https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

Snowmelt Influence on Northern Hemisphere River Discharge - The Potential of Causal Inference for Assessing Long-Term Trends

Samuel Schilling[1], Tobias Bolch[2], Andreas Dietz[1], Rebecca Jean Herman[3,4], and Claudia Kuenzer[1,5]

[1]German Remote Sensing Data Center, German Aerospace Center, DLR, 82234 Weßling, Germany
[2]Institute of Geodesy, Graz University of Technology, Graz, Austria
[3]Center for Scalable Data Analytics and Artificial Intelligence, ScaDS.AI Dresden/Leipzig, 01062 Dresden, Germany
[4]Department of Computer Science, University of Potsdam, Potsdam, Germany
[5]Institute for Geography and Geology, University of Wuerzburg, 97074 Wuerzburg, Germany

Correspondence: Samuel Schilling (Samuel.schilling@dlr.de)

Abstract. Snowmelt is a vital contributor to river discharge across the Northern Hemisphere, supplying freshwater to over 1.5 billion people and supporting key economic sectors such as agriculture and hydropower. However, climate change has led to a decline in snow water equivalent (SWE) on almost the entire Northern Hemisphere, reducing snow-based water availability. Despite the importance of snowmelt and the pressure imposed by climate change, no large-scale studies have examined the connection of snowmelt dynamics and river discharge beyond statistical measures, which fail to capture the complexity of hydrological regimes. To address this gap, we perform causal discovery using PCMCI, a method that adapts the PC proposed by Peter Spirtes and Clark Glymour to the time series setting, to obtain qualitative causal structure across 119 basins from 1980 to 2022 and then quantify the causal effects using causal effect estimation with a 20-year moving window and a random forest estimator. Our results show that the role of snowmelt in streamflow generation is changing. In various basins where the method allows for trend detection, the ratio of the causal effect of snowmelt on river discharge to the mean of the river discharge is increasing despite declining SWE. This suggests that as precipitation patterns shift and intra-annual variability increases, snowmelt may become more important for streamflow generation in certain basins despite a generally declining SWE. While regional differences emerge, causal effects do not consistently correlate with geographical factors such as latitude or basin characteristics. Analyses in six basins that serve as illustrative examples, indicate that changes in seasonal hydrology, particularly the timing and distribution of precipitation, influence the relative role snowmelt plays for river discharge. These findings highlight the power of causal inference over conventional statistical measures in enhancing the analysis of large-scale snow hydrological regimes by adding depth to existing approaches.

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

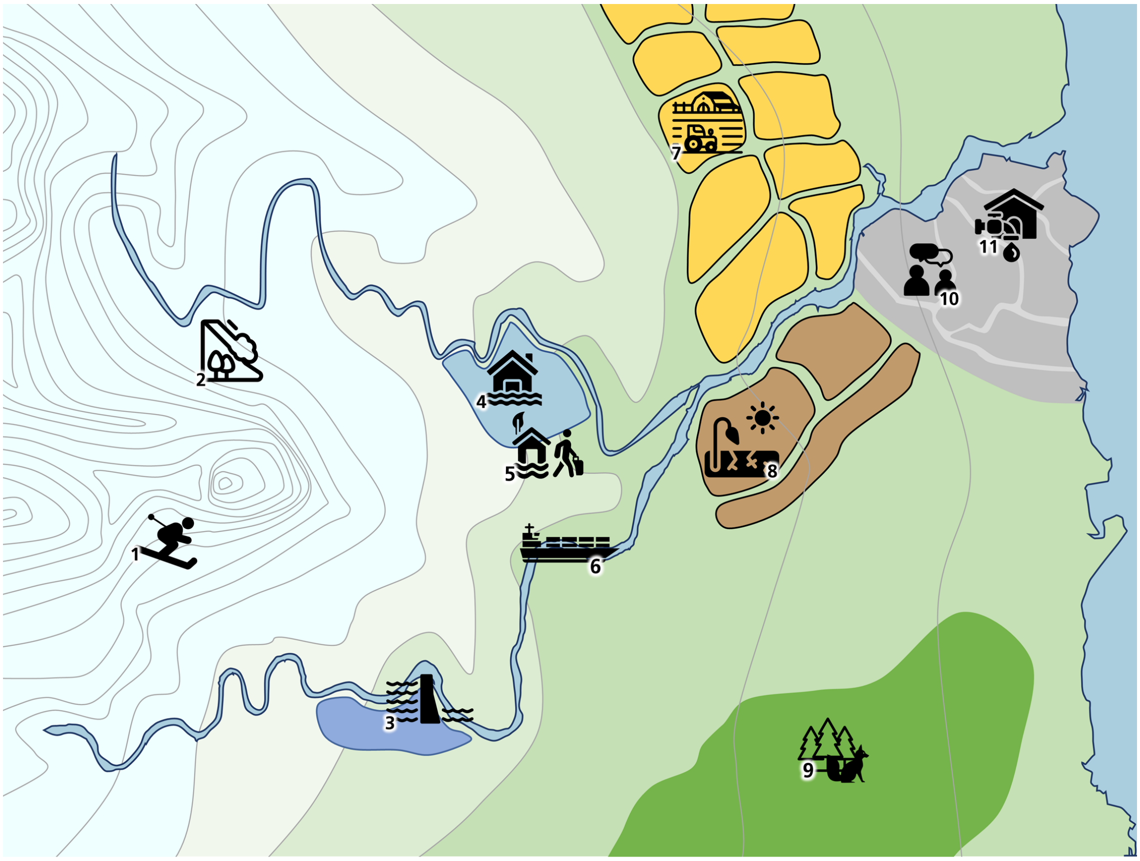
1 Introduction

1.1 Snow as a river flow driver

In various regions of the world, especially on the Northern Hemisphere, snowmelt is the dominant streamflow driver and serves as the primary freshwater source for over 1.5 billion people worldwide and thus their economic, societal and environmental livelihoods. (Barnett et al., 2005; UN DESA, 2022). Unlike rain, snow not only serves as a water resource but also as a storage mechanism. Snow accumulates mainly during winter and contributes to streamflow during the ablation phase, entering the stream through overland flow, subsurface flow, or intermediate storage such as glaciers and groundwater (DeWalle and Rango, 2008; Viviroli et al., 2007; Tague and Grant, 2009). Downstream, the water is subsequently used for various purposes.

However, the reliability of snow-dominated rivers as a freshwater resource is deteriorating due to changes induced by anthropogenic climate change in the upstream snowpacks (Fig. 1, label 11, Immerzeel et al. (2020); Gottlieb and Mankin (2024)). The most fundamental change is a decline in snow cover in the Northern Hemisphere. An analysis of various large-scale studies, with over 30 years of temporal coverage, has shown that there is a consensus on a decreasing snow water equivalent (SWE) trend, considering certain regional and seasonal differences (Schilling et al., 2024). This declining trend has various consequences; for instance, a smaller snowpack means reduced snowmelt and seasonality of the streamflow. However, since the decreasing trend does not preclude years with high snowpacks, the annual variability of SWE is increasing (Pulliainen et al., 2020; Gottlieb and Mankin, 2024). Combined, these effects decrease the temporal reliability of snow as a freshwater resource (Han et al., 2024; Wang et al., 2024). In addition, higher temperatures, especially in spring, can cause earlier and faster snowmelt, and can further raise flood risk by increasing the occurrence of rain-on-snow events (Fig. 1, label 4, Musselman et al. (2018); Maina and Kumar (2023)).

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026



1. Winter Tourism (less snow, higher operating cost, possible total loss)
2. Snow Avalanches
3. Hydropower (reduced potential, possible total loss)
4. Floods
5. Migration
6. Transport (riverbound cargo cannot be transported during low water levels)
7. Agriculture (reduced harvest, crop resistance)
8. Droughts
9. Flora & Fauna (changing habitats, color mismatches, forging issues)
10. Endangered Culture & Languages
11. Freshwater Scarcity

Figure 1. Schematic illustration of the impacts of changing snowpacks.

Downstream, several systems crucial for human livelihood are increasingly subjected to the impacts of these changes, as schematically shown in figure 1. Agriculture in snow-dominated regions, for example, is closely tied to the availability of water from snowmelt and can therefore suffer reduced harvests and crop failure (Fig. 1, label 7, Qin et al. (2022); Huning and AghaKouchak (2020)). Other economic sectors such as hydropower (Fig. 1, label 3, Soomro et al. (2024)), inland cargo shipping (Fig. 1, label 6, Schweighofer (2014); Bedoya-Maya et al. (2024)), and tourism (Fig. 1, label 1, François et al. (2023)), which in some regions are reliant on consistent snowpacks, are also affected. Additionally the changing snowpack intensifies the demand on civil infrastructure regarding heightened flood risk (Fig. 1, label 4, (Zhou et al., 2022)), or snow avalanches (Fig. 1,

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

label 2, Eckert et al. (2024)). Communities, especially indigenous peoples, who are heavily affected by these developments also experience changes in their cultures and languages (Fig. 1, label 10) and are sometimes also forced to migrate to safer places (Fig. 1, label 5, (Ford et al., 2021; Reyes-García et al., 2024)). Finally, the effects of changing global snow cover extend beyond human systems, influencing flora and fauna through numerous ecological processes (Fig. 1, label 9 (Inouye, 2022; Slatyer et al., 2024; Wenzl et al., 2024)).

A brief overview of the role of snow on the hydrological regime in various basins is provided in figure 2 by displaying the ratio of Snow Water Equivalent (SWE) to total precipitation in 119 river basins. This ratio serves as a measure of snow dominance, highlighting regions where and to what extent snow contributes to streamflow generation. Generally the snow dominance increases by latitude, and around major mountain ranges (compare figure 2 right insert (c)). Figure 2b shows the normalized average of total precipitation, as an indication for the general hydroclimatology in the analyzed basins. This provides context for interpreting the SWE-to-precipitation ratio, as basins with lower total precipitation tend to show relatively higher ratios.

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

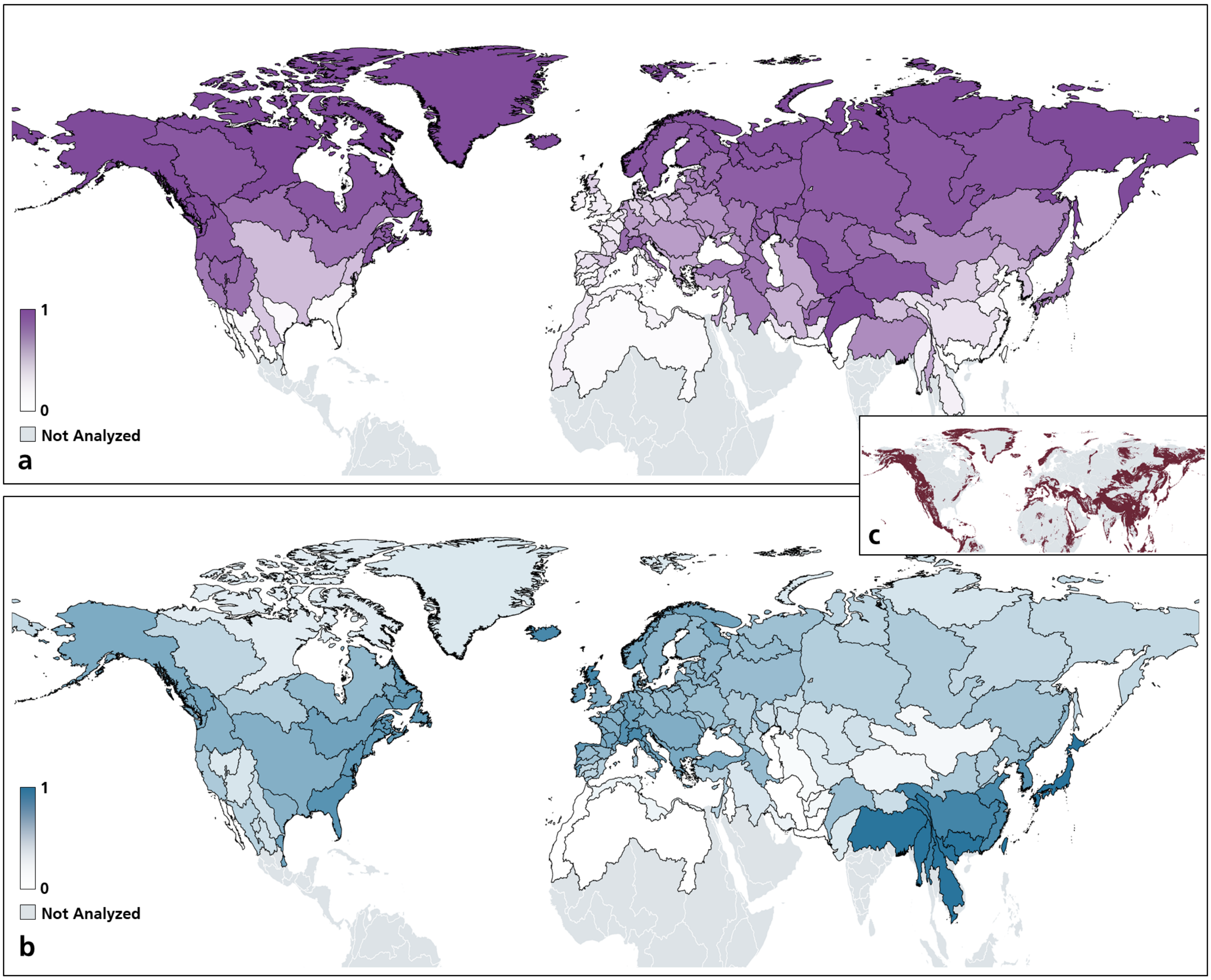


Figure 2. Top: Normalized average ratio between snowmelt and total precipitation in the analyzed river basins for 1980-2022 (Data: Snow CCI (Luojus et al., 2024), ERA 5 (Muñoz Sabater, 2019)), Bottom: Normalized average monthly total precipitation (1980-2022) in the analyzed river basins (Data: Era 5 (Muñoz Sabater, 2019)). Middle right (c): Mountainous areas of the Northern Hemisphere (Data: GMBA Inventory v2.0 (Snethlage et al., 2022)).

Despite extensive research on Northern Hemisphere snow water equivalent (SWE), only a minority of large-scale studies connected SWE with broader contexts in their design or data use since the year 2000 (Schilling et al., 2024; Gordon et al., 2022). When such links were made, they focused almost exclusively on water availability, including terrestrial water storage (TWS), river discharge, or droughts, with few studies extending beyond these themes. There are two studies that link SWE to TWS on a global scale (Zhang et al., 2019; Tangdamrongsub et al., 2021) and one hemispherical analysis (Girotto et al., 2021), but no studies linking SWE to river discharge on a hemispherical or global scale (Schilling et al., 2024; Gordon et al.,

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

2022). The only studies conducted beyond a national or basin scale linking river discharge to SWE were two Pan-Arctic studies (Rawlins et al., 2007; Biancamaria et al., 2011), and when the scope is extended to snow cover research, only one Arctic study linking snow cover to discharge, that relies on a precipitation model rather than remote sensing data (Park et al., 2024).

Generally three types of approaches are used to quantify the SWE contribution to river discharge. Firstly, most SWE–discharge investigations employ statistical measures of association, mostly correlations or regression approaches, which can only incorporate additional drivers or temporal lags to a limited extent (e.g.Xu et al. (2009); Tong et al. (2010); Biancamaria et al. (2011); Wang et al. (2017); Kumar et al. (2019)). Secondly, ratio-based approaches, such as the snow dominance ratio used globally by Barnett et al. (2005) and Gottlieb and Mankin (2024) or regionally by Li et al. (2017), assume total precipitation equals discharge and likewise do not explicitly address storage, evaporation or time lags. Finally, the analysis of stable oxygen isotopes can also distinguish snowmelt contributions in streamflow (Craig, 1961), but its reliance on intensive field sampling limits studies to small catchments (López-Moreno et al., 2023; Lucianetti et al., 2020; Beria et al., 2018).

In sum, no hemispherical-scale study currently quantifies snow's role in river discharge composition. Existing large-scale research relies on methods that do not fully explore multivariate and temporal dynamics, underscoring the need for analyses that extend beyond statistical associations and incorporate time-lagged, storage-sensitive mechanisms.

1.2 Background on Causal Inference in Environmental Science

Causal inference methods are driven by the question: "What effect does a certain trigger variable *X* have on a target variable *Y*?" An early attempt to address this question was made by Granger (1969), who introduced the concept of using the unique predictive power of *X* to identify causal relationships in time series. Later, Spirtes (1996) enabled the analysis of causal relationships along a causal graph. Furthermore, Pearlian approaches expanded this framework to multivariate and lag specific contexts, allowing tests of conditional independence across time as well as the quantification of the effect that an intervention *X'* has on *Y* (Runge et al., 2012; Pearl, 2000).

In environmental applications, such causal effects are often interpreted in terms of the contribution of individual processes or variables to a system response. In the context of snow hydrology, this naturally raises the question of how snowmelt contributes to river discharge and how this contribution varies across space and time. In this study, we apply a recently developed causal inference method, causal effect discovery, based on the Peter Clark Momentary Conditional Independence (PCMCI) framework developed by Runge et al. (2019), in combination with the causal effect estimation approach introduced by Runge (2021).

While initially developed for economic research (Granger, 1969), causal inference methods have recently gained traction in environmental and Earth observation (EO) studies. Granger causation has been applied in ecological research (e.g. Philippon et al. (2005); Cicuendez et al. (2015); Zhu and Meng (2015)) as well as in broader environmental and climate related studies (e.g. Beyers (1998); Capua et al. (2020); Pérez Valentín and Müller (2020)). With the development of PCMCI, the scope of causal inference applications in EO studies has further expanded, enabling multivariate and lag aware analyses of complex environmental systems (e.g. Uereyen et al. (2022); Sogno et al. (2024); Karmouche et al. (2023)).

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

Snow-related variables have been incorporated into multivariate environmental systems in a number of studies using causal inference. However, in most of these studies, snow was not the primary focus, but rather one of several variables considered in their causal networks, often without explicitly quantifying its contribution to river discharge or water availability (e.g. Kretschmer et al. (2016); Uereyen et al. (2022); Kolluru et al. (2024); Yuan et al. (2024)). Causal studies with a hydrological focus have instead concentrated on specific phenomena such as floods (Sun et al., 2024; Kashyap and Behera, 2024), rain on snow events (Koya et al., 2024), or groundwater dynamics (Zhang et al., 2019). A recent study by Kim et al. (2025) examined the influence of sea surface temperature variability on North American snow resources, but did not explicitly link snow dynamics to downstream hydrological responses. Therefore, to date, no large scale causal analysis has specifically examined the contribution of snowmelt or snow water equivalent to river discharge across extended spatial and temporal scales.

Given the demonstrated applicability of PCMCI to environmental time series, it can be considered a suitable framework for addressing this research gap. This study thus presents a hemispherical scale causal inference analysis of snow hydrology, targeting the contribution of snowmelt and rain to river discharge. The analysis incorporates variables beyond SWE and discharge, including rain, soil moisture, evapotranspiration, glacier runoff, baseflow flux, and temperature, while accounting for time lags of up to six months.

2 Data and Methods

The workflow in this study can be distinguished into three main phases: Downloading and Preprocessing, Statistical Metrics and Trend Calculation, and Causal Inference. In the following section we describe these working phases as well as the utilized data and the study area. A schematic overview of the used data, as well as the workflow is shown in 3. There is no validation section provided here, as no independent data are available that are both spatially and temporally suitable for the scale of this study. All utilized data, as well as the corresponding updates by the providing entities, was validated by the developers and published in peer-reviewed studies (cited in the corresponding sections), and is thereby meeting the qualitative requirements of the analysis at hand.

