Characteristics and process controls of statistical flood moments in Europe – a ~~data~~ data-based analysis

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Abstract. This paper analyses the spatial patterns and process controls of the mean annual flood (MAF), coefficient of variation (CV) and skewness (CS) of flood discharges in Europe. The data consist of maximum annual flood discharge series observed in 2370 catchments in Europe covering the period 1960-2010. On average, in Europe, the estimated moments MAF, CV and CS are 0.17 $m^3 s^{-1} km^{-2}$, 0.52 and 1.28, respectively.

The results indicate that MAF is largest along the Atlantic coast, the high rainfall areas of the Mediterranean coast and in ~~the mountain ranges of Europe~~mountainous regions, while it is smallest in the sheltered parts of the East European plain. The CV is largest in ~~Southern~~ southern and ~~Eastern~~ eastern Europe, while it is smallest in the regions subject to~~of~~ strong Atlantic influence. The pattern of CS is similar~~ to that of CV~~, albeit ~~a little~~ more erratic. In the Mediterranean, MAF, CV and CS decrease strongly with catchment area, suggesting that floods in small catchments are relatively very large, while in Eastern Europe ~~the~~ this dependence is much weaker.

The ~~Process~~ process controls on the flood moments in five predetermined hydroclimatic regions are identified ~~by~~ through correlation and multiple linear regression analyses with a range of covariates. Precipitation-related ~~variables~~ covariates are found to be the main controls of the spatial patterns of MAF in most of Europe except for ~~the~~ regions ~~with where~~ in which snowmelt contributes to MAFs~~ influence~~, where air temperature is more important. ~~Catchment area is another relevant variable~~. The Aridity Index is, by far, the most important control ~~of~~ on the spatial pattern of CV in all of Europe. ~~Precipitation-related variables are relevant in Southern Europe~~. Overall, the findings suggest that, at the continental scale, climate variables dominate over land surface characteristics, such as land use and soil type, in controlling the spatial patterns of flood moments.

Finally, the estimation accuracy of ~~the~~ regional multiple linear regression models for estimating flood moments in ungauged basins ~~is evaluated as~~provides an accuracy baseline for more ~~accurate~~ local studies.

1. Introduction

Understanding the spatial distribution of statistical flood characteristics is important from both practical and theoretical perspectives, assisting in estimating design floods in gauged and ungauged catchments, and shedding light on the regional processes of flood generation from a probabilistic perspective (Rosbjerg et al., 2013).

Commented [A1]: Instantaneous or daily flows? Minimally impacted basins?

Commented [A2]: Mention that these values vary widely due to catchment size, climate and other covariates. In my opinion, it's not necessary to state this in the abstract but there's nothing wrong with it either.

Commented [A3]: Due to the greater sensitivity of sampling variability to Cs in short records?

See general comments about regional skewness.

Commented [A4]: Can you state why briefly?

Commented [A5]: Do you need to describe this here? You already did above.

Commented [A6]: Is it aridity itself or do arid regions happen to greater interannual precipitation variability?

Commented [A7]: You already said that they are relevant in most of Europe earlier on in this paragraph.

Commented [A8]: Scientific?

Much research has been conducted on identifying process variables and mechanisms controlling the magnitudes of flood characteristics. Catchment area usually is the main control on the specific mean annual flood (MAF) as smaller basins tend to have larger specific MAFs than larger ones (Rosbjerg et al., 2013)~~. This is~~ because a large basin is less likely to be fully covered by a thunderstorm than a small basin. This ~~which~~ tends to reduce the variance of extreme catchment-average precipitation and thus the MAF (Viglione et al., 2010a, b). Additionally, there is an important space-time effect that explains the attenuation of specific floods as catchment areas increase. Event-scale catchment response times tend to increase with area (Gaál et al. 2012), which leads to a greater attenuation of the flood peaks. Meanwhile, ~~T~~the effect of catchment area on the CV (the ratio of standard deviation and annual means) tends to be more complex. For example, Smith (1992), based on data in the Appalachian region, found an increase in CV with catchment area up to about 100 km², and subsequently a decrease, which he ~~explained by~~attributed to the spatial organisation of precipitation and downstream changes in the floodplain system. Blöschl and Sivapalan (1997) suggested that space-time scale interactions may be the main reason for this ~~of the~~ scale dependence, while Merz and Blöschl (2003) noted that the strength of the dependence of CV on area will differ between regions ~~of~~ with different prevailing flood generation types such as synoptic floods and ~~snowmelt~~ snowmelt-driven floods. Based on an analysis of flood data in Slovakia,

Austria and Italy, Salinas et al. (2014b) found both CV and CS to decrease with catchment area, which they interpreted as the result of aggregation effects of the spatial heterogeneity of rainfall and the interaction between the spatial and temporal scales of rainfall and catchment size.

Runoff generation and thus flood moments are also controlled by soil characteristics, geology and land-use. Most ~~of the~~ knowledge ~~on~~ of these effects comes from simulation studies. For example, Gioia et al. (2012) demonstrated that infiltration and soil storage strongly affect ~~the~~ flood moments, and Brath et al. (2006) performed a similar analysis ~~for the case of~~on land use. The role of these variables can, to some extent, be inferred from their use as covariates in flood frequency regionalisation (~~see,~~ e.g. Zaman et al., 2012; Rosbjerg et al., 2013; Miller and Brewer, 2018). However, the type of soil, geology and land-use data available at the regional scale is often not consistent with the level of detail required for quantifying runoff generation processes, and therefore correlations with flood characteristics tend to be low (Weingartner et al., 2003).

Another important control is climate. Mechanistically, one would expect extreme precipitation to represent flood characteristics, as it is usually the main driver at the event scale (Viglione et al., 2009). However, many studies have shown that mean annual precipitation (MAP) is a better predictor of MAF (e.g. Madsen et al., 1997; Reed et al., 1999; Merz and Blöschl, 2009) for which a number of reasons have been suggested: MAP is usually highly correlated ~~to~~ with event precipitation; MAP is an important control of antecedent soil moisture on a seasonal scale (e.g. Grillakis et al., 2016); and climate, vegetation, soils and land~~-~~forms may co-evolve with MAP, thus exerting a ~~longer~~ longer-term influence (Gaál et al., 2012, Perdigão and Blöschl, 2014). Based on data from around the world, Farquharson et al. (1992) found CV to increase with the ~~a~~Aridity Index (the ratio of potential evaporation and MAP)~~, and~~ Merz and Blöschl (2009) found potential evaporation to be an excellent predictor of both MAF

Commented [A9]: Storm events in general? Not always T-storms.

Commented [A10]: See Pallard et al. (2009) on the effect that drainage density has on the Cv https://hess.copernicus.org/articles/13/1019/2009/hess-13-1019-2009.pdf

Commented [A11]: Floods from synoptic-scale precip events (e.g. frontal systems)?

Commented [A12]: Many USGS regional flood frequency studies based on observed data have revealed non-climatic controls.

Commented [A13]: Attributing?

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Commented [A15]: Also, MAP might be better than event precip in places with snowmelt-driven floods

Commented [A16]: Is it aridity itself or does this stem from the tendency of more arid catchments to have greater interannual precipitation variability?

and CV in the lowlands of Austria, which they interpreted in terms of the increasing non-linearity of the rainfall-runoff process with aridity. Iacobellis et al. (2002), found that CV behaviour is controlled mainly by the long-term climate and the abstraction characteristics at the catchment scale. While a decrease in CV with ~~the~~ catchment area is attributed to more arid and impermeable catchments where the infiltration excess (Horton type) mechanism dominates, ~~as in arid and impermeable basins,~~ an increase of CV with the catchment ~~size~~ area is attributed to humid and vegetated catchments with dominant saturation excess runoff generation.

Commented [A17]: The greater the PET, the higher the Cv in lowlands of Austria?

Commented [A18]: This sounds very interesting, but could you explain in a sentence or two why Cv becomes lower with higher DA's in basins where infiltration-excess flow dominates and why it becomes higher with DA in basins where saturation-excess flow predominates?

~~The c~~Climate controls, including rainfall, soil moisture and snowmelt are usually subject to strong seasonality. An analysis of the seasonality of floods (Bayliss and Jones, 1993; Merz and Blöschl, 2003) has therefore been an efficient way to shed light on the interaction of these processes. For example, based on ~~a~~ the seasonality of 4262 catchments in Europe, Blöschl et al. (2017) and Hall et al. (2018) identified extreme winter precipitation in northwestern Europe, snowmelt in northeastern and eastern Europe and summer precipitation and snowmelt in the Alpine regions of Europe to be important flood drivers. Using their data set, Berghuijs et al. (2019) found soil moisture excess to explain flood seasonality better than other variables, such as extreme precipitation, particularly in the western part of Europe, in line with a similar study in the United States (Berghuijs et al., 2016).

While substantial understanding of regional flood controls has been achieved in the past, few studies have analysed large, consistent data sets of flood discharges in terms of their statistical moments. Large data sets provide the opportunity ~~of~~to obtain~~ing~~ more robust and generalisable findings than studies containing a smaller number of catchments. The aim of this paper is therefore to identify ~~the continental scale~~ patterns of flood moments and their controls across Europe. We use a data set of flood discharges of 2370 catchments across Europe for the period 1960-2010 and apply correlation and regression analyses to identify climatic and catchment process controls on the moments.

2. Data and Methodology

2.1 Data

This study uses the data set of European flood discharges of Blöschl, Hall et al. (2019), which can be found in their supplementary material. It consists of 2370 annual maximum peak discharge series from 33 countries. Catchment areas range from 5 to 100,000 km², with a median of 383 km². The observation period is 1960 to 2010, and record lengths range from 30 to 51 years, with a median of 51 years.

Commented [A19]: Please describe the degree to which and the types of anthropogenic perturbations to which basins in your sample are subject.

Commented [A20]: Assuming instantaneous peaks?

In order to analyse process controls, a range of catchment attributes and climatic indicators are used. In addition to catchment area, we used catchment-averaged climate indicators, including long-term mean annual precipitation (MAP), long-term mean potential evaporation (PET) and the aridity index, PET/MAP. Extreme precipitation is quantified by the daily rainfall rate that is not exceeded in 95% of the days, and the long-term mean of the maximum 2-day precipitation of each year. As a proxy for snowmelt we used the mean air temperature in spring (MAM) and winter (DJF). Soil moisture was taken from the CPC Soil moisture database, which contains model-calculated soil moisture values. We used the mean of the annual maximum monthly

Commented [A21]: Total days or wet days?

Commented [A22]: The duration of precipitation to examine varies substantially by region and catchment size. Can you convey an awareness of this in your introduction of these covariates?

Commented [A23]: How accurate are these modeled values? Can you add a sentence or so stating this and any places where inaccurate estimates may distort your analyses?

values over the observation period. Topographical indicators include the mean catchment elevation and the mean topographical slope of each catchment. Land use was quantified ~~by the~~as a percentage of ~~land use classes~~total catchment area. Soil characteristics were quantified in terms of five soil~~-~~texture ~~classified into five~~ categories. The data used are summarised in Table 1.

Commented [A24]: Can you mention forest and water body categories here?

