Flood-type trend analysis for alpine catchments

Sikorska-Senoner, Anna E ; Seibert, Jan

Abstract: In many places, magnitudes and frequencies of floods are expected to increase due to climate change. To understand these changes better, trend analyses of historical data are helpful. However, traditional trend analyses do not address issues related to shifts in the relative contributions of rainfall versus snowmelt floods, or in the frequency of a particular flood type. We present a novel approach for quantifying such trends in time series of floods using a fuzzy decision tree for event classification and applied it to maximal annual and seasonal floods in 27 alpine catchments for the period 1980–2014. Trends in flood types were studied with Sen's slope and double mass curves. Our results reveal a decreasing number of rain-on-snow and an increasing number of short rainfall events in all catchments, with flash floods increasing in smaller catchments. Overall, the results demonstrate the value of incorporating a fuzzy flood-type classification into flood trend analyses.

DOI: https://doi.org/10.1080/02626667.2020.1749761

Originally published at:
Sikorska-Senoner, Anna E; Seibert, Jan (2020). Flood-type trend analysis for alpine catchments. Hydrological Sciences Journal, 65(8):1281-1299.
DOI: https://doi.org/10.1080/02626667.2020.1749761

HYDROLOGICAL SCIENCES JOURNAL
https://doi.org/10.1080/02626667.2020.1749761

Flood-type trend analysis for alpine catchments

Anna E. Sikorska-Senoner [a] and Jan Seibert [a,b]

[a]Department of Geography, University of Zurich, Zürich, Switzerland; [b]Department of Aquatic Sciences and Assessment, Swedish University of Agricultural Sciences, Uppsala, Sweden

ABSTRACT
In many places, magnitudes and frequencies of floods are expected to increase due to climate change. To understand these changes better, trend analyses of historical data are helpful. However, traditional trend analyses do not address issues related to shifts in the relative contributions of rainfall *versus* snowmelt floods, or in the frequency of a particular flood type. We present a novel approach for quantifying such trends in time series of floods using a fuzzy decision tree for event classification and applied it to maximal annual and seasonal floods in 27 alpine catchments for the period 1980–2014. Trends in flood types were studied with Sen's slope and double mass curves. Our results reveal a decreasing number of rain-on-snow and an increasing number of short rainfall events in all catchments, with flash floods increasing in smaller catchments. Overall, the results demonstrate the value of incorporating a fuzzy flood-type classification into flood trend analyses.

ARTICLE HISTORY
Received 29 January 2019
Accepted 19 February 2020

EDITOR
A. Castellarin

ASSOCIATE EDITOR
A. Domenghetti

KEYWORDS
Flood type; flood trends; decision tree; fuzzy approach; flood contribution; change indicating area

1 Introduction

Climate change affects climate conditions not only with regard to mean values but also in terms of precipitation and temperature extremes (Frei *et al.* 1998, Scherrer *et al.* 2016) and, consequently, it is expected to result in changed magnitudes and frequencies of floods (Kundzewicz 2002, Wilby *et al.* 2008, Berghuijs *et al.* 2017). Flood magnitudes and frequencies estimated from data for past flood events under non-stationary conditions allow the evaluation of trends in flood properties (Hall *et al.* 2014) using methods such as a data-based approach, relying on statistical methods (Hundecha and Merz 2012, Vorogushyn and Merz 2013), or a simulation-based study, using the projection of hydrological models (Rojas *et al.* 2012, Gobiet *et al.* 2014). The reader is referred to Madsen *et al.* (2014) for a detailed review of flood trend analysis.

One major concern about these methods, and of most previous flood trend studies, is that they pool all flood events together making an implicit assumption of the homogeneity of flood causes. Although, for certain purposes, related for example to the estimation of the exceedence of a certain flood magnitude in recent floods, pooling all floods together may be useful for studying flood trends or flood frequency analyses, the neglect of different causes of floods may indeed impair the analysis (Fischer 2018). The homogeneity assumption implies that floods are considered as one group even if the floods may significantly vary in terms of their genesis. Hence, changes in magnitudes and frequencies of these possibly distinctive floods may not be detected. On the one hand, Brunner *et al.* (2018) have shown that season-specific analysis of floods already improves understanding of flood changes in the context of climate change. On the other hand, Blöschl *et al.* (2017) have revealed that climate change induces a shift in the timing of river floods across Europe. Thus, analysis of seasonal floods without underlying flood drivers may not reveal possible changes in flood magnitudes or frequencies. Changes in precipitation alone cannot explain changes in flood generating mechanisms (Vormoor *et al.* 2016, Berghuijs *et al.* 2019, Tarasova *et al.* 2019). Hence, understanding why floods are changing becomes particularly important for developing mitigation tools that are dedicated to a particular change in flood characteristics.

Identification of flood changes is, however, hampered by the fact that floods occurring in reality have been shown to be heterogeneous and driven by different processes, such as intensive snowmelt or heavy rainfall (Merz and Blöschl 2003, 2008, Sikorska *et al.* 2015, Berghuijs *et al.* 2019). Because of different driving factors, different types of floods demonstrate distinctive behaviours in terms of the time of flood cumulation (Gáal *et al.* 2012), flood shape (hydrographs) and flood magnitude (Merz and Blöschl 2003, Sivapalan *et al.* 2005, Diezig and Weingartner 2007, Archfield *et al.* 2014, Singh *et al.* 2014, Sikorska *et al.* 2015). Thus, they may possess different hazard potentials that can potentially be generated in the same catchment (Brunner *et al.* 2017), but they might also show different trends in terms of both their frequency of occurrence and their magnitude. Different trends of different flood types cannot be diagnosed with trend analyses on all data at once because the positive and negative trends of subgroups may be suppressed (Vormoor *et al.* 2016). Therefore, the introduction of some flood classes into the flood trend analysis can be very useful. Such class-based approaches have been proven to be a very

CONTACT Anna E. Sikorska-Senoner anna.sikorska@geo.uzh.ch Department of Geography, University of Zurich, Winterthurerstrasse 190, Zürich 8057, Switzerland

powerful tool for synthesizing our understanding of complex hydrological processes (Carillo *et al.* 2011, Sawicz *et al.* 2011). In this context, floods can be classified into three types: river flood, flash flood and storm surge flood, as proposed for European rivers by Barredo (2007), or US rivers by Perry (2000), and Berghuijs *et al.* (2016). Other less frequent flood types include ice-jam floods, dam- and levee-failure floods, debris, landslide, and mudflow floods (Perry 2000). Other classification schemes distinguish between rainfall- and snow-melt-driven floods (Vormoor *et al.* 2016, Fischer *et al.* 2019), or between nival, pluvial and mixed-event types (Burn and Whitfield 2016). More recently, a classification based on seasonality statistics has been proposed for Europe by Berghuijs *et al.* (2019). Alternatively, floods can also be classified based on their probability of occurrence (Fischer and Schumann 2018). For a recent review on existing classifications (grouped into hydroclimatic, hydrological and hydrogrpah perspectives), the reader is referred to Tarasova *et al.* (2019).

In mountainous catchments, different flood types can also occur that are linked to the specific characteristics of mountainous regions (topography, zero temperature line, the presence of snowpack or glaciers). For these regions, different flood classes have been proposed, e.g. for Austrian catchments by Merz and Blöschl (2003, 2008) and for Swiss catchments by Diezig and Weingartner (2007) and Sikorska *et al.* (2015). These classes, also called flood types, can be identified from observed data on past flood episodes using a data-based approach. By further analysing how characteristics (frequency or contribution) of such flood types change in time, one can track changes in flood drivers in the catchment, which should be of a benefit for water management.

Even though a flood-specific analysis appears very promising, it may fail when confronted with flood events that are often of mixed genesis. Such a mixed genesis makes it difficult to cluster floods into distinctive groups in an unequivocal way because some floods may fall into multiple classes (Sikorska *et al.* 2015). As a result, a misclassification of events can occur, leading to wrongly identified flood trends. This is a major drawback of all classical flood classifications (such as based on crisp thresholds), which assume that a single driver per flood event can be isolated.

In this study, we thus propose a novel method for trend analysis of flood-type contributions that is based on a fuzzy concept. This method relies on a flood-type classification introduced by Sikorska *et al.* (2015) and categorizes flood events into distinctive groups using information on static (catchment-specific) and dynamic (event-specific) characteristics. Yet, in contrast to previous flood-specific analyses (e.g. Merz and Blöschl 2003), the fuzzy approach enables the identification of mixed events (Sikorska *et al.* 2015). We further compare the fuzzy approach with a classical (crisp) approach in the context of flood trend detection and evaluate its applicability for tracing changes in flood-type contributions in the catchment. Here, we adapt the definition of the trend detection following IPCC (2007) and Merz *et al.* (2012) as a change that has been observed that is significantly different from what can be explained by the natural internal variability of the system. Trends are assessed by two methods: the method of slopes, Sen's slope (Sen 1968), and the double mass curve (DMC; Searcy and Hardison 1960). As the traditional DMC method relies on the computation of slope of regression lines, it is more suitable for detection of sharp changes than smooth transitions (Rutledge 1985). Therefore, we introduced a new metric called a change indicating area (CIA) that better allows the inspection of year-to-year transitions in data.

The specific research questions of our study were:

(1) Did the frequencies of occurrence and contributions of different flood types change across studied years?
(2) Does introducing fuzzy flood-type classification into trend analysis of floods provide new insights on changes in flood properties?
(3) Can the double mass curve method with the change indicating area index be used as an alternative to the method of slopes to assess trends in flood types?

These questions were addressed based on maximum annual and seasonal floods for 27 catchments in Switzerland.

2 Material

This study was based on the dataset of 27 (un-nested) Swiss catchments (Fig. 1) with continuous precipitation, temperature and discharge observations for 34 years on average; as we aimed to use all available data to cover as many different flood conditions as possible, the data length varies for the studied catchments. To enable the analysis of changes in natural flood generating processes, only catchments without any significant direct human impacts over the analysed period, such as due to river channel engineering, hydraulic structures, or land-use changes, and without any large lakes, were selected for the study. These study catchments have an area of 21.8–939 km^2, the mean elevation range from 485–2452 m a.s.l., and an areal glacier ratio in the range of 0–21% (see Table 1 for more details).

For observed precipitation and temperature data, we used information from hourly gauging stations, which were averaged to catchment mean precipitation totals and catchment mean temperature using a Thiessen polygon method and following elevation corrections: +5%/100 m and –0.6°C/100 m, respectively. The values were computed for the mean catchment elevation.

3 Methods

3.1 Flood types, flood tree and redefined flood-type signatures

In this study, we used six major distinctive flood types that are most commonly observed in Swiss mountainous catchments following Diezig and Weingartner (2007) and Sikorska *et al.* (2015): flash flood (FF), short-rainfall flood (SRF), long-rainfall flood (LRF), rain-on-snow flood (RoSF), snow-melt flood (SM) and glacier-melt flood (GMF). The main characteristics of these six types are summarized in Table 2.

Each selected event (see Section 3.2 for event selection) was next assigned to a flood type using the modified flood decision tree developed originally by Sikorska *et al.* (2015), which

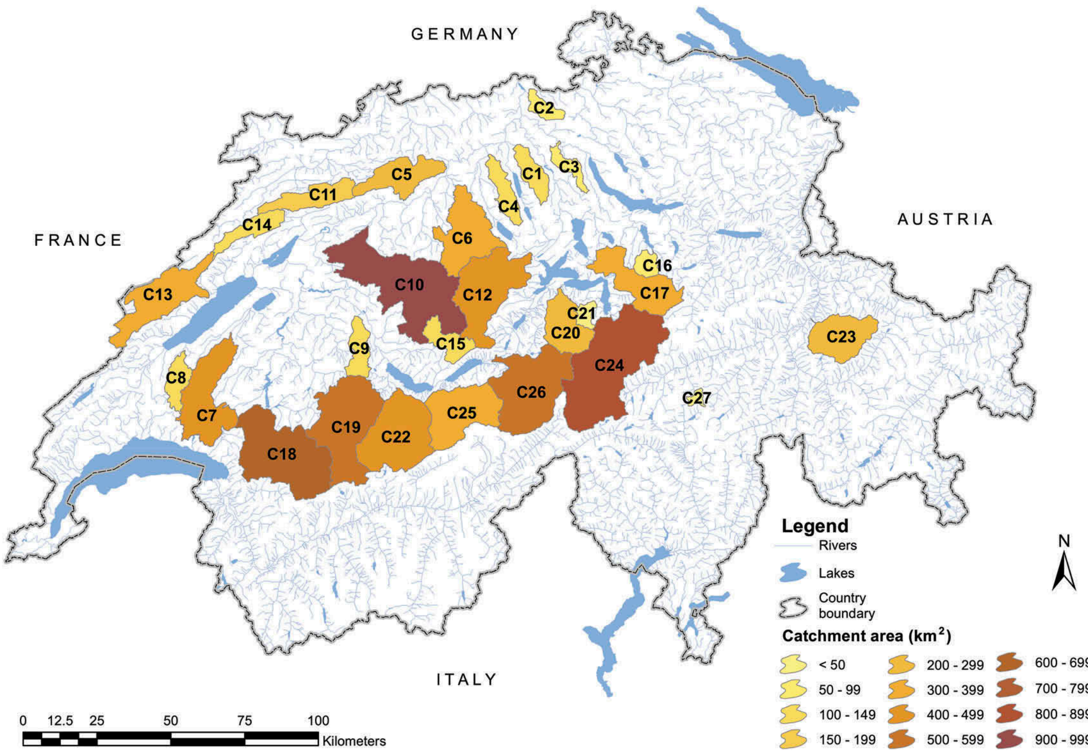

Figure 1. Selected 27 study catchments labelled according to the increasing mean altitude of the catchment.

