 2015). Potential applications include coupling the large-ensemble framework with impact
 405 models to quantify economic damages and risk to people (Mester et al., 2023, Goulart et al., 2025), critical infrastructure vulnerability (Mühlhofer et al., 2023, Goulart et al., 2024), and ecosystem disruption (Wright et al., 2015, Parasiewicz et al., 2019). The framework also allows for storylines to be created from the large ensemble to investigate specific flood events and their potential impacts in detail (Van den Hurk et al., 2023, Goulart et al., 2021). The data-driven clustering algorithm is transferable to other regions while preserving a high level of regional detail, provided sufficient data for training is available.
 410 In sum, this study introduces a data-driven, unsupervised machine learning framework to classify different types of riverine compound floods and assesses how the risk associated with each specific type evolves under climate change. The framework is applied to hydrometeorological data from a large ensemble chain of models that include historical and future time periods in four Bavarian pre-Alpine catchments. The unsupervised clustering identifies five physically distinct types of riverine compound floods in the areas studied, which offer more detail than a global classification framework. Our analysis reveals an
 415 increase in flood risk in the study area, and a shift in the dominant types of floods, from snow-based to precipitation-based floods. These findings carry practical applications to flood risk management and water resources operations, and they can be used to inform climate adaptation strategies.

Appendix A: Additional information

420 **Table A1:** Table comparing the equivalent classification of each method for the same events (in percentage).

Stein method/ clustering	Short rain	Long rain	Excess rain	Rain/snow	Snowmelt	Other
Rainfall-driven	12.05	9.83	3.34	0.35	0.45	0.32
Saturation excess (rain)	4.85	24.75	5.04	0.74	1.95	0.70
Rain-on-snow	2.11	5.68	1.24	5.38	2.09	0.00
Saturation excess (rain and snow)	0.06	0.12	0.07	8.98	3.70	0.12
Snowmelt-driven	0.10	0.00	0.01	0.76	4.79	0.43



Code and data availability

Code is available at <https://github.com/lilybellesweet/rain-on-snow>. Data used in this study is available at <https://doi.org/10.5281/zenodo.22859827>.

425 Author contribution

HMDG and LS designed the methodology and performed the formal analysis and validation. HMDG, LS, AD, SB and BP contributed to the conceptualization of the study. HMDG prepared the original draft with contributions from LS, BP, AD and SB. HMDG and BP prepared the figures. BP provided supervision.

Competing interests

430 The authors declare that they have no conflict of interest.

Acknowledgements

We cordially thank Jakob Zscheischler, Bart van den Hurk, Rita Pongracz, Freya Garry, Fiachra O'Loughlin, and all other organisers and lecturers of the Training School on Dynamical Modelling of Compound Events in Budapest on 18 July to 29 July 2022 funded by the EU COST-Action DAMOCLES. Furthermore, we thank Henry Wells and Iris de Vries for their initial
435 contributions and discussion during the group work of the training school in 2022.

Financial support

We acknowledge Natural Hazards and Risks in a Changing World (NatRiskChange) funded by the Deutsche Forschungsgemeinschaft (DFG; GRK2043/2).

References

- 440 Balkema, A. A. and de Haan, L.: Residual life time at great age, *Ann. Probab.*, 2, 792–804, <https://doi.org/10.1214/aop/1176996548>, 1974.
- Beniston, M. and Stoffel, M.: Rain-on-snow events, floods and climate change in the Alps: events may increase with warming up to 4 °C and decrease thereafter, *Sci. Total Environ.*, 571, 228–236, <https://doi.org/10.1016/j.scitotenv.2016.07.146>, 2016.
- Berghuijs, W. R., Harrigan, S., Molnar, P., Slater, L. J., and Kirchner, J. W.: The relative importance of different flood-
445 generating mechanisms across Europe, *Water Resour. Res.*, 55, 4582–4593, <https://doi.org/10.1029/2019WR024841>, 2019.



