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Future Trends in the Interdependence Between Flood Peaks and Volumes: Hydro-Climatological Drivers and Uncertainty

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Abstract Reliable flood estimates are needed for designing safe and cost-effective flood protection structures. Classical flood estimation methods applied for deriving such estimates focus on peak discharge and neglect other important flood characteristics such as flood volume and the interdependence among different flood characteristics. Furthermore, they do not account for potential nonstationarities in hydrological time series due to climate change. The consideration of both the interdependence between peak discharge and flood volume and its nonstationarity might help us derive more reliable flood estimates. A few studies have looked at changes in the general dependence of peak discharge and flood volume for small sets of catchments and explored ways of modeling such changes. However, spatial analyses of trends in this dependence or in their climatological drivers have not been carried out. The aim of this study was to help close this knowledge gap by first quantifying trends in the general dependence between peak discharge and flood volume as described by Kendall's tau on a spatially comprehensive data set of 307 catchments in Switzerland. Second, potential climatological drivers for changes in the dependence between peak discharge and flood volume were identified. Our results show that the dependence between peak discharge and flood volume and its trends are spatially heterogeneous. This pattern cannot be explained by one driver only but by an interplay of changes in precipitation, snowmelt, and soil moisture. Both the trends and the links between drivers and trends depend on the climate model chain considered and are therefore uncertain.

1. Introduction

Floods cause average annual damages worth 50 billion dollars globally, 7.7 billion dollars in Europe, and 4.5 billion dollars in the United States (Aon Benfield, 2016). To reduce such damages and the related costs, reliable flood estimates are needed that make it possible to design suitable flood protection structures and to increase flood preparedness. Flood estimation methods aimed at deriving such flood estimates usually focus on a single flood characteristic, that is, peak discharge, by performing univariate frequency analysis and assume that the frequency of occurrence and the magnitude of events does not change over time (see, e.g., BWG, 2003; Deutsche Vereinigung für Wasserwirtschaft Abwasser und Abfall, 2012). These classical approaches fall short for two main reasons. First, floods are characterized not only by peak discharge but also by other important variables such as flood volume and duration. These variables have been shown to be interdependent (Gaál et al., 2015; Genest et al., 2007; Szolgay et al., 2016), and this interdependence should not be neglected when estimating bivariate design floods characterizing an event in terms of peak discharge and flood volume (Brunner et al., 2017; Grimaldi et al., 2012; Mediero et al., 2010). Otherwise, flood magnitude might be either overestimated or underestimated (Brunner et al., 2016; Salvadori & De Michele, 2004). Second, the climate and/or land use conditions under that floods occur are subject to changes which might lead to a nonstationarity in the flood behavior over time. Several studies have shown that flood characteristics have changed in the past (e.g., Archfield et al., 2016; Mangini et al., 2018) and might change under future climate conditions (for an overview, see Madsen et al., 2014). Most of these studies have focused on changes in one variable, usually peak discharge, or on multiple individual variables such as peak discharge and flood volume (Archfield et al., 2016; Bard et al., 2012; Giuntoli et al., 2012). However, changes are not restricted to these individual variables but have been shown to extend to the strength of dependence between them. Bender et al. (2014) detected an increase in the dependence between peak discharge and flood volume in a long time series of the Rhine River. Likewise, Ben Aissia et al. (2014) showed for two watersheds in

the province of Québec that the dependence of peak discharge and flood volume can increase or decrease over time.

The derivation of bivariate design estimates for future climate conditions characterizing a flood in terms of both peak discharge and flood volume therefore must not stop at taking into account changes in the marginal distributions of individual variables. Instead, it should also consider potential changes in the strength of dependence between peak discharge and flood volume. To do so, Ben Aissia et al. (2014), Bender et al. (2014), and Qi and Liu (2018) introduced time-dependent copula parameters, and Brunner et al. (2018) estimated design floods using simulated runoff time series generated by feeding a hydrological model with climate simulations. These previous studies dealing with changes in the peak discharge-volume (*Q-V*) dependence have concentrated on only a few catchments for detecting and modeling changes. Therefore, little is known about spatial differences in trends of *Q-V* dependence in areas with diverse catchment and hydrological characteristics. The main aim of this study is therefore to assess the evolution of *Q-V* dependence expressed by Kendall's tau on a spatially comprehensive set of 307 medium-sized catchments in Switzerland with contrasting hydrological, that is, rainfall- and melt-dominated, regimes. The focus is on the general dependence structure as described by Kendall's tau because the quantification of other important dependence properties such as tail dependence requires large data sets and is associated with large uncertainties (Serinaldi et al., 2015).

The climatological processes governing changes in the *Q-V* dependence are also unclear, even though such process-based knowledge might help researchers improve their modeling efforts and derive more reliable flood estimates (Merz & Blöschl, 2008). Although potential climatological drivers behind changes in the *Q-V* dependence have not yet been investigated, a few studies have been conducted with the aim of understanding the factors controlling the relationship between flood peaks and volumes in a stationary setting. Gaál et al. (2015) found that climate-related factors were more important than physiographic factors in controlling the consistency of the *Q-V* dependence and that the dependence was rather weak in high alpine catchments, owing to the existence of a mix of flood types. Similarly, Grimaldi et al. (2016) found that the *Q-V* dependence is more controlled by rainfall excess than by the concentration time which is mainly controlled by catchment characteristics such as soil type or slope. Renard and Lang (2007) found that peak discharge and flood volume were more correlated for snow-related than for rain-fed floods. These studies have shown that precipitation and snowmelt influence the strength of the *Q-V* dependence, although catchment soil moisture has also been found to be an important factor controlling floods (Berghuijs et al., 2016; Blöschl et al., 2015). A second aim of this study is therefore to build upon this existing knowledge about possible drivers of the *Q-V* dependence to be able to explain potential future changes in the *Q-V* dependence.

This analysis will help us develop ideas of how to handle changing *Q-V* dependence in modeling efforts regarding the estimation of bivariate design quantiles.

The next section describes the data set used for this study consisting of discharge time series simulated using the hydrological model PREVAH for current and future climate conditions. Section 3 describes (1) the flood sampling strategy, (2) the *Q-V* dependence analysis, (3) the correlation analysis between the *Q-V* dependence and potential hydro-climatological drivers, and (4) the trend analysis. Section 4 presents the outcomes of the different analyses, which are put into perspective in section 5.

2. Study Catchments and Data

For this study, analyses were performed on a data set consisting of 307 catchments in Switzerland for which daily discharge time series were simulated (Figure 1). These catchments are similar in area, with a median of 117 km² and a range between 70 and 180 km², and lie at mean elevations between 300 and 3,000 m above sea level (m a.s.l.), with a median of 1,079 m a.s.l. Annual precipitation ranges from a first quartile of 1,170 mm to a third quartile of 1,650 mm, and annual runoff ranges from a first quartile of 636 mm to a third quartile of 1,243 mm. The catchments' flood events are mainly driven either by snowmelt (Alps) or rainfall (Jura, Plateau, and Southern Alps) or by a mixture of the two processes (Pre-Alps; Froidevaux et al., 2015). The 307 catchments together form a set representative of the climatological conditions and runoff characteristics in Switzerland and thanks to their full spatial coverage allow for spatial assessments of trends in the dependence between peak discharge and flood volume.
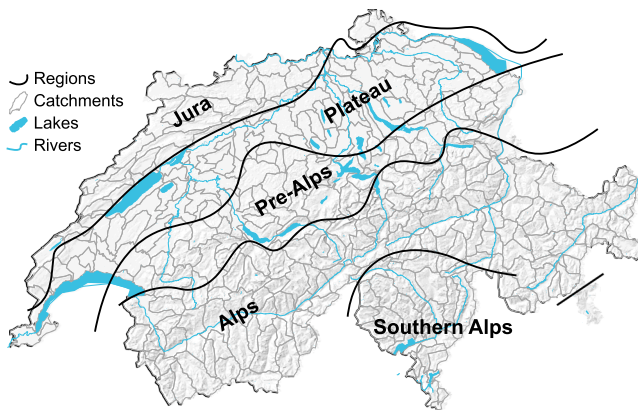
Figure 1. The 307 study catchments and the five geographical regions of Switzerland: Jura, Plateau, Pre-Alps, Alps, and Southern Alps.