Table 1. Properties of the study catchments sorted according to increasing catchment mean altitude.

Catchment		Catchment properties				Runoff properties	
ID	Name	Mean altitude (m a.s.l.)	Area (km^2)	Areal glacier ratio (%)	Topographic region	Record length used	Regime type[a]
Lowland (<1000 m a.s.l.)							
C1	Bünz at Othmarsingen	485	111	0	Swiss Plateau	1980–2014	8
C2	Surb at Döttingen	511	67	0	Swiss Plateau	1980–2014	8
C3	Reppisch at Dietikon	543	69	0	Swiss Plateau	1986–2014	8
C4	Wyna at Suhr	566	120	0	Swiss Plateau	1980–2014	8
C5	Dünnern at Olten	657	196	0	Jura	1980–2014	9
C6	Wigger at Zofingen	660	368	0	Swiss Plateau	1980–2014	8
C7	Broye at Payerne	669	392	0	Swiss Plateau	1980–2014	8
C8	Mentue at Ivonand	679	105	0	Swiss Plateau	1980–2014	9
C9	Gürbe at Belp	799	117	0	Swiss Plateau	1980–2014	7
C10	Emme at Wiler	841	939	0	Pre-alpine	1981–2012	7
C11	Birse at Moutier	907	183	0	Jura	1981–2012	10
Middle (≥1000 & <1500 m a.s.l.)							
C12	Kleine Emme at Littau	1050	478	0	Pre-alpine	1980–2014	6
C13	Areuse at Boudry	1060	377	0	Jura	1983–2014	10
C14	Suze at Sonzeboz	1076	150	0	Jura	1980–2012	10
C15	Emme at Eggiwil	1249	124	0	Pre-alpine	1981–2012	6
C16	Minster at Euthal	1318	59	0	Pre-alpine	1980–2012	5
C17	Muota at Ingenbohl	1360	316	0.1	Pre-alpine	1980–2014	5
High altitude (≥1500 m a.s.l.)							
C18	Sarine at Broc	1520	637	0.6	Alpine	1980–2014	5
C19	Simme at Latterbach	1598	564	2.2	Alpine	1984–2014	5
C20	Engelberger Aa at Buochs	1620	227	4.3	Alpine	1983–2014	3
C21	Grosstalbach at Isenthal	1820	44	9.3	Alpine	1980–2014	4
C22	Kander at Hondrich	1900	491	7.9	Alpine	1980–2014	3
C23	Plessur at Chur	1917	263	0	Alpine	1981–2012	4
C24	Reuss at Seedorf	2010	832	9.5	Alpine	1980–2014	3
C25	Lütschine at Gsteig	2050	379	17.4	Alpine	1980–2014	2
C26	Aare at Brienzwiler	2150	554	21.0	Alpine	1980–2014	1
C27	Somvixer Rhein at Somvix	2421	22	6.7	Alpine	1981–2012	3
Average over all sample catchments		1253	303	2.9		34 years	

[a]Defined according to Weingartner and Aschwanden (1992); 1: b-glaciaire, 2: a-glacio-nival, 3; b-glacio-nival, 4; nival alpin, 5: nival de transition, 6: nivo-pluvial préalpin, 7: pluvial supérieur, 8: pluvial inférieur, 9: pluvial jurassien, 10: nivo-pluvial jurassien.

Table 2. Considered major flood types that may occur in alpine catchments.

Flood type	Explanation
Flash floods (FF)	Induced by short intensive rainfalls usually lasting less than half a day and locally exceeding the infiltration capacity, occurring mostly in the storm season (months: May–September) and of a local range (here limited to catchments of area <200 km^2).
Short-rainfall floods (SRF)	Occurring due to short rainfall events, usually with a duration of up to one day and a high intensity rapidly exceeding the infiltration capacity, usually of a larger range than FF and possible all year round.
Long-rainfall floods (LRF)	Driven by long lasting rainfalls of several days or weeks and usually of low intensity that gradually fill the storage capacity, usually of a regional range covering nested catchments, possible all year round.
Rain-on-snow floods (RoSF)	Occurring due to rainfall on existing snow cover (or ice cover in glaciated catchments), which initiates melting, possible during the whole year but conditioned on the availability of the snow cover.
Snowmelt floods (SMF)	Caused by melting of snow cover initiated by a rapid increase in air temperature with an insignificant rainfall amount. SMF are possible during the whole year but with a peak seasonality depending on the catchment altitude, i.e. in lowlands rather at the end of winter or beginning of spring, in the mountains mainly in spring and summer due to delayed melting of the snowpack.
Glacier-melt floods (GMF)	Caused by glacier melting due to an increase in air temperature with an insignificant rainfall amount, possible only in glaciated catchments (with an areal glacier percentage ≥5% of the catchment area). The seasonal peak is usually shifted towards summer with respect to SMF, due to higher solar radiation required to initiate melting of glacier ice located at higher altitudes (and lower air temperatures). Possible months of occurrence in alpine catchments: May–September.

classifies events based on flood and catchment indices calculated for each event independently. This tree is shaped in a binary scheme, in which at each node there are two branches that can be taken. Choices at each node are controlled by the threshold values assigned based on literature and experts' knowledge. Each branch terminates with a flood type being assigned based on preceding choices. Note that, depending on the type of event and node (i.e. the path through the decision tree), not all of the flood types defined in Table 2 are actually used in the classification of individual events. Thus, assigning flood types to events follows a deduction rule, according to which a pool of possible types to be attributed is gradually decreased along the tree branch.

In this study, the original tree of Sikorska *et al.* (2015) was modified to improve the division between six different flood types and to make the tree independent from simulations of a hydrological model. The specific modifications include:

(1) The distinction between FF and SRF was improved, first, by limiting the occurrence of FF exclusively to the catchments with a contributing area smaller than 200 km^2, which can be assumed as small to middle-size catchments in the alpine region (Sikorska and Seibert 2018). Second, the occurrence of FF was restricted to spring and summer (i.e. May–September) thunderstorms only, which are most typical conditions for the development of FF in this region (Diezig and Weingartner 2007). In the original tree, FF could also be classified in bigger catchments and outside these seasons and the distinction between FF and SRF was often made based only on the catchment wetness index (C_W). This division was hence not always straightforward because similar wetness conditions may occur prior to SRF and FF. As the C_W index was also linked with the use of a hydrological model, it was removed from the indices in the classification used here.

(2) Snow accumulation and snowmelt in the catchment was computed by means of the degree-day method, as implemented in the hydrological model HBV (Seibert and Vis 2012). In this method, it is assumed that the snowmelt ratio is linearly proportional to the air temperature above the melting temperature. Thus, the snowmelt, S_{Mi} (mm d^{-1}), is computed from the actual temperature using a degree-day melt factor (here assumed as 2 mm C^{-1} d^{-1}), and the threshold temperature at which the snowmelt is initiated, assumed as 0°C. Use of a degree-day method for computing the snowmelt makes this classification independent from the hydrological model and also allows for its application in catchments where model calibration is not possible.

As a consequence of these modifications, only four flood types are considered during autumn-winter seasons: SRF, LRF, RoSF and SMF, while all six types are possible during spring-summer seasons. This restriction allows for a better representation of flood processes in the Alps (Diezig and Weingartner 2007). The modified decision tree is presented in Fig. 2.

Following the modifications, signatures for each of the six flood types were redefined and these are presented in Table 3.

Note that the areal percentage of glacier cover (G_C) is considered in our study as a static index, as changes in the glacier cover occur at a long-term scale rather than at the event scale. Thus, no changes in G_C over the 34 years of available observations were considered. As this index is only used here to determine whether glacier-melt floods are possible ($G_C \geq$ 5%, which was the case for six catchments), slight changes in this index can be assumed as irrelevant in this context.

3.2 Selection of maximum annual and seasonal flood events

For the purpose of this study, we selected flood events that corresponded to the annual and seasonal maxima. The seasons were defined following Sikorska *et al.* (2018) as: season I: winter (January–March), season II: spring (April–June), season III: summer (July–September) and season IV: autumn (October–December). Annual and seasonal flood events within each year were then defined following the flood-event separation method described in detail in Sikorska *et al.* (2015, 2018). This method defines a flood event between the local minimum directly preceding the event peak (here maximum event flow) and the point on the recession curve that corresponds to 0.2 of the peak value. Such selected flood events formed discrete time series of flood events (annual or seasonal floods), which were further analysed for trend changes. All other floods (smaller than selected) were excluded from further analysis.

Note that selecting seasonal maxima in catchments without pronounced flood events in certain seasons (e.g. winter in

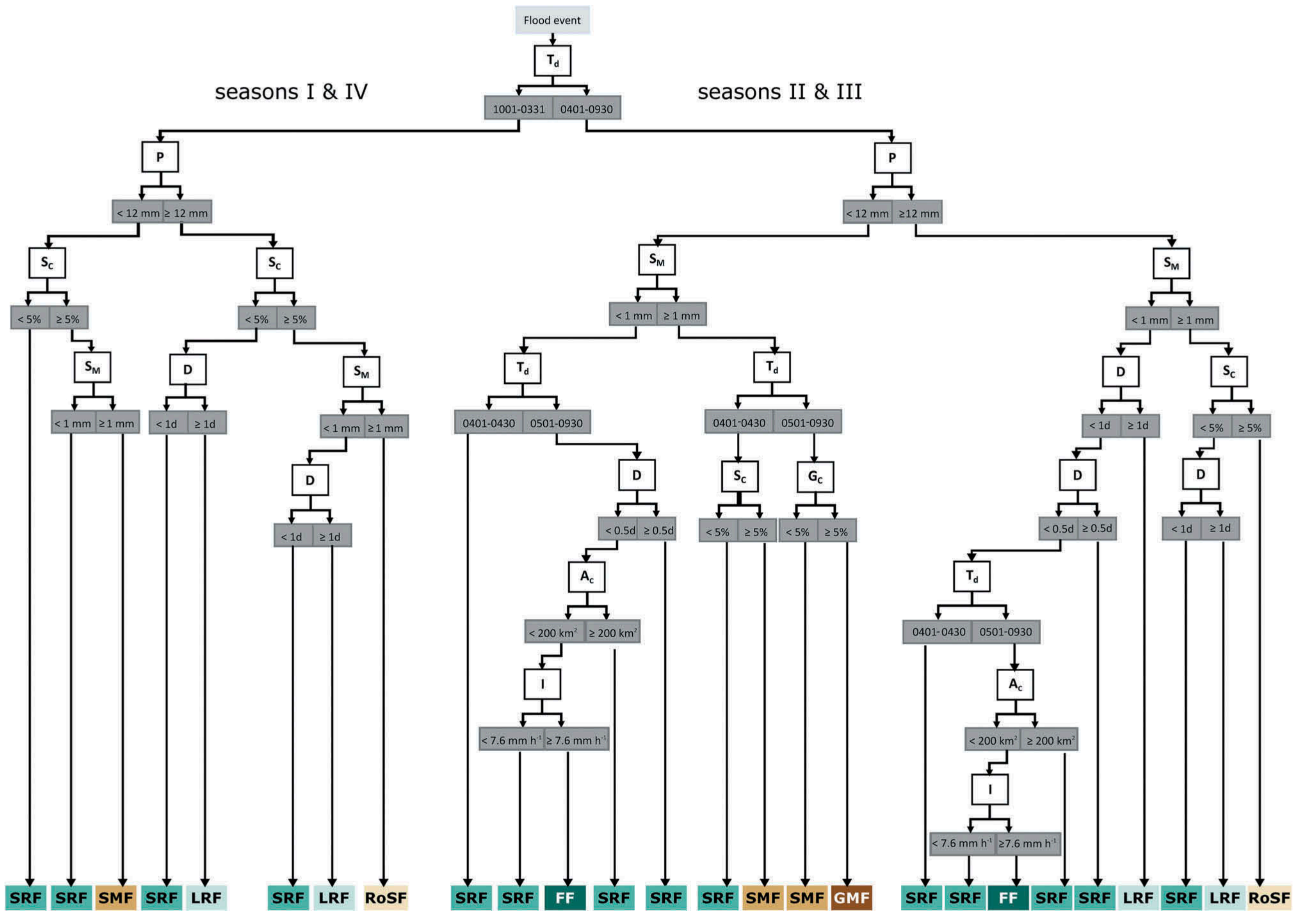

Figure 2. Schema of the modified flood decision tree; flood types and flood indices are described in Tables 2 and 3, respectively.

high-altitude catchments) results in events in those seasons with relatively small peak flows being chosen, while events with larger peak flows from other seasons are discarded. Although such small seasonal flood events may not cause any hazards, they are still very important to identify transitions in dominant generation processes of the seasonal event runoff.

3.3 Assignment of flood type to flood events with fuzzy and crisp approaches

For each of the selected seasonal and annual flood events, flood indices shown in Table 3 were calculated and the flood decision tree (Section 3.1) was applied. This tree can be used in two different variants: crisp or fuzzy (see Sikorska *et al.* 2015 for

Table 3. Typical signatures of the six major flood types and their thresholds. Modified from Sikorska *et al.* (2015).