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

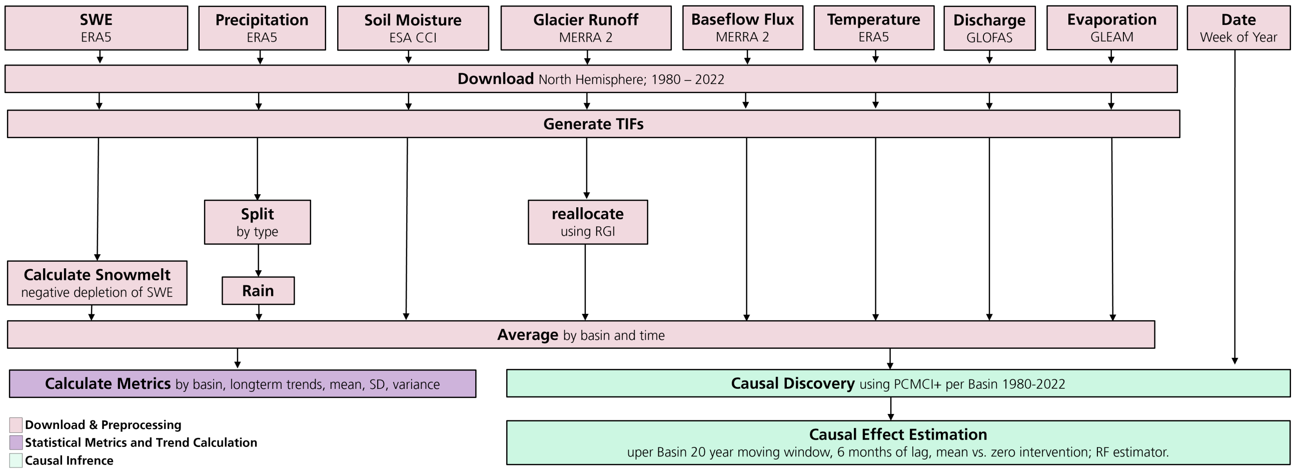


Figure 3. Schematic illustration of the applied workflow.

120 ## 2.1 Studied Basins and Period

For the delineation of the hydrological basins we use the "Major Hydrological Basins of the World" dataset from the Food and Agriculture Organization of the United Nations (FAO, 2011). The dataset defines basins as top-level drainage areas bounded by topographic divides, within which all surface water flows toward a common outlet such as a river, lake, or ocean (FAO, 2011). Based on the Climate Change Initiative Data by the European Space Agency (ESA) for Snow (SnowCCI), version 3.1 (Luojus et al., 2024) and ECWMF reanalysis land (ERA 5 Land/ ERA 5) (Muñoz Sabater, 2019) SWE datasets, we determine the number of years each basin had snow coverage between 1980 and 2022. We select basins that have snow coverage for at least 30 years during this time period, yielding 119 basins for examination. We focus on the Northern Hemisphere because, although there are snow-dominated regions in the Southern Hemisphere, the majority of the world's SWE, snow-dominated rivers, and thus the human populations affected by the described effects in the introduction, are found in the Northern Hemisphere (Barnett et al., 2005; UN DESA, 2022; Tangdamrongsub et al., 2021). We choose the period from 1980 to 2022 because of the availability of the employed soil moisture dataset, which is based on passive microwave satellite data. The extent of the analyzed basins can be seen in the figure 2.

2.2 Data

Table 1 provides an overview of the datasets used and their sources. Generally, spatial and temporal considerations guide the data selection. When multiple comparable datasets were available, we select the dataset based on practical handling aspects (e.g. evapotranspiration datasets). For rain and temperature we use the ERA 5 and ERA 5 Land data respectively, provided by the European Centre for Medium-Range Weather Forecasts (ECMWF) and which is available in the Copernicus Climate Data Store (CDS). River discharge data is provided by the Global Flood Awareness System (GloFAS), and the soil moisture (SM) data by the European Space Agency (ESA) Climate Change Initiative (CCI), both datasets are also obtained from the

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

140 CDS. The baseflow flux, which serves as a proxy for groundwater runoff, and the glacier runoff data come from the Modern-Era Retrospective analysis for Research and Applications Version 2 (MERRA 2) provided by the Global Modeling and Assimilation Office (GAMO) of the National Aeronautics and Space Administration (NASA).. Finally, for evapotranspiration we use the evapotranspiration variable from the Global Land Evaporation Amsterdam Model (GLEAM) version 4.1, which is maintained by the University of Gent.

Table 1. Data used for the analysis with the corresponding sources. Biweekly averages were used for all datasets.

Variable	**Source**	**Unit**	**Data Type**	**Remarks**
Basin Outlines	FAO Major Hydrological Basins (FAO, 2011)	-	Vectorized Basin Outlines	-
Rain	ERA 5; ECWMF (CDF) (Hersbach et al., 2023)	m	Reanalysis	Liquid precipitation classification using the precipitation type variable of ERA 5.
Temperature	ERA 5 Land; ECWMF (CDF) (Muñoz Sabater, 2019)	K	Reanalysis	2m temperature.
Snowmelt	Snow CCI v3.1 (Luojus et al., 2024); ERA 5 Land; ECWMF (CDF) (Muñoz Sabater, 2019)	mm; m	PMW & in-situ; Reanalysis	ERA 5 used to fill data gaps in SnowCCI data. Snowmelt defined as the negative depletion of SWE.
River Discharge	GloFAS (Grimaldi et al., 2022)	m^3/s	Reanalysis	-
Soil Moisture	ESA CCI (Dorigo et al., 2019)	m^3/m^3	Passive & Active MW	No data days interpolated.
Baseflow Flux	MERRA-2 (GMAO, 2015a)	m^3/s	Reanalysis	-
Glacier Runoff	MERRA-2 (GMAO, 2015b)	m^3/s	Reanalysis	-
Evapotranspiration	GLEAM v4.1 (Miralles et al., 2024)	mm	Model	-

2.3 Preprocessing

We download all data in the provided temporal resolution and average by calculating the biweekly mean. Spatially we average the data by basin, using a proportional approach to avoid values being attributed to multiple basins. Therefore we overlay the variable data, which are all provided as raster data over the vector geometries of the basins. For all pixels that touch more than one basin, we calculate the share of each basin, and attribute the value accordingly. The individual preprocessing steps applied per variable are described in the following subsections. Note that stationarity is a requirement for PCMCI and therefore detrending and a seasonal decomposition of the time series is suggested by Runge et al. (2023). Our objective, however, is to preserve possible long-term trends in the causal factors. We therefore do not detrend the data or subtract a fixed seasonal climatology. Instead, we incorporate a deterministic seasonality variable to allow causal relationships to vary within seasons and repeat the analysis using a sliding window to assess the impact of climate change. This avoids filtering aggregated seasonality and accounts for the potential shift of seasonal patterns under climate change. This approach is described in more detail in section 2.5.1.

2.3.1 SWE / Snowmelt

Since the causal inference focuses exclusively on the snowpack's contribution to river discharge, thus the ablation phase, we convert SWE into snowmelt, defined as the depletion of the SWE between successive time steps (Musselman et al., 2017; Wu et al., 2022). For each pixel we calculate the difference in SWE between consecutive time steps and sum all negative changes as absolute values to quantify total snowmelt.

2.3.2 Precipitation / Rain

To avoid redundant inclusion of the contribution of snow to river discharge, we subtract it from the ERA5 total precipitation data to generate an intermediary liquid precipitation dataset, referred to as *rain* throughout this paper. We distinguish between frozen and liquid precipitation, using the precipitation type from the CDS (Hersbach et al., 2023), on an hourly basis, and only perform the biweekly averaging on the resulting liquid preciptation dataset *rain*. The rain data are finally averaged biweekly.

2.3.3 Glacier Runoff

The MERRA-2 data, used for the glacier runoff variable, has a resolution of 0.625° × 0.5° (GMAO, 2015b). This resolution occasionally results in pixels with runoff values touching basins that have no glaciers. In our proportional approach for attributing the pixel values to the basins, glacier runoff would thus be falsely included in the analysis of these basins, if not addressed. To counteract this issue, we identify glacier locations using the Randolph Glacier Inventory (RGI) v7.0 (RGI 7.0 Consortium, 2023). We use spatial overlap analysis to reveal basins which contain no glaciers but have runoff attributed to them and manually reallocate their glacier to reflect hydrological conditions as accurately as possible.

2.4 Statistical Metrics and Trend Calculation

For all data-based variables (see Table 1), we computed a range of statistical measures (mean, median, variance, and standard deviation [StDev]) for each basin to characterize the data distribution and behavior. Additionally, we apply a Theil-Sen estimator (Sen, 1968) to each variable and basin to estimate trends while minimizing outlier influence. Since the Theil-Sen estimator lacks an inherent significance measure, we combine it with a Mann-Kendall test to evaluate trend significance. We also normalize the Theil-Sen slope by the basin average per variable. These statistical analyses and trend estimations provide a

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

comprehensive understanding of the data across the study region and support a detailed discussion of causal effects and trends across basins.

2.5 Causal Inference

Our causal inference framework consists of two phases; causal discovery and causal effect estimation. The causal discovery phase constrains the causal graph based on a series of unconditional and conditional independence tests. The causal graph describes the relationships between the different variables over the defined time lags. The causal effect estimation phase uses the causal graph to determine the effect that an intervention on a trigger variable has on a target variable (Runge et al., 2023; Pearl, 2000). A schematic overview of the causal inference framework as well as its utilization in this study is displayed in figure 4.

We run PCMCI+ once per basin over the entire study period to detect basin specific relationships between the examined variables. This is possible because we assume that basic hydrological principles remain unchanged for the entire study period. Following causal discovery we perform a series of causal effect estimations on 23 subperiods of 20 years (1980-1999, 1981-2000, ..., 2003-2022) for each basin. This moving window design allows us to depict changes in the effect size within the examined time period. We average the values from the subperiods per year resulting in a 43-year yearly time series of causal effects per basin and trigger variable. The effect estimation is run for the 119 basins mentioned in section 2.1 and for the trigger variables snowmelt and rain, as these variables may be regarded as primary drivers within our assumed system, which subsequently influence all other hydrological variables (DeWalle and Rango, 2008).To confirm the basic functionality of the method, we carry out a set of sanity checks. We introduce modifications to selected variables (snow or rain) and examine whether the detected effects (on river discharge) changed in the expected qualitative manner. These checks serve as sanity tests rather than a sensitivity analysis.

The following subsections further describe our application and parametrization of the two causal inference phases on the snowmelt river discharge relationship.

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

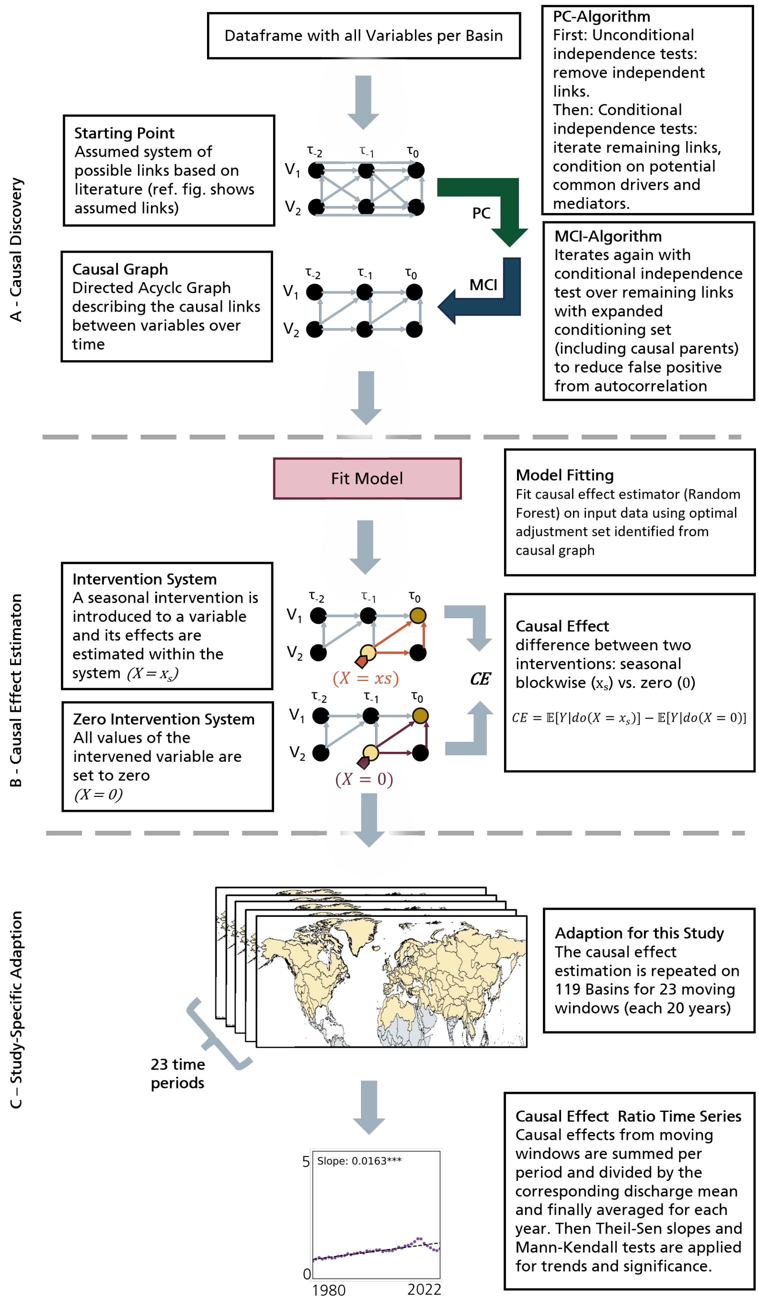


Figure 4. Schematic illustration of the causal inference framework applied in this study. A) Causal Discovery; PC and MCI algorithms examine statistical conditional independences of relationships between variables, which in turn are used to draw the causal graph. B) Causal Effect Estimation; The causal model is fit to the input data, and then two systems, one intervened with a seasonal intervention x_s and one intervened with a zero intervention (0) are compared. The difference between the value of the two systems is the causal effect. C) Study Specific Adaption; Causal effects are estimated in 20-year moving windows across the 43-year time series, allowing the derivation of a causal-effect time series and its trend.

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

2.5.1 Causal Discovery

For the causal discovery we use PCMCI+ (Gerhardus and Runge, 2020; Runge et al., 2023), with eight biweekly variables obtained from time series data. These are river discharge, snowmelt, rain, glacier runoff, soil moisture, baseflow flux, evapotranspiration and temperature. Additionally, we include the calendar week as an index variable, which accounts for seasonal non-stationarity. PCMCI+ is run with $\tau_{max} = 12$, thus comprising one contemporaneous and twelve biweekly lagged effects (six months). Within PCMCI+ we specify a system of connections among the variables based on established hydrological and atmospheric relationships (DeWalle and Rango, 2008; Tague and Grant, 2009; Huss and Hock, 2018; Hammond and Kampf, 2020; Slater and Binley, 2021).These constraints are implemented as allowed relationships rather than fixed assumptions, restricting the search space without imposing causal links. Some link directions are predetermined by hydrological theory, while others remain unconstrained and are oriented by PCMCI+ using the PC algorithm's orientation rules. A schematic illustration of the assumed hydrological system is provided in Appendix A. The PCMCI+ algorithm consists of two substages. Firstly, the Peter Clark (PC) algorithm which builds a causal graph based on two key assumptions: the Markov condition (dependence implies connection) and the faithfulness condition (conditional independence implies no direct causation). Variables without unconditional dependencies are removed, after which the algorithm iteratively tests the remaining links for conditional independence, eliminating those that become independent once the common drivers and mediators are accounted for (see Fig. 4A, green arrow). This procedure continues until no further tests are possible, yielding the set of candidate parents (Runge et al., 2023, 2019). Secondly, the Momentary Conditional Independence (MCI) test evaluates the candidate parents using an expanded conditioning set (see Fig. 4A,blue arrow). By conditioning on the lagged parents of the driver and target variables, MCI refines the causal graph and reduces autocorrelation effects (Runge et al., 2023, 2019). The conditional independence test for the PCMCI+ can be adapted for the research problem at hand. We use the Conditional Mutual Information (CMIknn), as a conditional independence test, as it does not assume any parametric form for the of relationship between variables (Runge, 2018). This was crucial, given the presence of nonlinear relationships in our system.

2.5.2 Causal Effect Estimation

While the causal graph reveals the presence and direction of causal effects between variables over time, it does not quantify the strength of these effects. To estimate the magnitude of the causal relationships causal effect estimation is conducted (see figure 4B). After the full causal model is fit using the input data and parametric assumptions, an intervention can be introduced into the model using causal "do" calculus, or in this case optimal adjustment. By comparing two systems that are differently intervened, the difference in predictions provides the final causal effect (Runge et al., 2023; Runge, 2021). This is done using an estimator which can be selected for the examined study setup (Runge, 2021). For our setup we utilize a random forest (RF) estimator to account for the versatile nature of the relationships examined in this study, since the RF does not presume the type of relationship between two variables Breiman (2001); Geurts et al. (2006). We configure the RF with 1000 estimators to enhance model robustness, using the absolute error criterion to make the model more sensitive to small deviations in the data. To avoid overfitting, the maximum depth is set to 10, as this value results from a global hyperparameter search in which different tree

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

depths were evaluated across all basins and time periods.

Since the resulting effect estimates are directly shaped by how the intervention is defined, the intervention in our causal effect estimation setup has to reflect conditions that may realistically occur in the data. In our case with multiple basins that vary in location, topography, and climate, another requirement for the intervention is the comparability across basins. Therefore in our setup the intervention is not a single global value but it is based on the seasonal structure of each basin and to the specific time lag under investigation. For, each basin, and year, we divide the variable time series into 26 parts, representing the seasonal cycle of the year. For every of these 26 parts, we compute the mean across all years and apply it as the intervention value for the corresponding period in specific position within the seasonal cycle. We ensure that these block-specific interventions and the responses of the target are associated with the seasonal block they represent, also intervening the index variable (calendar week). This way the interventions and responses are anchored in time and correctly aligned with each seasonal block.

We run the causal effect estimation for two variables. Firstly to estimate the causal effect of snowmelt on river discharge and secondly to estimate the causal effect of rain on river discharge. For both snowmelt and rain we use the same methodological setup. The causal effect estimation is run using a 20 year moving window, over our 43 years of data. For every period used, we determine the interventions separately using the corresponding time series. This 20-year window size balances the need for sufficient data points to reliably estimate causal effects while enabling the detection of long-term temporal trends. We then calculate the causal effect as the difference between the model prediction under the blockwise intervention (4B, orange arrows) and the prediction under an intervention in which all snowmelt related lagged values are set to zero (4B, dark red arrows). This yields a total causal effect per 20 year period, which we then divide by the mean river discharge of the corresponding 20 year period. We average these effects by year, which results in a 43 year time series (4C). Finally we apply a a Theil-Sen estimator and Mann-Kendall test per basin and target variable. If in a basin at least one yearly average is zero, we exclude the basin from the trend analysis, as zeros near the edges of the time series can lead to unstable or notably steep trend slopes.

3 Results

3.1 Variable Trends

The normalized Theil-Sen trends of all variables in the analyzed basins were computed using the basin mean and the maximum absolute value for each variable, allowing for comparability across basins and variables. These trends are illustrated in figure 5. A selection of basins, together with the corresponding causal trends, is examined in more detail in Section 3.4. As a comprehensive discussion of all variables and basins is beyond the scope of this publication, the full set of statistics per basin is provided in the supplementary materials (Appendix B).