For each of these 307 catchments, runoff time series at a daily resolution were simulated using the hydrological model PREVAH (Viviroli, Zappa, Gurtz, et al., 2009) for a control period and until the end of the century. PREVAH is a conceptual process-based model that was run in this study in its fully distributed version on a 500m grid. It consists of several submodels representing interception storage, soil water storage, and depletion by evapotranspiration, groundwater, snow accumulation and snowmelt, glaciermelt, runoff and baseflow generation, and discharge concentration and flow routing. A gridded version of the model (Speich et al., 2015) at a spatial resolution of 500 m was set up for Switzerland. For the calibration, runoff time series from 140 mesoscale catchments covering the different runoff regimes were used. The model calibration was conducted over the period 1993–1997. Verification was performed on the period 1983–2005 using (i) volumetric deviation (Viviroli et al., 2007) and (ii) benchmark efficiency (Schaefli & Gupta, 2007) as objective functions. The calibration and evaluation procedures are described in detail in Köplin et al. (2010). The parameters for each model grid cell were derived by regionalizing the parameters obtained for the 140 catchments with a procedure based on ordinary kriging (Köplin et al., 2010; Viviroli et al., 2009). Viviroli, Zappa, Schwanbeck, et al. (2009) have shown that PREVAH performs well in modeling high flows both during the calibration and evaluation periods (Nash-Sutcliffe efficiency values > 0.7). They obtained best results for catchments with areas between 100 and 500 km², which covers the range of catchment areas considered in this study. Orth et al. (2015) evaluated PREVAH for eight catchments in Switzerland and found a slightly better performance for low-elevation catchments than for high-elevation catchments. Köplin et al. (2010) showed that model performance was higher for the southern Alpine than for the Northern Alpine catchments based on a data set of 49 catchments in Switzerland.

The model was then driven with transient meteorological data (precipitation, temperature, radiation, and wind) representing both reference (1981–2017) and future climate conditions (2018–2099). The data were derived from the CH2018 climate scenarios (National Centre for Climate Services, 2018) provided by the Swiss National Centre for Climate Services. These scenarios were obtained from climate experiments produced with different climate model chains within EUROCORDEX (Jacob et al., 2014). Each of these model chains consists of a global and a regional climate model and is driven with one out of three representative concentration pathway emission scenarios (Moss et al., 2010). We considered the downscaled output of 10 climate model chains derived by quantile mapping. We focused on the chains of the EUR-11 domain with a horizontal resolution of 0.11° (roughly 12.5 km). We used chains that provide information on radiation, relative humidity, and wind, in addition to temperature and precipitation, as these data are required for the model simulations with PREVAH (Table 1). The transient meteorological data were interpolated to a 2 × 2 km grid using detrended inverse distance weighting, where the detrending was based on a

Table 1
Summary of the 10 Climate Model Chains Considered in This Study: Global Circulation Model (GCM), Regional Climate Model (RCM), and Representative Concentration Pathway (RCP)

Chain number	GCM	RCM	RCP
1	ICHEC-EC-EARTH	DMI-HIRHAM5	2.6
2	ICHEC-EC-EARTH	DMI-HIRHAM5	4.5
3	ICHEC-EC-EARTH	DMI-HIRHAM5	8.5
4	ICHEC-EC-EARTH	SMHI-RCA4	2.6
5	ICHEC-EC-EARTH	SMHI-RCA4	4.5
6	ICHEC-EC-EARTH	SMHI-RCA4	8.5
7	MOHC-HadGEM2-ES	SMHI-RCA4	4.5
8	MOHC-HadGEM2-ES	SMHI-RCA4	8.5
9	MPI-M-MPI-ESM-LR	SMHI-RCA4	8.5
10	MPI-M-MPI-ESM-LR	SMHI-RCA4	4.5
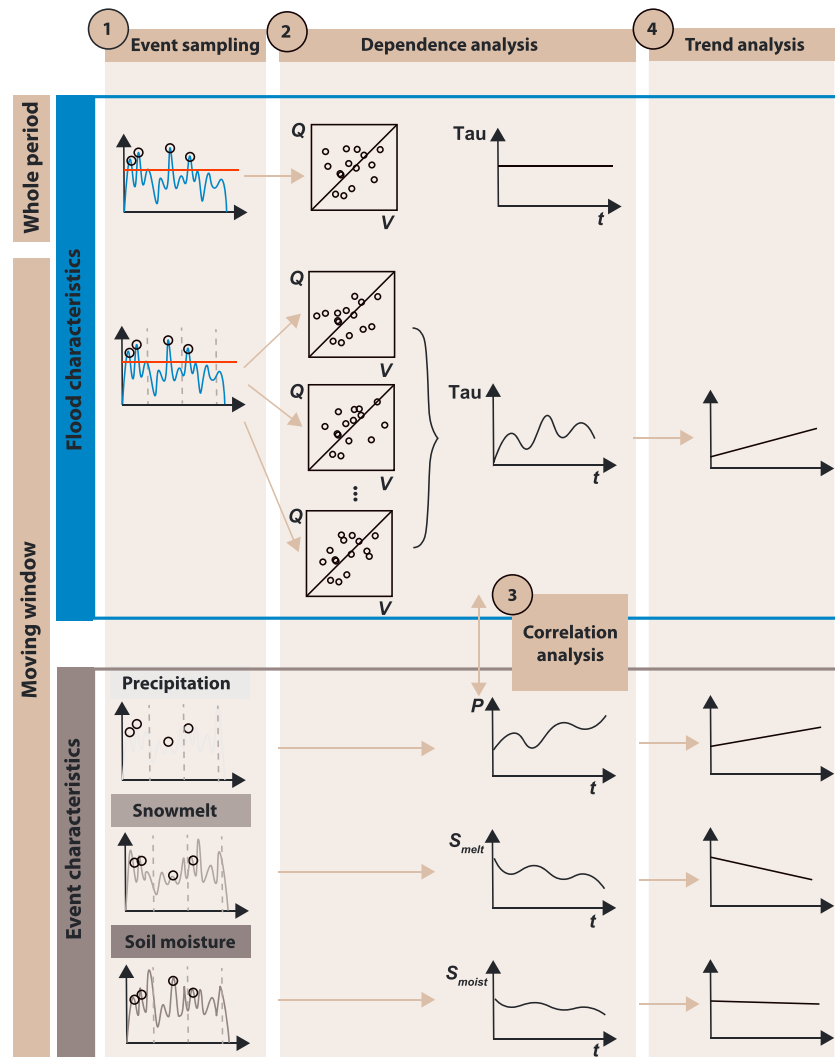
Figure 2. Illustration of the analysis framework: (1) flood event sampling; (2) dependence analysis between flood peak (Q) and volume (V); (3) correlation analysis between Q-V dependence and the three event characteristics precipitation, snowmelt, and soil moisture over a moving window; and (4) trend analysis of flood and event characteristics.

regression between climate variables and elevation (Viviroli, Zappa, Gurtz, et al., 2009). During the model run, PREVAH reads the meteorological grids and further downscales the data to the computational grid of 500×500 m using bilinear interpolation. For temperature, a lapse rate of -0.65 °C/100 m was additionally used. This two-step procedure has been introduced to cope with the large amount of data needed to run PREVAH for 120 years in the transient mode for 10 scenarios.