Index	Index unit	Flood type and thresholds (Fuzzy range)*					
		FF	SRF	LRF	RoSF	SMF	GMF
Dynamic (event dependent)							
T_d	Timing[(a)] (day of year)** (No. of days)	0501–0930 (±7)	0101–1231 (±7)	0101–1231 (±7)	0101–1231 (±7)	0101–1231 (±7)	0501–0930 (±7)
P	Precipitation total amount[(b)] (mm)			≥12 (±2)	≥12 (±2)	<12 (±2)	<12 (±2)
D	Precipitation duration[(b)] (days)	<0.5 (±0.25)	<1 (±0.25)	≥1 (±0.25)			
I	Maximum hourly precipitation intensity[(c)] (mm h^{-1})	≥7.6 (±1.3)					
S_M	Snowmelt total amount[(a)] (mm)				≥1 (±0.5)	≥1 (±0.5)	≥1 (±0.5)
S_C	Areal percentage of snow cover[(a)] (%)				≥5 (±1)	≥5 (±1)	
Static (event independent)							
A_C	Catchment area[(d)] (km^2)	<200 (± 20)					
G_C	Areal percentage of glacier cover[(a)] (%)						≥5 (±1)

Thresholds chosen according to: [(a)] Sikorska *et al.* (2015); [(b)] Geiger *et al.* (1991), Diezig and Weingartner (2007); [(c)] Grebner (1990); and [(d)] Sikorska and Seibert (2018).
* Fuzzy ranges used in the fuzzy approach are represented in the same units as their thresholds unless stated differently.
** A day of the year is expressed in mmdd format, where 0101 refers to 1 January and 1231 to 31 December.

details). The essential difference between these two tree variants lies in the way the tree's thresholds are defined. While in the crisp approach these thresholds are formed as strict divisions, in the fuzzy approach the thresholds are defined as gradual transitions (see Fig. 3). The latter implies that, in contrast to the crisp approach, both branches can be taken at the same node and the strength of their belonging is determined with a fuzzy membership m_f. This membership is defined in the range from 0 to 1, with these two values corresponding to the fuzzy threshold ranges, and under the condition that memberships at two related branches always have to sum up to one. The fuzzy threshold ranges were assumed here as 7 days for the timing within the year (T_d) and 6 h for precipitation duration (D) for all flood types. Although a 6-h fuzzy window may appear too large for FF (with a crisp threshold of 12 h), we prefer to set the same length of the fuzzy window for all flood types, thus not favouring any type over another. For all other quantitative variables (P, I, S_M, S_C, G_C, A_C), the fuzzy ranges indicated in Table 3 were used. Note that if the fuzzy tree is applied, FF and GMF may occur outside of their typical occurrence seasons (due to a 7-day fuzzy window).

As a result of applying the fuzzy tree variant, each flood event was defined by a mixture of six flood types and their fuzzy memberships m_f determined from data. These membership values reflect the relative importance of different flood-generating mechanisms. In the crisp tree, only one flood type per event was determined with the membership of 1 by definition.

3.4 Quantification of trends with the method of slopes

Series of annual and seasonal flood events with assigned flood types were next examined for changes in the event contribution (assignment of specific flood types) across years. To quantify these changes, we performed trend analysis using Sen's method, the method of slopes (Sen 1968), while the significance of these trends was assessed using the Mann-Kendall test (Déry *et al.* 2009) at the significance level of $\alpha = 0.05$. The method of slopes is based on the computation of individual slopes between consecutive variable entries:

$$s_j = \frac{(y_j - y_i)}{(t_j - t_i)} \tag{1}$$

where $j > i$, y_i is a variable at time t_i, and s_j is a slope at time t_j. Then, the median over all individual slopes is computed and assumed as a measure of a trend:

$$s = M(s_{j:n}) \tag{2}$$

where n is the number of observations.

The method of slopes is often applied in the analysis of flood trends and hydrological variables (Groleau *et al.* 2007, Stahl *et al.* 2010) together with the Mann-Kendall test for identifying the significance in changes (Déry *et al.* 2009, Duethmann *et al.* 2015, Mangini *et al.* 2018). In this study, slopes were computed for the entire observation period (1980–2014) for changes in flood-type contributions using a 5-year running mean. Using a running mean enables computation of slopes also for flood

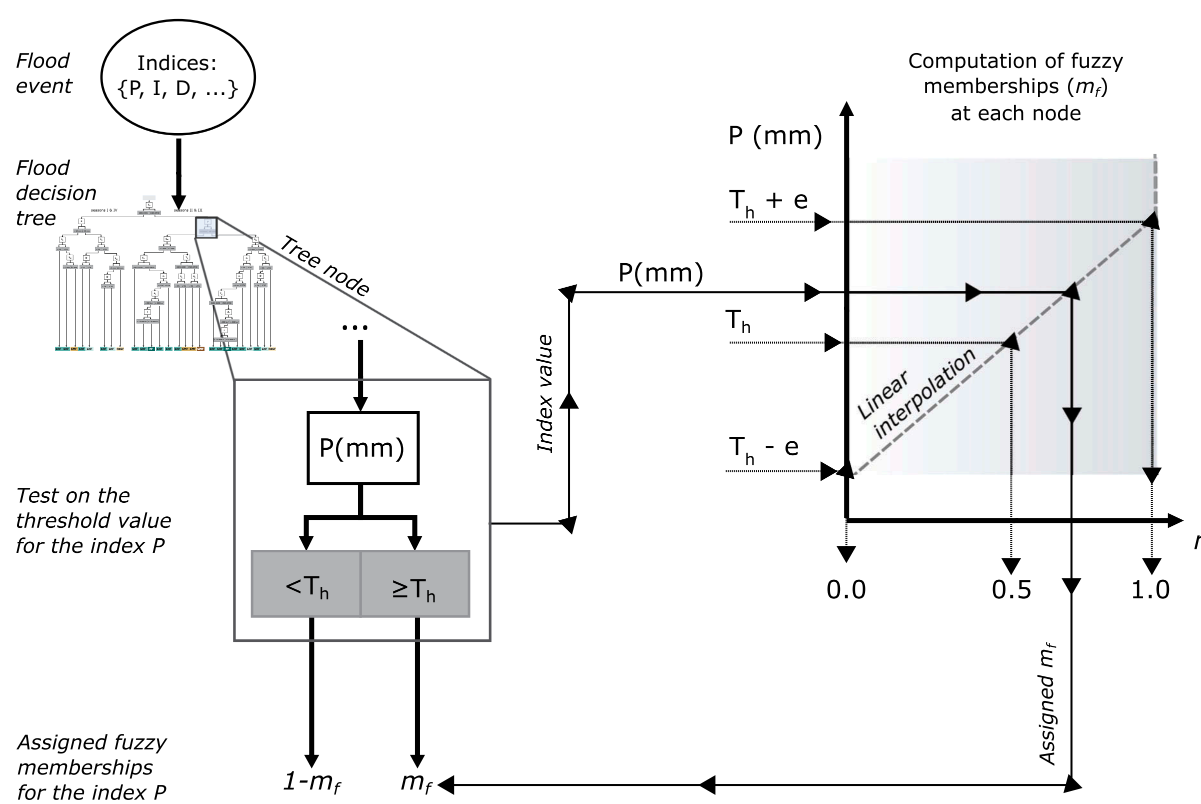

Figure 3. Assignment of fuzzy memberships, m_f, in the fuzzy variant of the decision tree. T_h: threshold value for the flood index; e: fuzzy range for the threshold; P, I, D, …: flood indices defined as in.Table 3. In this example P, which describes the precipitation amount in mm per event, is used for illustration. Adapted from Sikorska *et al.* (2015).

types which occur unequally in time. The slopes and their significance were also computed for indices of precipitation, temperature and maximum floods at annual and seasonal scales. The Sen's slope and Mann-Kendall tests were here computed using *sens.slope* and *mk.test* functions within the package "trend" (Pohlert 2018) of R programming language (R Core Team 2019).

3.5 Field significance

For variables with significant trends estimated by the Mann-Kendall test for different catchments, a field significance was computed. The field (also called global) significance (Douglas *et al.* 2000, Birsan *et al.* 2005, Wilks 2006) for trends in meteorological and hydrological variables, as well as for flood-type contributions, was assessed using a bootstrap method similar to that described in Burn and Elnur (2002). This method relies on resampling with a replacement and was executed in the following five steps:

Step 1. The new indices $\tilde{j}:\tilde{n}$ for a variable y are resampled from the original observation years *j:n* preserving the original length of records;

Step 2. The entries for the resampled variable $\tilde{y}$ are attributed for each site (catchment) following the new (resampled) indices $\tilde{j}:\tilde{n}$;

Step 3. The Mann-Kendall test for significance is performed for each resampled variable site;

Step 4. A fraction of the results for all sites that are significant at the defined (local) significance level α_l is computed;

Step 5. Steps 1–4 are repeated N times and the computed fraction values retained, resulting in a distribution of the fraction of results being significant.

From this distribution, the value that was exceeded α_g% of time was determined as a critical value p_{cr}; α_g is the field significance level. Results with a fraction higher than p_{cr} were considered as being significant at the significance level of α_g. Here, we used the following settings for assessing the field significance: $N = 1000$, and α_l and α_g as 0.1.

Note that in this method temporal structures that exist in the original variable y will not be reproduced in the resampled variable $\tilde{y}$ due to the nature of the resampling process (years chosen independently). Yet, the cross-correlations between the catchments will be included in the resampled variables as these are constrained using the same indices sequence (years) for all catchments. Preserving the cross-correlations helps in establishing the critical value p_{cr} needed to be exceeded for the fraction of sites (catchments) exhibiting a trend. In this way, a fraction of results that is expected to show a trend at a given local significance level purely by chance can be determined.

3.6 Identification of changes in the catchment flood-type contribution with double mass curves (DMC)

Changes in the flood-type contributions were also assessed with the DMC method (Searcy and Hardison 1960). The DMC method is commonly applied to test the consistency of meteorological or hydrological records (Searcy and Hardison 1960, Pirnia *et al.* 2018), and recently also for detecting changes resulting from anthropogenic impacts (Kliment *et al.* 2011, Wang *et al.* 2013, Bažatová and Šimková 2015, Gao *et al.* 2017). This simple graphical method is based on the assumption that the cumulation of two quantities plotted against each other will follow a straight line if the data are proportional over time (no change occurred in their proportion). A change (break) in the slope of the DMC indicates a change in the proportion of these two variables. If one or more break points in the DMC are identified, the degree of change in the relation can be identified by means of the slopes of the regression lines that are computed before and after the break points. According to Searcy and Hardison (1960), this method is suitable for analysing changes that last at least a few years, i.e. with (a) visible break point(s) that split the variable into two or more sub-periods. Moreover, the application of this method is valid only if in the period before and after the break no change occurs, i.e. a state of equilibrium is reached allowing the construction of a regression line for each period (Rutledge 1985).

Note that because of this condition of sub-periods with equilibrium present in data, the DMC method in its traditional description is less suitable for analysis of slow and constant transitions with no clear break points due to the difficulty in defining (long enough) equilibrium periods. Such transitions are particularly the case for changes in flood-type contributions that are expected to occur on a year-to-year basis rather than demonstrating sharp breaks. Therefore, to identify such transitions in flood-type contribution with the help of DMCs, we introduced a quantitative metric, the change indicating area (CIA), described in detail below.

3.7 Change indicating area (CIA) and its significance

The CIA describes the deflection of the DMC in the specified flood contribution from the unity (1:1) line, i.e. from the contribution of the reference flood type. To compute this area, the constructed DMC (Fig. 4(a)) is first rescaled so that the maximum point of the DMC falls on the unity line (Fig. 4(b)). Next, knowing values at each step of the rescaled DMC, the area of the polygon restricted by the rescaled DMC and the 1:1 line can be computed as the difference between the polygon of the reference flood type and the total polygon restricted by the rescaled DMC and the *x*-axes (Fig. 4(c)). This computed area, rescaled by the area of the reference polygon, finally returns the CIA index.

A no-change case in the flood-type contribution would be depicted by a straight (cumulative) line falling at the 1:1 line, with CIA equal to 0. Any deviation in the behaviour of the rescaled cumulative line from the 1:1 line indicates a change in the flood-type contribution *versus* the reference type, while the sign of the CIA indicates the location of the rescaled DMC below or above the 1:1 line for most of the observation period. If the rescaled DMC lies above the 1:1 line, CIA takes a negative value that corresponds to a decreasing trend in the contribution towards the reference type. For the rescaled DMC lying below the 1:1 line, the opposite trend is observed (CIA > 0).