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

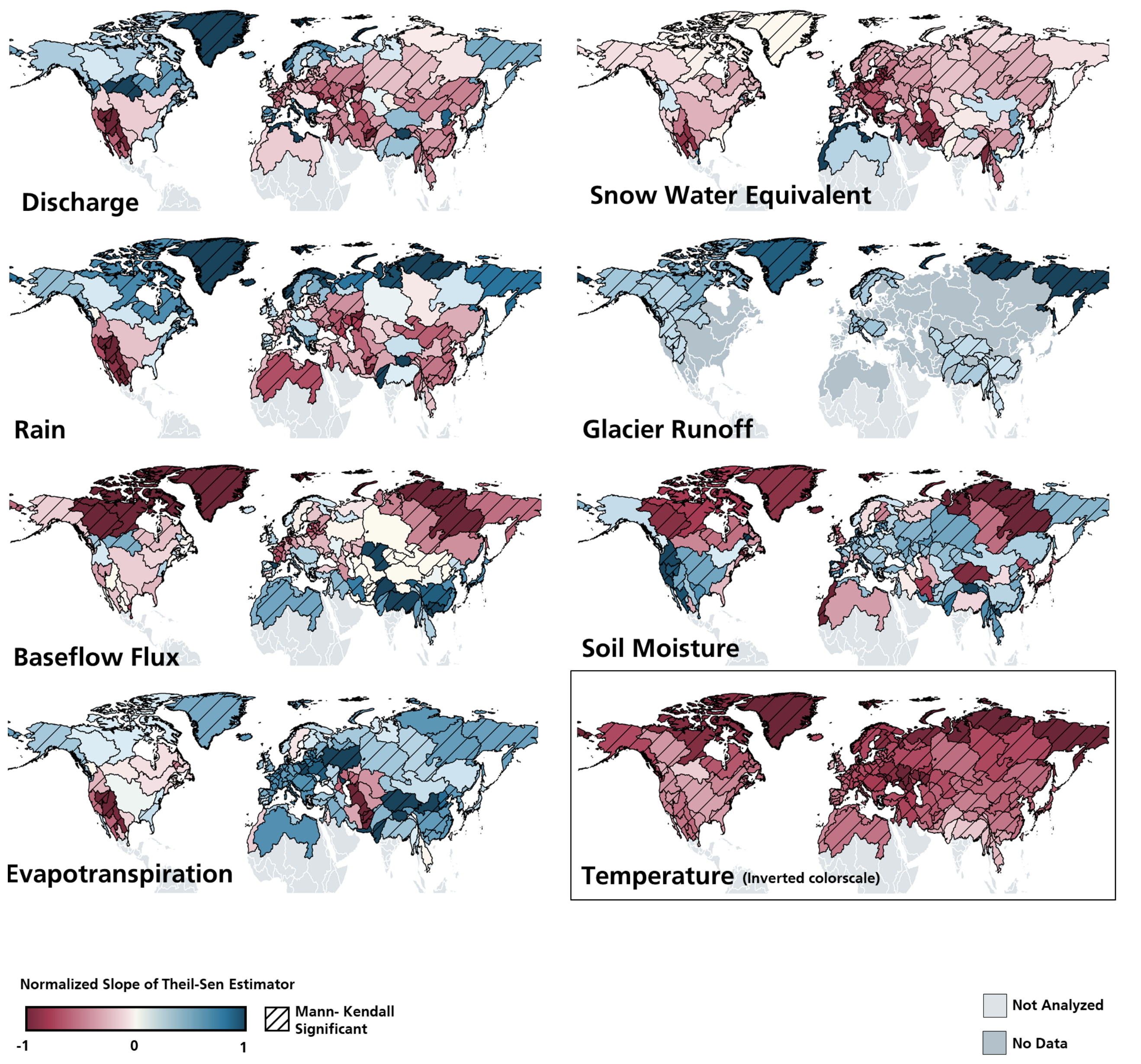
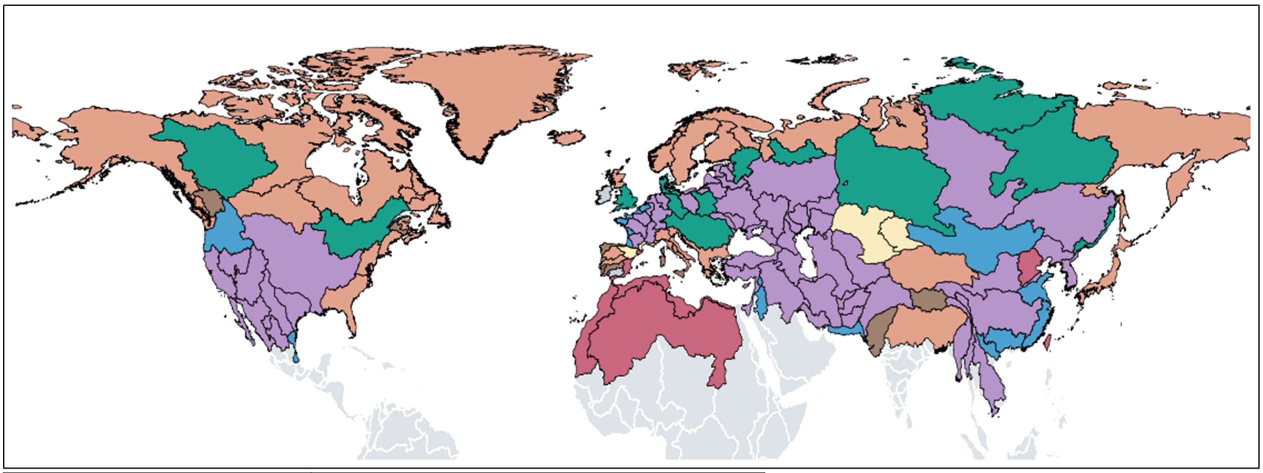


Figure 5. Normalized Theil-Sen trend with Mann-Kendall significance for all utilized variables in the 119 analyzed river basins. The color scale for all plots is scaled using the 5% and 95% percentile to ensure comparability between the different variables). The colorscale for the temperature is inverted.

265 Figure 6 contains the same information as figure 5, however the basins are grouped by their river discharge, snow, and rain trend slopes, to generate a general impression of the dynamics in the basins. Note that for visualization purposes we refrained from generating intermediate categories, therefore also minor, and non-significant trends were considered for the grouping.

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

Even though eight groups are possible, there are four groups to which a majority of the analyzed basins can be attributed (105/119). 52 basins saw a decreasing trend for river discharge, SWE, and rain (purple). An additional twelve basins saw a decrease in river discharge and SWE but an increase in rain (green). This contrasts with 28 basins where the SWE decreased but rain and river discharge increased (orange). Finally the group where river discharge and rain were decreasing comprises 13 basins (blue). Considering these groups, the data furthermore suggests that in nearly all Arctic and Pan-Arctic basins, with the exception of the Yenisey Basin, the SWE was decreasing while rain was increasing, with various outcomes on the river discharge. Also, in the latitude band south of the Arctic, between around 60° and 20° North, a predominant majority of basins saw a decreasing trend in all three variables considered for the grouping.



Variable	Trend Direction							
River Discharge	↑	↑	↑	↑	↓	↓	↓	↓
SWE	↑	↑	↓	↓	↓	↑	↓	↑
Rain	↑	↓	↑	↓	↓	↓	↑	↑

Figure 6. The 119 analyzed river basins, categorized by their river discharge, snow, and rain trend slopes.

3.2 North Hemisphere Causal Trends

The causal effect trends for snowmelt and rain on river discharge were assessed across all 119 basins, as shown in figures 7 and 8 respectively. Areas colored in light brown were examined but no causal link, effect, or trend could be derived. This does not imply that no connection exists between the trigger variables (snow and rain) and the target variable (river discharge), or that no trend is present, but rather that our setup could not detect a connection, or the basin was excluded due to years with zero values. For the causal effect of snowmelt on river discharge our method detected a continuous effect and thus trend in 73 basins, out of these 32 had a positive trend, 29 of those trends were significant. Of the 41 basins with negative trends, 34 had a significant trend. For the causal effect of rain on river discharge, the method detected a continuous effect and therefore trend in 117 basins. The effect of rain on river discharge was positive in 57 basins (51 significant), and negative in 60 basins (56

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

significant). The largest increase for the causal effect of snowmelt on river discharge was found in the Dnieper basin in eastern Europe. In contrast, the steepest decrease in the causal effect of snowmelt on river discharge occurred at the Mediterranean Sea east coast basin, which includes southern Türkyie, and parts of Lebanon, Syria, Israel, Jordan and Palestine. For rain the corresponding extreme values were found in the Hamun-e Mashkid basin in Iran (steepest increase), and in the Rio Grande in the USA and Mexico (steepest decrease). If normalized with the basin mean, the steepest increase is to be found in the Central Iran (snowmelt) and on the Siberia West Coast (rain), thee steepest decrease in the Nelson basin (Canada, snowmelt), and on the North West coast of Mexico (rain). Overall, for all regions where a trend was calculated, no apparent overarching correlations or patterns emerged. Thus, no latitude or mountain effect could be observed when correlating the trend slope with the corresponding data. Furthermore, no correlation to the snow dominance (compare 2) or the overall discharge of the corresponding rivers could be identified. All results and trends can be found with the variable trends, grouped by basin, in Appendix B.

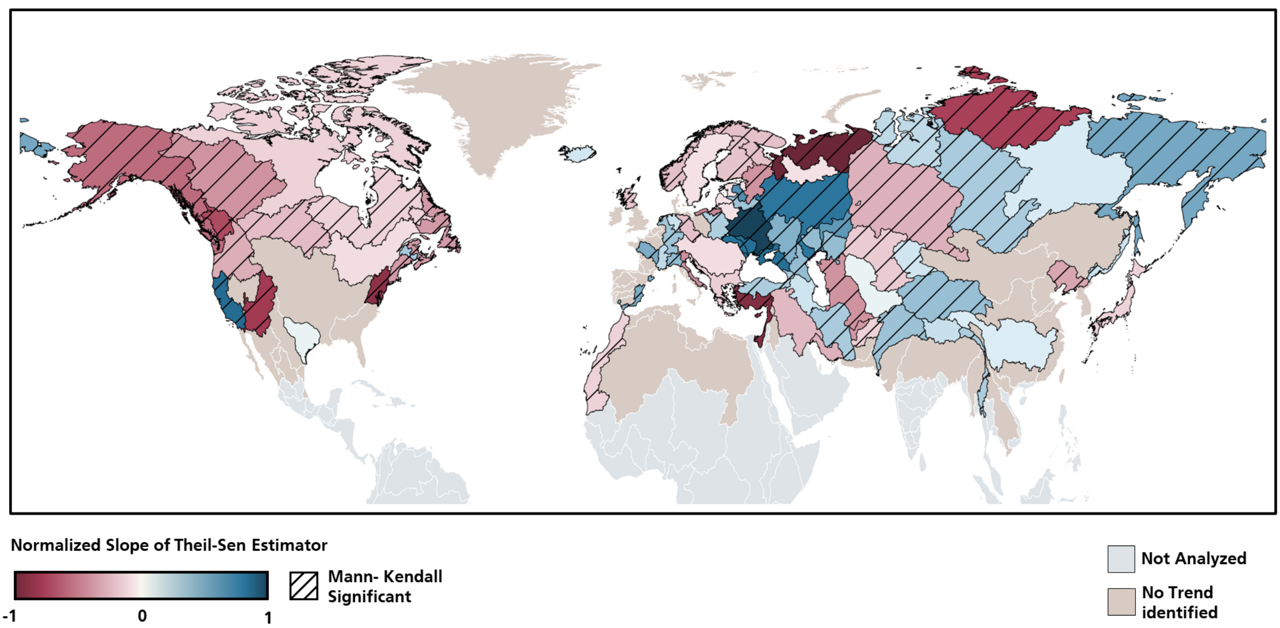


Figure 7. Normalized Theil-Sen trend with Mann-Kendall significance for the causal effect of snowmelt on river discharge between 1980 and 2022.

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

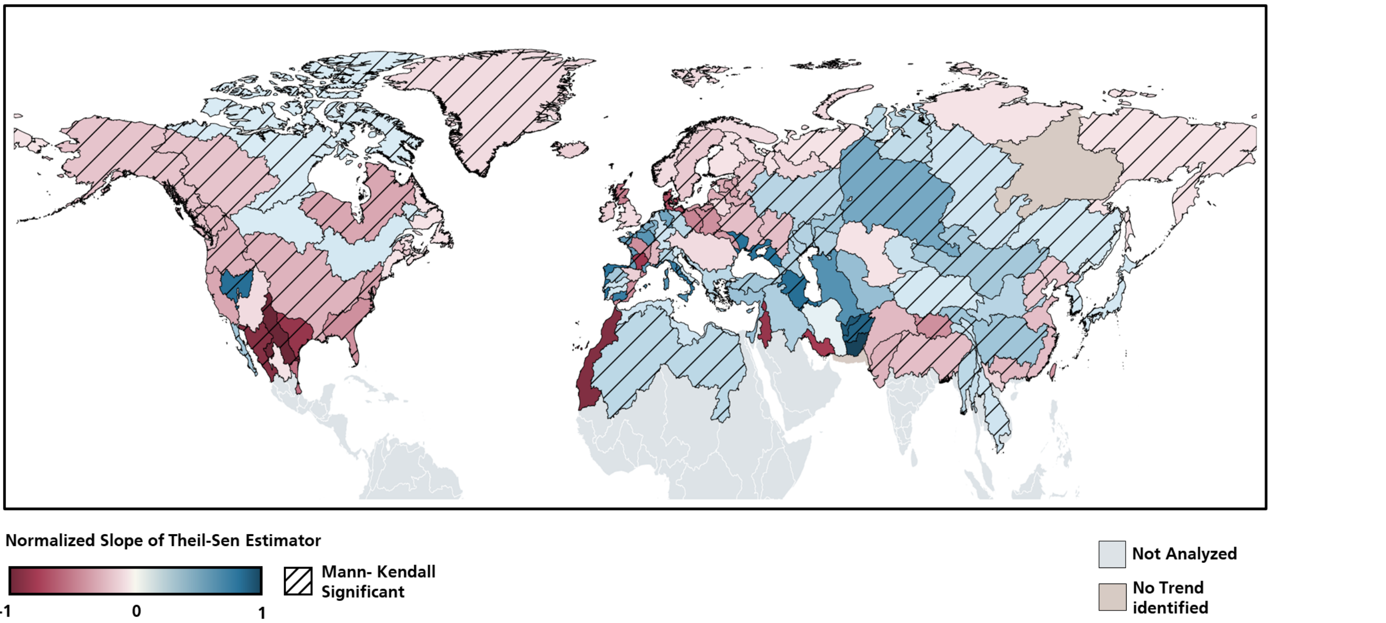


Figure 8. Normalized Theil-Sen trend with Mann-Kendall significance for the causal effect of rain on river discharge between 1980 and 2022.

3.3 Using Causal Effects as Indicators of Water Stress

One reason to study the relationship between SWE and river discharge, or other measures of water availability, is the increasing occurrence of droughts and snow droughts due to climate change (Cowherd et al. (2023); Gottlieb and Mankin (2024)). Identifying regions where SWE is declining alongside river discharge, can therefore indicate where snow loss is a key driver of water stress, given the degree of snow dominance in those basins. Relying on the variable trends of SWE and river discharge we used our results to identify such regions in our scope. A majority of the basins with a negative discharge trend also have a negative SWE trend (64/79). The remaining 15 basins that show a negative discharge trend despite an increasing SWE trend are shown in light green in figure 9. However, apart from the Fraser basin (USA/Canada), these all lie in rain dominated or very arid regions. In 45 of the 64 basins with decreasing discharge and decreasing SWE our method was able to identify a causal trend. Of those 22 showed an increasing causal effect trend (blue in figure 9). In another 23 basins the causal effect of snowmelt on river discharge was decreasing (red in figure 9). Overall 20 out of the 22 basins with decreasing river discharge trend, decreasing SWE trend, and increasing causal effect trend of snowmelt or river discharge are located on the Eurasian landmass.

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

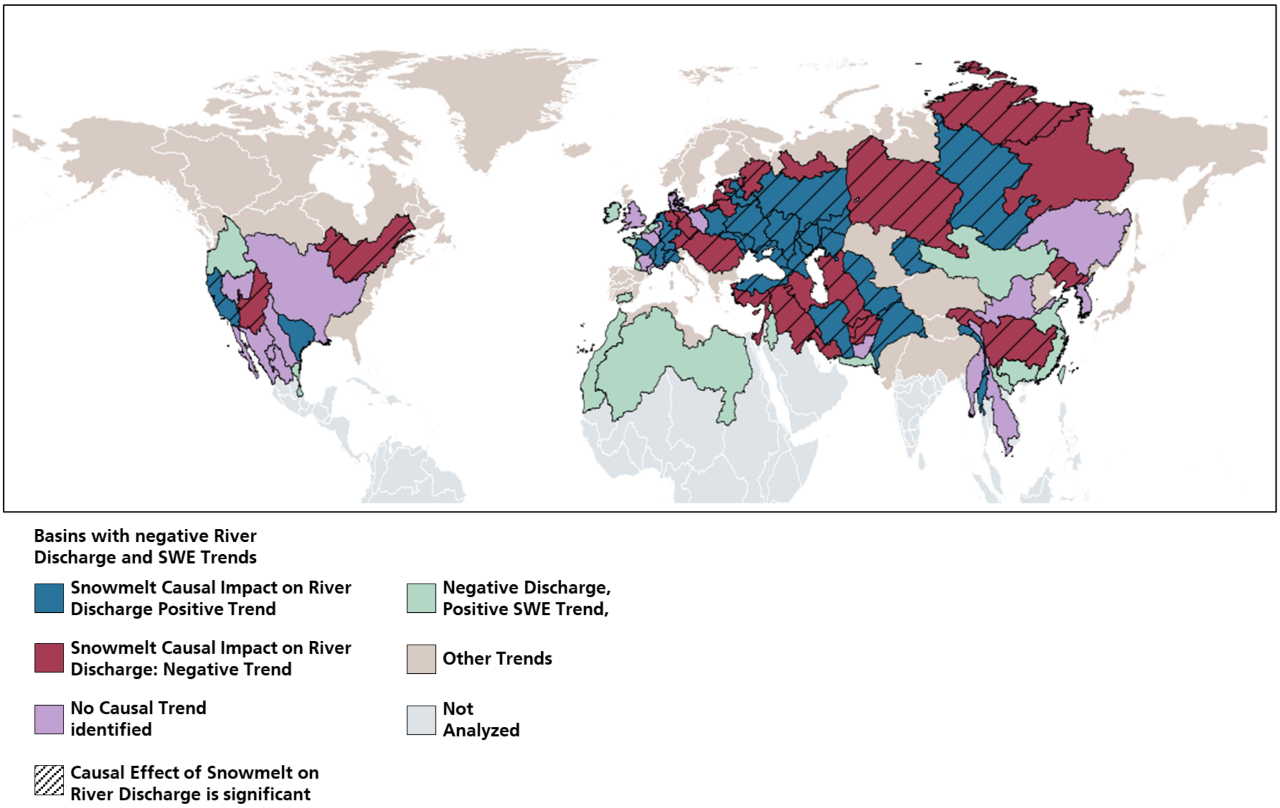


Figure 9. River basins with negative river discharge and rain trend, colored by the trend of the causal effect of snowmelt on river discharge.

3.4 Exemplary Basins Analysis

As an analysis of all examined basins would fall outside the scope of this publication, we selected six basins on three continents for an exemplary analysis in this section. The basins can all be attributed to the three main groups setup in section 3.1. Figure 10, shows an overview of the course of the causal effects of snowmelt and river rain on river discharge, from 1980-2022 for the exemplary basins. We selected the basins based on location, their classification in section 3.1, and the dynamics among the variables. Note, that some basins span over multiple climate zones and encompass several land-cover types, as well as subbasin dynamics, therefore the analysis on the basin might fall short of explaining the complete range of mechanisms and developments that took place within the basin region during the study period.