Table 1: Data used in this study including quantiles of the variables and source information. Sources:
[1]Data base on European floods: https://github.com/tuwhydro/europe_floods
[2]CCM River and Catchment Database. Vogt et a., 2017. https://data.europa.eu/
[3]E-OBS gridded dataset (v18.0e), 0.1 deg. Cornes at al., 2018. https://www.ecad.eu/
[4]Global Aridity Index and Potential Evapo-Transpiration (ET0) Climate Database V2. Trabucco and Zomer, 2019 https://figshare.com/articles/Global_Aridity_Index_and_Potential_Evapotranspiration_ET0_Climate_Database_v2/7504448/3
[5]CPC Soil Moisture (V2), NOAA Climate Prediction Center. Fan and Dool, 2004. https://www.cpc.ncep.noaa.gov/
[6]Global Multi-resolution Terrain Elevation Data GMTED2010, 7.5 arc-seconds. https://www.usgs.gov/
[7]Corine Land Cover (CLC) 2000, Version 20b2, https://land.copernicus.eu/

Commented [A25]: Proper name?

Commented [A26]: Check for change?

Units	25 / 50 / 75% quantiles	Source
$m^3\ s^{-1}$	0.06/0.11/0.22 km^{-2}	Data base on European floods[1]
$m^3\ s^{-1}$	0.08/0.16/0.28 km^{-2}	Data base on European floods[1]
-	0.36/0.46/0.61	Data base on European floods[1]
-	0.62/1.09/1.69	Data base on European floods[1]
km²	135.90/382.80/1264.80	CCM River and Catchment Database[2]
mm yr^{-1}	621.28/798.69/1057.76	EOBS[3]
mm d^{-1}	8.40/10.54/13.45	EOBS[3]
mm d^{-1}	18.00/22.45/28.51	EOBS[3]
□C	5.03/7.15/8.42	EOBS[3]
□C	-3.35/-1.16/1.05	EOBS[3]
mm	368.38/424.93/507.20	CPC Soil Moisture (V2)[5]
mm yr^{-1}	749.02/817.73/897.98	Global Aridity Index and Potential Evapo-Transpiration (ET0) Climate Database V2[4]

[8]European Soil DataBase (ESDB), Soil Geographical DataBase (SGDB), TEXT_SRF_DOM, 10x10km. Panagos et al., 2012. https://esdac.jrc.ec.europa.eu

Variable group	Symbol	Data Description			
Flood Moments	MAF	Mean annual specific flood			
	MAF_{α}	Mean annual specific flood normalized to catchment area of α =100km²			
	CV	Coefficient of variation of annual maximum flood peaks			
	CS	Coefficient of skewness of annual maximum flood peaks			
Catchment Area	A	Catchment area			
Precipitation	MAP	Long-term mean annual precipitation			
	P95	Daily precipitation rate, that is higher than what is observed on 95% of days in the observed period			
	Pmax	Mean of maximum of 2-day precipitation of each year			
Air temperature	Tspr	Mean daily temperature in MAM (Celsius)			
	Twin	Mean daily temperature in DJF (Celsius)			
Soil moisture	SM	Mean of annual maximum monthly soil moisture			
Evaporation	PET	Long-term mean potential evaporation			
Aridity	AI	Aridity index (PET/MAP)	unitless	0.72/1.00/1.25	Global Aridity Index and Potential Evapo-Transpiration (ET0) Climate Database V2[4]
Topography	Elev	Mean catchment elevations	m a.s.l.	199.04/472.58/833.12	GMTED2010[6]
	Slope	Mean topographic slope (mean of tangent of angle of slope)	unitless	0.03/0.08/0.18	GMTED2010[6]
Land use	LUF	Fraction of catchment area covered by forest and seminatural areas	%	31.66/54.59/79.62	CORINE[7]
	LUW	Fraction of catchment area covered by water bodies	%	0/0.05/0.57	CORINE[7]
Soils	Stex	Dominant surface textural class of the STU (Soil Typological Unit), mean value of categories (1=coarse, 5=fine)	class	1.77/2.00/2.25	ESDB[8]

2.2 Hydroclimatic regions

For the statistical analyses, Europe was subdivided into five regions based on ~~a particularization of~~ the eleven biogeographic regions of Roekaerts (2002) and guided by the flood seasonalities of Blöschl et al. (2017) and Hall et al. (2018). In the Northeastern region, floods are mainly due to snowmelt during spring and early summer. The Atlantic region is characterised by mild, wet winters and cool, humid summers; floods mainly occur in winter following rain events. The Central-Eastern region has a continental climate with cold winters and warm summers and floods mainly occur in spring with snow-melt contributions. The Alpine region comprises ~~involves~~ the Alps and the Carpathians, where floods mainly occur in summer due to summer storms and/or snow melt. The Mediterranean region is characterised by hot, dry summers and mild, wet winters; floods occur in autumn and winter. For simplicity, each catchment was allocated to one of the regions according to the location of its stream gauge.

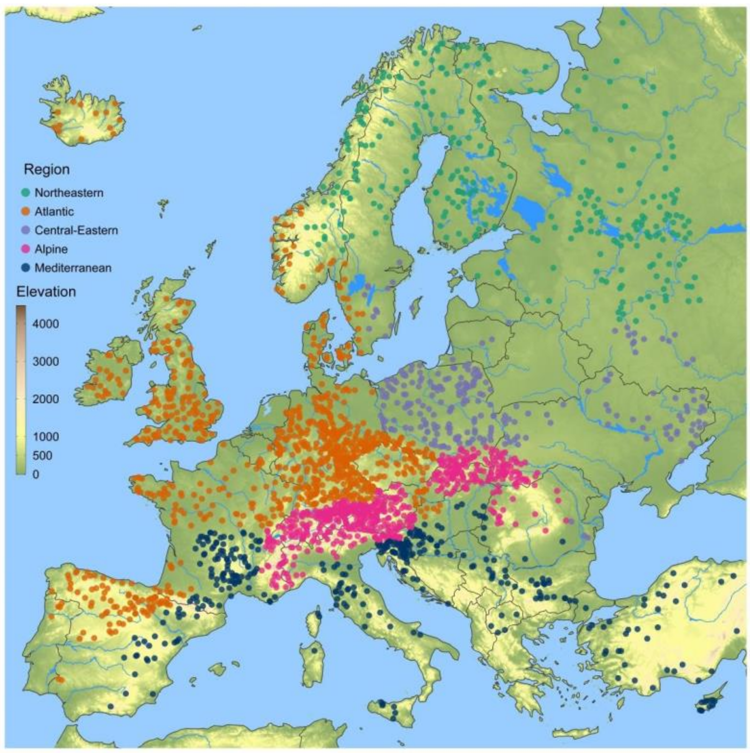


Figure 1: Location of the 2370 hydrometric stations analyzed. Colours of dots indicate five hydro-climatic regions (Northeastern, Atlantic, Central-Eastern, Alpine, Mediterranean). Background colour is elevation (m a.s.l.).

2.3 Analysis method

The statistical flood moments, the specific mean annual flood (MAF), the coefficient of variation (CV) and the coefficient of skewness (CS), were estimated from the annual maximum peak discharges series by:

Commented [A27]: What about lower-altitude streamgages draining primarily alpine catchments? How often is this is an issue? Generally, it looks like you have a reasonable alpine region

Commented [A28]: Make NE region color standout more. Its shade of blue is too similar to the dark green lowlands and plentiful blue lakes of this region

$$MAF = \frac{1}{n}\sum_{i=1}^{n} Q_i \quad (1)$$

$$S^2 = \frac{1}{n-1}\sum_{i=1}^{n}(Q_i - MAF)^2 \quad (2)$$

$$CV = \frac{S}{MAF} \quad (3)$$

$$CS = \frac{n\sum_{i=1}^{n}(Q_i - MAF)^3}{(n-1)(n-2)S^3} \quad (4)$$

where Q_i is the annual maximum peak discharge of a record in year *i*, divided by the catchment area. Estimation uncertainty of the statistical flood moments decreases with record length and increases with the moment order. While the estimation uncertainty of the mean is small, the uncertainty of CS can be substantial. For a record length of 50 years and a series with the average estimated moments of the entire dataset (MAF=0.17 m³ s^{-1} km^{-2}, CV=0.52, CS=1.28), the standard error of the CS estimate is σ_{CS}= 0.56, which is about half of the underlying true moment (assuming a GEV-distribution as the data-generating process). The estimation uncertainties need to be accounted for when interpreting the process controls on the flood moments. Since the specific mean annual flood is often strongly controlled by catchment area which may mask other controls that vary regionally, we ~~additionally~~ also considered the specific mean annual flood, MAF_α, normalised to a catchment area of α=100km²

$$MAF_\alpha = MAF A^{-\beta MAF} \alpha^{\beta MAF} \quad (5)$$

MAF_α and β_{MAF} were found by ordinary least squares regression.

~~In a first step~~First, we estimated what fraction of the spatial variability of the estimated flood moments can be explained by subdividing Europe into five regions (Figure 1), using a simple one-way analysis of variance (ANOVA). This can be interpreted as a simple regression model, where the dependent variables are the estimated flood moments and the only explanatory variables are indicators corresponding to the regional partition. The coefficient of determination of this model corresponds to the fraction of variance explained by the partition over the total variance in estimates of the flood moments.

~~In a second step~~Second, we evaluated the role of catchment area, since it is almost always the main control on the mean annual flood when examining a sample of catchments varying by orders of magnitude, and it reflects the aggregation behaviour of the floods and ~~its~~ their climatic and catchment controls. Specifically, we estimated the dependence of MAF, CV and CS on catchment area in a double logarithmic relationship from Eq. (5) and analogous equations for CV and CS.

~~In a third step~~Third, we conducted a seasonality analysis to assist in the process interpretations. We represented the date of occurrence, *D*, of the maximum annual flood as a number from 1 to 365 (Julian dates) in polar coordinates on a unit circle with angle $\theta = D\frac{2\pi}{365}$. For a flood series, the direction $\bar{\theta}$ of the average vector from the origin indicates the

Commented [A29]: Is there a reference describing the computations you made?

Commented [A30]: In your discussion, consider commenting on Salinas et al. (2014) who investigated how well the GEV distribution performed throughout Europe

https://www.researchgate.net/publication/267865581_Regional_parent_flood_frequency_distributions_in_Europe_-_Part_1_Is_the_GEV_model_suitable_as_a_pan-European_parent

Commented [A31]: Transforming both sides logarithmically before fitting? How well did this equation fit the data? Please present goodness-of-fit stats and a graphic in the SI.

Commented [A32]: Log-log? Where both the independent and dependent variables are log-transformed?

Commented [A33]: Nice. Try to emphasize this throughout the paper a bit more.

mean date of occurrence of the flood events around the year. The length of the vector from the origin is a measure of the variability of the date of occurrence, ranging from 0 (uniformly distributed across the year) to 1 (all events on the same day).

In a fourth step, we analysed the effects of individual hydro-climatic controls (see Table 1) on the spatial distribution of the flood moments. ~~We used the attributes of Table 1 for the analysis.~~ To assist in the interpretation, we first evaluated the Spearman rank correlation coefficients between the attributes, followed by an analysis of the Spearman rank correlation coefficients between the flood moments and the attributes. We used Spearman's rank correlation coefficients, as non-linear associations between variables are possible. The corresponding significance tests for the estimates of Spearman's rho are employed with the assumption of an asymptotic t distribution under the ~~Null~~ null ~~Hypotheses~~ hypotheses (Gibbons and Chakraborti, 2010). The correlations were evaluated for all of Europe and the five regions separately.