The daily runoff time series resulting from running the hydrological model with these meteorological time series were used as input for the analysis of trends in the dependence between peak discharge and flood volume.

3. Methods

The analysis of trends in the dependence between flood peaks and volumes and their drivers consisted of four main steps (Figure 2): (1) flood event sampling, (2) dependence analysis, (3) correlation analysis, and (4) trend analysis.

3.1. Step 1: Event Sampling

Flood events were identified in the runoff time series simulated using the hydrological model introduced in the previous section (Figure 2, step 1). We used a peak-over-threshold approach (Lang et al., 1999) to

sample flood events with the 0.99 quantile of peak discharge as a threshold, resulting in two flood samples per year on average. A sensitivity analysis showed that the strength of Q-V dependence was only slightly affected by the choice of this threshold. The independence of events was ensured by sampling only one flood event per week. The flood volumes corresponding to these peak-over-threshold events sampled according to peak discharge had to be determined. The start and end of an event were defined as the points where the discharge rose above 0.4 times the peak discharge or receded below this value, respectively. The factor 0.4 was considered suitable for identifying events that were meaningful in terms of the hydrographs selected, and the strength of the dependence between peak discharge and flood volume was hardly affected by the exact value of this factor. The start and end of an event were limited to 4 days before and 4 days after the occurrence of peak discharge, respectively. Four days were chosen since Froidevaux et al. (2015) found that only precipitation periods up to 4 days prior to the flood event determine its characteristics. The volume was then computed for the event delimited by these start and end points. This flood sampling procedure resulted in flood peak-volume pairs that describe a flood in terms of not one but two important characteristics and can be used as input for the dependence analysis between flood peak and volume (step 2). For each of these flood events, we also determined selected event characteristics including antecedent conditions such as soil moisture, as simulated by the hydrological model, and meteorological conditions such as precipitation and snowmelt. These event characteristics were used in step 3 of the analysis to establish a link between the Q-V dependence during a specific period and potential climatological drivers.

3.2. Step 2: Q-V Dependence Analysis

We assessed the Q-V dependence using the two nonparametric dependence measures Kendall's tau and Spearman's rho, as well as Pearson's classical correlation coefficient, and all measures produced similar results. We focused on Kendall's (1937) tau for the subsequent analysis because nonparametric measures can depict nonlinear dependence and are more robust in the case of small samples (Genest & Favre, 2007). When interested in extremes, the tail dependence that characterizes the dependence between the most extreme events is also important. However, its estimation is very uncertain when the sample size is too small (Lavaud, 2018; Serinaldi et al., 2015), and we therefore focused on the overall dependence of the sample of Q-V pairs measured by Kendall's tau. The evolution of the general dependence was assessed over the period 1981–2100 using a moving window of 60 events, corresponding to roughly 30 years. The suitable length of the time window was determined in a sensitivity analysis, which showed that results stabilized at 60 events per window and that further increasing the window size did not significantly change the results. The Kendall's tau values for each of these windows (roughly 30 values for the control period and roughly 120 for the future period) formed a time series that could be analyzed for the variability and trends in Q-V dependence, as suggested by Bender et al. (2014).

3.3. Step 3: Correlation Analysis With Possible Explanatory Variables

The variability and trends in the Q-V dependence time series were linked to flood characteristics and event descriptors representing potential climatological drivers, such as precipitation, snowmelt, and soil moisture. The flood event characteristics considered included peak discharge; flood volume; the ratio between volume and peak (V/Q ratio), which characterizes the duration of an event (Gaal et al., 2012); and the flood-type ratio, defined here as the ratio between the number of rainfall-influenced and the number of snow-influenced events, that is, number of rainfall-influenced events/number of snow-influenced events, where rainfall-influenced events are those with less than 1 mm of snowmelt. The event descriptors included the 4-day precipitation sum before the event and the snowmelt and soil moisture when the maximum flood discharge occurred. Each of these characteristics was summarized over a moving window of 60 events, in analogy to the procedure applied to the Q-V dependence, by the mean value of the respective characteristics (Figure 3). Please note that these values represent average values over the moving window and do not give any information about single events. The correlation between these summary statistics and the Q-V dependence across the different windows was then assessed. The significance of the correlation was tested at a level of 0.05 and found to be significant in most of the catchments. This procedure made it possible to detect potential links between the Q-V dependence and hydro-climatological drivers. The trends in Q-V dependence were linked to trends in the climatological drivers by combining the insights on future trends gained in step 4 and knowledge about the correlation of the Q-V dependence with climatological characteristics derived in step 3. The analysis of different climate model chains allowed us to quantify the uncertainty in the links between trends and drivers.
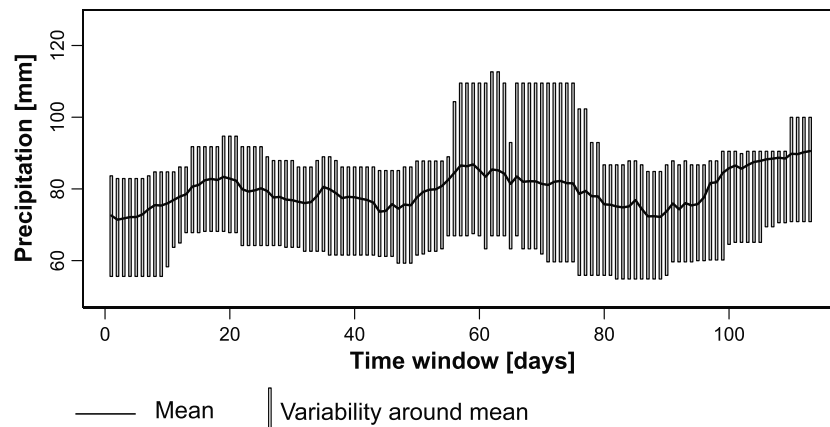
Figure 3. Illustration of the variability of the event precipitation 4 days prior to the event within the different moving windows. The black line shows the mean event precipitation within the different windows, and the gray boxplots indicate the variability (lower quartile to upper quartile) of event precipitation in the corresponding window.

3.4. Step 4: Trend Analysis

The trend in both the *Q-V* dependence and the potential climatological drivers over the period 1981–2099 was assessed by using three statistical approaches because Svensson et al. (2006) and Wijngaard et al. (2003) indicated that different methods may result in different trend estimates. As a first approach, we used the commonly applied nonparametric Mann-Kendall test (Mann, 1945), for identifying significant trends at a level of 0.05 together with Sen's (1968) test, for determining the direction and magnitude of change. As a second approach, we fitted a trend to the data using linear regression and defined the direction and magnitude of the trend via the regression coefficient. As a third approach, we used the Lombard (1987) test based on both the Cramér von Mises and the Kolmogorov-Smirnov test statistics, which enabled testing of trend significance, but not magnitude, and detection of change points and their time of occurrence (Quessy et al., 2011). A comparison of these three approaches showed that they produced almost identical results regarding the significance of trends in the *Q-V* dependence over the whole simulated time series (1981–2099). We therefore focused on the nonparametric Mann-Kendall test for subsequent analyses because it is often used in studies aimed at detecting trends in flood frequency (e.g., Archfield et al., 2016; Mangini et al., 2018). The application of the Mann-Kendall trend test in combination with Sen's slope test allowed us to divide catchments into three types: (1) no significant trend, (2) significant positive trend, and (3) significant negative trend. This was done for both the *Q-V* dependence and the potential climatological drivers (precipitation, snowmelt, and soil moisture). These drivers were derived for each of the flood event sets identified within the runoff time series generated by feeding the hydrological model with the meteorological output of the 10 climate model chains.