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

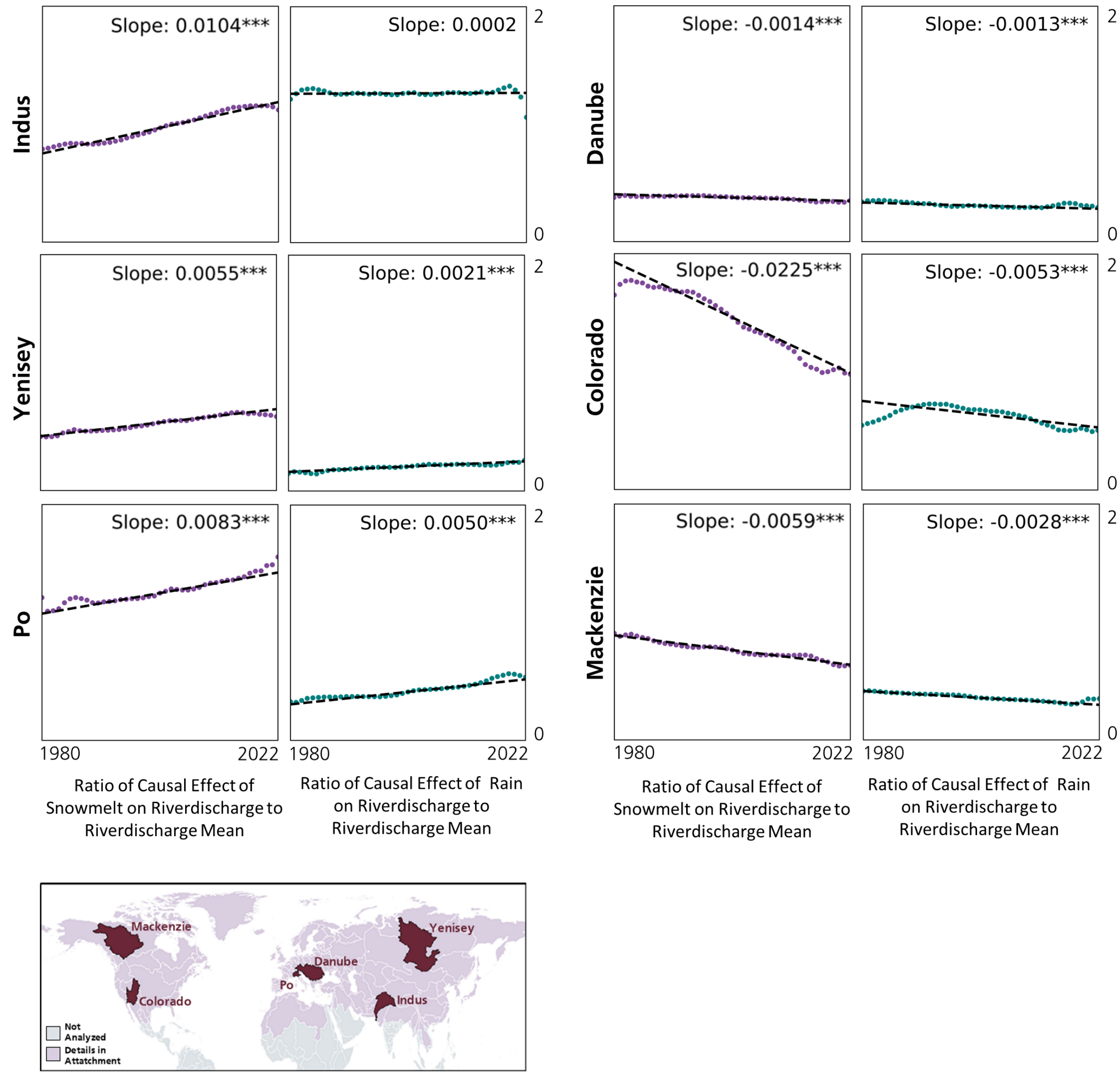


Figure 10. The causal effect of snowmelt on river discharge (both columns on the left - purple) over the examined time period and the six exemplary basins. Causal effect of rain on river discharge (both columns on the right - teal) over the examined time period and the six exemplary basins. Displayed as a ratio of causal effect to mean discharge. Significant trends are indicated with asterisks (***). The exemplary basins are marked on the map.

3.4.1 Mackenzie

The Mackenzie basin is located in northern Canada and mainly characterized by a subarctic climate (Beck et al., 2023). The basin extends approximately from 52°N to 69°N, contains two major lakes (Great Bear Lake, Great Slave Lake) and is primarily

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

dominated by tundra and taiga land cover types (Friedl et al., 2019). Generally the discharge in the Mackenzie basin is mainly snow dominated Woo et al. (2018), and while glacier runoff plays a role as well it appears to be less dominant as in other, more costal basins adjacent to the Rocky Mountains (Clarke et al., 2015). In our categorization (Figure 6), the basin shows a decreasing SWE trend alongside an increasing rain trend, resulting in an increasing discharge trend. However, these trends are relatively stable. In contrast, glacier runoff has increased significantly over the study period, indicating that glaciers are melting and their storage capacity is diminishing. Additionally, both baseflow flux and soil moisture trends are significantly negative. When examining the causal effect trends, they appear somewhat counterintuitive, as both the effects of rain and snow on river discharge are negative. For snow, this corresponds to the variable trend itself, whereas for rain, it acts in the opposite direction. This pattern might be explained by a combination of two processes: a gradual shift from a snowmelt-driven regime towards an increasingly rainfall-driven regime, and a higher infiltration potential resulting from increased permafrost thaw due to climate change.

3.4.2 Colorado

The Colorado stretches from 32°N to 43°N over the southwestern United States and northern Mexico. Despite the mountains in the northeast, the basin generally has an arid climate (Beck et al., 2023), and is mainly covered by grass-, and shrublands (Friedl et al., 2019), as well as extensive agriculture areas (Norton et al., 2021). In the Colorado basin, both snow and rain have declined, corresponding with the observed decrease in river discharge. Also both the snowmelt causal effect on river discharge and the rain causal effect on river discharge have decreased. Thus overall, the basin is experiencing lower flow conditions due to reductions in both SWE and precipitation. The causal effect trends suggest that rainfall dynamics remain largely unchanged, apart from a general decrease in volume. In contrast, shorter and faster snowmelt periods appear to reduce snowmelt's ability to sustain river flow year-round, either directly or via intermediate drivers such as baseflow flux or soil moisture. Consequently, snow not only diminishes in quantity but also loses its effectiveness in maintaining streamflow.

3.4.3 Danube

The Danube is the largest river basin in central Europe, following an eastward course reaching from the Alps (8°E) to the Black Sea (45°E) and laying in between 42°N and 52°N. The climate is mainly humid, continental in the North of the basin and subtropical in the south, with some arid steppes in the east (Beck et al., 2023). The basin is located over a series of highly populated and industrialized regions, and generally covered with either forest, or grass- and croplands (Friedl et al., 2019). In the Danube SWE is decreasing, rain is increasing, and discharge is decreasing slightly. The causal effect trends are similar to those of the Mackenzie and Colorado, with both the causal effect of snowmelt and the rain causal effect on river discharge decreasing. In the Danube however, the precipitation contribution is generally less snow dominated than in the Mackenzie (compare figure 2), and the trends for both baseflow flux and soil moisture are increasing. The results suggest that river discharge in the Danube Basin is becoming less directly controlled by individual precipitation components. Instead, buffering processes in the soil, vegetation, and baseflow flux may be strengthening, which appears to dampen the immediate hydrological response. At the same time, higher evaporation rates and anthropogenic interventions might cause a larger share

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

of precipitation to no longer contribute directly to river discharge. Overall, this points to a more diffusely regulated flow regime in which the direct contributions of rain and snow seem to be declining, even though the climatic conditions themselves are changing.

3.4.4 Po

The Po basin is one of the smallest basins in the analysis, located south of the Alps in northern Italy and southern Switzerland between 44°N and 46°N. It is characterized by continental climate in the north and a humid climate in the rest of the basin (Beck et al., 2023). The basin is predominantly characterized by croplands, with occasional forests (Friedl et al., 2019). The trends for river discharge, and SWE are decreasing, while the rain trend is increasing. The trends, for soil moisture and baseflow flux are contrary to each other, but in a comparatively flat nature. As in all exemplary basins, the glacier runoff is increasing, which in a small basin as the Po might have a larger influence compared to the larger basins that are also showed in this section. While most large-scale trends remain relatively flat, the causal relationships between precipitation and discharge reveal a more dynamic picture. Both snowmelt and rain causal effects increase, but snowmelt rises significantly faster. Despite declining SWE, streamflow becomes progressively snow-controlled. As the snowpack diminishes, snowmelt concentrates in spring, with remaining snow reliably driving discharge. Rainfall's more modest increase reflects greater variability. The basin thus becomes dependent on fewer but structurally critical melt events. This intensification of snow dependence despite ongoing snowpack loss renders the Po basin particularly vulnerable to further SWE reductions.

3.4.5 Yenisey

Reaching, from arid steppes in Mongolia (46°N) over subarctic climate with tundra and taiga to the estuary into the Kara Sea in Siberia/Russia (71°N), the Yenisey basin is fairly diverse and the largest one in this exemplary analysis. In the Yenisey basin river discharge, SWE, and rain all experienced negative trends from 1980 to 2022, whereby the trends for river discharge and SWE are steeper and significant, while the rain trend is only subtly negative and not significant. Both, the causal effect of snowmelt and rain on river discharge were increasing slightly over the study period. As the Yenisey is generally a snow-dominated basin (compare Figure 2), and the trends for soil moisture and baseflow flux are both significantly decreasing, the observed causal dynamics appear to be well represented. Despite the decreasing SWE trend, snow remains the most important contributor to river discharge. With rainfall remaining relatively stable, and both soil moisture and baseflow flux showing negative trends, the increasing causal effects of rain and snow on river discharge likely reflect changes in the basin's storage behavior. As these storage components decline, precipitation and snowmelt events translate more directly into runoff. In the Yenisey, this suggests that the role of snow as an active storage and release component is becoming increasingly important, as indicated by the rising causal influence of snowmelt on discharge.

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

3.4.6 Indus

Among others, the Indus Basin is home to some of the tallest mountains in the world (e.g. K2) as well as some of the world's largest non-polar glaciers (e.g. Siachen Glacier). The basin which is located between 23°N/66°E and 38°N/83°E, is climatically very diverse, reaching from subarctic and tundra climate in the north, subtropic and savannah climate in the central basin and hot arid desert climate in the south (Beck et al., 2023). The land cover is similarly diverse with the mountains in the north, a mix of grass- shrub- and croplands in the center and along the Indus river itself, and barren deserts in the southeast (Friedl et al., 2019). The Indus basin has seen a significant decrease of SWE, discharge, and a non-significant decrease of rain. All these trends are, if not all significant, of a medium steepness in the global comparison. The causal effect of snowmelt on river discharge has increased over our study period, while the causal effect of rain on river discharge has remained essentially non-significant. Since the Indus basin is highly glacierized, glaciers play a major role in streamflow generation. In contrast, summer rainfall often coincides with peak glacier melt, when meltwater already dominates streamflow. This temporal overlap might explain why the causal effect of rain remains essentially non-significant, as rainfall contributions are masked by the glacier melt signal during the main runoff season (Lutz et al., 2014; Bolch et al., 2012; Pritchard, 2019; Immerzeel et al., 2010). Thus, the increasing causal effect of snowmelt on river discharge corresponds to increased winter precipitation, which typically occurs before the main glacier melt season. During this period, the snow cover also protects the glacier surface from direct exposure (Lutz et al., 2014; Pritchard, 2019), delaying melt onset and stabilizing runoff. In contrast, summer rainfall often coincides with peak glacier melt, when meltwater already dominates streamflow, which potentially explains the decreasing causal effect of rain on river discharge in the Indus basin.

3.5 Consistency and Fluctuations of Trends

For this study, only peer-reviewed and validated data were utilized. However, the methodological outcomes cannot be adequately validated with independent data, as no comparable datasets documenting the contribution of individual factors to river discharge exist with the required spatial and temporal scope. The analysis of the calculated data shows that the absolute values of the causal effects depend on a wide variety of factors. These are not always to be understood from the data or from the real-world system, but also how capable the random forest is of recognizing the effects of the individual variables on each other. Therefore, the most suitable approach to evaluate the performance of the method is to focus on the dispersion of the results within the individual basins. For each basin, we calculate the coefficient of variation (CV) as well as a trend corrected version of it (Trend-CV) using the Theil-Sen slopes described in 3.2. The CV is defined as:

$$\mathrm{CV} = \frac{\sigma}{\mu} \qquad (1)$$

where σ is the standard deviation and μ is the mean of the dataset.

The Trend-CV respectively is calculated as follows:

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

$$\text{Trend-CV} = \frac{\sigma_{\text{residual}}}{\mu_{\text{residual}}} \tag{2}$$

Here, σ_{residual} is the standard deviation of the residuals, and μ_{residual} is the mean of the residuals, defined as:

$$\text{residual} = y_i - \hat{y}_i \tag{3}$$

where y_i is the actual value and $\hat{y}_i$ is the predicted value. CV and Trend-CV were calculated for the full time series of snowmelt and rain causal effects on river discharge, as well as for a truncated time series (1985–2017). This truncation is necessary because the moving window approach used in the method leads to smaller sample sizes at the beginning and end of the time series, compared to the center. A Wilcoxon signed-rank test reveals that a significant portion of the dispersion arises from these time series ends. Furthermore, comparing the CV with the Trend-CV indicates that the trend itself accounts for a substantial part of the observed dispersion. This pattern also holds for the Trend-CV, where the ends of the time series contribute markedly to the overall variability. A summary of the dispersion metrics is shown in figure 11.

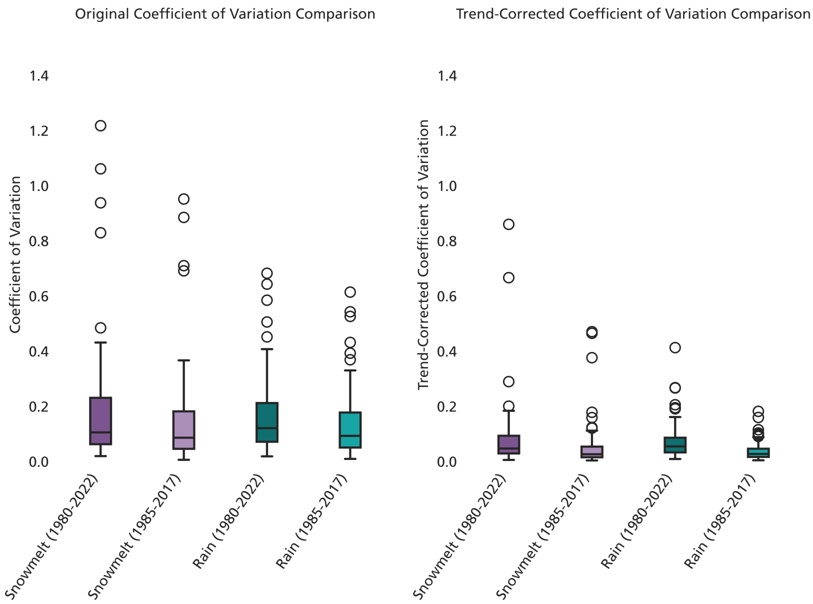


Figure 11. Measures of Dispersion for causal effect on river discharge trends of both snowmelt and rain over all basins. Left: coefficient of variation. Right: Normalized RMSE, corrected for the Theil-Sen trend displayed in section 3.2.

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

4 Discussion

4.1 Contextualization of Results

As mentioned in the sections 2 and 3.5 no adequate and independent validation data is currently available to validate a study of the scope presented in this paper. While our plausibility tests with modified trigger variables demonstrated that the method adequately captures such changes, this only validates its internal functionality and does not confirm the accuracy of the actual effects. Therefore, the study should be viewed as an experimental data analysis to test the applicability of the presented methods. Nevertheless, we aimed to contextualize our results with already published studies. Accordingly, we incorporated global studies from a review (Schilling et al., 2024) and conducted a systematic literature search via Web of Science (WOS), using various terms concerning SWE, streamflow and driving factors, subsequently evaluating their relevance to our findings. Given the use of partly identical data, the global trends align with those already published at the global level, as expected. While differences in aggregation and representation might result in differing interpretations, the trends presented here are consistent with what is to be expected and fall within the anticipated range (TWS; Zhang et al. (2019), river discharge: Shi et al. (2019); Park et al. (2024), SWE; Pulliainen et al. (2020), precipitation; Sun et al. (2021), SM; Mohseni et al. (2023), groundwater (baseflow flux); Hasan et al. (2023), temperature Wang et al. (2022), evapotranspiration; Li et al. (2023)).

Expanding the scope to river discharge contribution, as well as flood generating studies, several studies align with the general mechanisms and snow dominance depicted in our analysis (Do et al., 2020; Zhang et al., 2023; Robinson and Clark, 2020) on a global level, or on continental (Europe; Jiang et al. (2022); Fang et al. (2024), North America; Li et al. (2019)) and Arctic scale (Park et al., 2024). These studies confirm the trends described in section 1.1, towards earlier and faster snowmelt periods. Examining the exemplary basins shows that the Colorado and Indus basins are well represented in the literature, the Danube, Po, and Mackenzie basins have somewhat lower coverage, and the Yenisey basin shows very limited documentation based on English-language publications. In terms of content, the smaller-scale studies confirm the global trends and certain regional patterns emerge.

In the Danube and Po basins, which both have their headwaters in the Alps, the discharge in the entire basin is dependent on the corresponding snowpack, especially in drought years (Chen et al., 2020; Stagl and Hattermann, 2015; Guastini et al., 2019; Coppola et al., 2014; Vezzoli et al., 2015; Avanzi et al., 2024). The causal trends in the Po and the Danube developed in opposite directions for both rain and snowmelt. In the Danube both trends are negative, whereas in the Po both are positive, suggesting that the hydrological mediation of precipitation is changing in different ways in the two basins. In the Po, increasing causal effects of both snowmelt and rain indicate that a larger fraction of precipitation is transformed into discharge directly, with snowmelt gaining relative importance compared to rain in a strongly snow-dominated and comparatively small basin. Fewer but more concentrated melt and rainfall events increasingly control annual flow, and appear to make the system more sensitive to changes in SWE and event timing. This is consistent with the higher contribution of snowmelt to total discharge in the Po compared to the Danube, where rainfall accounts for a larger share of the annual water balance (Stagl and Hattermann, 2015; Vyshnevskyi and Shevchuk, 2022; Formetta et al., 2022). In the Danube, by contrast, decreasing causal effects for both components point to a more buffered flow regime, in which soil moisture, groundwater and human regulation increasingly

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

decouple precipitation inputs from immediate river discharge. As a result, even with increasing rainfall the direct causal effects weaken, and low-flow resilience depends more on the state of subsurface and managed water stores than on single snowmelt episodes. Additional factors such as topography, river regulation and urbanisation may further shape these contrasting responses but cannot be fully resolved without more detailed local analyses. In both basins, glaciers currently help to stabilise discharge as long as they continue to melt at approximately present rates (Van Tiel et al., 2021; Lambrecht and Mayer, 2024; Penna et al., 2017; Huss, 2011), which is consistent with global evidence for a transient stabilising role of glacier melt under warming conditions (Ultee et al., 2022).

The Colorado basin shows similar characteristics with the Po and Danube basins, with headwaters in mountains flowing into a plain with limited snowfall. However, the plains in the Colorado basin are more arid than in the European examples, which imparts its specific characteristics to the basin. Therefore, the basin is very dependent on its seasonal snow pack (Webb et al., 2024), but as it is drier than the Po and Danube, the amount of summer precipitation seems to have a more crucial impact on the overall hydrological balance (Flynn et al., 2024; Ban et al., 2023). This is also supported by Wolf et al. (2023), who states, that groundwater is a crucial streamflow driver during late summer and autumn. Additionally the soil moisture seems to play an not fully understood role in the Colorado basin, for example, Talsma et al. (2022) have observed strongly erratic behavior of soil moisture data in the Colorado Basin (as also seen in our findings), and Julander and Clayton (2018) found for small basins in Utah that above-average rainfall does not drive runoff proportionally. Also it is to consider that other storage mechanisms such as soil moisture and groundwater become more crucial, which complies with the findings of Wolf et al. (2023) as well as Julander and Clayton (2018), even tough they are declining (5). Overall this paints a picture of a basin that experiences increasingly dry conditions, and has to rely more and more on single weather events to recharge its storage, as the general storage level has decreased in the last years. The causal effects of both snowmelt and rain on river discharge are both decreasing significantly. This indicates that rain and snowmelt are translated into runoff less efficiently. This decline in hydrological effectiveness has been demonstrated in recent years: even record-high snowpack in 2023 failed to adequately recharge groundwater reserves or generate proportional streamflow increases (Carroll et al., 2024). Recent isotope studies show that during peak snowmelt, streamflow is increasingly dominated by aged groundwater rather than direct snowmelt contributions, indicating that precipitation is increasingly delayed and decoupled from immediate runoff (Brooks et al., 2025). Taken together, earlier and faster snowmelt driven by warming temperatures compresses the melt period and reduces water availability during critical late-summer low-flow periods. Similarly, summer rainfall becomes increasingly decoupled from runoff generation, potentially due to increased evapotranspiration or limited soil infiltration capacity under water stress. The Colorado thus faces a dual challenge: declining water availability combined with reduced efficiency of the water that does arrive, a pattern that underscores the basin's heightened vulnerability to further climate change.