In a fifth step we evaluated the effect of multiple controls on the flood moments. Multiple linear regression models were fit~~ted~~ to the estimated moments. The emphasis was on obtaining parsimonious models, therefore the number of selected variables for a regression equation was limited to four. The variables were log-transformed if feasible. The attributes were selected according to a stepwise selection procedure (Weisberg, 2005). The criterion for model comparison was Mallow's Cp

$$C_p = \frac{RSS_p}{\hat{\sigma}^2} + 2p - n \qquad (6)$$

where p refers to the number of coefficients in the current model including the intercept and n to the number of observations. RSS_p is the residual sum of squares of the model being considered with p covariates and $\hat{\sigma}^2$ is the residual error variance of the model including all possible covariates. For the comparisons of information criteria such as C_p, a complete set of observations is required, therefore 22 catchments, where some observations of covariates were not available, were excluded from this part of the analysis.

In order to assess which of the covariates in each regression provided the most explanatory power, a dominance analysis was conducted (Azen and Budescu, 2003). We used the measure for general dominance, which summarizes the average increase in the measure for the goodness of fit, when a given covariate is included in a regression model, for all possible model subsets for a fixed set of predictors. The sum of all measures for general dominance of each variable results in the R^2 of the full regression. The general dominance measure (average contributions) provides a ranking of the variables in terms of their contributions to the fit of the models (R^2). However, this is only valid in the context of the model and the selected variables. These contributions can and most likely will change when variables are added to or subtracted from the regressions. To facilitate the interpretation of results, in section 3.5 we present the general dominance measure of individual covariates, divided by the R^2 of the regression, and refer to this as the normalised general dominance measure. This does not affect the ranking of the variables.

Commented [A34]: Nice description. Did you formally test any hypotheses related to seasonality using circular stats?

Commented [A35]: And are a limitation of the regression analysis

Commented [A36]: Just the explanatory variables? Or also the peak flows?

Commented [A37]: Can you note which ones were excluded in SI or Git repo?

In a sixth step the predictive accuracy of the fitted regression models was assessed in a leave-one-out cross-validation. The errors are evaluated on the scale of the data, instead of the scale of the regression models (i.e. log scale) and normalized, e.g. in the case of the MAF:

Commented [A38]: Good. Can you mention earlier that you log-transformed the moment values after computing them in real-space? (At least this is what it sounds like you did)

$$ANE_{MAF} = \left|\frac{MAF-MAF}{MAF}\right| \qquad (7)$$

ANE stands for absolute normalized error. MAF are the predictions of the regression models and MAF are the at-site estimates. The analogous holds for CV.

Commented [A39]: Are subscripts missing here or is this a pdf conversion issue?

In addition, ordinary kriging is used for interpolating the at-site estimates of flood moments (Cressie, 1993) and the interpolated values are contrasted with the predictions of regional regression models.

Commented [A40]: The kriging results look visually pleasing and reveal broad spatial patterns, but what if nearby basins have greatly different drainage areas or pronounced diffs in other catchment characteristics that can change abruptly? In the future, you could consider kriging in attribute space instead if all your covariates can be gridded. In this paper (or another one), you should consider stating the limitations of this kriging analysis and perform a split-sample validation experiment to see how well it does at ungaged locations. You could also take this out and make it a separate paper.

3. Results

3.1 Characteristics of flood moments

Table 2 shows the characteristics of the estimated flood moments for the five hydroclimatic regions and the entire data set. On average over the entire data set, the mean specific annual flood is 0.17 m³ s^{-1} km^{-2}, while the mean specific annual flood normalised to a catchment area of 100 km² (MAF_{α}) is 0.21 m³ s^{-1} km^{-2}. The latter is somewhat larger, as 100 km² is smaller than the median catchment size of 383 km². On average over the entire data set, the CV and CS are 0.52 and 1.28, respectively. The regions differ in terms of the moments. The largest average MAF_{α} occurs in the Alpine region and in the Mediterranean (0.30 m³ s^{-1} km^{-2}). The smallest average MAF_{α} (0.05 m³ s^{-1} km^{-2}) occurs in the Central Eastern region, but this is also the region where the average CV and CS are largest (0.69 and 1.59, respectively). On the other hand, the Northeastern region has the smallest average CV and CS (0.39 and 0.82, respectively).

Commented [A41]: Consider showing histograms

The coefficient of determination R^2 of the one-way ANOVA is an indicator of how much of the spatial variability is explained by the partitioning into the five regions. The partitioning explains 17% of the spatial variance of MAF_{α}, but only 9% and 5% of the spatial variance of CV, CS, respectively. This means that the spatial variability of CV and CS within ~~the regions of CV and CS~~each region is similar to that over all of Europe. Part of that variability may be sampling uncertainty, but Figure 2 indicates that, at least for MAF_{α} and CV, there are clear spatial patterns ~~which, however,~~ that are not aligned with the regions. As the regions have not been chosen to reflect flood magnitudes but ~~a range of~~ rather a range of hydro-climatic processes, this is not surprising.

Commented [A42]: In other words, most of the variability lies within the regions and not between them.

Commented [A43]: Something to think about: how much of the partitioning would the regions explain if you considered of basins different sizes separately?

The largest MAF_{α} occur in wet, mountainous regions, including the Alps, the Appenines (Italy), the Carpathian Flysch Belt, adjacent to the Ligurian and Adriatic Seas, the Languedoc, and the western coasts of Great Britain and Norway~~, which are all high rainfall areas~~. The lowest MAF_{α} occurs in much flatter regions, such as the North and East European Plains, Dnieper Lowland, Finnish Lakeland and southern Sweden and south-eastern England (Fig. 2c). MAF_{α} exhibits slightly more homogeneous spatial patterns than MAF, as the effect of catchment size has been removed. The spatial distribution of CV is, to some degree, a mirror image of that of MAF_{α}, as CV and MAF_{α} are slightly negatively correlated with a Spearman correlation coefficient of r=-0.12 (-0.06 for CV vs MAF). However, there are deviations from this general pattern. Along the

Commented [A44]: Does this mean that you have larger catchments in some regions than others?

Mediterranean coast between ~~Genua~~ Genoa, Italy and Valencia, CVs are rather large even though MAF_α are large ~~too~~as well. The spatial ~~distribution~~ coherence of CS is less apparent, as roughly half the spatial variability is likely attributable to sampling variability (the standard error of the CS estimate for average parameters is σ_{CS} = 0.56). However, there seems to exist a general pattern of larger than average CS along the Mediterranean coast and the mountainous areas of Europe, and smaller than average CS in Scandinavia and northern Russia. There is a strong positive Spearman correlation between CS and CV (r=0.63), which points towards non-linear runoff generation processes affecting both CS and CV (Rogger et al., 2013), although, again, the correlation may be partly due to the sampling variability resulting in correlations between the estimators of CV and CS (see chapter 10 in Kendall and Stuart, 1969).

Commented [A45]: Flashy mountainous watersheds with high rainfall

Commented [A46]: Consider mentioning the extremely low R^2 here

Commented [A47]: Interesting since Cs is normalized by sd^3. An increase in sd raises Cv but lowers Cs.

Table 2: Regional mean (m) and ~~regional~~ coefficient of variation (cv) of the mean annual specific flood (MAF, ($m^3 s^{-1} km^{-2}$)), mean annual specific flood normalised to catchment area of $100 km^2$ (MAF_α, ($m^3 s^{-1} km^{-2}$)), coefficient of variation (CV) and coefficient of skewness (CS) for the entire data set and the five regions. n is the number of stations per region. R^2 is the fraction of the spatial variance explained by the partitioning into the five regions.

	Europe (n=2370)		Northeastern (n=288)		Atlantic (n=875)		Central-Eastern (n=236)		Alpine (n=622)		Mediterranean (n=349)		R^2
	m	cv	m	cv	m	cv	m	cv	m	cv	m	cv	
MAF	0.171	1.114	0.126	0.939	0.137	0.981	0.037	1.095	0.264	0.816	0.222	1.223	0.140
MAF_α	0.211	0.961	0.176	0.655	0.166	0.875	0.047	0.942	0.304	0.728	0.304	0.938	0.173
CV	0.518	0.492	0.386	0.347	0.494	0.435	0.695	0.583	0.516	0.381	0.571	0.529	0.090
CS	1.278	0.773	0.821	0.779	1.216	0.882	1.59	0.727	1.466	0.565	1.263	0.785	0.047

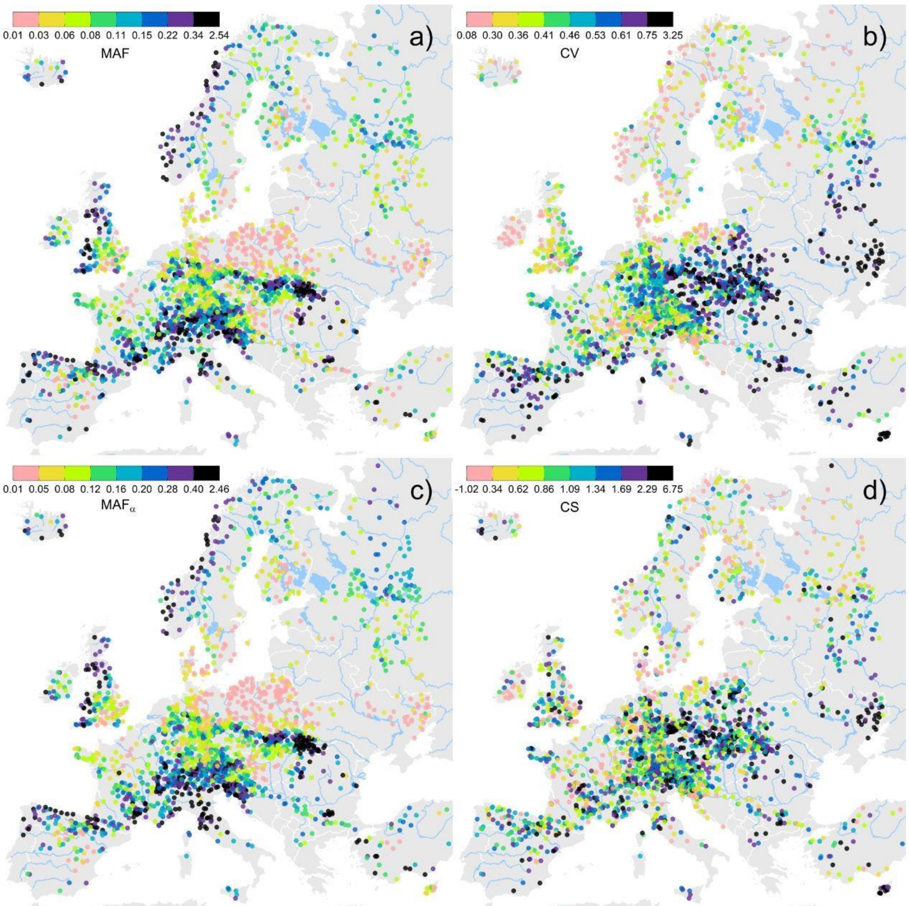


Figure 2: Mean specific flood (MAF ($m^3 s^{-1} km^{-2}$)) (a), Coefficient of variation (CV) (b), Mean specific flood normalised to a catchment area of $100 km^2$ (MAF_{α} ($m^3 s^{-1} km^{-2}$)) (c), and Coefficient of skewness (CS) (d). Colours represent the estimate partitioned into eight classes of equal frequency.