- Böhnisch, A., Felsche, E., Mittermeier, M., Poschlod, B., and Ludwig, R.: Future patterns of compound dry and hot summers and their link to soil moisture droughts in Europe, *Earth's Future*, 13, e2024EF004916, <https://doi.org/10.1029/2024EF004916>, 2025.
- Bonsoms, J., López-Moreno, J. I., Alonso-González, E., Deschamps-Berger, C., and Oliva, M.: Rain-on-snow responses to warmer Pyrenees: a sensitivity analysis using a physically based snow hydrological model, *Nat. Hazards Earth Syst. Sci.*, 24, 245–264, <https://doi.org/10.5194/nhess-24-245-2024>, 2024.
- Brakenridge, G. R.: Global Active Archive of Large Flood Events, Dartmouth Flood Observatory, University of Colorado, available at: <http://floodobservatory.colorado.edu/Archives/index.html> (last access: 3 July 2026), 2018.
- Brunner, M. I., Farinotti, D., Zekollari, H., Huss, M., and Zappa, M.: Future shifts in extreme flow regimes in Alpine regions, *Hydrol. Earth Syst. Sci.*, 23, 4471–4489, <https://doi.org/10.5194/hess-23-4471-2019>, 2019.
- Brunner, M. I., Swain, D. L., Wood, R. R., Willkofer, F., Done, J. M., Gilleland, E., and Ludwig, R.: An extremeness threshold determines the regional response of floods to changes in rainfall extremes, *Commun. Earth Environ.*, 2, 173, <https://doi.org/10.1038/s43247-021-00248-x>, 2021.
- Bueche, T., Wenk, M., Poschlod, B., Giadrossich, F., Pirastru, M., and Vetter, M.: glmGUI v1.0: an R-based graphical user interface and toolbox for GLM (General Lake Model) simulations, *Geosci. Model Dev.*, 13, 565–580, <https://doi.org/10.5194/gmd-13-565-2020>, 2020.
- Coles, S.: *An Introduction to Statistical Modeling of Extreme Values*, Springer, London, UK, <https://doi.org/10.1007/978-1-4471-3675-0>, 2001.
- Corral, C., Berenguer, M., Sempere-Torres, D., Poletti, L., Silvestro, F., and Rebora, N.: Comparison of two early warning systems for regional flash flood hazard forecasting, *J. Hydrol.*, 572, 603–619, <https://doi.org/10.1016/j.jhydrol.2019.03.026>, 2019.
- Davenport, F. V., Herrera-Estrada, J. E., Burke, M., and Diffenbaugh, N. S.: Flood size increases nonlinearly across the western United States in response to lower snow-precipitation ratios, *Water Resour. Res.*, 56, e2019WR025571, <https://doi.org/10.1029/2019WR025571>, 2020.
- Davison, A. C. and Smith, R. L.: Models for exceedances over high thresholds, *J. Roy. Stat. Soc. B Met.*, 52, 393–442, <https://doi.org/10.1111/j.2517-6161.1990.tb01796.x>, 1990.
- Deser, C., Lehner, F., Rodgers, K. B., Ault, T., Delworth, T. L., DiNezio, P. N., Fiore, A., Frankignoul, C., Fyfe, J. C., Horton, D. E., Kay, J. E., Knutti, R., Lovenduski, N. S., Marotzke, J., McKinnon, K. A., Minobe, S., Randerson, J., Screen, J. A., Simpson, I. R., and Ting, M.: Insights from Earth system model initial-condition large ensembles and future prospects, *Nat. Clim. Change*, 10, 277–286, <https://doi.org/10.1038/s41558-020-0731-2>, 2020.
- Dobler, C., Bürger, G., and Stötter, J.: Assessment of climate change impacts on flood hazard potential in the Alpine Lech watershed, *J. Hydrol.*, 460–461, 29–39, <https://doi.org/10.1016/j.jhydrol.2012.06.027>, 2012.