In the Arctic, the Mackenzie, but not the Yenisey, aligns with the general Arctic trend of increased discharge (Park et al., 2024), however in the Mackenzie the discharge trend is basically flat, while it is significantly decreasing in the Yenisey. Generally and comparable to the alpine basins, these basins see faster and shorter melt periods (Yang et al., 2021; Mavromatis et al., 2016). Also several regional dynamics seem to apply, for instance Krogh and Pomeroy (2018) showed that a series of

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

snow-hydrological processes in a small subbasin of the Mackenzie are slowing down, and sublimation and evapotranspiration have dropped, mitigating the reduced precipitation in the subbasin. The latter is not true for the entire basin, could however be an indication of changing dynamics within the basin, in which, among deceasing soil moisture and baseflow flux trends, snow as a storage becomes more important, as indicated by our findings. For the Yenisey, Zakharova et al. (2011) shows that over time, less snowmelt was ending up as river discharge in the region due to increased evaporation and sublimation. Also Gordeev et al. (2024) suggests that a decreasing influence of bogs could cause an observed increasing role of Al-rich colloids and subcolloids. These results suggest that rising temperatures increase sublimation, and the correspondingly thawing permafrost allows for greater water infiltration into the ground (Kurylyk and Walvoord, 2021). Consequently, less water flows directly into rivers. However, reduced precipitation (both snow and rain) leads to lower soil moisture and groundwater recharge, making the storage function of SWE increasingly important. Therefore, although local research indicates increased infiltration of precipitation into the ground and delayed river flow, our identified causal effects suggest that the general pattern of decreasing total precipitation and increasing intra-annual variability supersedes changes in soil infiltration in terms of streamflow generation. Therefore, an increasing causal influence of snowmelt on river discharge and changes in infiltration processes can occur simultaneously, reflecting that several hydrological developments can occur in parallel, although some may dominate at larger scales. These dynamics could also apply for the Mackenzie basin, where permafrost is also thawing (Kurylyk and Walvoord, 2021), and apart from the river discharge and rain trend all other variable trends develop in the same direction as the trends in the Yenisey.

Since climate in the Indus basin is mostly dominated by the Westerlies instead of Monsoon seasons, as it is in other Himalayan basins, the Indus basin shares various similarities with other basins in this analysis. It has snow-rich, glacierized mountains in the headwaters, and arid regions downstream. However, the Indus stands apart from Colorado, Danube, and Po, since its glacier mass surpasses the others by magnitudes. Therefore the main driver in streamflow generation is the glacier melt Immerzeel et al. (2010); Bolch et al. (2012); Yao et al. (2022) and snowmelt seems to only play a secondary role (Kumar et al., 2024; Soheb et al., 2024; Joshi et al., 2023; Shafeeque et al., 2023). Glacier melt has been increasing during our study period, though it is believed that peak water has not yet been reached Lutz et al. (2014); Pritchard (2019). The increasing contribution of glacier melt, may explain why the causal effect of rain on river discharge remains essentially flat and non-significant, as their main occurrence mostly coincide. However, our finding of an increased causal impact of snowmelt on river discharge is partially contradictory to the findings of Adnan et al. (2022); Ali et al. (2023); Adnan et al. (2024); Chandel and Ghosh (2021), which however all were conducted in the mountainous parts of the basin. It is also to note that Immerzeel et al. (2015) found that precipitation in high altitudes in the Himalayas is systematically underestimated in most models. Furthermore there is also evidence, that the earlier snowmelt influences the spring runoff in the Indus basin, which in turn supports our findings of an increased causal impact of snowmelt on river discharge Wang et al. (2025); Hasson et al. (2017); Sharif et al. (2013); Guo et al. (2025). Therefore, our findings can be reasonably aligned with existing literature. Given indications of earlier snowmelt onset and an overall increase in snowfall, it appears possible that snowmelt has become relatively more important for basin-wide streamflow generation, although its overall role likely remains secondary to glacier melt.

Finally, we can conclude that our results support the qualitative examination for the exemplary basins and align well with the existing body of knowledge. However, it is important to acknowledge that studies verifying the relative influence of snowmelt

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

on river discharge, particularly at our spatial and temporal scales, remain scarce. As a result, our qualitative analysis relies more on indicative findings and approximations than on direct empirical evidence. It is worth noting that although our primary focus is on snowmelt and rain, glacier melt plays a crucial role in certain hydrological systems. We included glacier melt in our analysis to account for its presence, but we did not compute its causal effects. Therefore, glacier melt remains a source of uncertainty when explaining the causal effects of snowmelt and rain. This uncertainty may influence the interpretation of results in basins where glaciers are present. A similar challenge applies to human influences. Currently, there is no comprehensive global dataset quantifying human impacts on hydrological regimes. For this reason, we chose not to include human influences in our setup, even though they can have a considerable effect on certain variables. For example, irrigation in agriculture appears to alter groundwater signals and seasonality in some regions (Carlson et al., 2025; Hall et al., 2024). Similarly, thawing permafrost dynamics remain a major source of uncertainty in especially arctic regions Wang et al. (2021). Despite these complexities in the explainability of our findings, our results focusing on snowmelt and rain remain valuable, especially given the prevailing consensus that declining snow water equivalent trends in the Northern Hemisphere lead to faster and earlier melt. These changes, combined with more erratic precipitation patterns and prolonged drought periods, make snow increasingly important as a water storage resource. This is particularly relevant in 22 basins where our method detected an increasing trend in the causal effect of snowmelt on river discharge, even though both snow water equivalent and river discharge showed declining trends. Such regions warrant special attention from researchers and policymakers alike, as regional water availability appears increasingly dependent on snow as a diminishing resource.

Our research also shows that the causal effect of snowmelt on river discharge, as examined in this study, can add a new relative dimension to snow hydrology, which is linked, but not the same, as sole snow dominance. Therefore, snow dominance can decline in a certain region, while the causal effect, and thus the relative impact is increasing, as it quantifies the influence of snowmelt on river discharge as is carried out trough the overall system. For a deeper understanding of the dynamics in a basin, these two measures should therefore be considered together. The qualitative analysis also shows that the method developed here can be applied in various hydrological regimes and climates, and thus can support hydrological studies in a wide range of basins.

4.2 Methodological Discussion

The general intention of this study was to design a causal inference setup capable of capturing the dynamics between snowmelt and river discharge across various regions and extended time periods, enabling comparisons across these spatial and temporal scales. This became necessary as our literature revealed a lack of large-scale studies in the intersection of snow, SWE, and river discharge, using advanced analytical methods. Therefore, all decisions concerning the study design, served the purpose of setting up a resilient and widely applicable method, rather than providing a precise depiction of various local conditions across the study region. Accordingly, the methodological set-up comprises multiple considerations which reflect this optimization towards a broad framework, rather than local accuracy.

Firstly, the selection of data was constrained by spatial and temporal requirements, and while all incorporated datasets are validated and peer-reviewed, they each carry inherent strengths, limitations, and uncertainties. Some datasets also required

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

preprocessing to align with the time-series requirements of the PCMCI+, involving several assumptions that, while necessary and well-supported by literature, may have affected local accuracy. Furthermore, the data was spatially and temporally aggregated, which affects the ability to capture small scale variations in the data, both spatial and temporal. However, these aggregations were necessary to balance the representation of large spatial and temporal scales with the need for an expedient time lag within the causal inference framework, while minimizing computational demands. Moreover, depicting hydrological context within a scientific approximation is a complex task, which by itself normally already includes various simplifications and assumptions, based on the current knowledge of the topic. For our study, this meant that not all relevant processes could be incorporated in the system, which is additionally limited by the informative capability of the utilized datasets. However, by focusing on the land surface dynamics of the systems, leaving out all atmospheric processes and land-atmosphere interactions, we could include the key variables for streamflow generation in the studied river basins. However, LPCMCI can be considered as an alternative to PCMCI+ for accounting for additional, potentially hidden variables influencing the estimated causal effects. During our development process, we tested the LPMCI in multiple set-ups, which however did not yield realistic causal effects. One key decision, where we opted to represent local conditions as well as possible was the selection of the intervention in the causal effect estimation. By intervening the system seasonally and per basin, we adequately depict each basins conditions, even though the intervention values are still averaged over the full basin, thus potentially loosing more small scale details. The intervention choice (mean vs. zero intervention) was furthermore driven the initial research question regarding the total contribution of snowmelt and rain to river discharge. However, while zero or near zero values of snowmelt and rainfall occur at the two week temporal resolution used in this study, such conditions can be less well represented for specific combinations of season, tau, and period. In these cases, the estimated causal effects are partly informed by model extrapolation rather than being fully constrained by the data. This may affect the magnitude of the estimated contributions and reflects our decision to address the research question of total snowmelt and rainfall contribution to river discharge.

Besides the various decisions towards better comparability over the depiction of local mechanisms, the development process was also characterized by the balance between enabling the PCMCI+ to detect effects, and managing the computational demand. The causal inference requires a certain data sample to reliably detect causal effects for a system (Kathpalia et al. (2022)), therefore the sample used to calculate the causal effects needed to be chosen adequately, but in a fashion that within the moving window approach, the computational demand lies within the possibilities of our available infrastructure. The moving window approach itself, which was superimposed on to the causal inference framework, adds certain challenges, mainly concerning the yearly averaging, the years on the temporal edges of the time-series are underrepresented, and are thus susceptible to outliers. As most of the calculated averages used for the trend derivation rely on a broad sample, we refrained from clipping the time-series or introducing shorter additional windows at the edges of the time-series. However, this is one reason why we present trends and not absolute values in this study. Another reason is because absolute values of causal effects are generally dependent on how well the methodical setup recognizes them within the data, which might not always represent the reality. Another sign pointing to this circumstance is that for rain, the relationship between trigger and target variable was

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

found more often than for snowmelt. This might be attributed to the signal, which, for rain is nearly detectable all year round. In contrast, snowmelt signal for only occurs in spring and early summer, and is thus detectable in less data points.

The presented results are all a ratio of the causal effect to the mean dicharge in a certain basin, thus showing a relative change within a basin, which is less dependent of the ability of recognition within the data by the PCMCI. Within basins the analyzed performance metrics (see section 3.5 show that the yearly values fluctuate on an acceptable level, and the trend derivation thus can be regarded as robust. Also by fitting Theil-Sen slopes we additionally mitigate against any kind of fluctuation within the results, adding to the resilience of the trend statements.

Nevertheless, despite the Theil-Sen method being more robust concerning outliers, it is still a linear fitting method, and thus only remains valid under the assumption of a linear trend. Therefore, for causal and variable trends, we classified the trends by the sign of the slope regardless of the gradient. This was necessary to enable a comprehensive comparison of the method among the basins, and a possibility to categorize them. It however, might suggest that conditions in a basin being more severe or extreme, then they are if one considers the actual data. It however also became an inevitable step, to avoid a multitude of potential additional categorizations, which aggravates an expedient comparison. However, it also underscores the need for a thorough analysis of basin-specific data, as exemplified in Section 3.4 for select basins, to inform qualified statements about the unique circumstances within a given basin.

Generally, as shown in the analysis of exemplary basins in section 3.4, the estimation of causal effect serves as a valuable measure for understanding hydrological dynamics that cannot be captured by individual variables alone. The causal effect can support the determination of certain dynamics and narrowing down unknown developments. However, the PCMCI is calculated per basin, and thus referenced to the corresponding basin discharge, which limits the comparability among basins generally. Because of this, but also given the complexities in detecting effects based on sample size, we recommend using the causal effects computed in this study only to assess relative changes, and as a complementary rather than standalone measure when examining snow-hydrological systems in a given study region.

The use of trends as indication of relative change is additionally supported by the statistical metrics presented in section 3.5. The analysis of the dispersion of the calculated causal effects shows that significant portions of the dispersion are due to the trend itself and the small sample size at the ends of the time series. For a predominant majority of the basins, the trend-corrected dispersion falls within a suitable range for this analysis. Considering that with the Theil-Sen estimator, we used a fitting method which is robust against outliers, we regard the use of trends and thus relative changes as justified.

To conclude, we acknowledge the simplifications and compromises inherent in our study. Our results must be interpreted within the context of individual basins, regional climate dynamics, and broader continental influences. It should be noted that, with the current setup, the results reflect the method's ability to identify causal structures in the data, which may not always translate directly into absolute real world effect magnitudes. Nonetheless, this study introduces a novel, data-driven approach to snow-hydrology that extends beyond conventional statistical measures and small-scale applications. The method has demonstrated adequate responses in plausibility tests and, while still experimental, provides a foundation for future research, both methodologically and in more localized contexts. Despite the challenges of estimating causal effects in snow-

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

hydrology, our findings demonstrate the potential of this approach to complement established methodologies and advance the understanding of hydrological systems.

5 Conclusion

Snowmelt is a crucial contributor to river discharge in various regions on the Northern Hemisphere. It sustains over 1.5 billion people as a societal water supplier, supports key industries like agriculture and hydropower, and impacts regional ecosystems. Due to climate change, snow water equivalent (SWE) is declining, reducing snow-based water availability. A review of large-scale SWE studies reveals that the relationship between SWE and river discharge has rarely been examined beyond basic statistical measures, which cannot capture the complexity of hydrological regimes. To address this gap, we developed a causal inference approach based on Peter and Clark Momentary Conditional Independence Plus (PCMCI+). PCMCI+ performs causal discovery and detects a network of causal links within a multivariate system. The PCMCI+ is followed by a causal effect estimation which quantifies the effect of a trigger variable onto a target variable within the same system. Our system includes river discharge, snowmelt (defined as SWE depletion), rain, glacier runoff, baseflow flux, soil moisture, evapotranspiration, temperature, and the date as a deterministic time variable, with lags of up to six months. Causal effects of snowmelt and rain on river discharge were estimated applying a moving 20-year window the 1980–2022 time series. The resulting effects were summed and then divided by the period's mean river discharge and finally averaged by year. The yearly averages were used to quantify trends with a Theil-Sen estimator. We present these causal effect trends for 119 Northern Hemisphere basins, alongside Theil-Sen trends for individual variables. In addition, we examine six representative basins to illustrate differing hydrological and geographic dynamics. Based on these results, several overarching conclusions can be drawn:

- Our trend analysis confirmed a decreasing trend for SWE in a majority of the examined basins (94/119).
- Also, the trends for river discharge (79/119) and rain (71/119) in the catchments are predominantly negative.
- Looking at patterns among these discharge, rain, and SWE trends, two major dynamics become apparent. Firstly, in all Arctic basins (except Yenisey) the SWE trend is negative while the rain trend is positive. Secondly in lower latitudes, the basins where all these trends are negative make up the largest share of the basins (51/102).
- Of all basins where a causal effect for snowmelt on river discharge was detected, 32 of 73 (43%) showed an increasing trend. For the causal effect of rain on river discharge 57 of 117 (48.7%) had an increasing trend.
- For the causal effect of snowmelt on river discharge, the largest increasing trend was found in the Dnieper basin (Ukraine, Belarus, Russia), the most decreasing trend at the Mediterranean Sea east coast (Türkyie, Lebanon, Syria, Israel, Jordan, Palestine).
- Correspondingly the largest increasing trend was seen in the Hamun-e Mashkid basin (Iran), the steepest decreasing trend in the Rio Grande (USA/Mexico).
- No effects could be found using correlation of the causal effect trends against latitude, mountainous portion of the basin, or snow dominance.

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

- In 22 basins, 20 of which are located in Eurasia, our method detected an increasing causal effect of snowmelt on river discharge, despite declining trends in SWE and river discharge. These areas are critical for researchers and policymakers, as they indicate water availability is increasingly reliant on snow, despite it being a diminishing resource. This can have various implications for funding decisions in water management, conservation, and research.
- Looking at six exemplary basins (Mackenzie, Colorado, Danube, Po, Yenisey, and Indus) showed that partly similar dynamics appear in the Danube and Colorado basin, while Po and Indus, despite sharing geographical similarities to Danube and Colorado, stand alone in their dynamics. In the Arctic, Yenisey and Mackenzie show opposite causal trends.
- It is observed that the causal effect of snow on river discharge can increase despite decreasing SWE trends, and also despite increasing rain and rain causal effect on river discharge trends. This, in the scope of our analysis, seems to be due to changed seasonalities, and especially increased intra-annual variability of precipitation, thus that in drought periods the stored SWE has an increased influence, as precipitation during summer and autumn is occurring less.
- Dispersion metrics (Coefficient of Variation; CV, and trend-corrected CV, Trend-CV) show that generally our method is suited for trend derivation, especially as a significant portion of the dispersion is due to the ends of the time series and their reduced sample size in the moving window approach, as well as the trend itself.

Although our method did not detect causal effects, and therefore trends, in all basins, and the effect size depends on the selected random forest estimator, it advances large-scale snow hydrology by capturing the complexity of hydrological regimes beyond conventional statistical approaches. To enable large-scale comparison, we made several methodological decisions that prioritized comparability over local accuracy. While this allowed for the analysis presented in this study, it limits the resolution of local dynamics within basins. Despite these limitations, we demonstrated that causal effects, even within an experimental framework, are a suitable means of assessing relative changes in the importance of snowmelt, which does not necessarily align with snow dominance itself. Within this experimental framework, causal inference can add an additional layer to existing hydrological analyses, with further methodological refinements potentially expanding its applicability in future research.

Data availability. All data used in this study are publicly available. The datasets and their access details are listed in the manuscript and referenced with persistent identifiers (DOIs) in the reference list.

Code availability. The analysis code used in this study is available on reasonable request from the corresponding author.

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

690 ## Appendix A: Hydrological System for Causal Discovery

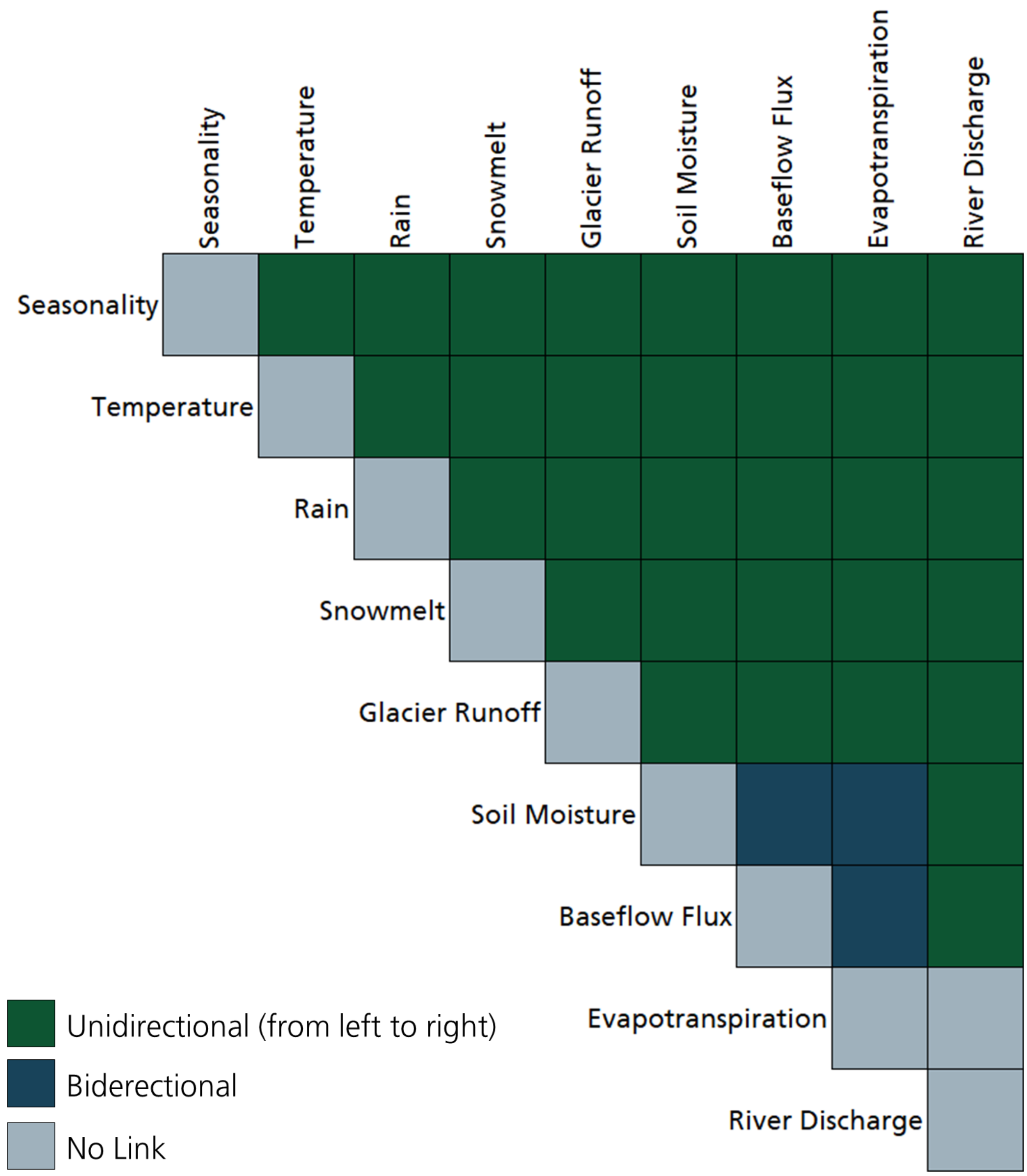


Figure A1. The assumed potential links between the variables used in the causal discovery phase .