3.2 Seasonality and flood moments

As an indicator of flood processes, the average direction of seasonality θ and the strength of seasonality *k* are plotted in Figure 3 for each catchment (see Figure 3 in Blöschl et al., 2017, for the spatial distribution). The closer the points are to the edge of the circle, the stronger the seasonality. Additionally, the magnitudes of MAF_{α}, CV and CS are indicated as colours as in Figure 3. The red circles in Figure 3 highlight geographic regions that are roughly homogeneous with respect to seasonality and the magnitude of the estimated flood moments, which were identified by examining seasonality maps (Blöschl et al., 2017).

In Northeastern Europe floods mainly occur in spring and early summer with a strong seasonality reflecting the role of snowmelt. MAF_{α} are in a medium range (green in Fig. 3) with the exception of the Norwegian coast (circle 1) where

MAF$_\alpha$ are much larger but with little seasonality because there is a mix of spring snow melt floods and winter rain floods (Kemter et al., 2020). The CVs of these catchments are small. On the other hand, floods in ~~Western~~ western Russia almost always occur in April with a large CV (circle 3). The June floods further in the North, adjacent to the White Sea, have much smaller CV because of a more consistent snow~~-~~melt influence (Kemter et al., 2020, circle 2).

In the northwestern part of the Atlantic region (Ireland, west coast of the UK), floods tend to occur in December and the estimates of MAF$_\alpha$ are large (circle 4). ~~In the~~ East of the Atlantic region (Southern Germany, Czech Republic, circle 5) the average occurrence of floods is in late spring, although the seasonality is weak but CVs are large.

In the Central-Eastern region (Poland, Ukraine, circle 6) where floods usually occur in spring, the MAF$_\alpha$ are generally low and the CVs are large.

The catchments in the Alpine region with summer floods (circle 9) show high MAF$_\alpha$ due to rainfall enhancement of the Alps. The catchments with autumn floods in Southern Austria and Slovenia (circle 7) exhibit very high MAF$_\alpha$ due to ~~a~~ the stronger influence of the Mediterranean Sea. ~~The~~ This region also contains the Carpathians and adjacent midlands (circle 8) where floods tend to occur in spring with lower MAF but rather high CV, likely because of a mix of snow, rain-on-snow and rainfall floods.

The Mediterranean region contains catchments with mostly winter floods with rather high MAF$_\alpha$. The autumn flood catchments in Slovenia have particularly high MAF$_\alpha$ (circle 10) and low CV while the catchments with spring floods on the Balkans (circle 11) possess medium MAF$_\alpha$ and CV.

Commented [A48]: Is this variability mainly due to snow cover, melt timing or also rain-on-snow events?

Commented [A49]: Is their CV large due to interannual snowpack variability? Timing issues with spring thaws? Mixture of spring rains and snowmelt?

Commented [A50]: Snow or rain-driven? Or both?

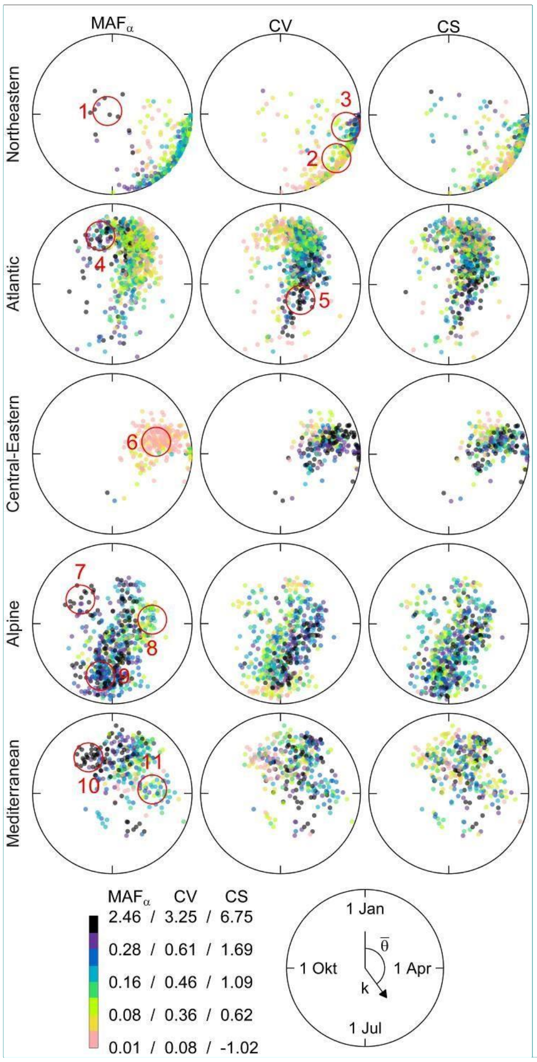


Figure 3: Seasonality of annual flood peaks. Position in circle indicates mean date of occurrence (angle) and variability of the date (inverse of distance from centre). Each point represents one catchment. Colours of the points indicate flood moments as in Figure 2. Small red circles highlight subregions referred to in the text (1: Norwegian coast, 2: Northwestern Russia, 3: Western Russia, 4: Western UK and Southwestern Norway, 5: Southern Germany and North of Czech Republic, 6: Parts of Poland and Ukraine, 7: Southern Austria and Northern Slovenia, 8: Alpine and Carpathian midlands, 9: Alpine region, 10: Slovenia and Southern France, 11: Balkans)

Commented [A51]: Nice figure

Commented [A52]: I like these circled areas

3.3 Scaling of flood moments with catchment area

The first control on the flood moments examined here is catchment area, as it is often the dominant and best understood control (Table 3, Fig. 4). The highest decrease in the mean annual flood (MAF) with catchment area occurs in the Mediterranean and the Alpine region with $\Box_{MAF}$ =-0.255 and -0.208, respectively, while the weakest the smallest decreases occur in the Northeastern and Central Eastern regions ($\Box_{MAF}$ =-0.163 and -0.108) where snow~~-~~melt is important. The coefficient of variation (CV) of the flood records ~~(CV)~~ decreases with catchment area in most regions. Again, the strongest decrease occurs in the Mediterranean while in the Northeastern and Central Eastern there is no significant relationship. There are few small catchments in the Central-Eastern region, which may make the regression with area less robust. Overall, there is a tendency for CS to decrease with catchment area and the strongest decrease occurs again in the Mediterranean.

Commented [A53]: Good obs

Commented [A54]: Could the paucity of small basins in Central-Eastern Europe contribute to the positive relation between Cs and basin area there?

Table 3: Dependence of the flood moments with catchment area in a double logarithmic relationship Eq. (5) and analogous equations for CV; and a semi logarithmic relationship for CS, i.e. $CS = \log A\, \beta_{CS}$. Last lines show the 5% and 95% quantiles of catchment area (km²). * indicates statistical significance (two-sided t-test) at the 5% level.

	Europe	Northeastern	Atlantic	Central-Eastern	Alpine	Mediterranean
$\Box_{MAF}$	-0.245*	-0.163*	-0.184*	-0.108*	-0.208*	-0.255*
$\Box_{CV}$	-0.030*	-0.015	-0.042*	0.025	-0.020*	-0.072*
$\Box_{CS}$	-0.133*	-0.054	-0.124*	0.280*	-0.177*	-0.232*
5% / 95% quantiles of area (km²)	35/11500	28/18010	37/5331	142/32509	26/4212	47/27251

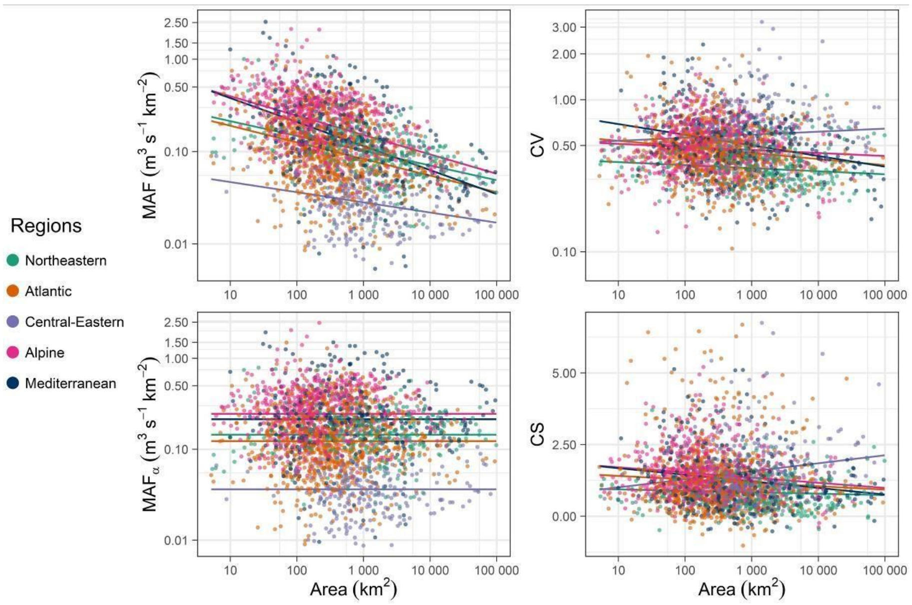


Figure 4: Mean annual specific flood (MAF), normalised mean annual specific flood (MAF_{α}), coefficient of variation (CV) and coefficient of skewness (CS) plotted against catchment area (km²). Colours indicate region. Lines are regression lines for each of the regions.

3.4 Individual controls on flood moments

When interpreting the association of climate and catchment attributes with flood characteristics, it is important to account for the correlation between the attributes themselves, which may mask causal relationships. Spearman correlation coefficients have therefore been estimated among all explanatory variables (Figure 5). The largest correlations occur among the precipitation characteristics, all of which are at least *r*=0.86. The correlation between long-term mean precipitation (MAP) and daily precipitation not -exceeded 95% of the time (P95) is even 0.96, indicating that the spatial patterns of these two variables in Europe are almost identical. The correlation between soil moisture (SM) and the precipitation variables is at least 0.78, and the correlation between the aridity index (AI) and the precipitation variables varies between -0.63 and 0.84. The latter may be partly related to the fact that AI is the ratio of potential evaporation (PET) and MAP. PET is related to spring temperature (*r*=0.73). Elevation and slope are closely related to each other (*r*=0.88) and they are also closely related to the precipitation variables with *r* of at least 0.56, reflecting orographic influences on precipitation. Forest cover (LUF) is related to elevation and slope (*r*= 0.67 and 0.72, respectively) reflecting the presence of forest in mountain areas. The positive correlation between lake area fraction (LUW) and catchment area (*r*=0.45) results from a tendency for large catchments to contain lowlands where lakes are more frequent than in the mountains, and the positive correlation between soil type (Stex) and spring temperature (Tspr) (*r*=0.37) is due to coarse soils prevailing in the (colder) north of Europe. Fig. 5 also shows 2d histograms of the variables as well as their kernel density estimates.