4. Results

4.1. Hydro-Climatological Characteristics and *Q-V* Dependence

Figure 4 shows the spatial distribution of the event characteristics precipitation (4-day precipitation sum), snowmelt, and soil moisture and the flood characteristics flood-type ratio, peak discharge, flood volume, *V/Q* ratio, and *Q-V* dependence of the control period (1981–2017). Event precipitation sums are relatively high in the southern part of Switzerland and lower on the northern side of the Alps, event snowmelt volume is relatively high in the catchments in the Alps and lower in the Plateau region, and soil moisture is relatively high on the northern side of the Alps and lower in the Southern Alps. The flood-type ratio is with a comparably high number of rainfall-influenced events highest on the northern side of the Alps, while peak discharge and flood volume are higher in the Alps and the Southern Alps. The *V/Q* ratio is highest in the Alps and low in the Southern Alps and the Plateau region. The *Q-V* dependence for floods observed in the control period is positive in most catchments and varies from catchment to catchment (Figure 4, lowest map). It is quite strong in the northeastern part of Switzerland and the Southern Alps (values of up to 0.87), while it is rather weak in the higher-elevation regions, that is, the Jura and the Alps.
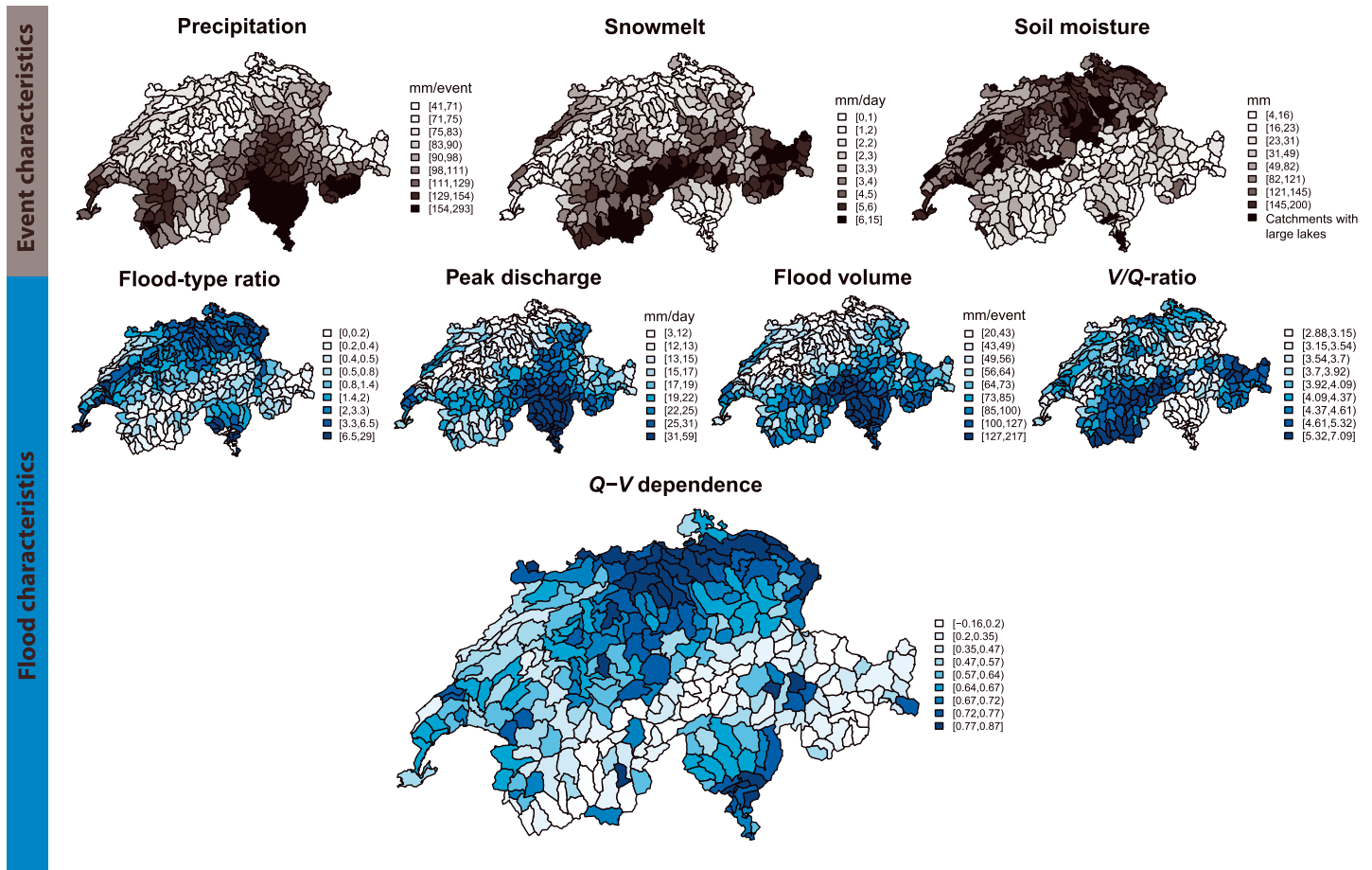
Figure 4. Spatial distribution of event and flood characteristics for the control period (1981–2017): precipitation, snowmelt, soil moisture, flood-type ratio, peak discharge, flood volume, V/Q ratio, and Q-V dependence.

4.2. Correlation Analysis With Possible Explanatory Variables

Figure 5 summarizes the correlation between the event characteristics and Q-V dependence over all climate model chains for all catchments and for high- (above 1,250 m a.s.l.) and low-elevation (below 1,250 m a.s.l.) catchments separately. The correlation between precipitation and Q-V dependence is positive for most of the model chains and catchments, independent of their elevation. In contrast, the strength of the correlation of Q-V dependence with snowmelt and soil moisture is different for high- and low-elevation catchments. Q-V dependence is mostly negatively correlated with snowmelt in high-elevation catchments, while the direction of the correlation can be positive or negative in low-elevation catchments. On the contrary, soil moisture is mostly positively correlated with Q-V dependence in high-elevation catchments and also mostly positively but less strongly correlated with Q-V dependence in low-elevation catchments. These differences in the relation between event characteristics and Q-V dependence for low- and high-elevation catchments lead to a clear spatial pattern in this dependence (Figure 4).