- Dottori, F., Szewczyk, W., Ciscar, J.-C., Zhao, F., Alfieri, L., Hirabayashi, Y., Bianchi, A., Mongelli, I., Frieler, K., Betts, R. A., and Feyen, L.: Increased human and economic losses from river flooding with anthropogenic warming, *Nat. Clim. Change*, 8, 781–786, <https://doi.org/10.1038/s41558-018-0257-z>, 2018.
- European Environment Agency (EEA): CORINE Land Cover 2018 (raster 100 m), Europe, 6-yearly – version 2020_20u1, Copernicus Land Monitoring Service [data set], <https://doi.org/10.2909/960998c1-1870-4e82-8051-6485205ebbac>, 2020.
- European Space Agency (ESA): Copernicus Global Digital Elevation Model (GLO-30), European Space Agency [data set], <https://doi.org/10.5270/ESA-c5d3d65>, 2025.
- Frei, P., Kotlarski, S., Liniger, M. A., and Schär, C.: Future snowfall in the Alps: projections based on the EURO-CORDEX regional climate models, *The Cryosphere*, 12, 1–24, <https://doi.org/10.5194/tc-12-1-2018>, 2018.
- Fyfe, J. C., Derksen, C., Mudryk, L., Flato, G. M., Santer, B. D., Swart, N. C., Molotch, N. P., Zhang, X., Wan, H., Arora, V. K., Scinocca, J., and Jiao, Y.: Large near-term projected snowpack loss over the western United States, *Nat. Commun.*, 8, 14996, <https://doi.org/10.1038/ncomms14996>, 2017.
- Goulart, H. M. D., van der Wiel, K., Folberth, C., Balkovic, J., and van den Hurk, B.: Storylines of weather-induced crop failure events under climate change, *Earth Syst. Dynam.*, 12, 1503–1527, <https://doi.org/10.5194/esd-12-1503-2021>, 2021.
- Goulart, H. M. D., Benito Lazaro, I., van Garderen, L., van der Wiel, K., Le Bars, D., Koks, E., and van den Hurk, B.: Compound flood impacts from Hurricane Sandy on New York City in climate-driven storylines, *Nat. Hazards Earth Syst. Sci.*, 24, 29–45, <https://doi.org/10.5194/nhess-24-29-2024>, 2024.
- Goulart, H. M. D., Athanasiou, P., van Ginkel, K., van der Wiel, K., Winter, G., Pinto, I., and van den Hurk, B.: Exploring coastal climate adaptation through storylines: insights from cyclone Idai in Beira, Mozambique, *Cell Rep. Sustain.*, 2, 100270, <https://doi.org/10.1016/j.crsus.2024.100270>, 2025.
- Green, J., Haigh, I. D., Quinn, N., Neal, J., Wahl, T., Wood, M., Eilander, D., de Ruiter, M., Ward, P., and Camus, P.: Review article: A comprehensive review of compound flooding literature with a focus on coastal and estuarine regions, *Nat. Hazards Earth Syst. Sci.*, 25, 747–816, <https://doi.org/10.5194/nhess-25-747-2025>, 2025.
- Hanus, S., Hrachowitz, M., Zekollari, H., Schoups, G., Vizcaino, M., and Kaitna, R.: Future changes in annual, seasonal and monthly runoff signatures in contrasting Alpine catchments in Austria, *Hydrol. Earth Syst. Sci.*, 25, 3429–3453, <https://doi.org/10.5194/hess-25-3429-2021>, 2021.
- Haslinger, K., Breinl, K., Pavlin, L., Pistotnik, G., Bertola, M., Olefs, M., Greiling, M., Schöner, W., and Blöschl, G.: Increasing hourly heavy rainfall in Austria reflected in flood changes, *Nature*, 639, 667–672, <https://doi.org/10.1038/s41586-025-08647-2>, 2025.
- Heggli, A., Hatchett, B., Schwartz, A., Bardsley, T., and Hand, E.: Toward snowpack runoff decision support, *iScience*, 25, 104240, <https://doi.org/10.1016/j.isci.2022.104240>, 2022.
- Herman, J. D., Quinn, J. D., Steinschneider, S., Giuliani, M., and Fletcher, S.: Climate adaptation as a control problem: Review and perspectives on dynamic water resources planning under uncertainty, *Water Resour. Res.*, 56, e2019WR025502, <https://doi.org/10.1029/2019WR025502>, 2020.