Commented [A55]: 95th percentile daily precipitation

Commented [A56]: CHECK correlation between precipitation and forest cover

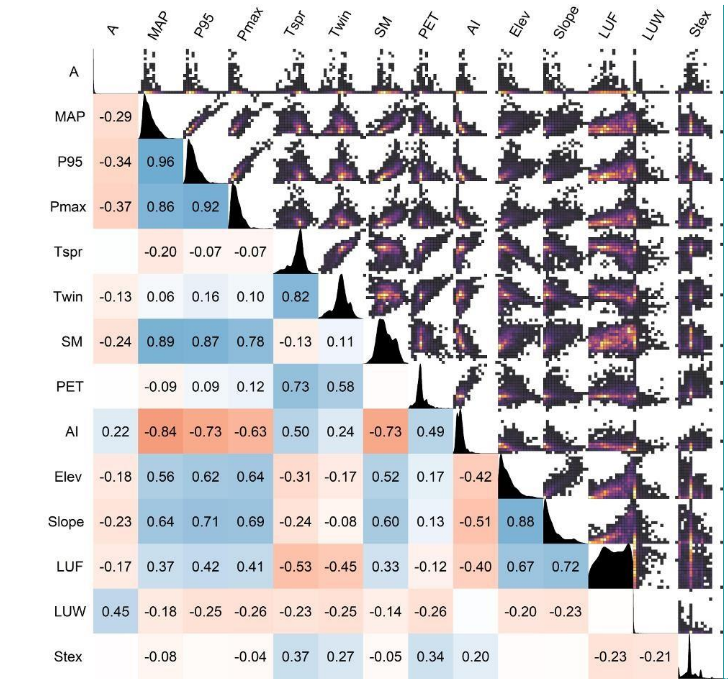


Figure 5: Correlation between explanatory variables as in Table 1. For each variable the data consist of n=2370 values, i.e. the number of catchments. Lower triangle: Spearman correlation coefficients. They are shown if they are statistically significant (α=0.05). Blue and red indicate positive and negative relationships, respectively. Upper triangle: 2d-histograms with colours indicating the frequency of observations in the bins (dark: few; bright: many, separate scale for each panel). Diagonal: kernel density estimate. All scales are linear.

Figure 6 gives the Spearman correlations of the flood moments MAF_α and CV with catchment attributes. We mainly examine MAF_α instead of MAF in order to minimise the effect of spatial differences in the catchment area on the correlations with the flood moments that may mask the direct effects of other variables. The correlations for CS are often weaker and more difficult to interpret, at least partly due to estimation uncertainty.

The corresponding correlations for MAF and CS with catchment attributes are given in Table A.1.5 in the Appendix.

While the correlations between MAF_α and catchment area are ~~of course~~inherently small in all regions (Table 4), the correlations between MAF and catchment area (Table A.1.5, appendix) are significant in all regions ranging between 0.31 and 0.48, with the exception of central Eastern where it is only 0.23, which may be related to the more important role of snowmelt there. Overall, in Europe, the relative large explanatory power of catchment area points to an important role of scale effects, although, in most regions, it is not the variable with the ~~largest~~ largest correlation~~r~~.

Commented [A57]: In which region are the largest basins?

Commented [A58]: Good

Commented [A59]: Explain a bit more. How might snowmelt temper this correlation?

MAF$_\alpha$ is significantly positively correlated with MAP in all regions (Figure 6) a~~,~~nd ~~the~~ its correlations with P95 and Pmax are similar. These high correlations may reflect the effect of not only event rainfalls, but also soil moisture as well as landscape evolution (Perdigão and Blöschl, 2014), as all rainfall variables as well as soil moisture are highly inter-correlated

(Figure 5). The correlations between MAF$_\alpha$ and precipitation (both MAP and P95) are largest in the Atlantic region, reflecting the dominant role of precipitation in explaining the spatial variability of MAF$_\alpha$ in this part of Europe. CV is significantly negatively correlated with MAP, P95 and Pmax, for almost all regions. The strongest relationship is observed in the Alpine and Mediterranean region. In drier catchments, the occurrence of floods is more irregular (large CV, e.g. in Spain) as opposed to wetter catchments where every year rather large floods occur (small CV e.g. in Norway).

One would expect the strongest correlations between flood moments and temperature in the regions with important snow~~-~~melt contributions (Northeastern, Central-Eastern regions), and this is actually the case (Figure 6). Spring (March-May) and winter (December-February) temperature are negatively correlated with MAF$_\alpha$ and positively correlated with CV.

The correlations between the flood moments and mean annual maximum monthly soil moisture (SM) are very similar to those with MAP as the two covariates are correlated with r=0.89. There are high positive correlations of MAF$_\alpha$, ~~in particular~~especially in the Atlantic and the Mediterranean, ~~and correspondingly~~but strongly negative correlations between CV and soil moisture. On the other hand, there is a small negative correlation between MAF$_\alpha$ and the mean annual potential evapotranspiration (PET) in all regions, ~~which can be interpreted in PET generally~~ as a higher PET generally reduces~~ing~~ the antecedent wetness conditions of floods and hence the flood discharges. More striking are the CVs that are strongly positively correlated with PET in most regions with *r* ranging between 0.1 and 0.7. Since ~~T~~the aridity index (AI), defined as the ratio of PET and MAP, it has correlations ranging around those of PET and/or the inverse of MAP (i.e. –r). The highest values of AI are observed in the Mediterranean region, where ~~high~~ strong negative correlations ~~(in absolute value)~~ are observed for all flood moments.

Mean catchment elevation (Elev) and mean topographic slope (Slope) are highly correlated with each other (r= 0.88) and therefore have similar correlations with the flood moments in most regions. MAF$_\alpha$ is highly positively correlated with both elevation and slope across all regions of Europe ~~similar to~~just as it is with the rainfall variables, which point~~ing~~s to an indirect effect of topography on mean floods through precipitation. This is consistent with high correlations of elevation and slope to the precipitation variables (around 0.6 and 0.7, respectively, Fig. 5).

MAF$_\alpha$ is positively correlated with the fraction of area covered by forest (LUF) in all regions and negatively correlated with the fraction of area covered by water bodies, i.e. lakes and reservoirs, (LUW) in most regions, including in the region with the largest fraction of water bodies (the Northeastern region where the median LUW is 5.7%). The positive correlation between MAF$_\alpha$ and LUF is most likely due to an indirect relationship, as areas with high forest cover tend to be high-elevation regions such as mountains, where precipitation is augmented through orographic effects.

While there is little correlation between MAF$_\alpha$ and soil texture, there is a clear effect of soil texture on CV with finer soils (Stex=5) being associated with higher CVs than coarse soils (Stex=1).

Commented [A60]: Not sure this is necessary to report in the text.

Commented [A61]: Good observation. I suggest adding a sentence saying that this should NOT suggest that deforestation reduces floods..

Commented [A62]: Explain this in terms of infiltration being greater in coarser soils, which tend to be more permeable

	Europe		Northeastern		Atlantic		Central – Eastern		Alpine		Mediterranean	
	MAF_α	CV	MAF_α	CV	MAF_α	CV	MAF_α	CV	MAF_α	CV	MAF_α	CV
A	-0.12	-0.13		-0.16		-0.19						-0.25
MAP	0.59	-0.33	0.15	-0.23	0.67	-0.33	0.24	-0.49	0.26	-0.61	0.48	-0.68
P95	0.60	-0.22			0.66	-0.22	0.31	-0.19	0.24	-0.58	0.52	-0.59
Pmax	0.55	-0.05			0.52	0.14	0.22	-0.18	0.26	-0.40	0.49	-0.36
TSpr	-0.22	0.26	-0.35	0.58	-0.29			0.50	-0.14	0.38	-0.12	0.17
TWin	-0.07	0.04	-0.20	0.20		-0.23	-0.33	-0.52	-0.10	0.10		0.27
SM	0.57	-0.31	0.16	-0.14	0.55	-0.29	0.28	-0.40	0.22	-0.56	0.50	-0.64
PET		0.39	-0.33	0.60	-0.22	0.34		0.68	-0.11	0.11	-0.21	0.63
AI	-0.53	0.46	-0.36	0.62	-0.53	0.38		0.63	-0.31	0.50	-0.43	0.69
Elev	0.55	0.08	0.47	-0.31	0.44	0.35	0.50	0.21	0.16	-0.47		0.20
Slope	0.65		0.39	-0.36	0.62	0.17	0.30		0.24	-0.40	0.37	
LUF	0.45	-0.10	0.28		0.45	0.14		-0.39	0.16	-0.26	0.32	
LUW	-0.16	-0.27	-0.21	-0.22		-0.20	-0.55	-0.50		-0.19		-0.19
Stex	-0.06	0.29		0.37		0.17	0.32	0.53		0.23	-0.18	0.26

Figure 6: Spearman-Correlation between statistical moments of flood series (mean specific discharge normalized to a catchment area MAF_α of α=100km^2 and the coefficient of variation CV) and catchment attributes. Correlations are shown if they are statistically significant (α=0.05). Blue and red indicate positive and negative relationships, respectively. The correlations for mean specific discharge MAF and coefficient of skewness CS with catchment attributes are given in Table A.1.5.

Commented [A63]: Is it worth going to into so much detail about the bivariate correlations when there are so many confounding factors, as you seem to recognize?

Commented [A64]: Suggest adding dark vertical lines to separate each region's results if possible

3.5 Multiple controls on the flood moments

While Figure 6 examines the relationships between flood moments and single covariates using Spearman correlation coefficients, in this section we test the relationship between flood moments and multiple covariates with regression models applied for each of the regions separately. Thus, the covariates with the largest contributions are those that explain most of the R^2 of the spatial variability of the flood moments within each of the regions. We used MAF, rather than MAF_α, in order to avoid prior assumptions regarding the role of catchment area. Given that CS was correlated with fewer covariates than the other flood moments, we focused here on MAF and CV (Table A.1.5). We represent each of four most important groups of covariates (area, precipitation, temperatures and water balance) by one covariate. The contributions to explaining the spatial variability of MAF in terms of the normalised general dominance measure (nGDM) are shown in Figure 7 and Table A.1.3 and are discussed below by region.

In Northeastern Europe, like in all regions, catchment area is an important predictor of MAF. Additionally, P95 and AI play an important role representing an East-West gradient with the largest MAF, largest P95 and the lowest AI in Norway.

In the Atlantic region, P95 is by far the most relevant covariate (nGDM= 0.8) as one would expect in a region where floods are rainfall driven and soil moisture tends to be high in the flood season (winter) (Blöschl, Hall et al., 2019 ; Kemter et al., 2020).

In the Central-Eastern region MAF is generally low with little spatial variability. The corresponding R^2 is small (Table A.1.1), as it is harder to explain the small spatial contrast. The largest contribution is winter temperature and P95. Negative coefficients for winter temperature ~~point to~~suggest that lower temperatures produce~~driving~~ deeper snow~~-~~packs and, in turn, higher floods.

In the Alpine region, area is most important and in fact relatively more important than in any other region. However, the R^2 of the model in the Alpine region is low.

In the Mediterranean catchment area is important (NGDM= 0.43), which is due to the small coastal catchments exhibiting much larger specific floods than the larger catchments that extend further ~~into the~~in~~-~~land, e.g. in Catalonia (Spain), Liguria (Italy), and Slovenia (e.g. Gaume et al., 2009). Additionally, P95 plays a relevant role.

Commented [A65]: Not normalized by area at all?

Commented [A66]: Is it worth including so much about Cs then?

Commented [A67]: What is the water balance group? Look at interaction effects?

Commented [A68]: Perhaps a proxy variable for snowmelt-driven floods is needed there

Also, do smaller headwater basins in the Alpine regioun have more snow cover and, if so, do they generate larger floods than larger ones with less snow cover?