The correlations between Q-V dependence and the event characteristics are rather low, owing to averaging effects of negative and positive correlations across the different model chains (Figure 6). All the climate model chains indicate a positive correlation between precipitation and Q-V dependence for a majority of the catchments. The correlation between snowmelt and Q-V dependence is positive or negative, depending on the model chain considered. The correlation between soil moisture and Q-V dependence tends to be positive for the 10 chains considered. The correlation between precipitation and Q-V dependence is similar from one chain to another. In contrast, the correlation between snowmelt and Q-V dependence or between soil moisture and Q-V dependence varies significantly between chains. This is illustrated by results from chains 1 and 2 in Figure 6.
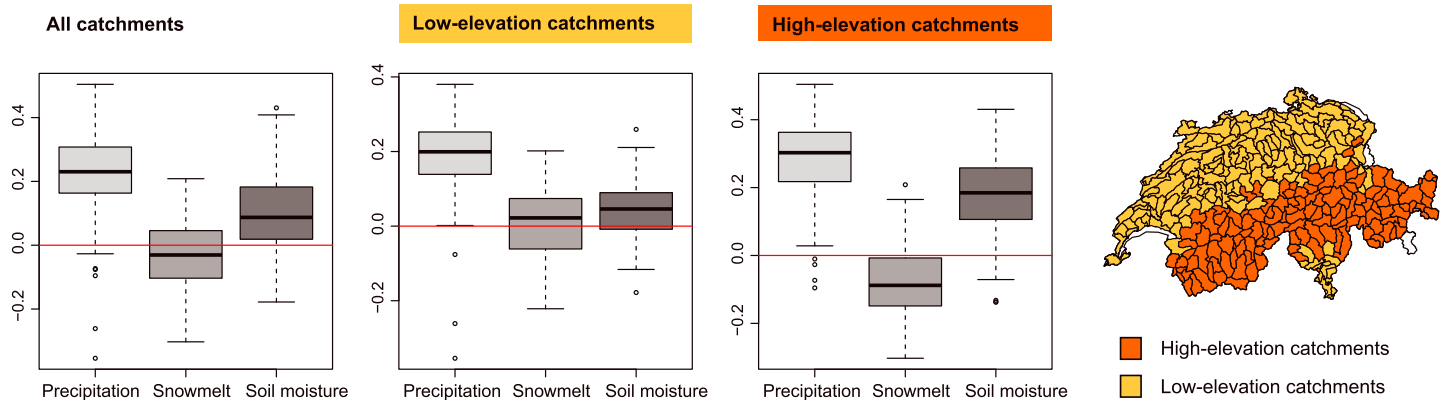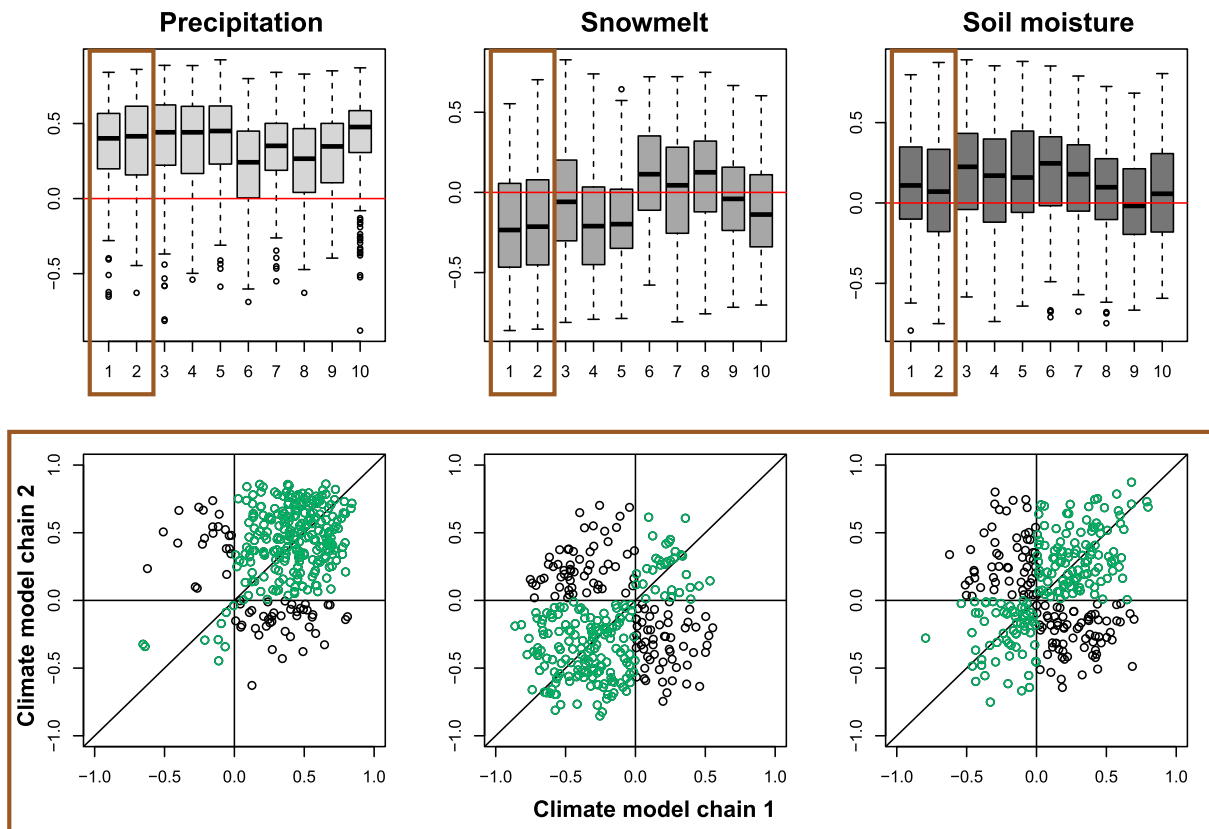
Figure 5. Correlation of the *Q-V* dependence with the event characteristics precipitation, snowmelt, and soil moisture over the period 1981–2099 over all catchments and model chains (left panel), over catchments at low elevation and all model chains (middle panel), and over catchments at high elevation and all model chains (right panel). The high- and low-elevation catchments are displayed on the map to the right. The red line represents zero correlation.

4.3. Trend Analysis

The trends in the *Q-V* dependence derived by using the different model chains are mostly significant but spatially rather inhomogeneous, with positive trends in some catchments and negative trends in others (Figure 7, right panels). However, trends tend to be rather positive in the Alps and rather negative in the Plateau region. The trends found for the event and flood characteristics are spatially more homogeneous and more consistent across the model chains than the trends found for *Q-V* dependence (Figure 7, panels
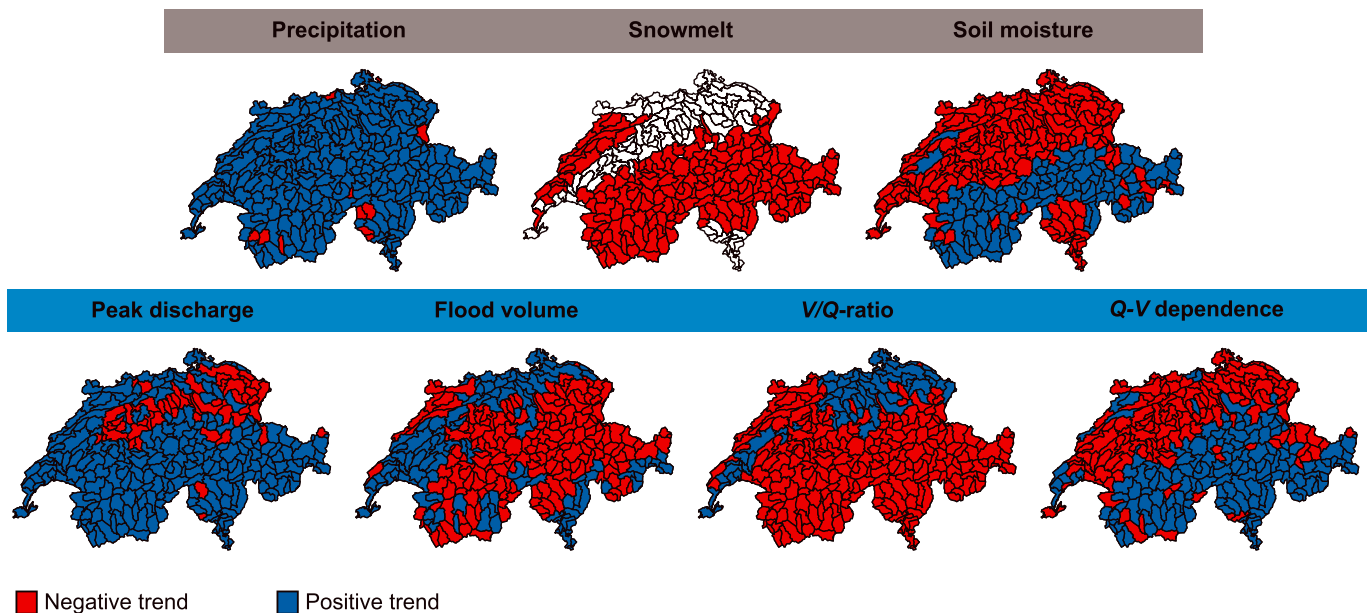