Significance levels of changes assessed by the CIA index were computed empirically using a Monte Carlo approach. In

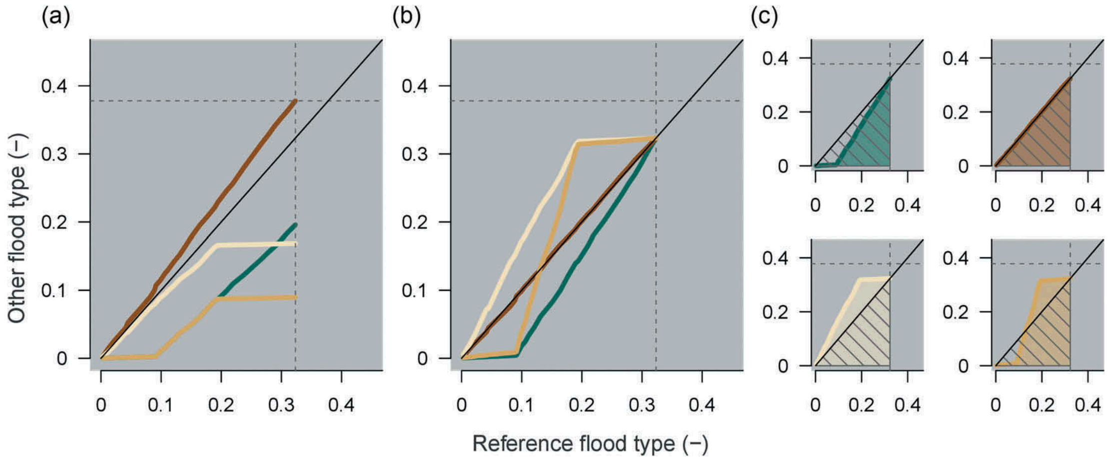

Figure 4. Illustration of the computation of the change indicating area (CIA) index within the double mass curve (DMC) method: (a) DMCs for the example flood types in relation to the reference flood type; (b) rescaled DMCs to the reference flood type; and (c) computation of the CIA (shaded polygon). The dashed polygons show an intermediate step in the estimation of the CIA. The solid black line navigates the state of even contributions between the selected and reference flood types.

particular, the order of years was perturbed by randomly resampling (with replacement) the occurrence of years. The same order of resampled years was kept for all flood types and catchments to preserve cross-correlations between the catchments and flood types. For such resampled years, a new CIA index was computed for each flood type. The resampling was repeated 1000 times resulting in the distribution of the CIA index per flood type and catchment. From this distribution, the value that was exceeded 5% of the time was determined as a critical value, i.e. a measure of change occurring simply by chance. Finally, a change in the flood-type contribution was assumed as significant if the absolute value of the CIA index estimated from original data for that flood type was higher than its critical value.

The DMC and the CIA index were applied here to cumulative contributions of each flood type along the entire observation period. To construct the DMC and to assess changes in these flood-type contributions, one flood type that occurred most often was chosen as the reference type. Note that the computation of the CIA requires that a flood type occurs more than a few times during the observation period to be able to construct the polygon. A minimum number of events is also required for a test of significance to exclude random changes. Thus, we set this number to five events per flood type and the CIA index and the tests on significance were performed only for those types that fulfilled this condition. For flood types with less than five events, changes were assumed to be random.

4 Results

4.1 Signals of climatic changes in recorded meteorological data

In all 27 study catchments, we detected a positive significant trend in the mean annual air temperature (see Table 4 and top panel of Fig. 5 for an example catchment). Regarding the annual precipitation totals, the signal was less clear, with a positive trend in four catchments and a negative trend in the remaining 23 catchments. However, these trends were not significant (thus field significance was not computed). Similar patterns were seen when stratifying catchments by their altitude (catchment groups in Table 4).

A significant positive trend was found for the temperature values for seasons I (winter), II (spring) and III (summer), and it was less pronounced for season IV (autumn) when looking at all catchments together. In detail, for high-altitude catchments (C18–C27), a positive significant trend was identified through all seasons, whereas for other catchments, a positive significant trend was always observed in seasons II and III (mid-altitude: C12–C17) and in seasons I, II and III (lowland: C1–C11). In the remaining seasons, this trend was assessed in the majority of individual catchments as positive but in others as negative.

These significant trends in temperature at annual and seasonal scales were assessed as significant with the field significance test (significance fraction equal to 1, meaning that all results were significant at the significance level of 0.1).

4.2 Non-specific flood analysis of recorded flow data

No clear trend could be detected in the annual peak magnitudes (Table 4). While a positive significant trend was estimated in 17 catchments, a negative significant trend was estimated in six catchments. Regarding the changes in peak magnitude of seasonal floods (Table 4, seasons I–IV), a significant positive trend was identified in the majority of the catchments at all elevation groups in season III (summer). In season IV (autumn), a negative significant trend was observed in the majority of high-altitude (C18–C27; also in season II) and mid-altitude catchments (C12–C17), but an opposite trend was observed in lowland catchments (C1–C11). In seasons I (winter) and II, the signal was not that clear.

These significant trends in flow peaks at annual and seasonal scales were also assessed as significant with the field significance test (significance fraction of 1 at the significance level of 0.1).

4.3 Flood-type based analysis of events

The application of the flood decision tree to the flood events demonstrated that some floods are classified differently

Table 4. Trends in annual and seasonal precipitation totals, mean daily temperatures and peak values in 27 study catchments assessed for their significance by Sen's slope and the Mann-Kendall significance test (with $p \leq 0.05$). Seasons I: winter, II: spring, III: summer, and IV: autumn. The number of catchments within each catchment group (lowland, mid-altitude, high altitude) is given in parentheses.

Period	Year			Season 1			Season II			Season III			Season IV		
Variable	*P*	*T*	*Q*	*P*	*T*	*Q*	*P*	*T*	*Q*	*P*	*T*	*Q*	*P*	*T*	*Q*
Lowland (11)															
Increasing trends (no.)	2	10	7	0	10	5	4	10	5	10	10	6	8	9	7
Decreasing trends (no.)	8	0	3	10	0	5	6	0	5	0	0	4	2	1	3
Significant trends (no.)	0	10	10	0	10	10	0	9	10	0	10	10	0	10	10
Global significance (fraction)		1	1		0.99	1		1	1		1	1		1	1
Mid-altitude (6)															
Increasing trends (no.)	1	6	3	2	5	2	1	6	3	5	6	4	3	5	0
Decreasing trends (no.)	5	0	3	4	1	4	5	0	3	1	0	2	3	1	5
Significant trends (no.)	0	6	6	0	6	6	0	6	6	0	6	6	0	6	5
Global significance (fraction)		1	1		0.98	1		0.99	1		1	1		1	1
High altitude (10)															
Increasing trends (no.)	1	11	7	1	11	6	1	11	2	9	11	9	8	11	4
Decreasing trends (no.)	10	0	3	10	0	5	10	0	8	2	0	2	3	0	7
Significant trends (no.)	0	11	10	0	11	11	0	8	10	0	11	11	0	11	11
Global significance (fraction)		1	1		0.98	1		1	1		1	1		1	1
All (27)															
Increasing trends (No.)	4	27	17	3	26	13	6	27	10	24	27	19	19	25	11
Decreasing trends (No.)	23	0	9	24	1	14	21	0	16	3	0	8	8	2	15
Significant trends (No.)	0	27	26	0	27	27	0	23	26	0	27	27	0	27	26
Global significance (fraction)		1	1		1	1		1	1		1	1		1	1

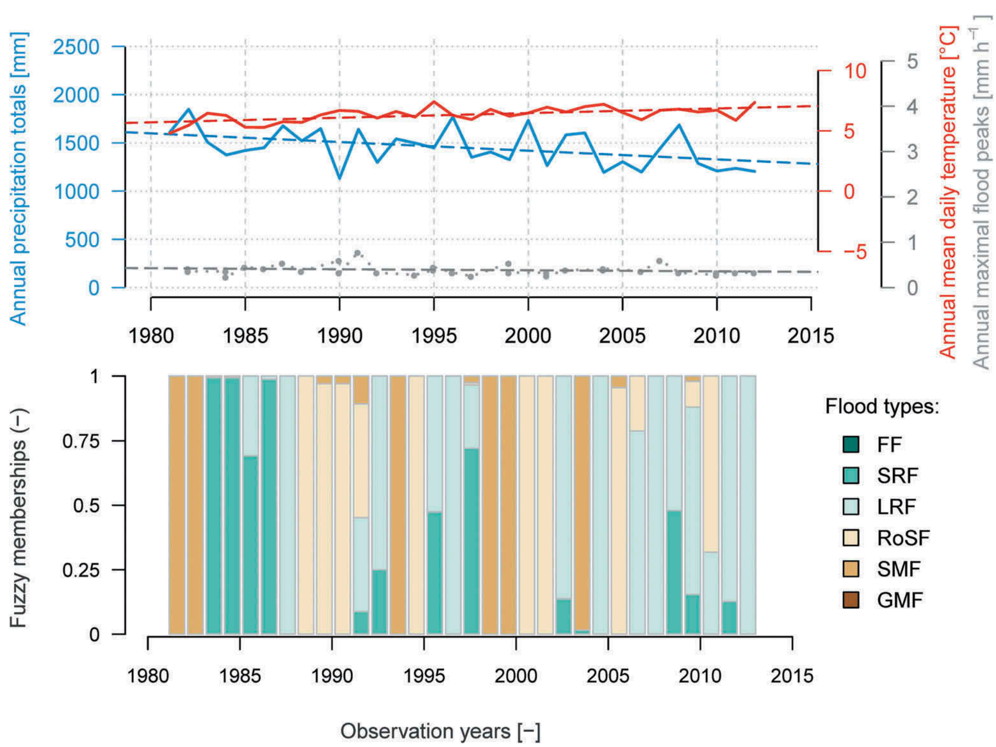

Figure 5. Illustration of trend analysis (top panel) of precipitation totals, mean daily temperature and annual maxima, and the flood type classification using the fuzzy approach (bottom panel) by an example of the Suze at Sonzeboz catchment (C14).

depending on which variant of the tree is used: crisp or fuzzy. Whereas some floods were classified as strongly determined by single flood types and thus were identified as the same type with both trees, i.e. with the fuzzy membership m_f equal to 1, other floods were classified as mixed types when using the fuzzy tree variant (see Fig. 5, bottom panel). On average, about 13% of all annual and 15% of all seasonal floods were classified as mixed events (Table 5). This number varied for different catchments between, respectively, 0% (C7, C21 and C24) and 51.4% (C14) and 2.9% in C21 and 32.1% in C14.

Looking at differences among different catchment altitudes and different seasons (Fig. 6), more mixed floods were identified in seasons III and IV than in seasons I and II at mid- (C12–C17) and high-altitude catchments (C18–C27), and when all catchments were grouped together. In lowland catchments (C1–C11), most mixed events occurred in seasons II and III.

Further insights can be gained by grouping mixed events by flood type (Fig. 7). It was observed that a short rainfall flood (SRF) was the flood type most often identified as a mixed flood

Table 5. Differences in the number of flood types identified with the fuzzy and crisp approaches for annual and seasonal floods in 27 study catchments. % mixed is the difference expressed as a percentage of mixed events identified with the fuzzy approach.

ID	Annual floods		Seasonal floods	
	No. of events	% mixed	No. of events	% mixed
Lowland (<1000 m a.s.l.)				
C1	35	22.9	140	18.6
C2	35	5.7	139	17.9
C3	29	17.1	115	15.7
C4	35	20.0	139	15.7
C5	35	8.6	139	15.7
C6	35	5.7	139	4.3
C7	35	0	139	7.9
C8	35	8.6	139	17.9
C9	35	22.9	139	20.0
C10	32	17.1	127	20.0
C11	32	31.4	127	30.0
Mid-altitude (≥1000 & <1500 m a.s.l.)				
C12	35	8.6	139	5.7
C13	32	2.9	127	5.7
C14	32	51.4	127	32.1
C15	32	17.1	127	15.7
C16	32	28.6	127	31.4
C17	35	11.4	139	10.0
High altitude (≥1500 m a.s.l.)				
C18	35	5.7	139	7.9
C19	31	17.1	121	15.0
C20	32	5.7	127	10.7
C21	35	0	139	2.9
C22	35	2.9	136	7.9
C23	32	14.3	127	20.7
C24	35	0	139	9.3
C25	35	2.9	139	14.3
C26	35	11.4	139	17.9
C27	32	11.4	127	15.0
All	33.6	13.0	128.3	15.0

type for annual (top panel) and seasonal (bottom panel) floods in all elevation groups. This flood type was in 5–18% of floods classified as a mixed event.

In lowland catchments, flash floods (FF) were the second flood type often identified as mixed events (6–9%). In the middle catchments, long rainfall floods (LRF) and rain on snow floods (RoSF) were also identified as mixed events in 4–9% of flood events. In high-altitude catchments, this contribution was different for annual and seasonal floods. Whereas among annual floods, LRF and RoSF were also often identified as mixed events (4%), for seasonal floods, RoSF, snowmelt floods (SMF) and glacier melt floods (GMF) were more frequently identified as mixed events than LRF.

4.4 Flood-type trends

Trends in flood-type contributions were analysed for changes in fuzzy membership at annual and seasonal scales using absolute membership values. These changes are plotted for the fuzzy approach in Fig. 8 for annual (all flood types) and seasonal floods (selected types) with a 5-year running mean.

Slightly increasing trend in flood contribution can be seen for SRF (Fig. 8) for both annual and seasonal floods and all elevation groups, whereas a decreasing trend can be observed for RoSF in annual and seasonal floods at all elevation groups. In high-altitude catchments (C18–C27) this pattern is only visible for annual floods and seasons III and IV. In addition, a slight decrease in LRF contribution can be observed in lowland (C1–C11) and mid-altitude (C12–C17) catchments. These visually assessed changes were quantified with Sen's slope method and their significance was assessed with the Mann-Kendall test (see Table 6 for both the crisp and fuzzy tree).

The quantitative analysis confirmed the visual assessment. These changes were also assessed as significant with the Mann-Kendall test. It has to be also noticed that the fuzzy tree allowed for better identifying these changes, whereas the crisp approach did not detect some changes in flood contributions (e.g. for LRF in middle catchments or RoSF in high altitude catchments).