Commented [A69]: Good interpretation

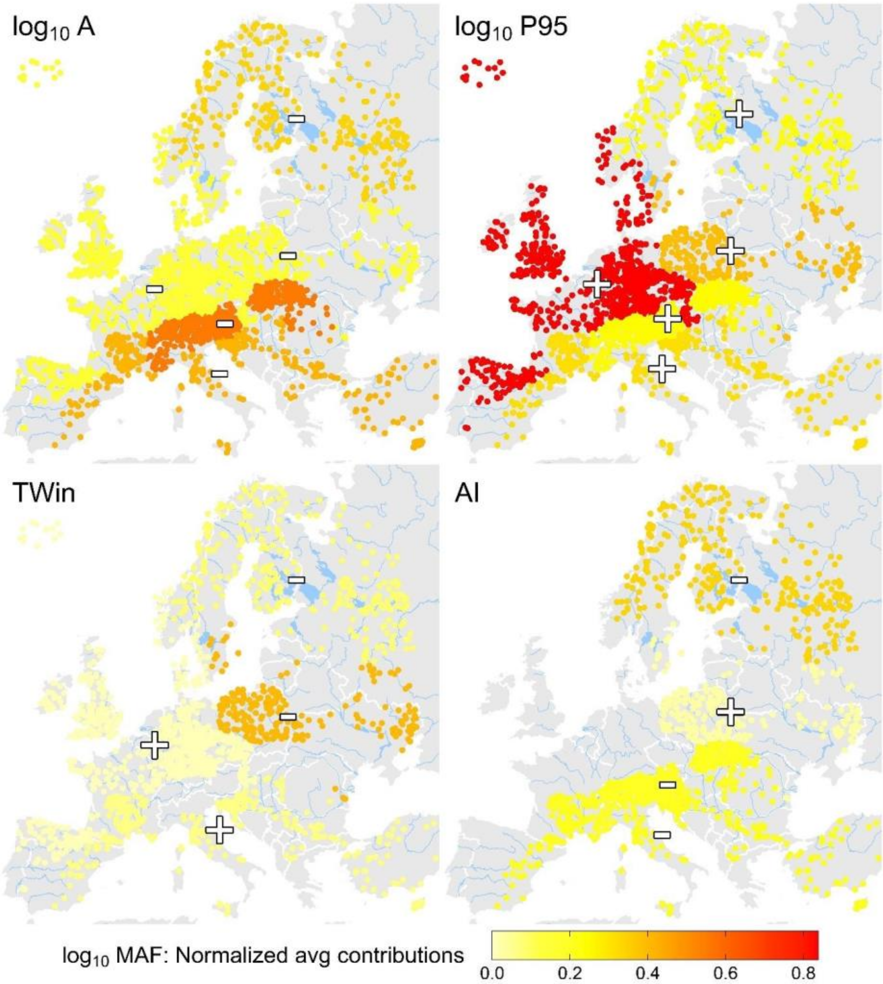


Figure 7: Results of dominance analysis for regional regression models for MAF. Panels depict the average contributions (normalised general dominance measure, nGDM) of the covariates included in the regressions (log of catchment area, log of extreme precipitation index P95, mean winter temperature and aridity index). Plus- and Minus-signs indicate sign of the regression coefficients.

For CV (Figure 8, Table A.1.4), in the Northeastern region the Aridity index (AI) is the most important covariate by far. This is due to Scandinavia being much wetter than ~~Northwestern~~ northwestern Russia translating into lower CVs.

In the Atlantic region AI is the most important variable for explaining the spatial variability of CV although the overall explanatory power of the regional model is rather low (R^2 of 0.27, Table A.1.2). The smaller CV closer to the ocean in the Atlantic region is partly explained by higher winter temperatures.

Commented [A70]: Please put all regional R^2 in parentheses as you describe them in the text. Also, it might help to put this table in the main text.

Check for other instances of this throughout the manuscript.

Commented [A71]: Please tell readers how higher winter temperatures lead to lower Cv's here.

In the Central-Eastern region AI dominates again with higher CV in the Ukraine correlated with higher aridity than further in the West, both due to higher PET and lower MAP.

The Alpine region is an exception in that P95 explains more of the spatial variability of CV than AI (nGDM of 0.54 and 0.35, respectively). This is because PET is negatively related to elevation but the flood magnitudes are controlled by the higher orographic rainfall on the windward (NW) side of the Alps.

Commented [A72]: Good analysis

In the Mediterranean both aridity and P95 are important predictors. For example, low aridity (because of high MAP) in Croatia and Slovenia is associated with low CV, and high P95 in Southern France is associated with moderately low CV.

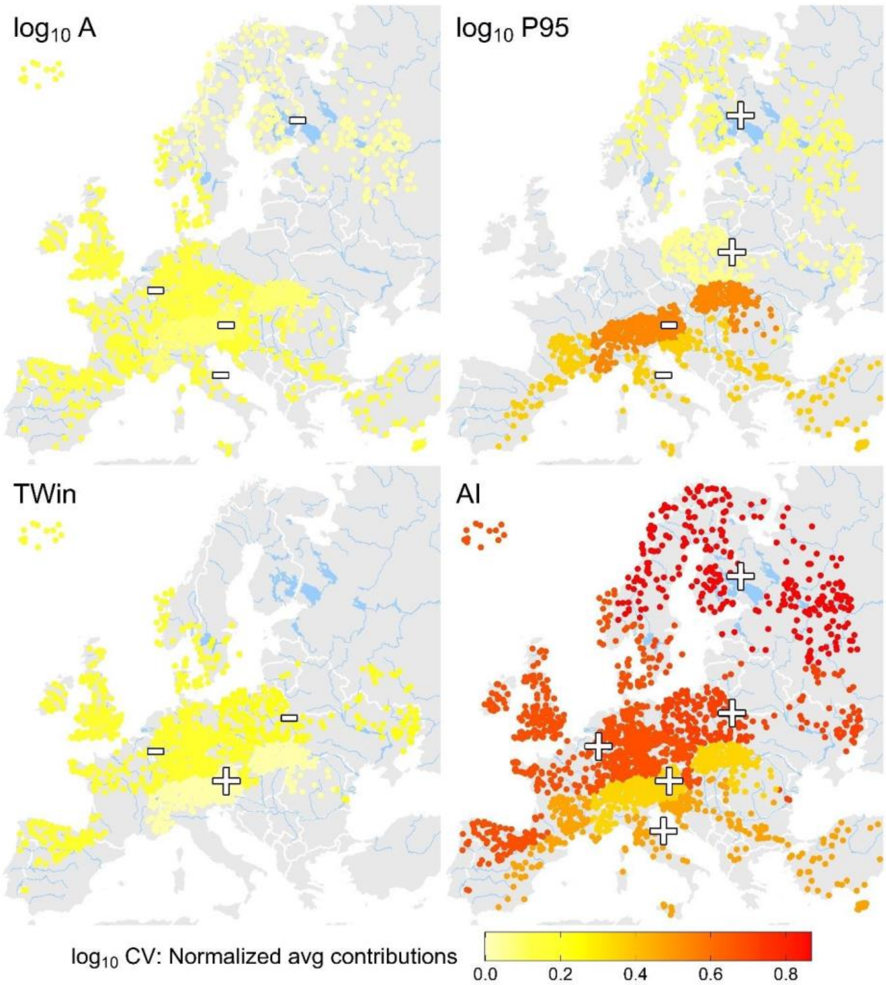


Figure 8: Results of dominance analysis for regional regression models for CV. Panels depict the average contributions

(normalised general dominance measure, nGDM) of the covariates included in the regressions (log of catchment area, log of extreme precipitation index P95, mean winter temperature and aridity index). Plus- and Minus-signs indicate sign of the regression coefficients.

Commented [A73]: If insignificant no sign shown? Please clarify this.

3.6 Estimating flood moments from multiple controls

In this section we analyse~~s~~ how well the regression models of the previous section (where A, P95, TWin and AI were used as covariates) are able to predict the moments at any location ~~in terms of~~using a leave-one-out-cross-validation (Figures 9 and 10). Overall, there is a tendency ~~of~~ for MAF to be overestimated in those areas where the observed values of MAF are small (e.g. Hungary and Denmark), and underestimated where they are large (e.g. Carpathians, Northern Italy) reflecting the ~~property~~ tendency of spatial estimators to underestimate spatial extremes. The overestimation in Finland may also be due to lake retention not being captured adequately in the model. To some degree CV is also overestimated in areas of low CV (e.g. southern Norway and Denmark) and underestimated in areas of high CV (e.g. Ukraine, Ore mountains) although there are also large CV areas it is overestimated (e.g. Southern Spain). The errors are smallest in Russia, Central Germany, British ~~Island~~ Isles and France where the spatial gradients in CV are relatively smooth.

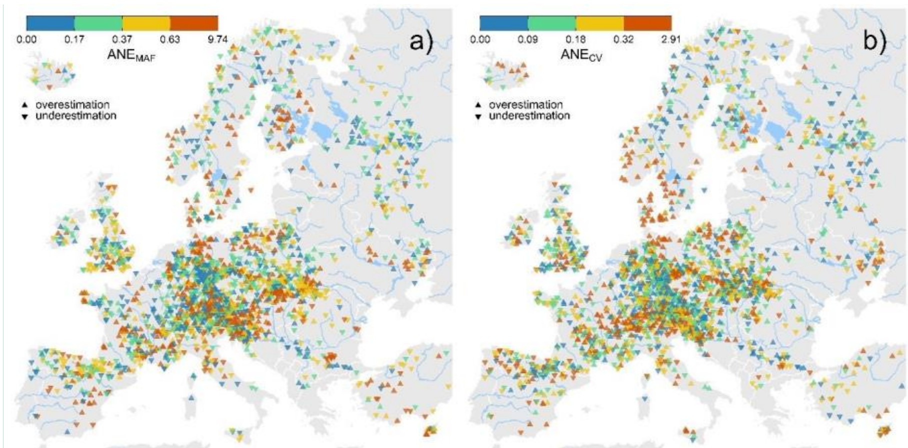
Commented [A74]: This suggests that you have heteroscedastic residuals, and that you haven't explained an important component of the variance in your data.

Commented [A75]: You mean LUW was not considered here…not any sort of man-made regulation

Commented [A76]: British Isles (Great Britain + Ireland)? Or the island of Great Britain?

The median absolute normalized error of MAF and CV is 0.37 and 0.18, respectively, with 25%-quantiles of 0.17 and 0.09 and 75%-quantiles of 0.63 and 0.32. This means that the absolute normalized error of CV is about half that of MAF, which seems to be related to the relatively smaller spatial variability of CV as compared to MAF (spatial cvs of 1.11 and 0.49, respectively, Table 2).

Commented [A77]: Throughout Europe?



Commented [A78]: Consider using a trichromatic legend where one color gets stronger as the errors become more negative, a neutral color indicates where errors are low, and a third color becomes stronger as error get positive.

Figure 9: Absolute normalised errors ANE$_{MAF}$ and ANE$_{CV}$ of the predictions of the regional regression models for MAF and CV. Errors are evaluated on scale of data (not logarithmised). Colours refer to binned classes of equal frequency. Triangles facing upwards indicate gauges where the model overestimates the moments, triangles facing downwards where the model underestimates.