- Hotovy, O., Nedelcev, O., Seibert, J., and Jenicek, M.: Rain-on-snow events in mountainous catchments under climate change, *Hydrol. Earth Syst. Sci.*, 29, 4199–4217, <https://doi.org/10.5194/hess-29-4199-2025>, 2025.
- Huang, X., Yin, J., Slater, L. J., Kang, S., He, S., and Liu, P.: Global projection of flood risk with a bivariate framework under
 515 1.5–3.0 °C warming levels, *Earths Future*, 12, e2023EF004312, <https://doi.org/10.1029/2023EF004312>, 2024.
- Jiang, S., Bevacqua, E., and Zscheischler, J.: River flooding mechanisms and their changes in Europe revealed by explainable machine learning, *Hydrol. Earth Syst. Sci.*, 26, 6339–6359, <https://doi.org/10.5194/hess-26-6339-2022>, 2022.
- Jiang, S., Tarasova, L., Yu, G., and Zscheischler, J.: Compounding effects in flood drivers challenge estimates of extreme river floods, *Science Advances*, 10, eadl4005, <https://doi.org/10.1126/sciadv.adl4005>, 2024.
- 520 Kelder, T., Heinrich, D., Klok, L., Thompson, V., Goulart, H. M. D., Hawkins, E., Slater, L. J., Suarez-Gutierrez, L., Wilby, R. L., Coughlan de Perez, E., Stephens, E. M., Burt, S., van den Hurk, B., de Vries, H., van der Wiel, K., Schipper, E. L. F., Carmona Baéz, A., van Bueren, E., and Fischer, E. M.: How to stop being surprised by unprecedented weather, *Nat. Commun.*, 16, 2382, <https://doi.org/10.1038/s41467-025-57450-0>, 2025.
- Keller, L., Rössler, O., Martius, O., and Weingartner, R.: Delineation of flood generating processes and their hydrological
 525 response, *Hydrol. Process.*, 32, 228–240, <https://doi.org/10.1002/hyp.11407>, 2018.
- Kellner, E. and Brunner, M. I.: Reservoir governance in world's water towers needs to anticipate multi-purpose use, *Earth's Future*, 9, e2020EF001643, <https://doi.org/10.1029/2020EF001643>, 2021.
- Köplin, N., Schädler, B., Viviroli, D., and Weingartner, R.: Seasonality and magnitude of floods in Switzerland under future climate change, *Hydrol. Process.*, 28, 2567–2578, <https://doi.org/10.1002/hyp.9757>, 2014.
- 530 Lallemand, D., Hamel, P., Balbi, M., Lim, T. N., Schmitt, R., and Win, S.: Nature-based solutions for flood risk reduction: a probabilistic modeling framework, *One Earth*, 4, 1310–1321, <https://doi.org/10.1016/j.oneear.2021.08.010>, 2021.
- Langridge, M., Gharabaghi, B., McBean, E., Bonakdari, H., and Walton, R.: Understanding the dynamic nature of time-to-peak in UK streams, *J. Hydrol.*, 583, 124630, <https://doi.org/10.1016/j.jhydrol.2020.124630>, 2020.
- Leduc, M., Mailhot, A., Frigon, A., Martel, J.-L., Ludwig, R., Brietzke, G. B., Giguère, M., Brissette, F., Turcotte, R., Braun,
 535 M., and Scinocca, J.: The ClimEx project: A 50-member ensemble of climate change projections at 12-km resolution over Europe and northeastern North America with the Canadian Regional Climate Model (CRCM5), *J. Appl. Meteorol. Climatol.*, 58, 663–693, <https://doi.org/10.1175/JAMC-D-18-0021.1>, 2019.
- Likas, A., Vlassis, N., and Verbeek, J. J.: The global k-means clustering algorithm, *Pattern Recognit.*, 36, 451–461, [https://doi.org/10.1016/S0031-3203\(02\)00060-2](https://doi.org/10.1016/S0031-3203(02)00060-2), 2003.
- 540 Liu, J., Feng, S., Gu, X., Zhang, Y., Beck, H. E., Zhang, J., and Yan, S.: Global changes in floods and their drivers, *J. Hydrol.*, 614, 128553, <https://doi.org/10.1016/j.jhydrol.2022.128553>, 2022.
- Maina, F. Z. and Kumar, S. V.: Global patterns of rain-on-snow and its impacts on runoff from past to future projections, *Nat. Commun.*, 16, 4731, <https://doi.org/10.1038/s41467-025-59855-3>, 2025.