The field significance was estimated only for these changes in flood-type contributions which were assesses as significant (Table 7) and it revealed that the fraction of the field significance was rather low, i.e. between 0 and 0.1. This means that roughly 5% (i.e. between 0 and 10%) of these results were significant at the global scale at the significance level of 0.1.

These annual and seasonal patterns in flood-type changes were determined only based on the maximum seasonal flood approach (i.e. only one flood per period was selected) and thus cannot be interpreted in terms of other (smaller) floods in the catchments that could release different patterns.

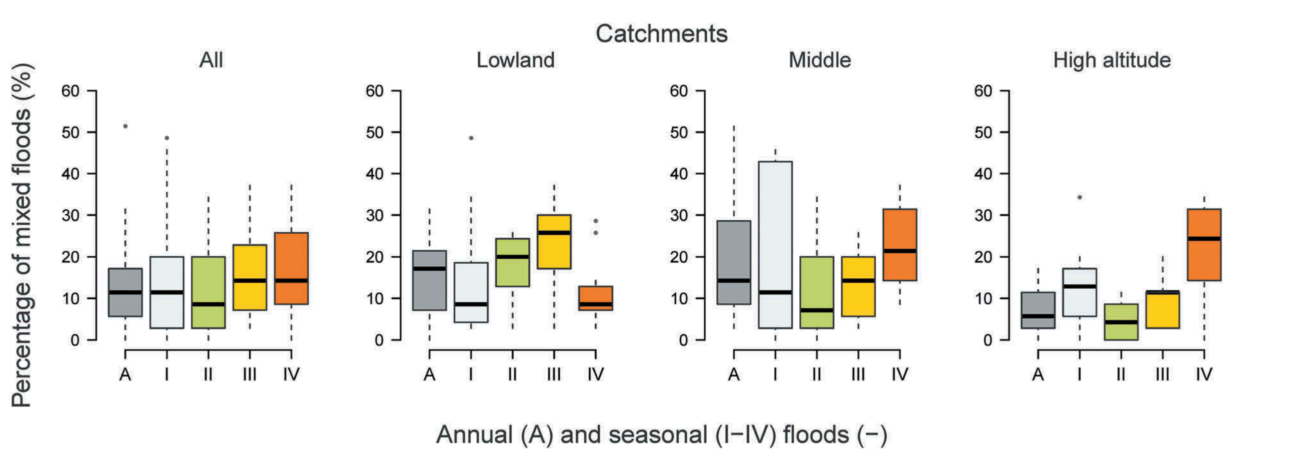

Figure 6. Differences between the fuzzy and crisp approaches expressed with the percentage of mixed flood events identified shown for different seasons and catchment altitude.

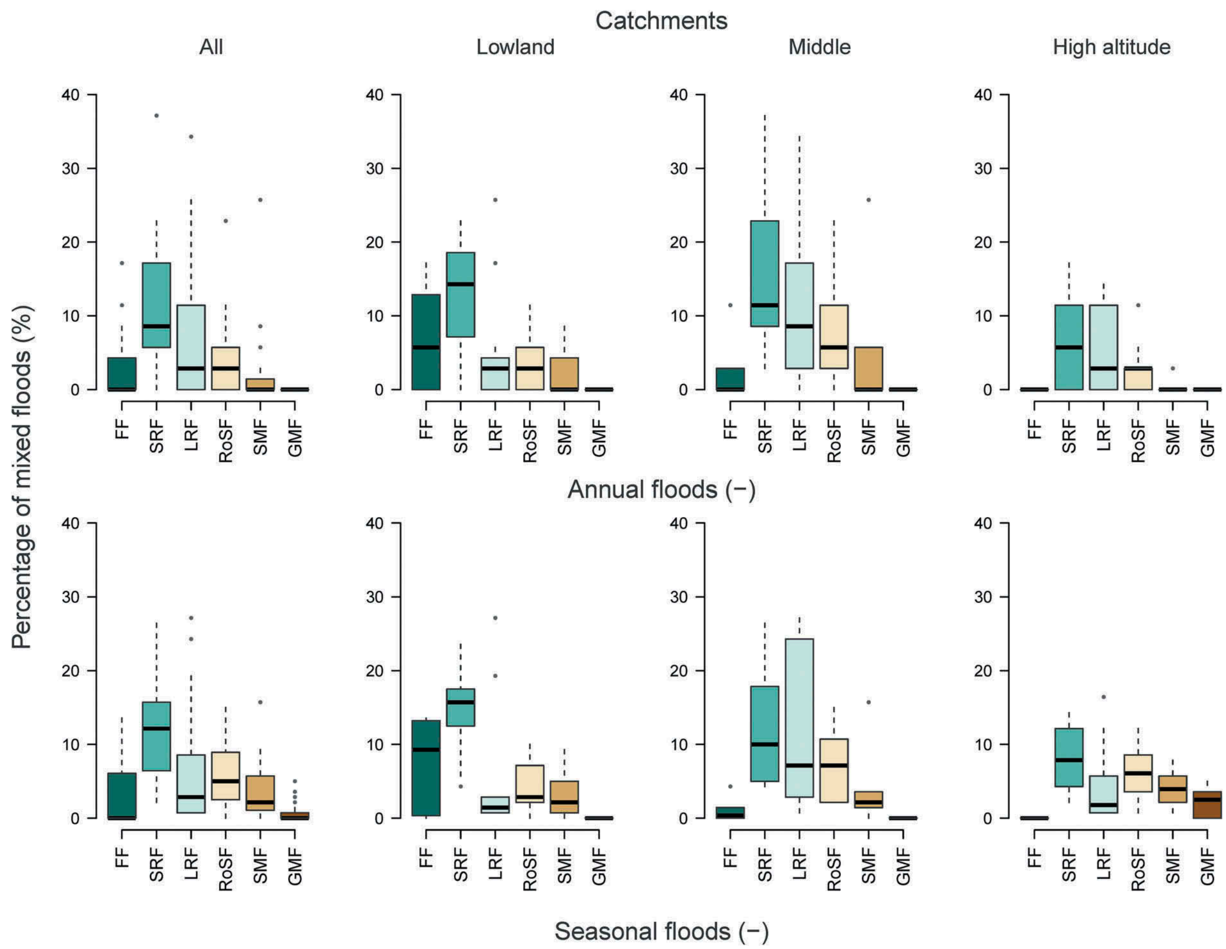

Figure 7. Differences between the fuzzy and crisp approach expressed with the percentage of mixed flood events identified showed by flood types and the catchment altitude.

4.5 Changes in flood-type contribution across years

Changes in flood contributions were further examined over the period 1980–2014 using the DMC and CIA index for annual and seasonal floods and all six flood types (Fig. 9). The SRF, which was most often identified in all catchments, was chosen as the reference type, which is then not plotted. Note that only the DMC for the fuzzy approach is presented here. For the crisp tree, the results were similar.

Most changes in flood contributors can be observed for RoSF and LRF for catchments at all elevation groups for annual floods (Fig. 9, left). Thus, only these two flood types were plotted for seasonal floods (Fig. 9, right) for legibility of the figure. Looking at the seasons, most changes were observed in seasons I (winter), II (spring) and III (summer). For lowland catchments (C1–C11), also a small change in FF could be observed among annual floods. For all other types, SMF and GMF, no change could be identified with the DMC method.

This visual assessment is supported by the calculated CIA index (Table 8), which presents a quantitative measure of the transition between different flood-type contributions and the reference flood type (i.e. SRF). Note that these values are comparable due to rescaling by the area of the reference polygon for each flood type.

The largest changes were identified for RoSF in high-altitude catchments (for the year and all seasons), in mid-altitude catchments for the year and in season III, and in lowland catchments for the year and in seasons I, II and IV. In most cases, the changes were decreasing (in relation to SRF), apart from season II in lowland and mid-altitude catchments, where an increasing trend was observed. Decreasing changes speak for the fact that the RoSF flood type is losing its importance in relation to SRF. For LRF, a transition was observed in lowland catchments, with an increasing trend for the year and season IV and a decreasing trend in season II. In mid-altitude catchments, a decreasing trend was observed in season III and for the year, while there was an increasing trend in seasons I and II. In high-altitude catchments, a decreasing trend was observed in all seasons apart from season I. For FF, an increasing trend was observed in lowland catchments for the year and in seasons II and III, and a decreasing trend in middle catchments for the year and in season III. For high-altitude catchments, a decreasing trend was observed for GMF in season III. In addition, SMF gained in their importance in lowland catchments (year and seasons II and IV) but lost in middle catchments (year and seasons II and IV). Note that these trends are described relative to the contribution of SRF and thus do not present absolute changes; they should be interpreted as changes in the importance of the flood type in relation to SRF. For other flood types and seasons, no transition in the flood-type contribution was observed. Most changes identified for RoSF and FF were assessed as significant at the significance level of 0.05.

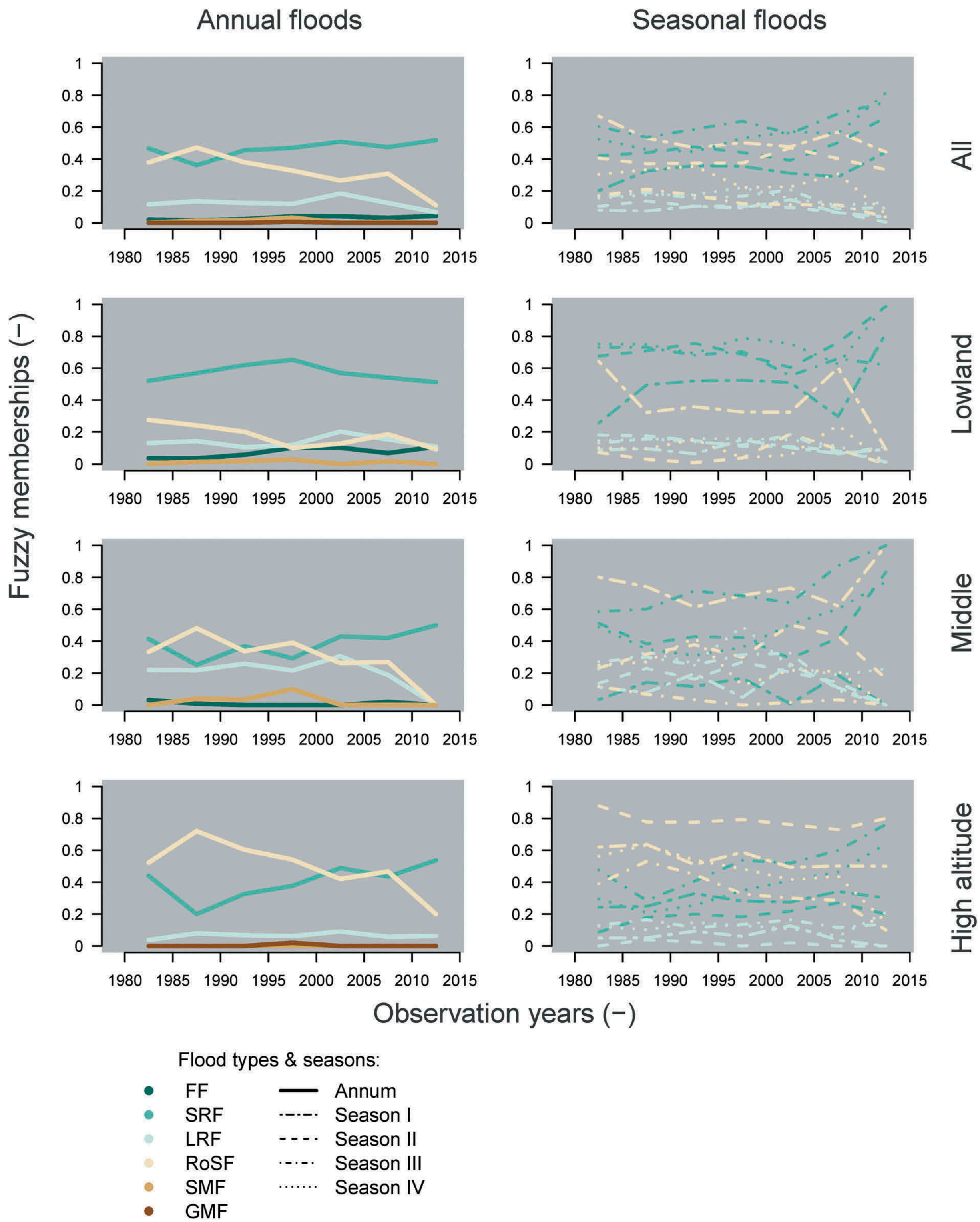

Figure 8. Changes in flood-type contribution (fuzzy membership) over the analysed period (1980–2014) for annual floods (left) and seasonal floods (right) when using the fuzzy approach. The 5-year running mean was applied.