Figure 10 depicts the predicted (leave-one-out) MAF and CV using the regressions (Circles in Figure 10, Tables

A.1.1 and A.1.2) and the predicted MAF and CV by spatial proximity through kriging of the observed moments (background colour). Predictions are shown on the scale of the data (not logarihmised) using the colour scale from figure 2. Notwithstanding the relatively large ANE (Fig. 9), the overall patterns of the moments are very similar to the observed ones (Figure 2). Notice that the regression models are not applied for all available sites because some of the local peculiarities (that may have physical reasons) are missed. Overall, the patterns of the moments are consistent with the process reasoning put forward in this paper.

Commented [A79]: List these in SI. I assume these were left out of the kriging analysis as well.

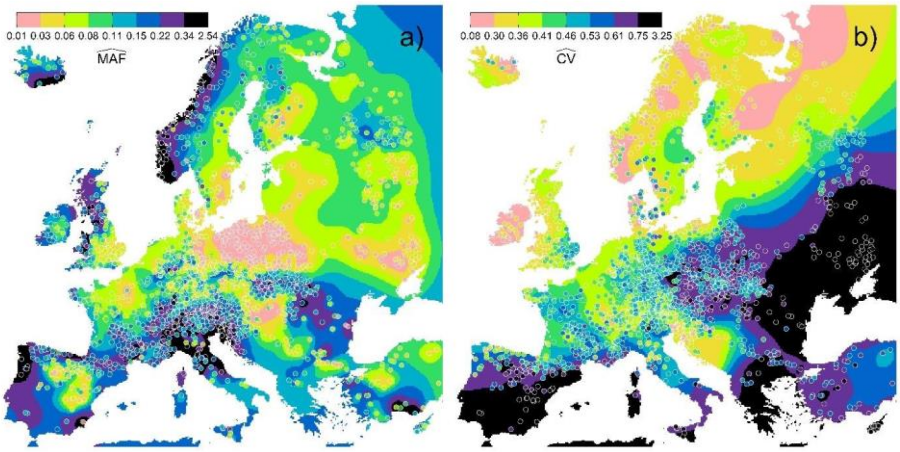


Figure 10: Predicted values of regional regression models and ordinary kriging for MAF ($m^3 s^{-1} km^{-2}$) and CV. Circles refer to predictions of regression models, background refers to predictions of kriging. Colours refer to binned classes of equal frequency for original data (estimated statistical moments) as in Figure 2.

4. Discussion and Conclusions

4.1 Patterns of flood moments in Europe

Overall, there are clear patterns of the flood moments across Europe. As ~~would be~~ expected, MAF shows the clearest patterns while they are less clear for CV and particularly CS, at least partly because of sampling variability.

In the Atlantic region, where floods mainly occur in winter as a result of moisture influx from the ocean, MAF_α is very high (above 0.5 m³/s/km² ~~at the West~~along the western coasts of Norway, Scotland and Galicia, Fig. 2). The CVs, on the other hand, are small (typically around 0.3 at the Norwegian coast and in Scotland and 0.5 in Galicia) as the atmospheric moisture influx tends to be consistent between years (Giorgi et al., 2004). As one moves towards the continent from the west coast of the British Isles, the MAF tends to decrease and the CV increases because of the decreasing moisture availability and floods tend to occur later in the ~~yea~~winter (i.e. Jan instead of Dec., Fig. 3).

Further inland, the various mountain ranges (Pyrenees, Massif Central, Alps Apennines, Ore mountains, Carpathians, Balkan mountains) stand out with higher MAF than the surrounding areas (mostly above 0.3

$m^3/s/km^2$) and summer as the dominant flood season due to their effects of enhancing rainfall and probably shallower soils.

On the other hand, there are clear differences between the CVs of these mountain ranges. While CVs in the Alps and the southern Slovenian mountains are low, they are high in the Ore mountains and some of the other mountain ranges which reflects the stronger influence of Mediterranean storm tracks (Hofstätter et al., 2018, Hofstätter and Blöschl, 2019) perhaps along with non-linear runoff generation (Viglione et al., 2009).

Commented [A80]: Are these storm tracks more regular?

As one moves inland in ~~the North of~~northern Europe from the Norwegian coasts towards the North European plain, MAF decreases to values around MAF_{α}=0.1 $m^3/s/km^2$ due to a decrease in the Atlantic influence and increase of snow processes resulting in late spring events with pronounced seasonality. As one moves southward from the Northeast, CV increases and flood seasonality decreases in line with the increased influence of rain-on-snow and rain floods, which tend to be more irregular than snowmelt floods alone.

Some of the continental regions of Europe (Hungary, Poland, Ukraine) are particularly sheltered by mountain chains, resulting in low precipitation, both at the annual scale and for extreme events which translates into low MAF and mostly high CV.

Commented [A81]: Explain a bit more

In the Mediterranean, where floods tend to occur in autumn and winter, MAF is generally high, particularly in Southern France, Slovenia and Croatia, Liguria (NW Italy), and parts of northern Italy, ~~as a result of the potential of~~due to heavy autumn storms ~~due to~~stemming from the warm ~~Sea~~sea-surface temperatures. In most regions this also results in a high CV, although this is not the case in Slovenia and Croatia, due to the consistency of these storms between years (Xoplaki et al., 2004, Salinas et al., 2014b).

4.2 Interpretation of controls of flood moments

The degree to which the moments change with catchment area is a fingerprint of the spatial variability of the flood producing processes (Merz et al., 2003, Sivapalan et al., 2005, Merz and Blöschl, 2009, Viglione et al., 2010ab) (Table 3, Figure 4). As expected, there is a strong scaling effect of MAF with area. The strongest decrease of MAF with area is observed for the Mediterranean region, which points to the important role of small scale, convective storms, patchy runoff generation processes, and more generally flash floods there (Gaume et al., 2009; Marchi et al., 2010; Amponsah et al., 2018). On the other hand, the smallest decrease is found in the Central-Eastern and Northeastern region, where snowmelt is a dominant flood driver. Snowmelt tends to occur over larger regions simultaneously, which results in a smaller reduction of MAF with catchment scale. This is consistent with Blöschl and Sivapalan et al. (1997) and Merz and Blöschl (2003). The relatively weak decrease in the Atlantic regions suggests an important role of ~~large~~ large-scale precipitation as would be expected (Kemter et al., 2020).

Commented [A82]: Good commentary about consistency with other studies

Commented [A83]: From large frontal systems?

CV decreases with area in most of the regions. Again, the strongest decrease is observed for the Mediterranean region, which can be interpreted in terms of similar aggregation processes as in the case of MAF. Additionally, the degree of non-linearity in runoff generation may decrease with catchment size (Sivapalan, 2003) as threshold processes associated with Hortonian runoff generation or soil storage homogeneity may be more relevant in small catchments (Penna et al., 2011; Rogger et al. 2012). On the other hand, the smallest decrease occurs in the Northeastern region and in the Central Eastern region, where the estimated regression coefficient is even positive. While both relationships are not significant, they do point towards the larger scale of snowmelt processes relative to other flood generation processes along with more linear runoff generation processes and the larger role of baseflow there (Blöschl and Sivaplan, 1997).

Commented [A84]: Will the thresholds vary more in larger basins due to their greater environmental heterogeneity? Also, consider spatiotemporal aggregation effects.

The strongest Spearman correlation for MAF (in absolute value) is observed for the Mediterranean region, while the weakest is observed in the Central-Eastern region (Table A.1.5), in line with the difference in the scale dependence between these two regions (Table 3). For CV (Figure 6) the spatial differences of the correlations between the regions are also consistent with the scaling regressions of Table 3 but, overall, they are smaller than those of MAF. This may be related to possible non-monotonous relationships between CV and area as suggested by Smith (1992), and more complex aggregation effects (Blöschl and Sivapalan 1997). The weakest relationships are ~~is~~ found in ~~Central~~ Central-Eastern Europe where snow is important, and in the Alpine region where the spatial variability of other controls is particularly large (r=0.09 and -0.03, respectively).

Commented [A85]: Can you show a figure of this in your regions?

As compared to the other controls on the flood moments, area plays an important role for MAF but less so for CV (Table A.1.5, Figures 7 and 8). In the Alpine region the Spearman correlations between MAF and area are larger than those between area and other covariates (Table A.1.5) and it has the large contributions to the fit of the regional model (Figure 7). However, this may not be because of the high explanatory power of area but of the lower explanatory power of the other covariates likely related to the complex topography. For CV, area has some explanatory power in the Atlantic and Mediterranean regions (Figure 6) and is used in most regional regression models, but the role of climate variables such as precipitation and aridity is always much higher than that of area (Figure 6, Figure 8) suggesting that aggregation effects are relatively less important at the European scale than at the regional scale.

Commented [A86]: Because more of the between-region variability is explained by hydroclimatic differences, which makes sense given that the regions are intended to represent distinct hydroclimatic zones in Europe

Precipitation characteristics are represented by three variables ~~in the present study~~, which are strongly correlated among themselves (Figure 5). The Spearman correlations between MAF and the precipitation characteristics are positive for Europe and in individual regions while for CV and precipitation they are negative (Figure 6) but there are some differences between the precipitation variables. MAP is a surrogate for event precipitation, antecedent soil moisture and landscape evolution, whereas P95 and Pmax are more representative of characteristics of event precipitation. Pmax is representative of a more extreme part of the daily precipitation distribution than P95 (typically Pmax is twice the value of P95, Table 1). The correlations of MAP and P95 with MAF_{α} are similar, but generally larger than that of Pmax which may be due to Pmax capturing antecedent soil moisture less. Mimikou and Gordios (1989) and Merz and Blöschl (2009) concluded that MAP was somewhat superior to other precipitation variables in explaining the spatial MAF variability in Greece and Austria, but at the European scale the predictive power of MAP and P95 are similar, and that of Pmax is slightly lower.

Commented [A87]: What exactly do you mean by landscape evolution?

Commented [A88]: This paragraph is comprehensive but a bit too long and reads like a lab report.

CV is always a better correlated with MAP than with P95 and Pmax, reflecting the decreasing degree with which antecedent soil moisture is captured as one moves from MAP to P95 and Pmax. Drier catchments ~~have the ability~~

~~to~~can produce larger CVs because some of the events may be a combination of both large precipitation and wet initial conditions such producing much larger floods than usual (Farquharson et al., 1992, Viglione et al., 2009; Kemter et a., 2020). This effect is also represented in the negative correlations between CS and MAP (r=-0.35) and CS and P95 (r=-0.34) (Table A.1.5) in the Mediterranean which is related to a particularly large potential for this contrast in initial conditions.

Commented [A89]: Because the antecedent soil moisture conditions tend to vary more than they do in human catchments?

In the context of multiple controls, rainfall (in this case only P95 was considered) is always among the important variables for explaining MAF (Figure 7). However, in the case of CV, aridity is vastly more important, as the combination of evaporation and precipitation better captures the typical initial condition state of the catchments before floods.

Mean spring and winter temperature were used in the analysis to capture snow processes. As would be expected, the Spearman correlations between temperature and MAF_α and CV are comparatively high in the Northeastern and Central-Eastern region, where snow-processes are important for floods. Temperatures are negatively correlated with MAF_α and positively correlated with CV. The colder it is, the more precipitation is stored as snowpack in winter, leading to, on average bigger snowmelt floods in spring/early sunmer, but they are less variable (smaller CV) which may be related to the smaller interannual variability of air temperature as compared to that of precipitation (Giorgi et al. 2004). Snowmelt floods are physically limited by the amount of water stored as snow and solar radiation. This upper limit ~~is~~ also contributes to less extreme and more regular floods (Merz and Blöschl, 2003). In these cold regions temperatures are better correlated with MAF_α and CV than with the precipitation variables and almost as well as with aridity, although this depends on the moment and the region.