Figure 6. Correlation of *Q-V* dependence with the event characteristics precipitation, snowmelt, and soil moisture over the period 1981–2099 for the 10 climate model chains analyzed (upper panels). Each boxplot is the result of 307 values, one for each catchment, and the red line indicates zero correlation. The scatterplots in the lower panels compare the correlations between *Q-V* dependence and the three event characteristics obtained for model chains 1 and 2. Green points highlight the catchments where both model chains agree on the direction (positive or negative) of the correlation between *Q-V* dependence and the event characteristic considered.
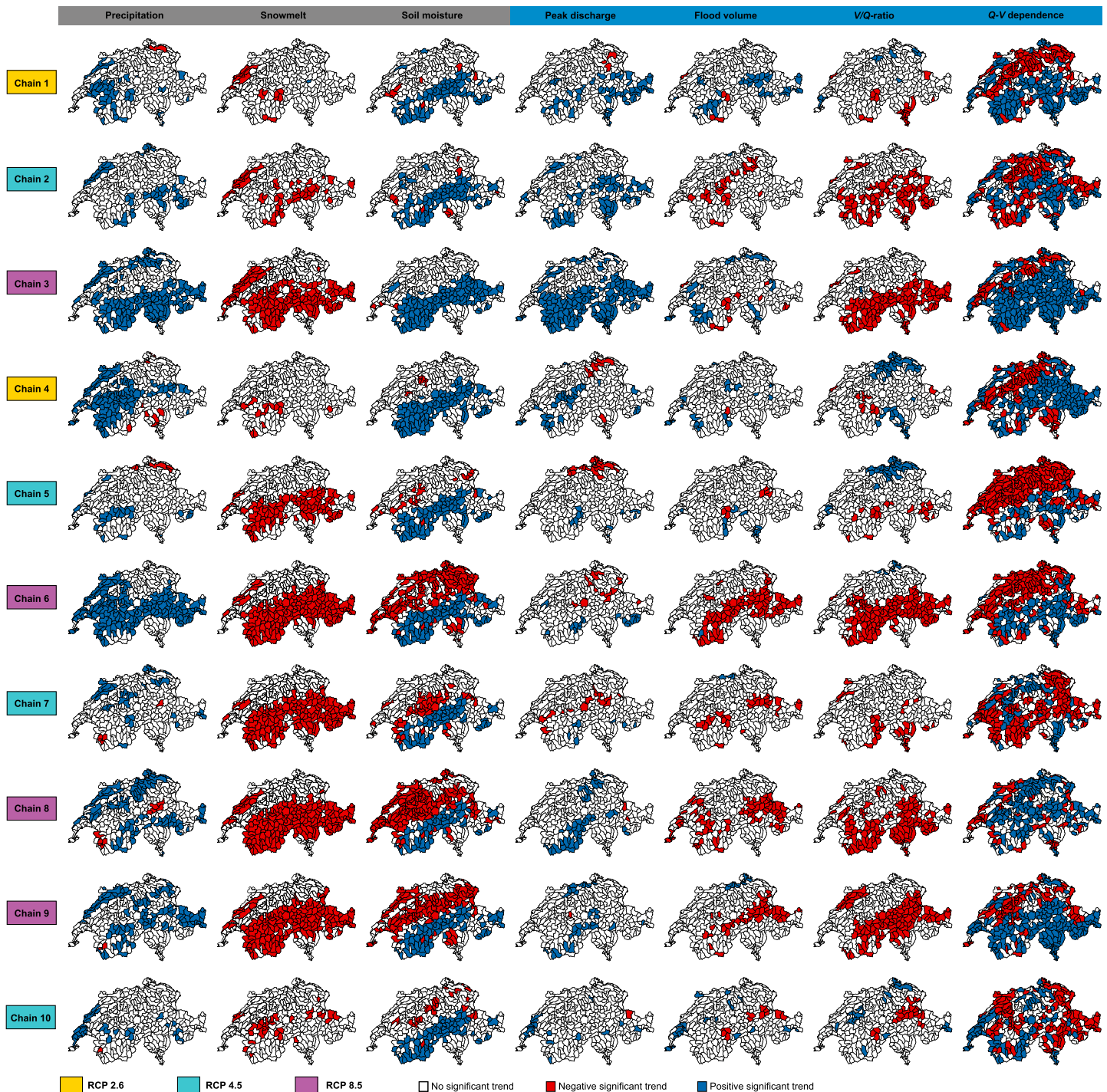
Figure 7. Maps of trends in the event and flood characteristics precipitation, snowmelt, soil moisture, peak discharge, flood volume, V/Q ratio, and $Q-V$ dependence. Catchments with no significant trend are shown in white, catchments with a significant positive trend are shown in blue, and catchments with a significant negative trend are shown in red. The trends were computed over the period 1981–2099. RCP = representative concentration pathway.

1–6). The trend in event precipitation is positive in the majority of catchments but significant in only some of them. In contrast, the trend in event snowmelt is negative in all of the catchments and significant in most catchments in the Pre-Alps and Alps but not for all model chains. The trend pattern for event soil moisture is predicted to be more diverse, with negative trends on the northern side of the Alps and the Southern Alps that are only visible in some of the model chains and positive trends in the Alps that are visible in all model chains. The trends in these meteorological event characteristics are predicted to be mostly significant, except

Figure 8. Positive and negative trends over all climate model chains (i.e., sign of sum of Sen's slope values over all model chains) over the period 1981–2099 for the event characteristics precipitation, snowmelt, and soil moisture and for the flood characteristics peak discharge, flood volume, V/Q ratio, and Q-V dependence. Red areas indicate catchments with an overall negative trend, and blue areas indicate catchments with an overall positive trend. The significance of the trend is not clear because the mean of different trend analyses is shown.

for precipitation, and spatially coherent. In contrast, the trends in the flood event characteristics are more heterogeneous and significant in only a small subset of catchments for most of the model chains. Estimated trends in peak discharge are mostly positive but hardly significant, trends in flood volume are negative in most catchments but also hardly significant, and the resulting trends in the V/Q ratio are mostly negative but not significant in most of the catchments and model chains. While the trends in flood characteristics are hardly significant, those in Q-V dependence are significant in most catchments, but their direction is spatially quite heterogeneous and only partly consistent across the model chains.