5 Discussion

5.1 Flood-type trends and changes in flood-type contribution

Overall, our results from 27 Swiss meso-scale catchments with 34 observation years demonstrate a significant positive trend in the mean annual air temperature and in the mean temperature for all seasons. Changes in annual and seasonal precipitation totals are not significant. The significant trends are in agreement with Scherrer *et al.* (2016), who found significant positive trends in mean temperature but also in annual precipitation when analysing the years 1901–2014 for Swiss stations. The fact that no significant trends were found in annual precipitation and seasonal variables may be due to

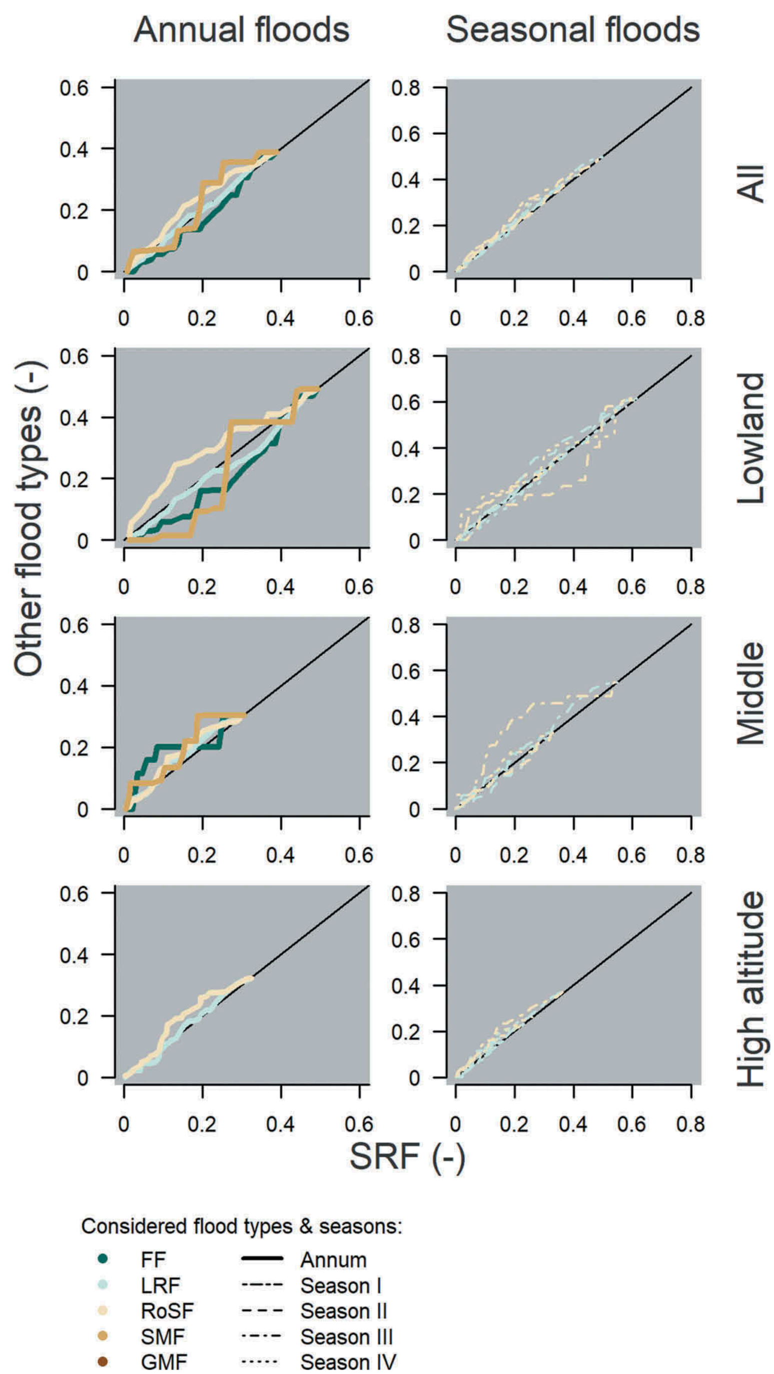

Figure 9. Rescaled DMCs of flood-type contributions (fuzzy membership) over the analysed period (1980–2014) in annual floods (left) and seasonal floods (right) when using the fuzzy approach. SRF was chosen as a reference flood type.

a too short period of observations used in this study (Wilby *et al.* 2008).

In reference to flood flows, no clear signal of changes in the magnitude of annual and seasonal floods could be established over all catchments. For annual floods a positive significant trend was estimated in 17 catchments, a negative significant trend was estimated for six catchments, and for one catchment no trend could be identified. For seasonal floods, changes were dependent on season and elevation, with increasing trends at low elevations and decreasing trends at high elevations. For example, for high-altitude catchments, where spring and summer seasons play a major role in the runoff generation process (Birsan *et al.* 2005), we found decreasing trends for spring and increasing trends for summer, which can be linked to an increased temperature in both seasons and decreased spring and increased summer precipitation totals. These results are slightly different from those of Birsan *et al.* (2005), who found decreasing trends in summer flows and increasing trends in spring flows. These changes in temperature means and flow peaks were assessed to be field significant at the 0.1 significance level.

While no clear pattern in changes was found across all catchments in flood-peak (maxima), at neither an annual nor a seasonal scale, changes could be observed in the flood-type

Table 6. Trend analysis (Sen's slope) of changes in the flood-type contribution using the crisp and fuzzy approaches. Slopes are computed from the fuzzy memberships over the entire observation period (1980–2014) using a window of a 5-year running mean. Significant changes assessed by the Mann-Kendall significance test (with $p \leq 0.05$) are indicated in bold font. See Table 2 for flood types.

Flood type	Crisp					Fuzzy				
		Season					Season			
	Year	I*	II	III	IV	Year	I	II	III	IV
Lowland (<1000 m a.s.l.)										
FF	0		0	0.005		>0		0.002	0.005	
SRF	0	0.005	0	0	0	0.002	0.005	0.001	−0.002	>0
LRF	0	0	0	0	0	0.002	0.001	−0.002	−0.001	>0
RoSF	−0.005	0	0	0	0	−0.005	0.003	0	0	0
SMF	0	0	0	0	0	0	0	0	0	0
GMF										
Mid-altitude (≥1000 & <1500 m a.s.l.)										
FF	0		0	0		0		0	0	
SRF	0	0	0	0.010	0.006	0.006	0	<0	0.010	0.006
LRF	0	0	0	0	0	0	0.002	0.002	−0.002	0
RoSF	0	0	0	0	0	−0.003	0	0	0	0
SMF	0	0	0	0	0	0	0	0	0	0
GMF										
High-altitude (≥1500 m a.s.l.)										
FF	0		0	0		0		0	0	
SRF	0.006	0.004	0.004	0.009	0.008	0.007	0.004	0.005	0.009	0.008
LRF	0	0	0	0	0	>0	0	0	>0	0
RoSF	0	0	0	−0.005	−0.005	−0.005	−0.002	−0.002	−0.006	−0.005
SMF	0	0	0	0	0	0	0.002	0	0	0
GMF	0		0	0		0		0	0	
All catchments										
FF	0		0	0.002		>0		0.001	0.002	
SRF	0.004	0.003	0	0.004	0.006	0.005	0.004	0.001	0.004	0.006
LRF	0.001	0	0	0	0	0.001	0.001	<0	−0.001	0.001
RoSF	−0.005	−0.002	0	−0.002	−0.004	−0.005	−0.002	>0	−0.003	−0.004
SMF	0	0.001	0	0	0	0	0.002	<0	0	0
GMF	0		0	0	0	0		0	0	

* Changes are only indicated for seasons and catchment groups where flood types were, by definition, expected to play a role. Average changes in GMF and FF were computed only for catchment groups where these processes were assumed to be important, i.e. for FF in catchments with an area <200 km^2 and for GMF in catchments with the areal glacier ratio ≥5%. Whereas <0 (>0) indicates a slight negative (positive) trend, 0 stands for no trend being determined.

Table 7. Field significance (fraction) for the significant changes in flood type contributions (only assessed for significant trends from Table 6).

Flood type	Crisp					Fuzzy				
		Season					Season			
	Year	I	II	III	IV	Year	I	II	III	IV
Lowland (<1000 m a.s.l.)										
FF				0.03		0.07		0.02	0	
SRF		0.04				0.02	0.04	0.02	0.04	0.09
LRF						0.02	0.03	0.10	0.07	0.10
RoSF	0.05					0.04	0.03			
SMF										
GMF										
Mid-altitude (≥1000 & <1500 m a.s.l.)										
FF										
SRF				0	0.08	0		0.01	0.04	0
LRF							0	0.02	0.04	
RoSF						0.09				
SMF										
GMF										
High altitude (≥1500 m a.s.l.)										
FF										
SRF	0.09	0.04	0.07	0.04	0.04	0.02	0.03	0.07	0.05	0.09
LRF						0.06			0.08	
RoSF				0.02	0.02	0.08	0.03	0.04	0.10	0
SMF							0.04			
GMF										
All catchments										
FF				0.05		0.10		0.04	0.07	
SRF	0.06	0.06		0.07	0.06	0.07	0.07	0.06	0.09	0.04
LRF	0.01					0.06	0.04	0.08	0.09	0.05
RoSF	0.07	0.07		0.09	0.07	0.05	0.06	0.09	0.02	0.09
SMF		0.07					0.07			
GMF										

Table 8. Changes in flood type over the entire observation period (1980–2014) assessed by the DMC method and the CIA index for the fuzzy approach. Negative values indicate a decreasing trend, while positive values indicate an increasing trend in the contribution of flood type in relation to SRF. Significant changes ($p \leq 0.05$) are indicated in bold font.

Flood type	Year	Season			
		I	II	III	IV
Lowland (<1000 m a.s.l.)					
FF	0.189		**0.178**	**0.187**	
LRF	0.071	−0.009	−0.101	−0.029	0.025
RoSF	**−0.209**	−0.136	0.162		−0.102
SMF	0.132	−0.020	0.053		0.449
GMF					
Middle (≥1000 & <1500 m a.s.l.)					
FF	−0.262			−0.364	
LRF	−0.103	0.089	0.135	−0.111	−0.084
RoSF	−0.154	−0.015	0.050	**−0.352**	−0.083
SMF	−0.267	0.116	**−0.470**		−0.353
GMF					
High altitude (≥1500 m a.s.l.)					
FF					
LRF	−0.018	0.015	−0.240	−0.042	**−0.151**
RoSF	**−0.167**	**−0.153**	**−0.217**	**−0.164**	**−0.226**
SMF		0.072			−0.078
GMF				−0.410	
All catchments					
FF	0.115		0.148	**0.121**	
LRF	−0.009	0.005	−0.044	−0.051	−0.046
RoSF	**−0.151**	**−0.122**	−0.020	**−0.112**	**−0.118**
SMF	−0.119	0.046	**−0.338**	0.064	−0.041
GMF				−0.350	

contribution analysed with Sen's slope method. These changes could be related to the catchment altitude and we found that, generally, more short rainfall floods (SRF) and fewer rain-on-snow (RoSF) events and long rainfall floods (LRF) were classified in lowland and mid-altitude catchments. In addition, slightly more flash floods (FF) occurred in lowland catchments towards the end of the observation period. In high-altitude catchments, we observed fewer RoSF but more SRF and LRF at the annual scale, but also more RoSF in spring towards the end of the observation period. These results can be explained by a decrease in the amount and a shift in the duration of the snow cover accumulated in these catchments. Thus, generally, there was an observed shift from snow-related floods towards rainfall-related floods in all catchments and this can be explained by a rise in the air temperature detected in all catchments, as confirmed by the analysis of meteorological variables (Table 4). These results are in agreement with the general trend observed for Europe (IPCC 2007). Similar results were found for Norwegian catchments by Vormoor *et al.* (2016), who reported a decreasing role of snowmelt compared to rainfall in flood-generation processes in Norway. A decreasing role of snowmelt floods was also found for Canadian catchments (Burn and Whitfield 2016) and Swedish catchments (Arheimer and Lindström 2015). Recently, Fischer *et al.* (2019) also reported an increase in short intensive rainfall floods for German catchments, while they did not find any change for other rain flood types (of a moderate or long duration), nor for snowmelt-induced floods.

It might be surprising that no clear change was identified for SMF and GMF. Note, however, that generally a small number of GMF and SMF was identified. This finding suggests that most of this type of flood event occurred in combination with rainfall events (i.e. with $P \geq 12$ mm) and, thus, were classified as RoSF events rather than pure snowmelt or glacier-melt events. The RoSF was also the flood type most often identified in these catchments. In addition, in smaller catchments (area: <200 km^2), we also observed more FF in annual floods and in spring and summer seasons (in larger catchments this flood type was by definition not classified). Without looking at seasonal floods and their flood types, these changes could not be noticed. Thus, these findings demonstrate the need for extending the analysis of annual and seasonal floods with a type-specific diagnosis, as already suggested by Hall *et al.* (2014). Yet no clear link could be established between changes in flood magnitude and in flood-type contribution. In addition, although most of these trends were estimated as significant at a local scale using the Mann-Kendall test, only roughly 5% of all results were significant at the global scale ($p < 0.1$). Too short record length and too few events per flood type for trend analysis may explain this finding.

Further analysis of the cumulative contributions of different flood types with double mass curves (DMC) and the change indicating area (CIA) index showed a decreasing importance of the RoSF (in comparison to SRF) in all catchment elevation groups, similarly to the method of slopes. Thus, RoSF is likely to further lose on its importance soon if the trend of reducing RoSF and increase in the SRF/LRF relationship continues. Interestingly, we also found that FF became more frequent in lowland catchments and less frequent in middle elevation catchments in relation to SRF. A similar trend was also identified with the method of slopes. This finding suggests that, at the catchment scale, this flood type is becoming more prevalent in relation to SRF. The changes assessed for RoSF and FF were significant ($p < 0.05$). Finally, we found that SMF decreased in spring in mid-altitude catchments and GMF decreased in summer in high-altitude catchments, which indicates the increasing importance of rainfall floods and the intensification of melting processes in these catchments. Changes in GMF and SMF were not significant. The results of the analysis of CIA index demonstrate that changes in relative contributions occur more slowly than the changes in the number of flood types identified. This confirms the findings of Berghuijs *et al.* (2019), who showed that, for most catchments in Europe, the relative importance of flood-generating mechanisms has not changed over the past five decades.