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

Appendix B: Results Heatmap

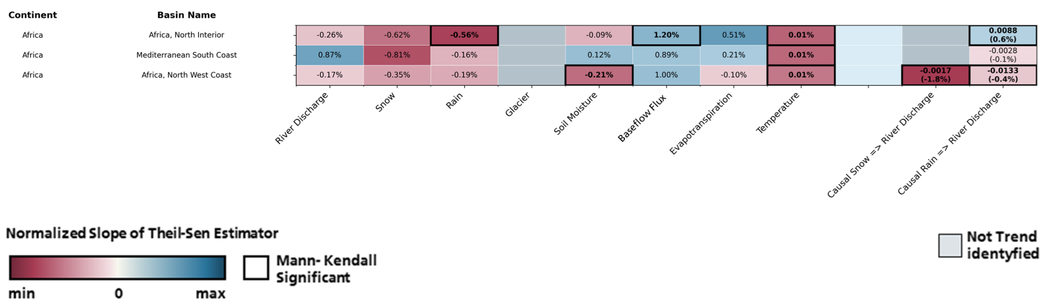


Figure B1. Relative variable trend slopes for all African basins normalized with the basin mean per variable (left) and causal effect trend slopes as absolute values (ratio of causal effect to mean discharge) as well as relative values, normalized with the basin mean (right). The colorscale for the temperature is inverted

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

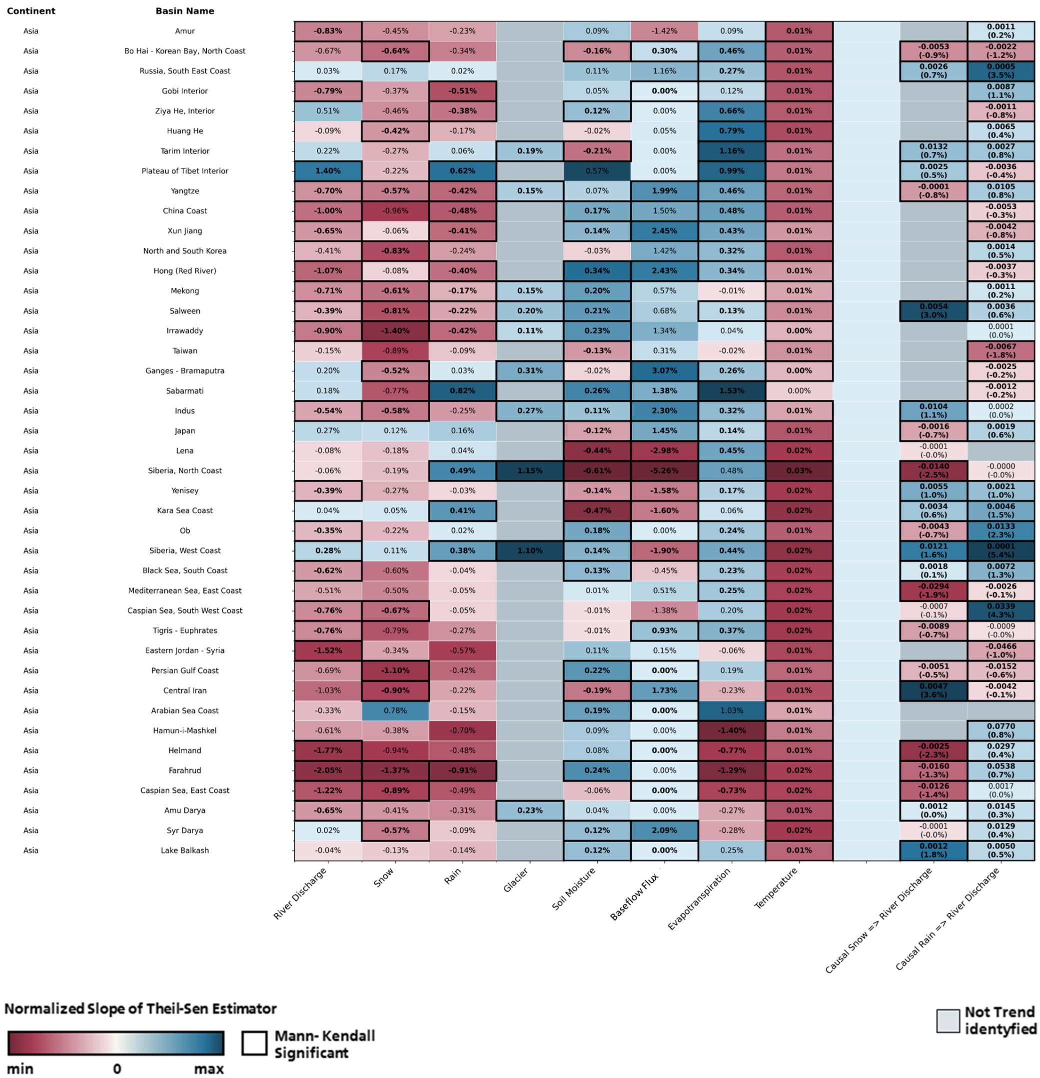


Figure B2. Relative variable trend slopes for all Asian basins normalized with the basin mean per variable (left) and causal effect trend slopes as absolute values (ratio of causal effect to mean discharge) as well as relative values, normalized with the basin mean (right). The colorscale for the temperature is inverted

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

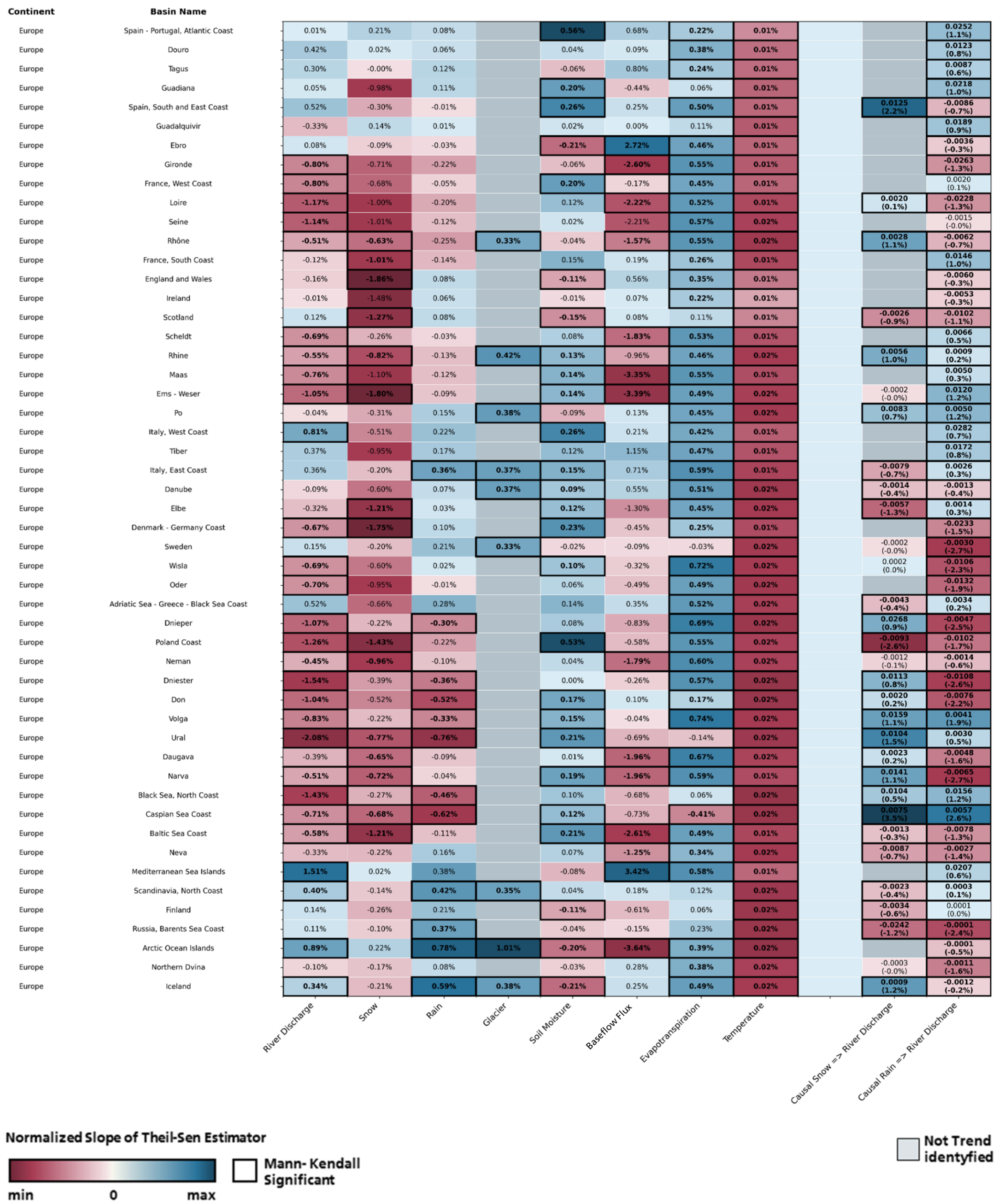


Figure B3. Relative variable trend slopes for all European basins normalized with the basin mean per variable (left) and causal effect trend slopes as absolute values (ratio of causal effect to mean discharge) as well as relative values, normalized with the basin mean (right). The colorscale for the temperature is inverted

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

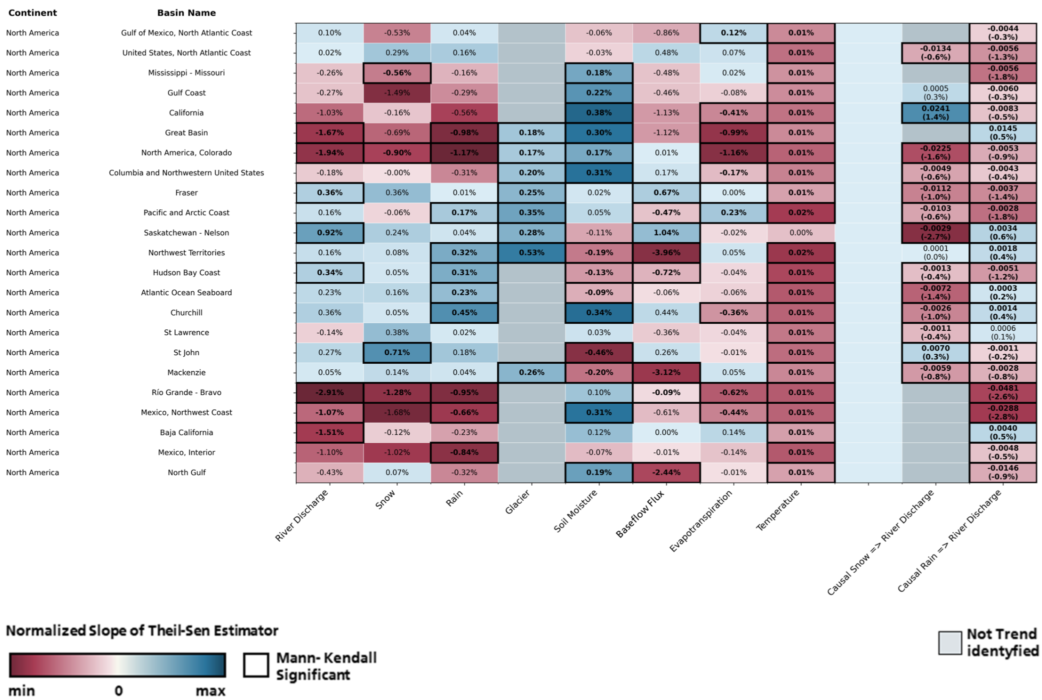


Figure B4. Relative variable trend slopes for all North American basins normalized with the basin mean per variable (left) and causal effect trend slopes as absolute values (ratio of causal effect to mean discharge) as well as relative values, normalized with the basin mean (right). The colorscale for the temperature is inverted

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

Author Contributions. Initial conceptualization, S.S., A.D. and C.K.; Causal inference setup S.S. and R.J.H.; hydrological setup and contextualization S.S. and T.B.; writing—original draft preparation, S.S.; writing—review and editing, all authors; visualization, S.S.; supervision, C.K. All authors have read and agreed to the published version of the manuscript.

Competing Interests. At least one of the (co-)authors is a member of the editorial board of The Cryosphere.

Acknowledgments. We would like to thank Prof. Dr. John Pomeroy for his initial consultation on hydrological systems in the Northern Hemisphere. Furthermore we would like to express our gratitude to Sanju Sajimon for his support in various parts of the literature research.

The work and publication of this study were supported by the DLR EO4AlpineRisks project.

R.J.H. has received funding from the European Research Council (ERC) Starting Grant CausalEarth under the European Union's Horizon 2020 research and innovation program (Grant Agreement No. 948112).

Large Language Models were used to support code development in this study and to refine the language of this publication.

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

References

Adnan, M., Liu, S., Saifullah, M., Iqbal, M., Ali, A. F., and Mukhtar, M. A.: Spatiotemporal variations in runoff and runoff components in response to climate change in a glacierized subbasin of the Upper Indus Basin, Pakistan, Frontiers in Earth Science, 10, 970 349, https://doi.org/10.3389/feart.2022.970349, 2022.

Adnan, M., Liu, S., Saifullah, M., Iqbal, M., Saddique, Q., Ul Hussan, W., and Latif, Y.: Estimation of changes in runoff and its sources in response to future climate change in a critical zone of the Karakoram mountainous region, Pakistan in the near and far future, Geomatics, Natural Hazards and Risk, 15, 2291 330, https://doi.org/10.1080/19475705.2023.2291330, 2024.

Ali, Z., Iqbal, M., Khan, I. U., Masood, M. U., Umer, M., Lodhi, M. U. K., and Tariq, M. A. U. R.: Hydrological response under CMIP6 climate projection in Astore River Basin, Pakistan, Journal of Mountain Science, 20, 2263–2281, https://doi.org/10.1007/s11629-022-7872-x, 2023.

Avanzi, F., Munerol, F., Milelli, M., Gabellani, S., Massari, C., Girotto, M., Cremonese, E., Galvagno, M., Bruno, G., Morra di Cella, U., Rossi, L., Altamura, M., and Ferraris, L.: Winter snow deficit was a harbinger of summer 2022 socio-hydrologic drought in the Po Basin, Italy, Communications Earth & Environment, 5, 1–12, https://doi.org/10.1038/s43247-024-01222-z, 2024.

Ban, Z., Li, D., and Lettenmaier, D. P.: The Increasing Role of Seasonal Rainfall in Western U.S. Summer Streamflow, Geophysical Research Letters, 50, e2023GL102 892, https://doi.org/10.1029/2023gl102892, 2023.

Barnett, T. P., Adam, J. C., and Lettenmaier, D. P.: Potential impacts of a warming climate on water availability in snow-dominated regions, Nature, https://doi.org/10.1038/nature04141, 2005.

Beck, H. E., McVicar, T. R., Vergopolan, N., Berg, A., Lutsko, N. J., Dufour, A., Zeng, Z., Jiang, X., van Dijk, A. I. J. M., and Miralles, D. G.: High-resolution (1 km) Köppen-Geiger maps for 1901–2099 based on constrained CMIP6 projections, Scientific Data, 10, 724, https://doi.org/10.1038/s41597-023-02549-6, 2023.

Bedoya-Maya, F., Shobayo, P., Beckers, J., and van Hassel, E.: The impact of critical water levels on container inland waterway transport, Transportation Research Part D: Transport and Environment, 131, 104 190, https://doi.org/10.1016/j.trd.2024.104190, 2024.

Beria, H., Larsen, J. R., Ceperley, N. C., Michelon, A., Vennemann, T., and Schaefli, B.: Understanding snow hydrological processes through the lens of stable water isotopes, WIREs Water, 5, e1311, https://doi.org/10.1002/wat2.1311, 2018.

Beyers, D. W.: Causal inference in environmental impact studies, Journal of the North American Benthological Society, 17, 367–373, https://doi.org/10.2307/1468339, 1998.

Biancamaria, S., Cazenave, A., Mognard, N. M., Llovel, W., and Frappart, F.: Satellite-based high latitude snow volume trend, variability and contribution to sea level over 1989/2006, Global and Planetary Change, 75, 99–107, https://doi.org/10.1016/j.gloplacha.2010.10.011, 2011.

Bolch, T., Kulkarni, A., Kääb, A., Huggel, C., Paul, F., Cogley, J. G., Frey, H., Kargel, J. S., Fujita, K., Scheel, M., Bajracharya, S., and Stoffel, M.: The State and Fate of Himalayan Glaciers, Science, 336, 310–314, https://doi.org/10.1126/science.1215828, 2012.

Breiman, L.: Random Forests, Machine Learning, 45, 5–32, https://doi.org/10.1023/a:1010933404324, 2001.

Brooks, P. D., Solomon, D. K., Kampf, S., Warix, S., Bern, C., Barnard, D., Barnard, H. R., Carling, G. T., Carroll, R. W. H., Chorover, J., Harpold, A., Lohse, K., Meza, F., McIntosh, J., Neilson, B., Sears, M., and Wolf, M.: Groundwater dominates snowmelt runoff and controls streamflow efficiency in the western United States, Communications Earth & Environment, 6, 341, https://doi.org/10.1038/s43247-025-02303-3, 2025.

Capua, G. D., Runge, J., Donner, R., Hurk, B. v. d., Turner, A., Vellore, R., Krishnan, R., and Coumou, D.: Dominant patterns of interaction between the tropics and mid-latitudes in boreal summer: causal relationships and the role of timescales, Weather and Climate Dynamics, https://doi.org/10.5194/wcd-1-519-2020, 2020.

Carlson, G., Massari, C., Rotiroti, M., Bonomi, T., Preziosi, E., Wilder, A., Whitaker, D., and Girotto, M.: Intensive irrigation buffers groundwater declines in key European breadbasket, Nature Water, 3, 683–692, https://doi.org/10.1038/s44221-025-00445-4, 2025.

Carroll, R. W. H., Niswonger, R. G., Ulrich, C., Varadharajan, C., Siirila-Woodburn, E. R., and Williams, K. H.: Declining groundwater storage expected to amplify mountain streamflow reductions in a warmer world, Nature Water, 2, 419–433, https://doi.org/10.1038/s44221-024-00239-0, 2024.

Chandel, V. and Ghosh, S.: Components of Himalayan River Flows in a Changing Climate, Water Resources Research, https://doi.org/10.1029/2020wr027589, 2021.

Chen, X., Parajka, J., Széles, B., Valent, P., Viglione, A., and Blöschl, G.: Impact of Climate and Geology on Event Runoff Characteristics at the Regional Scale, Water, 12, 3457, https://doi.org/10.3390/w12123457, 2020.