- Massari, C., Pellet, Vi., Trambly, Y., Crow, W. T., Gründemann, G. J., Hascoetf, T., Penna, D., Modanesi, S., Brocca, L.,
545 Camici, S., and Marra, F.: On the relation between antecedent basin conditions and runoff coefficient for European floods, *J.*
Hydrol., 625, 130012, <https://doi.org/10.1016/j.jhydrol.2023.130012>, 2023.
- McCabe, G. J., Clark, M. P., and Hay, L. E.: Rain-on-snow events in the Western United States, *Bull. Am. Meteorol. Soc.*, 88,
319–328, <https://doi.org/10.1175/BAMS-88-3-319>, 2007.
- Merz, B., Blöschl, G., Vorogushyn, S., Dottori, F., Aerts, J. C., Bates, P., Bertola, M., Kemter, M., Kreibich, H., Lall, U., and
550 Macdonald, E.: Causes, impacts and patterns of disastrous river floods, *Nat. Rev. Earth Environ.*, 2, 592–609, 2021.
- Mester, B., Vogt, T., Bryant, S., Otto, C., Frieler, K., and Schewe, J.: Human displacements from Tropical Cyclone Idai
attributable to climate change, *Nat. Hazards Earth Syst. Sci.*, 23, 3467–3485, <https://doi.org/10.5194/nhess-23-3467-2023>,
2023.
- Moriasi, D. N., Arnold, J. G., Van Liew, M. W., Bingner, R. L., Harmel, R. D., and Veith, T. L.: Model evaluation guidelines
555 for systematic quantification of accuracy in watershed simulations, *Trans. ASABE*, 50, 885–900,
<https://doi.org/10.13031/2013.23153>, 2007.
- Mühlhofer, E., Koks, E. E., Kropf, C. M., Sansavini, G., and Bresch, D. N.: A generalized natural hazard risk modelling
framework for infrastructure failure cascades, *Reliab. Eng. Syst. Saf.*, 234, 109194, <https://doi.org/10.1016/j.ress.2023.109194>,
2023.
- 560 Murphy-Barltrop, C. J. R., Richards, J., Poschlod, B., Sasse, A., and Zscheischler, J.: Exploring climate change effects on
concurrent floods and concurrent droughts via statistical deep learning, *arXiv [preprint]*,
<https://doi.org/10.48550/arXiv.2604.21647>, 2026.
- Musselman, K. N., Lehner, F., Ikeda, K., Clark, M. P., Prein, A. F., Liu, C., Barlage, M., and Rasmussen, R.: Projected
increases and shifts in rain-on-snow flood risk over western North America, *Nat. Clim. Change*, 8, 808–812,
565 <https://doi.org/10.1038/s41558-018-0236-4>, 2018.
- Niu, L., Wang, J., Li, H., and Hao, X.: Weakened snowmelt contribution to floods in a climate-changed Tibetan basin, *Water*,
17, 507, <https://doi.org/10.3390/w17040507>, 2025.
- Ombadi, M., Risser, M. D., Rhoades, A. M., and Varadharajan, C.: A warming-induced reduction in snow fraction amplifies
rainfall extremes, *Nature*, 619, 305–310, <https://doi.org/10.1038/s41586-023-06092-7>, 2023.
- 570 Parasiewicz, P., King, E. L., Webb, J. A., Piniewski, M., Comoglio, C., Wolter, C., Buijse, A. D., Bjerklie, D., Vezza, P.,
Melcher, A., and Suska, K.: The role of floods and droughts on riverine ecosystems under a changing climate, *Fish. Manag.*
Ecol., 26, 461–473, <https://doi.org/10.1111/fme.12388>, 2019.
- Poschlod, B., Willkofer, F., and Ludwig, R.: Impact of climate change on the hydrological regimes in Bavaria, *Water*, 12,
1599, <https://doi.org/10.3390/w12061599>, 2020b.
- 575 Poschlod, B., Zscheischler, J., Sillmann, J., Wood, R. R., and Ludwig, R.: Climate change effects on hydrometeorological
compound events over southern Norway, *Weather Clim. Extremes*, 28, 100253, <https://doi.org/10.1016/j.wace.2020.100253>,
2020a.