Figure 8 summarizes the trends of the event and flood characteristics over all 10 model chains. Trends in event precipitation are predicted to be mostly positive, while trends in event snowmelt are predicted to be mostly negative. Trends in soil moisture are predicted to be regionally distinct, with negative trends in the Plateau region and the Southern Alps and positive values in the Alps. Trends in flood characteristics are also expected to be spatially heterogeneous. Peak discharges are predicted to increase in most of the catchments if the trends over all model chains are summarized, except for the catchments in northeastern Switzerland. In contrast, flood volumes are predicted to decrease in most of the catchments, with exceptions mainly located in the Plateau region. A decrease is therefore also predicted in the V/Q ratio, except for in northeastern Switzerland where peak discharges are predicted to decrease. Finally, Q-V dependence decreases in the Plateau region but increases in the Alps and Southern Alps if trends are aggregated over all the climate model chains, although these trends are not always significant.

As discussed previously, the trend estimated by Sen's slope can differ from one modeling chain to another. The uncertainty in the trend, estimated by the coefficient of variation of Sen's slope over the 10 model chains, is given in Figure 9 for each variable. The magnitude of uncertainty depends not only on the event or flood characteristics but also on the geographical region considered. Uncertainty is highest for peak discharge, flood volume, and Q-V dependence. For soil moisture, peak discharge, and the V/Q ratio, uncertainty is higher in the Plateau than in the Alps. In contrast, the uncertainty is less dependent on the region considered for precipitation, snowmelt, flood volume, and Q-V dependence.
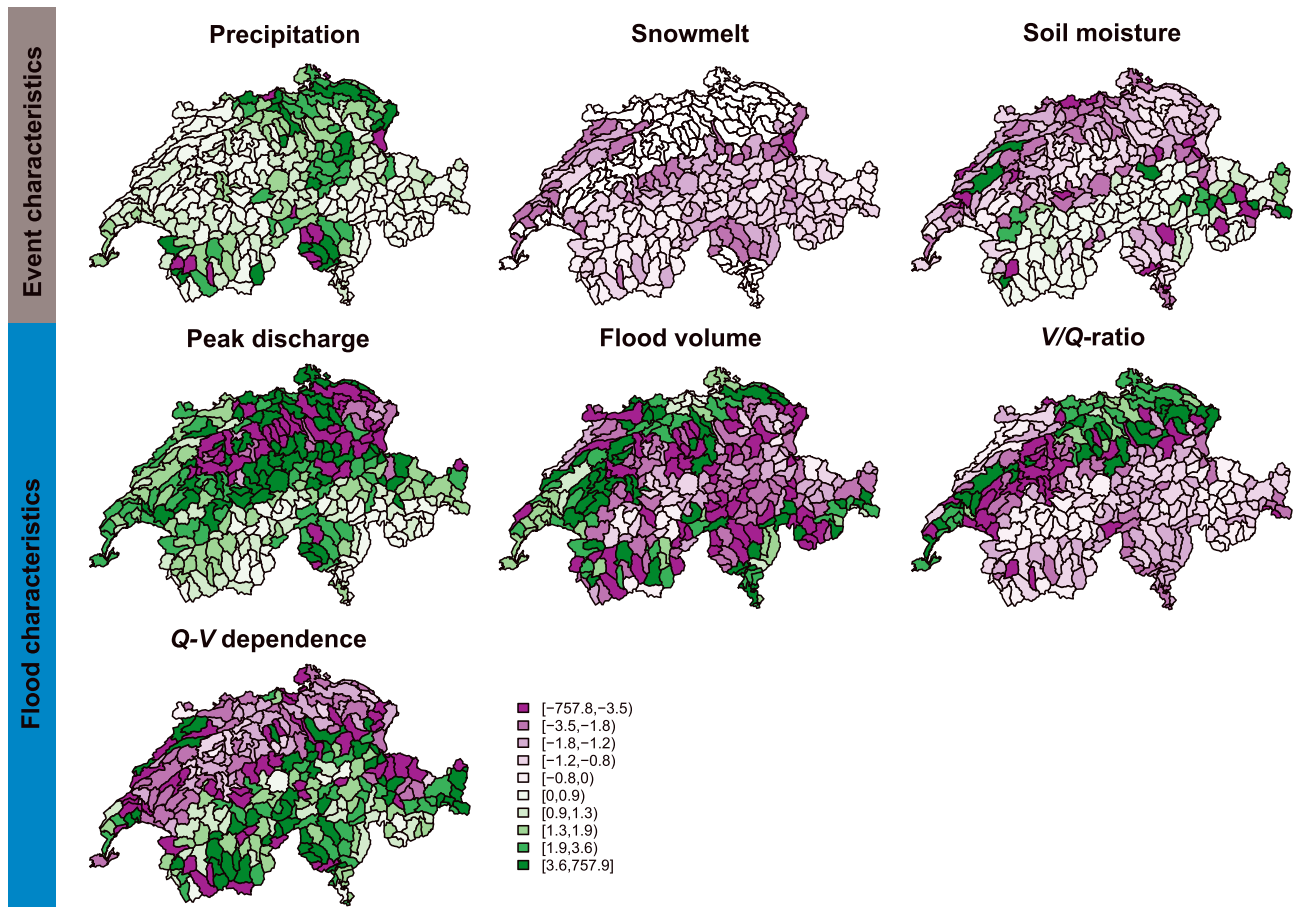
Figure 9. Uncertainty of trends expressed as the coefficient of Sen's slope over the 10 climate model chains over the period 1981–2099 for the event characteristics precipitation, snowmelt, and soil moisture and for the flood characteristics peak discharge, flood volume, V/Q ratio, and Q-V dependence. Purple areas represent catchments with negative mean trends, while green areas represent catchments with positive trends. Darker colors indicate a larger spread between model chains.

5. Discussion

5.1. Drivers of Trends in Q-V Dependence

Our results show that the Q-V dependence during the control period is spatially heterogeneous. The dependence is high in the Plateau, the Pre-Alps, and the Southern Alps, while it is low in the Alps. This finding is consistent with observations by Gaal et al. (2012) and Szolgay et al. (2015), who also found that peak discharge and flood volume are less dependent in mountainous catchments because of the existence of a mix of flood types. The spatial pattern of Q-V dependence does not coincide much with precipitation but rather with snowmelt contributions, which are higher in the Alps than in the Plateau and Pre-Alps, and with soil moisture, which is higher for flood events on the northern side of the Alps than those on their southern side. The results of the correlation analysis show that the Q-V dependence is indeed influenced by several factors whose change can lead to an increase or decrease in Q-V dependence. Besides precipitation, snowmelt and soil moisture were also found to be important. These results agree with the findings of Berghuijs et al. (2016) and Blöschl et al. (2015) that snowmelt and soil moisture are important for explaining the flood behavior of a catchment. The interplay between these factors seems to be important for explaining changes in Q-V dependence over time. This result is consistent with findings by Serinaldi and Kilsby (2013) that the relationships between peak and volume can be explained by the interplay of different variables. The importance of this interplay is supported by the observation that trends in event characteristics are spatially coherent, while the trends in Q-V dependence are spatially heterogeneous. Over all model chains, these trends are mainly negative in the Plateau region, where the highest Q-V dependence is observed for the control period, and mostly positive in the Alps, where the control period has low dependence values. In the Alps, the increase in Q-V dependence could be driven by several factors; for example, a decrease in snowmelt under a changing