Cicuendez, V., Litago, J., Huesca, M., Rodriguez-Rastrero, M., Recuero, L., Merino-de Miguel, S., and Palacios-Orueta, A.: Assessment of the gross primary production dynamics of a Mediterranean holm oak forest by remote sensing time series analysis, Agroforestry Systems, 89, 491–510, https://doi.org/10.1007/s10457-015-9786-x, 2015.

Clarke, G. K. C., Jarosch, A. H., Anslow, F. S., Radic, V., and Menounos, B.: Projected deglaciation of western Canada in the twenty-first century, Nature Geoscience, 8, 372–377, https://doi.org/10.1038/ngeo2407, 2015.

Coppola, E., Verdecchia, M., Giorgi, F., Colaiuda, V., Tomassetti, B., and Lombardi, A.: Changing hydrological conditions in the Po basin under global warming, Science of The Total Environment, 493, 1183–1196, https://doi.org/10.1016/j.scitotenv.2014.03.003, 2014.

Cowherd, M., Ruby Leung, L., and Girotto, M.: Evolution of global snow drought characteristics from 1850 to 2100, Environmental Research Letters, 18, 064 043, https://doi.org/10.1088/1748-9326/acd804, 2023.

Craig, H.: Isotopic Variations in Meteoric Waters, Science, https://doi.org/10.1126/science.133.3465.1702, 1961.

DeWalle, D. R. and Rango, A.: Principles of Snow Hydrology, Cambridge University Press, ISBN 978-0-521-82362-3 978-0-511-53567-3 978-0-521-29032-6, https://doi.org/10.1017/cbo9780511535673, 2008.

Do, H. X., Westra, S., Leonard, M., and Gudmundsson, L.: Global-Scale Prediction of Flood Timing Using Atmospheric Reanalysis, Water Resources Research, 56, e2019WR024 945, https://doi.org/10.1029/2019wr024945, 2020.

Dorigo, W., Preimesberger, W., Reimer, C., Van der Schalie, R., Pasik, A., De Jeu, R., and Paulik, C.: Soil moisture gridded data from 1978 to present, v202212, https://cds.climate.copernicus.eu/cdsapp#!/dataset/satellite-soil-moisture?tab=overview, 2019.

Eckert, N., Corona, C., Giacona, F., Gaume, J., Mayer, S., van Herwijnen, A., Hagenmuller, P., and Stoffel, M.: Climate change impacts on snow avalanche activity and related risks, Nature Reviews Earth & Environment, 5, 369–389, https://doi.org/10.1038/s43017-024-00540-2, 2024.

Fang, B., Bevacqua, E., Rakovec, O., and Zscheischler, J.: An increase in the spatial extent of European floods over the last 70 years, Hydrology and Earth System Sciences, 28, 3755–3775, https://doi.org/10.5194/hess-28-3755-2024, 2024.

FAO: Food and Agriculture Organization of the United Nations, Land and Water Division. Major hydrological basins of the world, 2011.

Flynn, H., Fassnacht, S. R., MacDonald, M. S., and Pfohl, A. K. D.: Baseflow from Snow and Rain in Mountain Watersheds, Water, 16, 1665, https://doi.org/10.3390/w16121665, 2024.

Ford, J. D., Pearce, T., Canosa, I. V., and Harper, S.: The rapidly changing Arctic and its societal implications, WIREs Climate Change, 12, e735, https://doi.org/10.1002/wcc.735, 2021.

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

Formetta, G., Tootle, G., and Therrell, M.: Regional Reconstruction of Po River Basin (Italy) Streamflow, Hydrology, 9, 163, https://doi.org/10.3390/hydrology9100163, 2022.

François, H., Samacoïts, R., Bird, D. N., Köberl, J., Prettenthaler, F., and Morin, S.: Climate change exacerbates snow-water-energy challenges for European ski tourism, Nature Climate Change, 13, 935–942, https://doi.org/10.1038/s41558-023-01759-5, 2023.

Friedl, M., Gray, J., and Sulla-Menashe, D.: MCD12Q2 MODIS/Terra+Aqua Land Cover Dynamics Yearly L3 Global 500m SIN Grid V006, https://doi.org/10.5067/modis/mcd12q2.006, 2019.

Gerhardus, A. and Runge, J.: High-recall causal discovery for autocorrelated time series with latent confounders, in: Advances in Neural Information Processing Systems, vol. 33, pp. 12 615–12 625, Curran Associates, Inc., https://proceedings.neurips.cc/paper/2020/hash/94e70705efae423efda1088614128d0b-Abstract.html, 2020.

Geurts, P., Ernst, D., and Wehenkel, L.: Extremely randomized trees, Machine Learning, 63, 3–42, https://doi.org/10.1007/s10994-006-6226-1, 2006.

Girotto, M., Reichle, R., Rodell, M., and Maggioni, V.: Data Assimilation of Terrestrial Water Storage Observations to Estimate Precipitation Fluxes: A Synthetic Experiment, Remote Sensing, 13, 1223, https://doi.org/10.3390/rs13061223, 2021.

GMAO: Global Modeling and Assimilation Office. MERRA-2 tavg1$_2 d_l nd_N x : 2d, 1 - Hourly, Time - Averaged, Single - Level, Assimilation, LandSurfaceDiagnostics V$5.12.4, https://doi.org/10.5067/$RKPHT8KC1Y1T$, 2015a.

GMAO: Global Modeling and Assimilation Office. MERRA-2 tavg3$_2 d_g lc_N x : 2d, 3 - Hourly, Time - Averaged, Single - Level, Assimilation, LandIceSurfaceDiagnostics V$5.12.4, https://doi.org/10.5067/$9ETB4TT5J6US$, 2015b.

Gordeev, V. V., Pokrovsky, O. S., Zhulidov, A. V., Filippov, A. S., Gurtovaya, T. Y., Holmes, R. M., Kosmenko, L. S., McClelland, J. W., Peterson, B. J., and Tank, S. E.: Dissolved Major and Trace Elements in the Largest Eurasian Arctic Rivers: Ob, Yenisey, Lena, and Kolyma, Water, 16, 316, https://doi.org/10.3390/w16020316, 2024.

Gordon, B. L., Brooks, P. D., Krogh, S. A., Boisrame, G. F. S., Carroll, R. W. H., McNamara, J. P., and Harpold, A. A.: Why does snowmelt-driven streamflow response to warming vary? A data-driven review and predictive framework, Environmental Research Letters, 17, 053 004, https://doi.org/10.1088/1748-9326/ac64b4, 2022.

Gottlieb, A. R. and Mankin, J. S.: Evidence of human influence on Northern Hemisphere snow loss, Nature, 625, 293–300, https://doi.org/10.1038/s41586-023-06794-y, 2024.

Granger, C. W. J.: Investigating Causal Relations by Econometric Models and Cross-spectral Methods, Econometrica, 37, 424–438, https://doi.org/10.2307/1912791, 1969.

Grimaldi, S., Salamon, P., Disperati, J., Zsoter, E., Russo, C., Ramos, A., Carton De Wiart, C., Barnard, C., Hansford, E., Gomes, G., and Prudhomme, C.: River discharge and related historical data from the Global Flood Awareness System, v4.0, https://doi.org/10.24381/cds.a4fdd6b9, 2022.

Guastini, E., Zuecco, G., Errico, A., Castelli, G., Bresci, E., Preti, F., and Penna, D.: How does streamflow response vary with spatial scale? Analysis of controls in three nested Alpine catchments, Journal of Hydrology, 570, 705–718, https://doi.org/10.1016/j.jhydrol.2019.01.022, 2019.

Guo, Y., Yang, Y., Yang, D., Zhang, L., Zheng, H., Xiong, J., Ruan, F., Han, J., and Liu, Z.: Warming leads to both earlier and later snowmelt floods over the past 70 years, Nature Communications, 16, 3663, https://doi.org/10.1038/s41467-025-58832-0, 2025.

Hall, D. K., Loomis, B. D., DiGirolamo, N. E., and Forman, B. A.: Snowfall Replenishes Groundwater Loss in the Great Basin of the Western United States, but Cannot Compensate for Increasing Aridification, Geophysical Research Letters, 51, e2023GL107 913, https://doi.org/10.1029/2023gl107913, 2024.

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

Hammond, J. C. and Kampf, S. K.: Subannual Streamflow Responses to Rainfall and Snowmelt Inputs in Snow-Dominated Watersheds of the Western United States, Water Resources Research, 56, e2019WR026 132, https://doi.org/10.1029/2019wr026132, 2020.

Han, J., Liu, Z., Woods, R., McVicar, T. R., Yang, D., Wang, T., Hou, Y., Guo, Y., Li, C., and Yang, Y.: Streamflow seasonality in a snow-dwindling world, Nature, 629, 1075–1081, https://doi.org/10.1038/s41586-024-07299-y, 2024.

Hasan, M. F., Smith, R., Vajedian, S., Pommerenke, R., and Majumdar, S.: Global land subsidence mapping reveals widespread loss of aquifer storage capacity, Nature Communications, 14, 6180, https://doi.org/10.1038/s41467-023-41933-z, 2023.

Hasson, S., Böhner, J., and Lucarini, V.: Prevailing climatic trends and runoff response from Hindukush–Karakoram–Himalaya, upper Indus Basin, Earth System Dynamics, 8, 337–355, https://doi.org/10.5194/esd-8-337-2017, 2017.

Hersbach, H., Bell, B., Berrisford, P., Biavati, G., Horanyi, A., Munoz Sabater, J., Nicolas, J., Peubey, C., Radu, R., Rozum, I., Schepers, D., Simmons, A., Soci, C., Dee, D., and Thepaut, J.-N.: ERA5 hourly data on single levels from 1940 to present, https://doi.org/10.24381/cds.adbb2d47, 2023.

Huning, L. S. and AghaKouchak, A.: Global snow drought hot spots and characteristics, Proceedings of the National Academy of Sciences, 117, 19 753–19 759, https://doi.org/10.1073/pnas.1915921117, 2020.

Huss, M.: Present and future contribution of glacier storage change to runoff from macroscale drainage basins in Europe, Water Resources Research, 47, https://doi.org/10.1029/2010wr010299, 2011.

Huss, M. and Hock, R.: Global-scale hydrological response to future glacier mass loss, Nature Climate Change, 8, 135–140, https://doi.org/10.1038/s41558-017-0049-x, 2018.

Immerzeel, W., Beek, L. V. v., and Bierkens, M.: Climate Change Will Affect the Asian Water Towers, Science, https://doi.org/10.1126/science.1183188, 2010.

Immerzeel, W. W., Wanders, N., Lutz, A. F., Shea, J. M., and Bierkens, M. F. P.: Reconciling high-altitude precipitation in the upper Indus basin with glacier mass balances and runoff, Hydrology and Earth System Sciences, 19, 4673–4687, https://doi.org/10.5194/hess-19-4673-2015, 2015.

Immerzeel, W. W., Lutz, A. F., Andrade, M., Bahl, A., Biemans, H., Bolch, T., Hyde, S., Brumby, S., Davies, B. J., Elmore, A. C., Emmer, A., Feng, M., Fernández, A., Haritashya, U., Kargel, J. S., Koppes, M., Kraaijenbrink, P. D. A., Kulkarni, A. V., Mayewski, P. A., Nepal, S., Pacheco, P., Painter, T. H., Pellicciotti, F., Rajaram, H., Rupper, S., Sinisalo, A., Shrestha, A. B., Viviroli, D., Wada, Y., Xiao, C., Yao, T., and Baillie, J. E. M.: Importance and vulnerability of the world's water towers, Nature, 577, 364–369, https://doi.org/10.1038/s41586-019-1822-y, 2020.

Inouye, D. W.: Climate change and phenology, WIREs Climate Change, 13, e764, https://doi.org/10.1002/wcc.764, 2022.

Jiang, S., Bevacqua, E., and Zscheischler, J.: River flooding mechanisms and their changes in Europe revealed by explainable machine learning, Hydrology and Earth System Sciences, 26, 6339–6359, https://doi.org/10.5194/hess-26-6339-2022, 2022.

Joshi, S. K., Swarnkar, S., Shukla, S., Kumar, S., Jain, S., and Gautam, S.: Snow/Ice Melt, Precipitation, and Groundwater Contribute to the Sutlej River System, Water, Air, & Soil Pollution, 234, 719, https://doi.org/10.1007/s11270-023-06744-4, 2023.

Julander, R. P. and Clayton, J. A.: Determining the proportion of streamflow that is generated by cold season processes versus summer rainfall in Utah, USA, Journal of Hydrology: Regional Studies, 17, 36–46, https://doi.org/10.1016/j.ejrh.2018.04.005, 2018.

Karmouche, S., Galytska, E., Runge, J., Meehl, G. A., Phillips, A. S., Weigel, K., and Eyring, V.: Regime-oriented causal model evaluation of Atlantic–Pacific teleconnections in CMIP6, Earth System Dynamics, 14, 309–344, https://doi.org/10.5194/esd-14-309-2023, 2023.

Kashyap, A. and Behera, M. D.: Excess topography and outburst flood: Geomorphic imprint of October 2023 extreme flood event in the Teesta catchment of Eastern Himalayas, Global and Planetary Change, 240, 104 540, https://doi.org/10.1016/j.gloplacha.2024.104540, 2024.

Kathpalia, A., Manshour, P., and Paluš, M.: Compression complexity with ordinal patterns for robust causal inference in irregularly sampled time series, Scientific Reports, 12, 14 170, https://doi.org/10.1038/s41598-022-18288-4, 2022.

Kim, H., Fastovich, D., Bhattacharya, T., and Tuttle, S.: Improving predictions of snow resources using midlatitude SSTs with convergent cross mapping, Environmental Research: Climate, 4, 021 001, https://doi.org/10.1088/2752-5295/add362, publisher: IOP Publishing, 2025.

Kolluru, V., John, R., Chen, J., Konkathi, P., Kolluru, S., Saraf, S., Henebry, G. M., Xiao, J., Jain, K., and Kussainova, M.: Dominant role of grazing and snow cover variability on vegetation shifts in the drylands of Kazakhstan, Communications Earth & Environment, 5, 424, https://doi.org/10.1038/s43247-024-01587-1, 2024.

Koya, S. R., Kar, K. K., and Roy, T.: Northern Pacific sea-level pressure controls rain-on-snow in North America, Communications Earth & Environment, 5, 260, https://doi.org/10.1038/s43247-024-01431-6, 2024.

Kretschmer, M., Coumou, D., Donges, J. F., and Runge, J.: Using Causal Effect Networks to Analyze Different Arctic Drivers of Midlatitude Winter Circulation, Journal of Climate, 29, 4069–4081, https://doi.org/10.1175/jcli-d-15-0654.1, 2016.

Krogh, S. A. and Pomeroy, J. W.: Recent changes to the hydrological cycle of an Arctic basin at the tundra–taiga transition, Hydrology and Earth System Sciences, 22, 3993–4014, https://doi.org/10.5194/hess-22-3993-2018, 2018.

Kumar, N., Ganguly, A., Biswal, K., Keesari, T., Pandey, A., and Deshpande, R.: Relative contribution from different water sources to supraglacial runoff in western Himalaya, Journal of Hydrology, 635, 131 137, https://doi.org/10.1016/j.jhydrol.2024.131137, 2024.

Kumar, S. V., Jasinski, M., Mocko, D. M., Rodell, M., Borak, J., Li, B., Beaudoing, H. K., and Peters-Lidard, C. D.: NCA-LDAS Land Analysis: Development and Performance of a Multisensor, Multivariate Land Data Assimilation System for the National Climate Assessment, Journal of Hydrometeorology, 20, 1571–1593, https://doi.org/10.1175/jhm-d-17-0125.1, 2019.

Kurylyk, B. L. and Walvoord, M. A.: Permafrost Hydrogeology, in: Arctic Hydrology, Permafrost and Ecosystems, edited by Yang, D. and Kane, D. L., Springer, Cham, https://doi.org/10.1007/978-3-030-50930-9_17, 2021.

Lambrecht, A. and Mayer, C.: The role of the cryosphere for runoff in a highly glacierised alpine catchment, an approach with a coupled model and in situ data, Journal of Glaciology, 70, e33, https://doi.org/10.1017/jog.2024.48, 2024.

Li, D., Wrzesien, M. L., Durand, M., Adam, J., and Lettenmaier, D. P.: How much runoff originates as snow in the western United States, and how will that change in the future?, Geophysical Research Letters, 44, 6163–6172, https://doi.org/10.1002/2017gl073551, 2017.

Li, D., Lettenmaier, D. P., Margulis, S. A., and Andreadis, K.: The Role of Rain-on-Snow in Flooding Over the Conterminous United States, Water Resources Research, 55, 8492–8513, https://doi.org/10.1029/2019wr024950, 2019.

Li, S., Wang, G., Zhu, C., Hannemann, M., Poyatos, R., Lu, J., Li, J., Ullah, W., Hagan, D. F. T., García-García, A., Liu, Y., Liu, Q., Ma, S., Liu, Q., Sun, S., Zhao, F., and Peng, J.: Spatial patterns and recent temporal trends in global transpiration modelled using eco-evolutionary optimality, Agricultural and Forest Meteorology, 342, 109 702, https://doi.org/10.1016/j.agrformet.2023.109702, 2023.

Lucianetti, G., Penna, D., Mastrorillo, L., and Mazza, R.: The Role of Snowmelt on the Spatio-Temporal Variability of Spring Recharge in a Dolomitic Mountain Group, Italian Alps, Water, https://doi.org/10.3390/w12082256, 2020.

Luojus, K., Venäläinen, P., Moisander, M., Pulliainen, J., Takala, M., Lemmetyinen, J., Derksen, C., Mortimer, C., Mudryk, L., Schwaizer, G., and Nagler, T.: ESA Snow Climate Change Initiative (Snow_cci): Snow Water Equivalent (SWE) level 3C daily global climate research data package (CRDP) (1979 - 2022), version 3.1, https://doi.org/10.5285/9d9bfc488ec54b1297eca2c9662f9c81, 2024.

Lutz, A. F., Immerzeel, W. W., Shrestha, A. B., and Bierkens, M. F. P.: Consistent increase in High Asia's runoff due to increasing glacier melt and precipitation, Nature Climate Change, https://doi.org/10.1038/nclimate2237, 2014.

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

López-Moreno, J., Granados, I., Ceballos-Barbancho, A., Morán-Tejeda, E., Revuelto, J., Alonso-González, E., Gascoin, S., Herrero, J., Deschamps-Berger, C., and Latron, J.: The signal of snowmelt in streamflow and stable water isotopes in a high mountain catchment in Central Spain, Journal of Hydrology: Regional Studies, https://doi.org/10.1016/j.ejrh.2023.101356, 2023.

Maina, F. Z. and Kumar, S. V.: Diverging Trends in Rain-On-Snow Over High Mountain Asia, Earth's Future, 11, e2022EF003 009, https://doi.org/10.1029/2022ef003009, 2023.

Mavromatis, V., Rinder, T., Prokushkin, A. S., Pokrovsky, O. S., Korets, M. A., Chmeleff, J., and Oelkers, E. H.: The effect of permafrost, vegetation, and lithology on Mg and Si isotope composition of the Yenisey River and its tributaries at the end of the spring flood, Geochimica et Cosmochimica Acta, 191, 32–46, https://doi.org/10.1016/j.gca.2016.07.003, 2016.

Miralles, D., Bonte, O., Koppa, A., Baez-Villanueva, O., Tronquo, E., Zhong, F., Beck, H., Hulsman, P., Dorigo, W., Verhoest, N., and Haghdoost, S.: GLEAM4: Global land evaporation datasets at 0.1° resolution from 1980 to near present, In Review, 2024.

Mohseni, F., Jamali, S., Ghorbanian, A., and Mokhtarzade, M.: Global soil moisture trend analysis using microwave remote sensing data and an automated polynomial-based algorithm, Global and Planetary Change, 231, 104 310, https://doi.org/10.1016/j.gloplacha.2023.104310, 2023.

Musselman, K. N., Clark, M. P., Liu, C., Ikeda, K., and Rasmussen, R.: Slower snowmelt in a warmer world, Nature Climate Change, 7, 214–219, https://doi.org/10.1038/nclimate3225, 2017.