5.2 Advantage of the fuzzy approach for flood trend analysis

In this study, two variants of the decision tree were used: crisp and fuzzy. While the crisp tree identifies only one (dominant) flood type per event, the fuzzy approach allows also floods between two classes to be identified and quantified with their memberships and not to be neglected. In this way, mixed flood types can be classified. Indeed, as shown by our results, on average 13% of annual and 16% of seasonal and in some catchments up to 51.4% of all analysed flood events were classified as mixed flood types. This is in agreement with previous researchers (Merz and Blöschl 2003, 2008, Sikorska *et al.* 2015, Berghuijs *et al.* 2019), who showed that floods are seldom driven purely by a single control and more often by multiple controls. This point is important for tracing long-term changes in flood types in the catchment, as climate change (rising temperature) occurs at a slow pace and thus may be observed only at the long-term scale (Scherrer *et al.* 2016). Thus, restricting the analysis to the dominant flood types only (as in the crisp approach) may result in neglecting changes in other flood types that are already occurring, which at that point are still non-dominant. Therefore, the overall picture of flood changes may become biased because some flood types may be rejected (although they are still present!), while too much weight may be put on others.

Another important feature is that the fuzzy approach enables the identification of floods outside their typical season of occurrence due to the strictly defined season length being extended with the fuzzy time window before and after the defined season. The definition of the fuzzy window leads to seasons being overlapped at their beginning and end. This issue becomes important if flood events lie on the border between two seasons. In this way, they may be identified as potentially belonging to any of the two adjacent seasons and to any type of flood occurring within these two seasons. This feature is also important for tracing changes in floods due to climate change, which may shift the flood time of occurrence within the year (Blöschl *et al.* 2017) and potentially also shift the seasonality of specific flood types.

As our results demonstrate, changes in flood type could be identified sooner with the fuzzy approach, which enables different flood-generating processes to be classified even with a slight contribution (with $m_f > 0$). This advantage was visible through the diagnosis of annual and seasonal floods with Sen's slope method, where some changes for RoSF and LRF could only be identified with the fuzzy approach (no change identified with the crisp approach). Interestingly, the use of the DMC method yielded very similar results for both trees. This finding shows that the transition in the importance of flood-type contributions in the catchment can be identified with both tree variants. Detailed quantification of flood-type changes within seasons or years, however, requires the fuzzy approach.

5.3 Double mass curve versus method of slopes

Changes in flood type were analysed with two methods: the method of slopes (Sen's slope method) and the double mass curve (DMC) method with the change indicating area (CIA) index. Both methods enable the investigation of changes in flood-type contribution and both pointed to a decreasing occurrence of RoSF events in most of the catchments and seasons. Similarly, an increasing number of FF events was identified with the method of slopes and its increasing importance in lowland catchments (decreasing importance in middle elevation catchments) was identified with the DMC. Note, however, that these two methods provide slightly different information. The DMC (together with the CIA index introduced here) provides an assessment of changes in the catchment and in flood contributors accumulated over the analysed period. This means that random and slight changes should be smoothed out, while constant changes should be highlighted. In addition, only relative values are analysed (here in relation to SRF) and thus changes in the long-term importance of a particular flood type can be assessed. In contrast, the method of slopes analyses absolute values of each flood-type contribution, thus providing an overall measure of discrete changes along the analysed period. To smooth random and slight changes, we introduced here a 5-year running mean. Therefore, these two methods complement each other showing whether a certain flood type is losing or gaining on its (relative) importance in the catchment (DMC) and how exactly its contribution is changing across years (method of slopes). Hence, we recommend the use of the DMC method with the CIA index introduced here as an extended analysis on the transition in the composition of flood-type contributions in catchments that should complete the method of slopes rather than being used as an alternative. The introduction of the CIA index for DMC enables one to assess slow changes or transitions in fuzzy membership of flood-type contributions that may change on a year-to-year basis. Such changes may be difficult to assess with regression lines in the traditional DMC method, for which equilibrium sub-periods (without any change) are required (Searcy and Hardison 1960, Rutledge 1985). Our results show that the use of DMC with the CIA index enabled us to deal with quantifying such changes.

5.4 Methodological aspects of observed trends

This study was based on a series of observed annual and seasonal floods with an average data length of 34 years. Regarding that, some aspects require further discussion. First, this amount of data may be considered not long enough to estimate clear signals of change in annual or seasonal floods, which in our case resulted in a set of 34 events on average per annum or season. These events were further split into different flood types, which potentially further reduced the number of events per flood type. The point of (too short) data length was already discussed by Déry *et al.* (2009), who suggested in such cases to consider only magnitude changes (e.g. with the method of slopes) without estimating their significance. In our case, we assessed the significance of changes observed in flood types of seasonal and annual floods, which were assessed as significant at the local scale but only roughly 5% was significant at the global scale. Such a small portion of significant results may suggest that data records were too short for analysis. It has to be stressed, however, that extending the data length is not straightforward because of the categorized values of flood types and thus their discontinuous occurrence. Thus, even with potentially longer records, some flood type could still be under-represented. The issue of there not being enough events per flood type was also mentioned by Brunner *et al.* (2017) and Brunner and Sikorska-Senoner (2019) as one of the major limitations in flood type specific analysis.

Second, floods classified in the crisp approach show only the dominant types (other types are still possible), whereas in the fuzzy approach floods are classified with a fuzzy membership ($0 \le m_f \le 1$). Thus, classification of events in the fuzzy tree variant relies on how high the threshold value for m_f is set so that the event is still classified as belonging to a specific flood type. In our study, we did not limit this threshold value and all events with $m_f > 0$ were analysed. Yet, setting such a threshold value may be required if memberships above a certain level are desired. For instance, by setting a threshold value for $m_f > 0.5$, outputs from the fuzzy tree become similar to those of the crisp tree which is based only on the exceedence/non-exceedence of the index threshold value.

Third, the presented approach relies on annual and seasonal floods which have to be selected from the time series that potentially contains more flood events. There could be disadvantages to such a selection of events as it neglects other events that may potentially be of a different flood type (or even of a higher magnitude). Here, our focus was on the largest floods and thus we limited our analysis to the largest seasonal and annual floods, i.e. only one flood per annum or season was selected. Although it has to be stressed that if a certain type of flood was not detected among the analysed annual or seasonal floods, it does not necessarily mean that it did not occur during the analysed period, but only that it was not present among the largest floods studied. Thus, flood trends analysed with flood types should always be interpreted in the context of the dataset considered (e.g. annual or seasonal floods), but they cannot be generalized for all flood conditions in the catchment. Nevertheless, our methodology relies on preselected series of flood events and, thus, is independent of time series. As such this approach is not limited to annual or seasonal floods, but any series of flood events such as, for instance, relying on a peak over threshold approach, may also be utilized (e.g. as in Vormoor *et al.* 2016).

In addition, the choice of threshold values for the indices requires additional justification. These values were chosen for this study following the literature and experts' knowledge. We have also shown in a previous study (Sikorska *et al.* 2015) that small changes in the threshold values do not influence the results obtained from the flood classification. For catchments with different climatological conditions, these thresholds have to be redefined.

Finally, our method relies on the classification of floods into six major flood types (and mixed types) which cannot be meaningfully validated as no information on real flood classes is available (see also the discussion in Sikorska *et al.* 2015). Thus, our methodology provides rather an alternative way to identify and quantify trends in flood types classified from observed data, while it does not allow one to determine trends in flood processes in catchments directly. Also, the classification of events into flood types relies on the proposed structure of the flood decision tree developed and tested by Sikorska *et al.* (2015). As the tree itself presents a conceptual representation of the flood classification, there is no true or wrong tree structure and other structures (using different indices) could also be designed.

5.5 Transferability and perspectives

Our results indicate that changes in flood-type contributions occurred within all seasons over the analysed years and there were significant changes in the flood runoff contributions. Evidence for a shift in the flood seasonality as a result of climate change was also demonstrated by Blöschl *et al.* (2017). Hence, it becomes increasingly clear that flood trends should be analysed in the flood-type context rather than at the seasonal scale only. For this purpose, our decision tree is a feasible tool for supporting such a process-oriented analysis of flood trends. In particular, the fuzzy approach appears to be suitable for tracing changes in flood type across seasons and years, while the crisp approach is suitable for indicating a general trend of changes in flood-type contribution.

The designed flood decision tree relies on the defined flood types, their indices and their threshold values. These flood types and flood indices were designed for alpine catchments and thus can be directly applied to other mountainous catchments with similar climatic conditions. Application of the tree in very different climatic conditions may be linked with a need to re-design flood types and their indices, for instance, if a certain flood type never occurs or other types are possible, or the same flood types happen in different seasons/months. However, the general concept of classifying flood types by means of binary decision trees remains the same.

In light of further climate change and global warming expected, even more extreme weather events with heavy precipitation and more days with hot temperatures are expected in the Alps (Gobiet *et al.* 2014, Scherrer *et al.* 2016). Moreover, shifting the timing of such extreme weather conditions increases the possibility of two meteorological phenomena occurring in a very short time, e.g. a strong increase in air temperature in winter or spring leading to snowmelt and short heavy rainfall; or snowfalls in spring melting after a very short time. These changes may cause shifts in the flood-generation processes (Berghuijs *et al.* 2019) and, thus, in flood types between their original seasons. These expected changes will make it more difficult to isolate a single (major) factor of flood generation because more controls may become of similar importance. Thus, attributing only one flood type per event (crisp approach) may become insufficient and may not provide enough information for decision making. This speaks for the fuzzy approach, which gives the possibility to identify mixed flood types at overlapping classes/seasons. By classifying mixed flood types, the fuzzy approach also becomes more sensitive to changes in flood-type contribution and already minor changes (determined with $m_f < 0.5$) can be identified.

One limitation of the trend analysis is that it is retrospective, while, from a practical point of view, future changes would be of interest. To better predict future conditions, a combination of the trend analysis with future climate projections could be of a great value (Burn *et al.* 2010). For this purpose, projections of flood conditions under future climate scenarios could be suitable (Brunner *et al.* 2019) but might require redefinition of seasonal time frames and flood indices due to projected shifts in the timing of floods (Blöschl *et al.* 2017).

6 Conclusions

In this study, we propose the use of a fuzzy flood-type classification for a more detailed flood trend analysis with decision trees. We demonstrate the use of this decision tree on the dataset of 27 Swiss meso-scale catchments with a data length of 34 years. Trends in flood types were analysed with two methods: Sen's method of slopes and the double mass curve (DMC) method with the introduced change indicating area (CIA) index. Despite the limited data length, we were able to draw the following conclusions:

(1) Some changes in flood types occurred at both the seasonal and the annual scale. These changes were demonstrated by shifts in contributions of flood types within and between neighbouring seasons. For the Swiss study catchments, we generally observed more short rainfall floods and fewer rain-on-snow floods in all catchments, and more flash floods in small lowland catchments towards the end of the observation period. These trends indicate that the amount and/or the duration of the snow cover has been reduced. This issue could be explained by a rise in the air temperature in these catchments. As on average only 5% of these changes in flood-type contributions were assessed as significant at the field significance level of 0.1, at present these patterns cannot be claimed as globally significant.

(2) These trends could be more accurate determined with the fuzzy tree, which enables identification of flood-type changes across neighbouring seasons and classes. We also showed that using a fuzzy membership enables detecting changes already when they are still minor ($m_f < 0.5$). In contrast, focusing only on the dominant flood

type (crisp approach) postpones the detection of change in the flood contribution till the new type becomes dominant (and ousts the previous one). An efficient tool for detecting changes in flood types is important for changes occurring gradually as changes induced by an increase in the air temperature resulting from the climate change.

(3) The method of slopes and the DMC method provide two different ways of looking at trends in flood-type contributions. While DMC works with cumulative values and, as such, assess long-term changes in flood-type contribution at the catchment scale, the method of slopes analyses absolute values and thus enables detailed investigation of discrete changes. Our results demonstrate that these methods complement each other and, thus, we recommend using both of them to evaluate changes in flood-type contributions.

Acknowledgements

The runoff data were kindly provided by the Swiss Federal Office for the Environment (FOEN), the Canton of Aargau (Bünz at Othmarsingen, Surb at Döttingen and Wyna at Suhr), and the Canton of Zürich (Reppisch at Dietikon). Precipitation and temperature observations were provided by the Swiss Federal Office of Meteorology and Climatology (MeteoSwiss). The authors thank the associate editor Alessio Domeneghetti, Klaus Vormoor and two anonymous reviewers for their useful comments, and Tracy Ewen for proofreading the manuscript.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This research has been partly supported by the Swiss Federal Office for the Environment (FOEN) under Project no [15.0054.PJ/O503-1381].