- Poschlod, B.: Using high-resolution regional climate models to estimate return levels of daily extreme precipitation over Bavaria, *Nat. Hazards Earth Syst. Sci.*, 21, 3573–3598, <https://doi.org/10.5194/nhess-21-3573-2021>, 2021.
- 580 Poschlod, B. and Koh, J.: Convection-permitting climate models can support observations to generate rainfall return levels, *Water Resour. Res.*, 60, e2023WR035159, <https://doi.org/10.1029/2023WR035159>, 2024.
- Rentschler, J., Salhab, M., and Jafino, B. A.: Flood exposure and poverty in 188 countries, *Nat. Commun.*, 13, 3527, <https://doi.org/10.1038/s41467-022-30727-4>, 2022.
- Rischmuller, A. L., Poschlod, B., and Sillmann, J.: Bayesian hierarchical modelling of intensity-duration-frequency curves
 585 using a climate model large ensemble, *Adv. Stat. Clim. Meteorol. Oceanogr.*, 12, 1–19, <https://doi.org/10.5194/ascmo-12-1-2026>, 2026.
- Rogers, J. S., Maneta, M. P., Sain, S. R., Madaus, L. E., and Hacker, J. P.: The role of climate and population change in global flood exposure and vulnerability, *Nat. Commun.*, 16, 1287, <https://doi.org/10.1038/s41467-025-56654-8>, 2025.
- Rössler, O., Froidevaux, P., Börst, U., Rickli, R., Martius, O., and Weingartner, R.: Retrospective analysis of a nonforecasted
 590 rain-on-snow flood in the Alps – a matter of model limitations or unpredictable nature?, *Hydrol. Earth Syst. Sci.*, 18, 2265–2285, <https://doi.org/10.5194/hess-18-2265-2014>, 2014.
- Sauer, I. J., Reese, R., Otto, C., Geiger, T., Willner, S. N., Guillod, B. P., Bresch, D. N., and Frieler, K.: Climate signals in river flood damages emerge under sound regional disaggregation, *Nat. Commun.*, 12, 2128, <https://doi.org/10.1038/s41467-021-22153-9>, 2021.
- 595 Schewe, J., Gosling, S. N., Reyer, C., Zhao, F., Ciais, P., Elliott, J., François, L., Huber, V., Lotze, H. K., Seneviratne, S. I., van Vliet, M. T. H., Vautard, R., Wada, Y., Breuer, L., Büchner, M., Carozza, D. A., Chang, J., Coll, M., Deryng, D., de Wit, A., Eddy, T. D., Folberth, C., Frieler, K., Friend, A. D., Gerten, D., Gudmundsson, L., Hanasaki, N., Ito, A., Khabarov, N., Kim, H., Lawrence, P., Morfopoulos, C., Müller, C., Müller Schmied, H., Orth, R., Ostberg, S., Pokhrel, Y., Pugh, T. A. M., Sakurai, G., Satoh, Y., Schmid, E., Stacke, T., Steenbeek, J., Steinkamp, J., Tang, Q., Tian, H., Tittensor, D. P., Volkholz, J.,
 600 Wang, X., and Warszawski, L.: State-of-the-art global models underestimate impacts from climate extremes, *Nat. Commun.*, 10, 1005, <https://doi.org/10.1038/s41467-019-08745-6>, 2019.
- Schulla, J.: Model Description WaSiM (Water balance Simulation Model), Hydrology Software Consulting J. Schulla, Zurich, Switzerland, available at: http://www.wasim.ch/downloads/doku/wasim/wasim_2021_en.pdf (last access: 3 July 2026), 2021.
- Shahapure, K. R. and Nicholas, C.: Cluster quality analysis using silhouette score, in: 2020 IEEE 7th International Conference
 605 on Data Science and Advanced Analytics (DSAA), 747–748, <https://doi.org/10.1109/DSAA49011.2020.00096>, 2020.
- Staudinger, M., Kauzlaric, M., Mas, A., Evin, G., Hingray, B., and Viviroli, D.: The role of antecedent conditions in translating precipitation events into extreme floods at the catchment scale and in a large-basin context, *Nat. Hazards Earth Syst. Sci.*, 25, 247–265, <https://doi.org/10.5194/nhess-25-247-2025>, 2025.
- Stein, L., Pianosi, F., and Woods, R.: Event-based classification for global study of river flood generating processes, *Hydrol. Process.*, 34, 1514–1529, <https://doi.org/10.1002/hyp.13678>, 2020.
- 610