climate could cause a reduction in snowmelt-driven flood events and therefore a reduction in the heterogeneity of flood types, an increase in event soil moisture, which was found to be positively correlated with Q-V dependence, or an increase in event precipitation, which was also found to have a positive effect on Q-V dependence. In the Plateau region, the decrease in Q-V dependence could not be explained by precipitation, as an increase in precipitation should lead to an increase in Q-V dependence because of the positive correlation between the two variables. The decrease in Q-V dependence also could not be driven solely by a reduction in snowmelt because a reduction in snowmelt had, depending on the catchments, either a positive or negative effect on Q-V dependence. Soil moisture seemed to be another important influencing factor because a decrease in soil moisture tended to lead to a decrease in the Q-V dependence. Soil moisture therefore needs to be considered, in addition to changes in snowmelt and precipitation, in efforts to understand predicted changes in Q-V dependence as it explains differences in the trends between low- and high-elevation catchments and because it has the opposite effect on the V/Q ratio. Given that soil moisture during flood events is highest in the Plateau region and that precipitation and snowmelt are highest in the Alps, one might conclude that drivers with a larger magnitude have a greater effect on trends in Q-V dependence than drivers with a smaller magnitude. More flood dampening is possible in regions with a high maximum soil moisture, if the soils are dry at the beginning of the event, than in regions with a low maximum soil moisture. The lack of spatial coherence in Q-V dependence matches the findings of Archfield et al. (2016), Mangini et al. (2018), and Svensson et al. (2006); these authors detected only weak geographic cohesion in the trends of flood peaks and volumes, even though robust regime changes are known to emerge with a shift toward more rain-driven regimes (Addor et al., 2014). Changes in Q-V dependence could therefore potentially be derived not only by looking at changes in hydro-climatological variables but also by applying knowledge about changes in flood type (Sikorska et al., 2015; Turkington et al., 2016).

The changes detected in various event characteristics and the Q-V dependence were found to be robust, in that several trend tests showed the same direction of change. However, the trends in Q-V dependence were influenced by the model chain considered because flood event characteristics were projected to change in different ways under various model chains. In addition, trends were rather weak because of fluctuations from one period to another, which were quite strong. Predicted changes in event characteristics emerged more clearly than those in flood characteristics. Trends in snowmelt were found to be mostly negative, independent of the model chain considered, as also found by Jenicek et al. (2018), while trends in extreme precipitation were mostly significantly positive, as also observed by Blöschl et al. (2015) and Tomassini and Jacob (2009). Trends in soil moisture were mostly positive in the Alps, while they were negative in the Plateau region. The uncertainty in trends in peak discharge and the V/Q ratio was higher in the Plateau region than in the Alps. In contrast to these variables, the uncertainty in Q-V dependence was spatially rather homogeneous.

The links between drivers and Q-V dependence were also partly dependent on the model chain chosen, as shown by the correlation analysis performed on several model chains (Figure 6). This correlation analysis showed that an increase in event precipitation is expected to lead to an increase in Q-V dependence, independent of the model chain considered, while a decrease in snowmelt or soil moisture can lead to an increase or decrease in Q-V dependence, depending on the model chain and catchment considered. The link between snowmelt and soil moisture and the Q-V dependence is independent of the model chain in high-elevation catchments, where snowmelt is negatively and soil moisture positively correlated with Q-V dependence. In contrast, snowmelt and soil moisture can be positively or negatively correlated with Q-V dependence in low-elevation catchments. The changes in Q-V dependence explained by changes in snowmelt, that is, the increase in the Alps, are expected to be rather robust, given that the direction of changes in snowmelt was found to be negative, independent of the model chain. The decrease in Q-V dependence in the Plateau region visible in most model chains cannot be explained by changes in precipitation or snowmelt but rather by the decrease in soil moisture, which is positively correlated with Q-V dependence.

5.2. Limitations and Perspectives

The trends detected in our analysis might be influenced by several choices in the modeling chain. First, the choice of flood sampling approach might be important. Mangini et al. (2018) and Svensson et al. (2006) found a larger number of significant trends in annual maxima than in partial duration series. By using partial duration series in this study, we might therefore have underestimated potential changes. Furthermore, the choice of the threshold and the factor used to determine the start and end of the flood events have a slight influence on the results. Second, the length of the moving window chosen to calculate Q-V

dependence might have impacted the results because rivers experience multidecadal variability (Svensson et al., 2006). Predicted changes in snowmelt have been found to be more reliable than changes in heavy precipitation (Blöschl et al., 2015), and regime changes have been found to be consistent across a wide range of scenarios (Addor et al., 2014). Third, the results of our analysis might also be affected by the limited ability of the hydrological model, especially when driven with the climate model output, to reproduce the *Q-V* dependence. The runoff time series driven by using the meteorological data produced by the climate model chains does not, in some catchments, accurately reproduce the flood statistics of the control simulations generated by the observed meteorological data. This is because quantile mapping does not introduce any small-scale variability and because the temporal structure is still that of the gridbox and not that of the local scale (Maraun, 2013). Fourth, the study focused on the general dependence structure between peak discharge and flood volume and neglected other important dependence characteristics such as tail dependence because the reliability of its estimators is limited for small samples.

The study of links between climatological drivers and *Q-V* dependence might be transferable to other regions with runoff regimes similar to those observed in the study catchments. While the results of this study could not be directly transferred to such regions, the framework for analyzing changes is transferable and could be set up in regions with other hydro-climatic characteristics.

Considering expected changes in *Q-V* dependence in modeling efforts when estimating bivariate design quantiles for future climate conditions is technically possible and may be of value. Bender et al. (2014) proposed a framework that makes it possible to take such changes into account by using a copula parameter that is time dependent. Given the uncertainty of changes in *Q-V* dependence, one might, however, prefer to choose an approach assuming stationarity in the dependence structure between peak discharge and flood volume.

6. Conclusions

The interdependence of peak discharge and flood volume shows a clear spatial pattern, with higher values in the Plateau and the Pre-Alps and lower values in the Alps and the Jura. This pattern can be partly explained by differences in event precipitation, snowmelt, soil moisture, and other factors. Changes in these climatological drivers also lead to changes in *Q-V* dependence. Even though changes in these drivers might be spatially coherent, changes in *Q-V* dependence are more heterogeneous because of an interplay of different factors influencing *Q-V* dependence, including precipitation, snowmelt, and soil moisture. The negative trend in the dependence between peak discharge and flood volume could, in the Alps, be partly explained by a decrease in snowmelt or an increase in event precipitation. The negative trends in this dependence in the Plateau region cannot be explained by precipitation. In some catchments, they can also be explained by changes in snowmelt, while they can only be explained by changes in soil moisture in other catchments. However, both the trends and the drivers of these trends are dependent on the model chain considered and are therefore uncertain. Despite this uncertainty, confidence in the expected changes in snowmelt by different climate model chains helps us to gain confidence on those expected changes in *Q-V* dependence that are driven by changes in snowmelt. The question remains as to whether future modeling efforts for deriving bivariate design estimates expressed by peak discharge and flood volume should take into account uncertain changes in their dependence structure. Adding this component might be relevant when considering rare events.

Author Contributions

A. C. F., B. H., and M. B. jointly developed the study design and methodology. M. Z. produced the hydrological model simulations. M. B. performed the analyses, produced the figures, and wrote the first draft of the manuscript. The manuscript was revised by B. H., M. Z., and A. C. F. and edited by M. B.

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