ORCID

Anna E. Sikorska-Senoner http://orcid.org/0000-0002-5273-1038
Jan Seibert http://orcid.org/0000-0002-6314-2124

References

Archfield, S.A., *et al.*, 2014. An objective and parsimonoious approach for classifying natural flow regimes at a continental scale. *River Research and Applications*, 30, 1166–1183. doi:10.1002/rra.2710

Arheimer, B. and Lindström, G., 2015. Climate impact on floods: changes in high flows in Sweden in the past and the future (1911–2100). *Hydrology and Earth System Sciences*, 19, 771–784. doi:10.5194/hess-19-771-2015

Barredo, J.I., 2007. Major flood disasters in Europe: 1950–2005. *Natural Hazards*, 42, 125–148. doi:10.1007/s11069-006-9065-2

Bažatová, T. and Šimková, J., 2015. Changes in runoff regime. The Lomnice catchment case study. *Soil and Water Research*, 10, 40–48. doi:10.17221/35/2014-SWR

Berghuijs, W.R., *et al.*, 2017. Recent changes in extreme floods across multiple continents. *Environmental Research Letters*, 12 (11), 114035. doi:10.1088/1748-9326/aa8847

Berghuijs, W.R., *et al.*, 2019. The relative importance of different flood-generating mechanisms across Europe. *Water Resources Research*, 55, 4582–4593. doi:10.1029/2019WR024841

Berghuijs, W.R., *et al.*, 2016. Dominant flood generating mechanisms across the United States. *Geophysical Research Letters*, 43, 4382–4390. doi:10.1002/2016GL068070

Birsan, M.-V., *et al.*, 2005. Streamflow trends in Switzerland. *Journal of Hydrology*, 314 (1–4), 312–329. doi:10.1016/j.jhydrol.2005.06.008

Blöschl, G., *et al.*, 2017. Changing climate shifts timing of European floods. *Science*, 357, 588–590. doi:10.1126/science.aan2506

Brunner, M.I., *et al.*, 2019. Future shifts in extreme flow regimes in Alpine regions. *Hydrology and Earth System Sciences*, 23, 4471–4489. doi:10.5194/hess-23-4471-2019

Brunner, M.I., Sikorska, A.E., and Seibert, J., 2018. Bivariate analysis of floods in climate impact assessments. *Science of the Total Environment*, 616–617, 1392–1403. doi:10.1016/j.scitotenv.2017.10.176

Brunner, M.I. and Sikorska-Senoner, A.E., 2019. Dependence of flood peaks and volumes in modeled discharge time series: effect of different uncertainty sources. *Journal of Hydrology*, 572, 620–629. doi:10.1016/j.jhydrol.2019.03.024

Brunner, M.I., *et al.*, 2017. Flood type specific construction of synthetic design hydrographs. *Water Resources Research*, 53, 1390–1406. doi:10.1002/2016WR019535

Burn, D.H. and Elnur, M.A.H., 2002. Detection of hydrologic trends and variability. *Journal of Hydrology*, 255, 107–122. doi:10.1016/S0022-1694(01)00514-5

Burn, D.H., Sharif, M., and Zhang, K., 2010. Detection of trends in hydrological extremes for Canadian watersheds. *Hydrological Processes*, 24, 1781–1790. doi:10.1002/hyp.7625

Burn, D.H. and Whitfield, P.H., 2016. Changes in floods and flood regimes in Canada. *Canadian Water Resources Journal*, 41 (1–2), 139–150. doi:10.1080/07011784.2015.1026844

Carillo, G., *et al.*, 2011. Catchment classification: hydrological analysis of catchment behavior through process-based modeling along a climate gradient. *Hydrology and Earth System Sciences*, 15, 3411–3430. doi:10.5194/hess-15-3411-2011

Déry, S.J., *et al.*, 2009. Detection of runoff timing changes in pluvial, nival, and glacial rivers of western Canada. *Water Resources Research*, 45 (6). doi:10.1029/2009WR008244

Diezig, R. and Weingartner, R., 2007. Hochwasserprozesstypen in der Schweiz -Schlüssel zur Hochwasserabschätzung. *Wasser und Abfall*, 4, 18–26.

Douglas, E.M., Vogel, R.M., and Kroll, C.N., 2000. Trends in floods and low flows in the United States: impact of spatial correlation. *Journal of Hydrology*, 240 (1–2), 90–105. doi:10.1016/S0022-1694(00)00336-X

Duethmann, D., *et al.*, 2015. Attribution of streamflow trends in snow and glacier melt dominated catchments of the Tarim River, Central Asia. *Water Resources Research*, 51, 4727–4750. doi:10.1002/2014WR016716

Fischer, S., 2018. A seasonal mixed-POT model to estimate high flood quantiles from different event types and seasons. *Journal of Applied Statistics*, 45 (15), 2831–2847. doi:10.1080/02664763.2018.1441385

Fischer, S. and Schumann, A., 2018. A distribution-free ordinal classification of floods based on moments. *Hydrological Sciences Journal*, 63 (11), 1605–1618. doi:10.1080/02626667.2018.1525614

Fischer, S., Schumann, A., and Bühler, P., 2019. Timescale-based flood typing to estimate temporal changes in flood frequencies. *Hydrological Sciences Journal*. doi:10.1080/02626667.2019.1679376

Frei, C., *et al.*, 1998. Heavy precipitation processes in a warmer climate. *Geophysical Research Letters*, 25, 1431–1434. doi:10.1029/98GL51099

Gáal, L., *et al.*, 2012. Flood timescales: understanding the interplay of climate and catchment processes through comparative hydrology. *Water Resources Research*, 48, 1166–1183. doi:10.1029/2011WR011509

Gao, P., *et al.*, 2017. Use of double mass curves in hydrologic benefit evaluations. *Hydrological Processes*, 31, 4639–4646. doi:10.1002/hyp.11377.hYP-17-0143.R2

Geiger, H., Zeller, J., and Roethlisberger, G., 1991. *Starkniederschlaege des schweizerischen Alpen- und Alpenrandgebietes. Grundlagen. Einführung, Methoden, Spezialstudien. Starkniederschläge*. Vol. 7, Birmensdorf: Eidgenössische Forschungsanstalt für Wald, Schnee und Landschaft, WSL.

Gobiet, A., *et al.*, 2014. 21st century climate change in the European Alps – A review. *Science of the Total Environment*, 493, 1138–1151. doi:10.1016/j.scitotenv.2013.07.050

Grebner, D., 1990. Starkniederschlag: Zum Spektrum des Begriffes, *Gas-Wasser-Abwasser*, Vol. 70, Jahrgang, Nr. 12. 870–873.

Groleau, A., Mailhot, A., and Talbot, G., 2007. Trend analysis of winter rainfall over southern Québec and New Brunswick (Canada). *Atmosphere-Ocean*, 45, 153–162. doi:10.3137/ao.450303

Hall, J., *et al.*, 2014. Understanding flood regime changes in Europe: a state-of-the-art assessment. *Hydrology and Earth System Sciences*, 18, 2735–2772. doi:10.5194/hess-18-2735-2014

Hundecha, Y. and Merz, B., 2012. Exploring the relationship between changes in climate and floods using a model-based analysis. *Water Resources Research*, 48. doi:10.1029/2011WR010527

IPCC, 2007. Summary for Policymakers. *In*: S. Solomon, *et al.*, eds.. *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge: Cambridge University Press, 996.

Kliment, Z., *et al.*, 2011. Trend analysis of rainfall-runoff regimes in selected headwater areas of the Czech Republic. *Journal of Hydrology and Hydromechanics*, 59, 36–50. doi:10.2478/v10098-011-0003-y

Kundzewicz, Z., 2002. Floods in the context of climate change and variability. *In*: M. Beniston, ed. *Climatic change: implications for the hydrological cycle and for water management*. Netherlands: Kluwer Academic Publishers, 225–247.

Madsen, H., *et al.*, 2014. Review of trend analysis and climate change projections of extreme precipitation and floods in Europe. *Journal of Hydrology*, 519, 3634–3650. doi:10.1016/j.jhydrol.2014.11.003

Mangini, W., *et al.*, 2018. Detection of trends in magnitude and frequency of flood peaks across Europe. *Hydrological Sciences Journal*, 63, 493–512. doi:10.1080/02626667.2018.1444766

Merz, B., *et al.*, 2012. Hess opinions "More efforts and scientific rigour are needed to attribute trends in flood time series". *Hydrology and Earth System Sciences*, 16, 1379–1387. doi:10.5194/hess-16-1379-10-2012

Merz, R. and Blöschl, G., 2003. A process typology of regional floods. *Water Resources Research*, 39, W1340. doi:10.1029/2002WR001952

Merz, R. and Blöschl, G., 2008. Flood frequency hydrology: 1. Temporal, spatial, and causal expansion of information. *Water Resources Research*, 44, W08432. doi:10.1029/2007WR006744

Perry, C., 2000. Significant floods in the United States during the 20th Century – USGS measures a century of floods. FS; 024-00, U.S. Geological Survey.

Pirnia, A., *et al.*, 2018. Using the Mann-Kendall test and double mass curve method to explore stream flow changes in response to climate and human activities. *Journal of Water and Climate Change*, jwc2018162. doi:10.2166/wcc.2018.162

Pohlert, T., 2018. Non-parametric trend tests and change-point detection. R package version 1.1.1. https://CRAN.R-project.org/package=trend

R Core Team, 2019. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/.

Rojas, R., *et al.*, 2012. Assessment of future flood hazard in Europe using a large ensemble of bias-corrected regional climate simulations. *Journal of Geophysical Research: Atmospheres*, 117, D17109. doi:10.1029/2012JD017461

Rutledge, A.T., 1985. Use of double-mass curves to determine drawdown in a long-term aquifer test in north-central Volusia County, Florida. Water-Resources Investigations Report, 84-4309, U.S. Geological Survey. doi:10.3133/wri844309.

Sawicz, K., *et al.*, 2011. Catchment classification: empirical analysis of hydrologic similarity based on catchment function in the eastern USA. *Hydrology and Earth System Sciences*, 15, 2895–2911. doi:10.5194/hess-15-2895-2011

Scherrer, S.C., *et al.*, 2016. Emerging trends in heavy precipitation and hot temperature extremes in Switzerland. *Journal of Geophysical Research: Atmospheres*, 121. doi:10.1002/2015JD024634

Searcy, J. and Hardison, C., 1960. Double-mass curves. Manual of hydrology: part 1. general surface- water techniques, Geological Survey Water-Supply Paper, 1541-B, pp. 31–66.

Seibert, J. and Vis, M.J.P., 2012. Teaching hydrological modeling with a user-friendly catchment-runoff- model software package. *Hydrology and Earth System Sciences*, 16, 3315–3325. doi:10.5194/hess-16-3315-2012

Sen, P.K., 1968. Estimates of the regression coefficient based on Kendall's Tau. *Journal of the American Statistical Association*, 63, 1379–1389. doi:10.1080/01621459.1968.10480934

Sikorska, A., Viviroli, D., and Seibert, J., 2018. Effective precipitation duration for runoff peaks based on catchment modelling. *Journal of Hydrology*, 556, 510–522. doi:10.1016/j.jhydrol.2017.11.028

Sikorska, A.E. and Seibert, J., 2018. Appropriate temporal resolution of precipitation data for discharge modelling in pre-alpine catchments. *Hydrological Sciences Journal*, 63 (1), 1–16. doi:10.1080/02626667.2017.1410279

Sikorska, A.E., Viviroli, D., and Seibert, J., 2015. Flood type classification in mountainous catchments using crisp and fuzzy decision trees. *Water Resources Research*, 51. doi:10.1002/2015WR017326

Singh, R., Archfield, S.A., and Wagener, T., 2014. Identifying dominant controls on hydrologic parameter transfer from gauged to ungauged catchments – A comparative hydrology approach. *Journal of Hydrology*, 517, 985–996. doi:10.1016/j.jhydrol.2014.06.030

Sivapalan, M., *et al.*, 2005. Linking flood frequency to long-term water balance: incorporating effects of seasonality. *Water Resources Research*, 41, 1166–1183. doi:10.1029/2004WR003439

Stahl, K., *et al.*, 2010. Streamflow trends in Europe: evidence from a dataset of near-natural catchments. *Hydrology and Earth System Sciences*, 14, 2367–2382. doi:10.5194/hess-14-2367-2010

Tarasova, L., *et al.*, 2019. Causative classification of river flood events. *WIREs Water*, 6, e1353. doi:10.1002/wat2.1353

Vormoor, K., *et al.*, 2016. Evidence for changes in the magnitude and frequency of observed rainfall vs. snowmelt driven floods in Norway. *Journal of Hydrology*, 538, 33–48. doi:10.1016/j.jhydrol.2016.03.066

Vorogushyn, S. and Merz, B., 2013. Flood trends along the Rhine: the role of river training. *Hydrology and Earth System Sciences*, 17, 3871–3884. doi:10.5194/hess-17-3871-2013

Wang, W., *et al.*, 2013. Quantitative assessment of the impact of climate variability and human activities on runoff changes: a case study in four catchments of the Haihe River basin, China. *Hydrological Processes*, 27, 1158–1174. doi:10.1002/hyp.9299

Weingartner, R. and Aschwanden, H., 1992. Abflussregimes als Grundlage zur Abschätzung von Mittelwerten des Abflusses. *In*: R. Weingartner and F. Hauser, eds.. *Hydrologischer Atlas der Schweiz*. Tafel 5.2. Bern: Bundesamt für Umwelt BAFU.

Wilby, R., Beven, K., and Reynard, N., 2008. Climate change and fluvial flood risk in the UK: more of the same? *Hydrological Processes*, 22, 2511–2523. doi:10.1002/hyp.6847

Wilks, D.S., 2006. On "Field significance" and the false discovery rate. *Journal Of Applied Meteorology And Climatology*, 45. doi:10.1175/JAM2404.1