- Stein, L., Clark, M. P., Knoben, W. J. M., Pianosi, F., and Woods, R. A.: How do climate and catchment attributes influence flood generating processes? A large-sample study for 671 catchments across the contiguous USA, *Water Resour. Res.*, 57, e2020WR028300, <https://doi.org/10.1029/2020WR028300>, 2021.
- 615 Tarasova, L., Merz, R., Kiss, A., Basso, S., Blöschl, G., Merz, B., Viglione, A., Plötner, S., Guse, B., Schröter, K., Vorogushyn, S., Günther, K., Gelfan, A., Anderson, R., and Dietze, M.: Causative classification of river flood events, *WIREs Water*, 6, e1353, <https://doi.org/10.1002/wat2.1353>, 2019.
- Tarasova, L., Lun, D., Merz, R., Blöschl, G., Basso, S., Bertola, M., Miniussi, A., Rakovec, O., Samaniego, L., Thober, S., and Kumar, R.: Shifts in flood generation processes exacerbate regional flood anomalies in Europe, *Commun. Earth Environ.*, 4, 49, <https://doi.org/10.1038/s43247-023-00714-8>, 2023.
- 620 Thieken, A. H., Samprognah Mohor, G., Kreibich, H., and Müller, M.: Compound inland flood events: different pathways, different impacts and different coping options, *Nat. Hazards Earth Syst. Sci.*, 22, 165–185, <https://doi.org/10.5194/nhess-22-165-2022>, 2022.
- Thompson, V., Dunstone, N. J., Scaife, A. A., Smith, D. M., Slingo, J. M., Brown, S., and Belcher, S. E.: High risk of unprecedented UK rainfall in the current climate, *Nat. Commun.*, 8, 107, <https://doi.org/10.1038/s41467-017-00275-3>, 2017.
- 625 Turkington, T., Breinl, K., Ettema, J., Alkema, D., and Jetten, V.: A new flood type classification method for use in climate change impact studies, *Weather Clim. Extremes*, 14, 1–16, <https://doi.org/10.1016/j.wace.2016.10.001>, 2016.
- van den Hurk, B. J. J. M., Baldissera Pacchetti, M., Boere, E., Ciullo, A., Coulter, L., Dessai, S., Ercin, E., Goulart, H. M. D., Hamed, R., Hochrainer-Stigler, S., Koks, E., Kubiczek, P., Levermann, A., Mechler, R., van Meersbergen, M., Mester, B., Middelani, R., Minderhoud, K., Mysiak, J., Nirandjan, S., van den Oord, G., Otto, C., Sayers, P., Schewe, J., Shepherd, T.
- 630 G., Sillmann, J., Stuparu, D., Vogt, T., and Witpas, K.: Climate impact storylines for assessing socio-economic responses to remote events, *Clim. Risk Manag.*, 40, 100500, <https://doi.org/10.1016/j.crm.2023.100500>, 2023.
- Velázquez, J. A., Schmid, J., Ricard, S., Muerth, M. J., Gauvin St-Denis, B., Minville, M., Chaumont, D., Caya, D., Ludwig, R., and Turcotte, R.: An ensemble approach to assess hydrological models' contribution to uncertainties in the analysis of climate change impact on water resources, *Hydrol. Earth Syst. Sci.*, 17, 565–578, <https://doi.org/10.5194/hess-17-565-2013>,
- 635 2013.
- von Trentini, F., Leduc, M., and Ludwig, R.: Assessing natural variability in RCM signals: comparison of a multi model EURO-CORDEX ensemble with a 50-member single model large ensemble, *Clim. Dynam.*, 53, 1963–1979, <https://doi.org/10.1007/s00382-019-04755-8>, 2019.
- Vormoor, K., Lawrence, D., Heistermann, M., and Bronstert, A.: Climate change impacts on the seasonality and generation processes of floods – projections and uncertainties for catchments with mixed snowmelt/rainfall regimes, *Hydrol. Earth Syst. Sci.*, 19, 913–931, <https://doi.org/10.5194/hess-19-913-2015>, 2015.
- 640 Vormoor, K., Lawrence, D., Schlichting, L., Wilson, D., and Wong, W. K.: Evidence for changes in the magnitude and frequency of observed rainfall vs. snowmelt driven floods in Norway, *J. Hydrol.*, 538, 33–48, <https://doi.org/10.1016/j.jhydrol.2016.03.066>, 2016.