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, Nature Climate Change, https://doi.org/10.1038/s41558-018-0236-4, 2018.

Muñoz Sabater, J.: ERA5-Land hourly data from 1950 to present, https://doi.org/10.24381/cds.e2161bac, 2019.

Norton, C. L., Dannenberg, M. P., Yan, D., Wallace, C. S. A., Rodriguez, J. R., Munson, S. M., van Leeuwen, W. J. D., and Smith, W. K.: Climate and Socioeconomic Factors Drive Irrigated Agriculture Dynamics in the Lower Colorado River Basin, Remote Sensing, 13, 1659, https://doi.org/10.3390/rs13091659, 2021.

Park, H., Kim, Y., Suzuki, K., and Hiyama, T.: Influence of snowmelt on increasing Arctic river discharge: numerical evaluation, Progress in Earth and Planetary Science, 11, 13, https://doi.org/10.1186/s40645-024-00617-y, 2024.

Pearl, J.: CAUSALITY: MODELS, REASONING, AND INFERENCE, Cambridge University Press, 2000.

Penna, D., Engel, M., Bertoldi, G., and Comiti, F.: Towards a tracer-based conceptualization of meltwater dynamics and streamflow response in a glacierized catchment, Hydrology and Earth System Sciences, 21, 23–41, https://doi.org/10.5194/hess-21-23-2017, 2017.

Philippon, N., Mougin, E., Jarlan, L., and Frison, P. L.: Analysis of the linkages between rainfall and land surface conditions in the West African monsoon through CMAP, ERS-WSC, and NOAA-AVHRR data, Journal of Geophysical Research-atmospheres, 110, D24 115, https://doi.org/10.1029/2005jd006394, 2005.

Pritchard, H. D.: Asia's shrinking glaciers protect large populations from drought stress, Nature, 569, 649–654, https://doi.org/10.1038/s41586-019-1240-1, 2019.

Pulliainen, J., Luojus, K., Derksen, C., Mudryk, L., Lemmetyinen, J., Salminen, M., Ikonen, J., Takala, M., Cohen, J., Smolander, T., and Norberg, J.: Patterns and trends of Northern Hemisphere snow mass from 1980 to 2018., Nature, https://doi.org/10.1038/s41586-020-2258-0, 2020.

Pérez Valentín, J. M. and Müller, M. F.: Impact of Hurricane Maria on Beach Erosion in Puerto Rico: Remote Sensing and Causal Inference, Geophysical Research Letters, 47, e2020GL087 306, https://doi.org/10.1029/2020gl087306, 2020.

Qin, Y., Hong, C., Zhao, H., Siebert, S., Abatzoglou, J. T., Huning, L. S., Sloat, L. L., Park, S., Li, S., Munroe, D. K., Zhu, T., Davis, S. J., and Mueller, N. D.: Snowmelt risk telecouplings for irrigated agriculture, Nature Climate Change, 12, 1007–1015, https://doi.org/10.1038/s41558-022-01509-z, 2022.

Rawlins, M. A., Fahnestock, M., Frolking, S., and Vörösmarty, C. J.: On the evaluation of snow water equivalent estimates over the terrestrial Arctic drainage basin, Hydrological Processes, 21, 1616–1623, https://doi.org/10.1002/hyp.6724, 2007.

Reyes-García, V., García-Del-Amo, D., Porcuna-Ferrer, A., Schlingmann, A., Abazeri, M., Attoh, E. M. N. A. N., Vieira da Cunha Ávila, J., Ayanlade, A., Babai, D., Benyei, P., Calvet-Mir, L., Carmona, R., Caviedes, J., Chah, J., Chakauya, R., Cuní-Sanchez, A., Fernández-Llamazares, A., Galappaththi, E. K., Gerkey, D., Graham, S., Guillerminet, T., Huanca, T., Ibarra, J. T., Junqueira, A. B., Li, X., López-Maldonado, Y., Mattalia, G., Samakov, A., Schunko, C., Seidler, R., Sharakhmatova, V., Singh, P., Tofighi-Niaki, A., Torrents-Ticó, M., Álvarez Fernández, S., Bulamah, R. C., Chambon, M., Chao, O., Chen, Z., Chengula, F., Cruz-Gispert, A., Demichelis, C., Dudina, E., Gallois, S., Glauser, M., Guillerminet, T., Hirsch, E., Izquierdo, A. E., Junsberg, L., Mariel, J., Miara, M. D., Miñarro, S., Porcher, V., Shrestha, U. B., Sharma, A., Ulambayar, T., Wu, R., Zakari, I. S., Zant, M., and LICCI Consortium: Local studies provide a global perspective of the impacts of climate change on Indigenous Peoples and local communities, Sustainable Earth Reviews, 7, 1, https://doi.org/10.1186/s42055-023-00063-6, 2024.

RGI 7.0 Consortium: Randolph Glacier Inventory - A Dataset of Global Glacier Outlines, Version 7.0, https://doi.org/10.5067/f6jmovy5navz, 2023.

Robinson, E. L. and Clark, D. B.: Using Gravity Recovery and Climate Experiment data to derive corrections to precipitation data sets and improve modelled snow mass at high latitudes, Hydrology and Earth System Sciences, 24, 1763–1779, https://doi.org/10.5194/hess-24-1763-2020, 2020.

Runge, J.: Conditional independence testing based on a nearest-neighbor estimator of conditional mutual information, in: Proceedings of the Twenty-First International Conference on Artificial Intelligence and Statistics, pp. 938–947, PMLR, https://proceedings.mlr.press/v84/runge18a.html, 2018.

Runge, J.: Necessary and sufficient graphical conditions for optimal adjustment sets in causal graphical models with hidden variables, in: Advances in Neural Information Processing Systems, vol. 34, pp. 15 762–15 773, Curran Associates, Inc., https://proceedings.neurips.cc/paper/2021/hash/8485ae387a981d783f8764e508151cd9-Abstract.html, 2021.

Runge, J., Heitzig, J., Marwan, N., and Kurths, J.: Quantifying Causal Coupling Strength: A Lag-specific Measure For Multivariate Time Series Related To Transfer Entropy, https://doi.org/10.48550/arxiv.1210.2748, 2012.

Runge, J., Nowack, P., Kretschmer, M., Flaxman, S., and Sejdinovic, D.: Detecting and quantifying causal associations in large nonlinear time series datasets, Science Advances, 5, eaau4996, https://doi.org/10.1126/sciadv.aau4996, 2019.

Runge, J., Gerhardus, A., Varando, G., Eyring, V., and Camps-Valls, G.: Causal inference for time series, Nature Reviews Earth & Environment, 4, 487–505, https://doi.org/10.1038/s43017-023-00431-y, 2023.

Schilling, S., Dietz, A., and Kuenzer, C.: Snow Water Equivalent Monitoring—A Review of Large-Scale Remote Sensing Applications, Remote Sensing, 16, 1085, https://doi.org/10.3390/rs16061085, 2024.

Schweighofer, J.: The impact of extreme weather and climate change on inland waterway transport, Natural Hazards, 72, 23–40, https://doi.org/10.1007/s11069-012-0541-6, 2014.

Sen, P. K.: Estimates of the Regression Coefficient Based on Kendall's Tau, Journal of the American Statistical Association, 63, 1379–1389, https://doi.org/10.1080/01621459.1968.10480934, 1968.

Shafeeque, M., Luo, Y., Arshad, A., Muhammad, S., Ashraf, M., and Pham, Q. B.: Assessment of climate change impacts on glacio-hydrological processes and their variations within critical zone, Natural Hazards, 115, 2721–2748, https://doi.org/10.1007/s11069-022-05661-9, 2023.

Sharif, M., Archer, D. R., Fowler, H. J., and Forsythe, N.: Trends in timing and magnitude of flow in the Upper Indus Basin, Hydrology and Earth System Sciences, 17, 1503–1516, https://doi.org/10.5194/hess-17-1503-2013, 2013.

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

Shi, X., Qin, T., Nie, H., Weng, B., and He, S.: Changes in Major Global River Discharges Directed into the Ocean, International Journal of Environmental Research and Public Health, 16, 1469, https://doi.org/10.3390/ijerph16081469, 2019.

Slater, L. and Binley, A.: Advancing hydrological process understanding from long-term resistivity monitoring systems, WIREs Water, 8, e1513, https://doi.org/10.1002/wat2.1513, 2021.

Slatyer, R. A., Umbers, K. D. L., and Arnold, P. A.: Ecological responses to variation in seasonal snow cover, Conservation Biology, 36, e13 727, https://doi.org/10.1111/cobi.13727, 2024.

Snethlage, M., Geschke, J., Spehn, E., Ranipeta, A., Yoccoz, N., Körner, C., Jetz, W., Fischer, M., and Urbach, D.: GMBA Mountain Inventory v2, https://doi.org/10.48601/earthenv-t9k2-1407, 2022.

Sogno, P., Klein, I., Uereyen, S., Bachofer, F., and Kuenzer, C.: Surface water dynamics of Africa: Analysing continental trends and identifying drivers for major lakes and reservoirs, International Journal of Remote Sensing, 0, 1–31, https://doi.org/10.1080/01431161.2024.2412802, 2024.

Soheb, M., Bastian, P., Schmidt, S., Singh, S., Kaushik, H., Ramanathan, A., and Nüsser, M.: Surface and subsurface flow of a glacierised catchment in the cold-arid region of Ladakh, Trans-Himalaya, Journal of Hydrology, 635, 131 063, https://doi.org/10.1016/j.jhydrol.2024.131063, 2024.

Soomro, S.-e.-h., Soomro, A. R., Batool, S., Guo, J., Li, Y., Bai, Y., Hu, C., Tayyab, M., Zeng, Z., Li, A., Zhen, Y., Rui, K., Hameed, A., and Wang, Y.: How does the climate change effect on hydropower potential, freshwater fisheries, and hydrological response of snow on water availability?, Applied Water Science, 14, 65, https://doi.org/10.1007/s13201-023-02070-6, 2024.

Spirtes, P.: Discovering causal relations among latent variables in directed acyclic graphical models, Tech. rep., Carnegie Mellon, Pittsburgh, https://www.cmu.edu/dietrich/philosophy/docs/tech-reports/69_Spirtes.pdf, 1996.

Stagl, J. C. and Hattermann, F. F.: Impacts of Climate Change on the Hydrological Regime of the Danube River and Its Tributaries Using an Ensemble of Climate Scenarios, Water, 7, 6139–6172, https://doi.org/10.3390/w7116139, 2015.

Sun, A. Y., Save, H., Rateb, A., Jiang, P., and Scanlon, B. R.: Deciphering the Role of Total Water Storage Anomalies in Mediating Regional Flooding, Geophysical Research Letters, 51, e2023GL108 126, https://doi.org/10.1029/2023gl108126, 2024.

Sun, Q., Zhang, X., Zwiers, F., Westra, S., and Alexander, L. V.: A Global, Continental, and Regional Analysis of Changes in Extreme Precipitation, Journal of Climate, 34, 243–258, https://doi.org/10.1175/jcli-d-19-0892.1, 2021.

Tague, C. and Grant, G. E.: Groundwater dynamics mediate low-flow response to global warming in snow-dominated alpine regions, Water Resources Research, 45, https://doi.org/10.1029/2008wr007179, 2009.

Talsma, C. J., Bennett, K. E., and Vesselinov, V. V.: Characterizing Drought Behavior in the Colorado River Basin Using Unsupervised Machine Learning, Earth and Space Science, 9, e2021EA002 086, https://doi.org/10.1029/2021ea002086, 2022.

Tangdamrongsub, N., Hwang, C., Borak, J. S., Prabnakorn, S., and Han, J.: Optimizing GRACE/GRACE-FO data and a priori hydrological knowledge for improved global terrestrial water storage component estimates, Journal of Hydrology, 598, 126 463, https://doi.org/10.1016/j.jhydrol.2021.126463, 2021.

Tong, J., Déry, S. J., Jackson, P. L., and Derksen, C.: Snow distribution from SSM/I and its relationships to the hydroclimatology of the Mackenzie River Basin, Canada, Advances in Water Resources, 33, 667–677, https://doi.org/10.1016/j.advwatres.2010.03.009, 2010.

Uereyen, S., Bachofer, F., and Kuenzer, C.: A Framework for Multivariate Analysis of Land Surface Dynamics and Driving Variables—A Case Study for Indo-Gangetic River Basins, Remote Sensing, 14, 197, https://doi.org/10.3390/rs14010197, 2022.

Ultee, L., Coats, S., and Mackay, J.: Glacial runoff buffers droughts through the 21st century, Earth System Dynamics, 13, 935–959, https://doi.org/10.5194/esd-13-935-2022, 2022.

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

UN DESA: United Nations Department of Economic and Social Affairs. World Population Prospects 2022: Summary of Results, Tech. Rep. 3, United Nations Department of Economic and Social Affairs, https://www.un.org/development/desa/pd/sites/www.un.org.development.desa.pd/files/wpp2022_summary_of_results.pdf, 2022.

Van Tiel, M., Van Loon, A. F., Seibert, J., and Stahl, K.: Hydrological response to warm and dry weather: do glaciers compensate?, Hydrology and Earth System Sciences, 25, 3245–3265, https://doi.org/10.5194/hess-25-3245-2021, 2021.

Vezzoli, R., Mercogliano, P., Pecora, S., Zollo, A. L., and Cacciamani, C.: Hydrological simulation of Po River (North Italy) discharge under climate change scenarios using the RCM COSMO-CLM, Science of The Total Environment, 521-522, 346–358, https://doi.org/10.1016/j.scitotenv.2015.03.096, 2015.

Viviroli, D., Dürr, H. H., Messerli, B., Meybeck, M., and Weingartner, R.: Mountains of the world, water towers for humanity: Typology, mapping, and global significance, Water Resources Research, 43, https://doi.org/10.1029/2006wr005653, 2007.

Vyshnevskyi, V. and Shevchuk, S.: Impact of climate change and human factors on the water regime of the Danube Delta, Acta Hydrologica Slovaca, 23, 207–216, https://doi.org/10.31577/ahs-2022-0023.02.0023, 2022.

Wang, H., Liu, J., Klaar, M., Chen, A., Gudmundsson, L., and Holden, J.: Anthropogenic climate change has influenced global river flow seasonality, Science, 383, 1009–1014, https://doi.org/10.1126/science.adi9501, 2024.

Wang, P., Huang, Q., Pozdniakov, S. P., Liu, S., Ma, N., Wang, T., Zhang, Y., Yu, J., Xie, J., Fu, G., Frolova, N. L., and Liu, C.: Potential role of permafrost thaw on increasing Siberian river discharge, Environmental Research Letters, 16, 034 046, https://doi.org/10.1088/1748-9326/abe326, 2021.

Wang, S., Zhou, F., and Russell, H.: Estimating Snow Mass and Peak River Flows for the Mackenzie River Basin Using GRACE Satellite Observations, Remote Sensing, 9, 256, https://doi.org/10.3390/rs9030256, 2017.

Wang, Y., Shen, Y.-J., Muhammad, M. Z., Muhammad, I. K., and Zhang, X.: Is Snowmelt Runoff Timing in the Upper Indus Basin Shifting Toward Earlier in the Year?, https://doi.org/10.2139/ssrn.5205511, 2025.

Wang, Y.-R., Hessen, D. O., Samset, B. H., and Stordal, F.: Evaluating global and regional land warming trends in the past decades with both MODIS and ERA5-Land land surface temperature data, Remote Sensing of Environment, 280, 113 181, https://doi.org/10.1016/j.rse.2022.113181, 2022.

Webb, R. W., Knowles, J. F., Fox, A., Fabricus, A., Corrie, T., Mooney, K., Gallais, J., Frimpong, N. A. G., Akurugu, C. A., Barron-Gafford, G., Blanken, P. D., Burns, S. P., Frank, J., and Litvak, M.: Energy-Water Asynchrony Principally Determines Water Available for Runoff From Snowmelt in Continental Montane Forests, Hydrological Processes, 38, e15 297, https://doi.org/10.1002/hyp.15297, 2024.

Wenzl, M., Baumhoer, C. A., Dietz, A. J., and Kuenzer, C.: Vegetation Changes in the Arctic: A Review of Earth Observation Applications, Remote Sensing, 16, 4509, https://doi.org/10.3390/rs16234509, 2024.

Wolf, M. A., Jamison, L. R., Solomon, D. K., Strong, C., and Brooks, P. D.: Multi-Year Controls on Groundwater Storage in Seasonally Snow-Covered Headwater Catchments, Water Resources Research, 59, e2022WR033 394, https://doi.org/10.1029/2022wr033394, 2023.

Woo, M.-k., Thorne, R., and Brown, L.: Comparison of runoff and river flow in two large northern basins, Hydrology Research, 50, 1609–1622, https://doi.org/10.2166/nh.2018.199, 2018.

Wu, X., Zhu, R., Long, Y., and Zhang, W.: Spatial Trend and Impact of Snowmelt Rate in Spring across China's Three Main Stable Snow Cover Regions over the Past 40 Years Based on Remote Sensing, Remote Sensing, 14, 4176, https://doi.org/10.3390/rs14174176, 2022.

Xu, C., Chen, Y., Hamid, Y., Tashpolat, T., Chen, Y., Ge, H., and Li, W.: Long-term change of seasonal snow cover and its effects on river runoff in the Tarim River basin, northwestern China, Hydrological Processes, 23, 2045–2055, https://doi.org/10.1002/hyp.7334, 2009.

https://doi.org/10.5194/egusphere-2025-6280
Preprint. Discussion started: 23 February 2026

Yang, D., Shrestha, R. R., Lung, J. L. Y., Tank, S., and Park, H.: Heat flux, water temperature and discharge from 15 northern Canadian rivers draining to Arctic Ocean and Hudson Bay, Global and Planetary Change, 204, 103 577, https://doi.org/10.1016/j.gloplacha.2021.103577, 2021.

Yao, T., Bolch, T., Chen, D., Gao, J., Immerzeel, W., Piao, S., Su, F., Thompson, L., Wada, Y., Wang, L., Wang, T., Wu, G., Xu, B., Yang, W., Zhang, G., and Zhao, P.: The imbalance of the Asian water tower, Nature Reviews Earth & Environment, 3, 618–632, https://doi.org/10.1038/s43017-022-00299-4, 2022.

Yuan, S., Liu, Y., Liu, Y., Zhang, K., Li, Y., Enwer, R., Li, Y., and Hu, Q.: Spatiotemporal variations of surface albedo in Central Asia and its influencing factors and confirmatory path analysis during the 21st century, International Journal of Applied Earth Observation and Geoinformation, 134, 104 233, https://doi.org/10.1016/j.jag.2024.104233, 2024.

Zakharova, E. A., Kouraev, A. V., Biancamaria, S., Kolmakova, M. V., Mognard, N. M., Zemtsov, V. A., Kirpotin, S. N., and Decharme, B.: Snow Cover and Spring Flood Flow in the Northern Part of Western Siberia (the Poluy, Nadym, Pur, and Taz Rivers), Journal of Hydrometeorology, 12, 1498–1511, https://doi.org/10.1175/jhm-d-11-017.1, 2011.

Zhang, Y., He, B., Guo, L., and Liu, D.: Differences in Response of Terrestrial Water Storage Components to Precipitation over 168 Global River Basins, Journal of Hydrometeorology, 20, 1981–1999, https://doi.org/10.1175/jhm-d-18-0253.1, 2019.

Zhang, Z., Wang, D., Wu, X., Mei, Y., Qiu, J., and Zhu, J.: Unveiling flood-generating mechanisms using circular statistics-based machine learning approach without the need for discharge data during inference, Hydrology Research, 54, https://doi.org/10.2166/nh.2023.058, 2023.

Zhou, H., Zhang, L., Liu, X., Liang, D., Zhu, Q., and Gou, Y.: Study of the Relationship between High Mountain Asia Snow Cover and Drought and Flood in the Yangtze River Basin during 1980-2019, Remote Sensing, https://doi.org/10.3390/rs14153588, 2022.

Zhu, L. and Meng, J.: Determining the relative importance of climatic drivers on spring phenology in grassland ecosystems of semi-arid areas, International Journal of Biometeorology, 59, 237–248, https://doi.org/10.1007/s00484-014-0839-z, 2015.