- 645 Willkofer, F., Schmid, F.-J., Komischke, H., Korck, J., Braun, M., and Ludwig, R.: The impact of bias correcting regional climate model results on hydrological indicators for Bavarian catchments, *J. Hydrol. Reg. Stud.*, 19, 25–41, <https://doi.org/10.1016/j.ejrh.2018.06.010>, 2018.
- Willkofer, F., Wood, R. R., von Trentini, F., Weismüller, J., Poschlod, B., and Ludwig, R.: A holistic modelling approach for the estimation of return levels of peak flows in Bavaria, *Water*, 12, 2349, <https://doi.org/10.3390/w12092349>, 2020.
- 650 Willkofer, F., Wood, R. R., and Ludwig, R.: Assessing the impact of climate change on high return levels of peak flows in Bavaria applying the CRCM5 large ensemble, *Hydrol. Earth Syst. Sci.*, 28, 2969–2989, <https://doi.org/10.5194/hess-28-2969-2024>, 2024.
- Wright, A. J., Ebeling, A., de Kroon, H., Roscher, C., Weigelt, A., Buchmann, N., Buchmann, T., Fischer, C., Hacker, P. W., Hildebrandt, A., Leimer, S., Mommer, L., Oelmann, Y., Scheu, S., Steinauer, K., Strecker, T., Weisser, W. W., Wilcke, W.,
- 655 and Eisenhauer, N.: Flooding disturbances increase resource availability and productivity but reduce stability in diverse plant communities, *Nat. Commun.*, 6, 6092, <https://doi.org/10.1038/ncomms7092>, 2015.
- Zhao, F., Nie, N., Liu, Y., Yi, C., Guillaumot, L., Wada, Y., Burek, P., Smilovic, M., Frieler, K., Büchner, M., Schewe, J., and Gosling, S. N.: Benefits of calibrating a global hydrological model for regional analyses of flood and drought projections: a case study of the Yangtze River Basin, *Water Resour. Res.*, 61, e2024WR037153, <https://doi.org/10.1029/2024WR037153>,
- 660 2025.