Winter temperatures add explanatory power to the regional regression models of MAF in the Central-Eastern region, but a rather small contribution for the other regions (Figure 7). For CV, temperatures explain some of the spatial variability in the Central-Eastern and the Atlantic region, but generally its contribution is low (Figure 8).

On the one hand, winter temperature may not be a perfect proxy for the spatial distribution of flood-relevant snowmelt. On the other hand, the other variables may more directly capture runoff generation processes.

Soil moisture, PET and the aridity index (AI) are related to long-term water balance characteristics and are significantly correlated with the estimated flood moments for almost all regions. Soil moisture is positively correlated with MAF_α and negatively correlated with CV, whereas the opposite holds for PET and AI. Soil moisture and MAP are highly correlated, which is related to soil moisture being driven by long term precipitation. The lower the wetness state, the more room for variations in the runoff coefficients between years, and therefore flood peaks and thus high CV (Viglione et al., 2009). For PET and AI the highest correlations with MAF_α are observed in the Northeastern, the Atlantic and the Mediterranean region. AI is strongly correlated with CV (Figure 6) and a particularly important variable for capturing the spatial variability of CV in regional regression models (Figure 8). High aridity implies a combination of low precipitation and high evaporation, leading to comparatively dry antecedent conditions. AI may also capture the non-linearity of runoff-generating mechanisms relevant for CV (Blöschl and Sivapalan, 1997). Additionally, precipitation tends to be more variable in the arid regions of Europe (e.g. Giorgi et al., 2004), so there may be both a precipitation and runoff generation effect, the latter being related to the stronger randomness of the runoff coefficient. The effect of the large variability of runoff coefficients between years in the arid catchments of Europe (large AI) is also apparent in the positive correlations with CS in the Mediterranean and Central-Eastern region (r=0.35 and 0.50, respectively) (Table A.1.5)

Topography is included via slope and elevation in the present analysis, but the observed effects of topography on the flood moments are most likely indirect. Precipitation characteristics are highly correlated with topographical indices (Figure 5) and their spatial patterns are very similar (not shown), suggesting little unique effect. Faster routing (flow velocity) due to topography does not seem to be a relevant factor for the spatial patterns of flood moments at the European scale, given that response times may be more closely related to geology than topography at the regional scale (Gaál et al., 2012).

Commented [A90]: Good pt

The fraction of area covered by forest (LUF) is positively correlated with MAF_{α} which is not consistent with the usual expectation of higher infiltration capacities and therefore smaller floods peaks for forest soils (Sun et al., 2018). At the European scale, apparently, this effect is masked by the correlations between forest cover and precipitation. In high elevation regions of Europe forest cover tends to be high as these areas have not been deforested for agricultural purposes, and these are also the areas of high rainfall because of topographic effects on rainfall. Additionally, runoff coefficients may be higher in these high rainfall areas due to shallower soils and water tables notwithstanding the forest cover (Merz et al., 2006, Rogger et al., 2017).

The fraction of area covered by water bodies reduces both MAF_{α} and CV. The former is consistent with retention effects while the relationship between CV and water body size may be non-linear (increasing CV up to a water body threshold and decreasing CV beyond, Wang et al., 2017) which is not captured by Spearman correlation.

Commented [A91]: Show this?

Soil texture, when interpreted in terms of pedotransfer functions (Picciafuoco et al., 2019), is expected to affect infiltration of event rainfall. Coarse soils (Stex=1) are therefore expected to be associated with smaller MAF_{α} than fine soils (Stex=5) but the data show no consistent relationship. In a similar vein, the data suggest that coarse soils tend to be associated with small CV, which contrasts what one would expect by reasoning in terms of runoff generation processes. For coarse soils one would expect that, for small events, most of the water infiltrates but when a threshold is exceeded the rainfall starts to run off from the surface, thus leading to larger CV relative to soils without threshold behaviour (Rogger et al., 2013). One reason for observing the opposite are the correlations between MAP and Stex within the regions which range between -0.08 and -0.36, i.e., coarse soils would be associated with high precipitation which would explain large MAF and small CV. Apparently at the scale of an entire continent, the soil characteristics (at least the texture available here) are less important than climate variables. The rather low explanatory power of soil texture and land use for hydrological response at the regional scale is a general concern that also affects the estimation of other variables in the context of predictions in ungauged basins (Blöschl et al., 2003).

Commented [A92]: Nice analysis.

4.3 Implications

Even though the main objective of this paper is to investigate why spatial patterns of flood moments occur, the results in Section 3.6 may be considered as a benchmark for flood moment estimation in ungauged basins at the European scale. The median absolute normalized error (ANE) of MAF and CV is 0.37 and 0.18, respectively. This is relatively large as compared to similar, but smaller scale, studies in the literature (Merz and Blöschl, 2009; Viglione et al., 2013). The fit of the regional models changes between the regions, which reflects the relative importance of the flood generating processes changes between the regions. For the case of MAF, R^2 is largest in the Atlantic and Mediterranean regions (Table A.1.1) and for CV it is largest in Eastern and Mediterranean regions. Clearly there is no ~~one-fits-all~~ model applicable to all regions of Europe. The regions here were derived based on previous climatic partitions of Europe and the goal of homogeneity with respect to flood generating processes and geographic coherence, rather than optimal predictive performance of the regional models.

Overall, the findings of this paper suggest that, at the continental scale, climate variables dominate over land surface characteristics as control of the spatial patterns of flood moments. Given the evidence for the coevolution of landscape and climate (Perdigao and Blöschl, 2014, Troch et al., 2015) but the general lack of predictive power of variables related to land use, soil and geology for hydrological quantities (Merz and Blöschl, 2009, Rogger et al., 2017), there is a need for new types of land characteristics, that are consistent across countries. Merz and Blöschl (2009) illustrate this notion by a comparison of two Austrian catchments that have strikingly similar geological characteristics in terms of percentage of area of certain geological types, but vastly different rainfall-runoff response-behaviour. At the plot, hillslope and catchment scales, runoff generation is strongly controlled by soil properties, including their~~which~~ control infiltration and saturation capacities (Peschke and Sambale, 1999; Scherrer et al., 2007; Rogger et al., 2012; Picciafuoco et al., 2019). There have been attempts to relate or upscale local soil characteristics and regional ones (e.g., Schmocker-Fackel et al., 2007). One successful example is the HOST classification used in the UK (Boorman et al., 1995; Lilly et al., 1998; Maréchal and Holman, 2005), which has been demonstrated to be able to capture runoff generation processes and their spatial variability. Of course, scaling becomes important as well and land-use may have larger explanatory power in small catchments than in larger ones (Viglione et al., 2016).

The finding that climate is the main control for the spatial variability of the flood moments, within the range of the variables considered, also has some implications for quantifying the temporal flood variability. If the spatial patterns of flood behaviour at the continental scale are primarily driven by climatic influences, their temporal fluctuations might be propagated to floods (Šraj et al., 2016, Blöschl, Hall et al., 2019, Bertola et al., 2020, Kemter et al., 2020) On the other hand: flood changes of small local streams may be much more controlled by land use change such as urban development and deforestation (Rogger et al., 2017). One should however be careful in trading space for time in the context of change, i.e. in assuming that future flood characteristics in one region will be similar to the present ones in another region because the climate in the former will be similar to the present climate in the latter. This is because of the space-time asymmetry discussed in Perdigao and Blöschl (2014), i.e. the fact that, because of the celerity of coevolution, spatial and temporal statistics are not necessarily the same.

~~Hydrology of flood frequency~~Flood-frequency analysis is challenging because it deals with the extreme limit of the natural variability of river flows. This paper is a step toward a better process-based understanding of ~~the hydrology of flood frequency~~the statistical properties of annual floods in Europe, ~~along with studies that combine process hydrology, comparative hydrology and paleohydrology, including learning the recent past history of floods (Merz and Blöschl, 2008ab, Viglione et al., 2013, Blöschl et al., 2020).~~ We believe that linking the hydrology of flood frequency to models of

Commented [A93]: What values did they obtain? For which regions?

Commented [A94]: Change term

Commented [A95]: If I understood you correctly, didn't you say earlier that these regions reflected general hydroclimatic properties rather than flood-generating processes in particular?

Commented [A96]: Mention this earlier

Commented [A97]: Is it worth mentioning that the lack of importance of land-surface characteristics in explaining the spatial variability of floods over large regions of Europe should not be construed to mean that land-surface perturbations have a second-order effect at individual sites compared to climate?

Commented [A98]: Can you describe this in simpler language a bit so a wider range of readers who are not familiar with Perdigao and Bloschl can understand this?

Commented [A99]: Good pt…expand on it a bit more coevolutionary indices of climate and landscape has the potential to reveal a lot about all aspects of catchment hydrology, ultimately leading to better predictions.

Commented [A100]: Can you give an example of such a coevolutionary index earlier on?

I would add a few more of your key accomplishments in this paper to the last paragraph as well as a sentence or two regarding more general future directions, and not a specific focus on coevolution. See ideas about nonstationarity and mixed distributions.

5. Appendix

Table A.1 Regression coefficients (standard errors), model error variance and R^2 of regional regression models for MAF

Log_{10} MAF	(Intercept)	Log_{10} A	Log_{10} P95	TWin	AI	sigma	R2
Europe	-2.18(0.09)	-0.16(0.01)	1.61(0.07)	-0.02(0.00)	-0.04(0.02)	0.31	0.47
Northeastern	-1.76(0.42)	-0.14(0.02)	1.22(0.31)	-0.05(0.01)	-0.33(0.08)	0.24	0.41
Atlantic	-3.31(0.11)	-0.13(0.01)	2.54(0.09)	0.01(0.00)		0.26	0.51
Central-Eastern	-4.54(0.62)	-0.09(0.03)	3.33(0.59)	-0.07(0.01)	0.10(0.07)	0.25	0.33
Alpine	-0.68(0.21)	-0.18(0.02)	0.47(0.14)		-0.16(0.06)	0.27	0.27
Mediterranean	-1.09(0.26)	-0.22(0.02)	0.94(0.19)	0.02(0.01)	-0.16(0.04)	0.32	0.47

Table A.2. Regression coefficients (standard errors), model error variance and R^2 of regional regression models for CV

Commented [A101]: Residual normality?

Log_{10} CV	(Intercept)	Log_{10} A	Log_{10} P95	TWin	AI	sigma	R2
Europe	-0.49(0.05)	-0.05(0.00)	0.06(0.03)	0.00(0.00)	0.22(0.01)	0.15	0.29
Northeastern	-1.31(0.10)	-0.02(0.01)	0.54(0.08)		0.47(0.03)	0.1	0.48
Atlantic	-0.40(0.02)	-0.05(0.01)		-0.02(0.00)	0.21(0.01)	0.14	0.28
Central-Eastern	-2.43(0.29)		1.42(0.29)	-0.04(0.00)	0.60(0.04)	0.13	0.61
Alpine	0.50(0.10)	-0.05(0.01)	-0.64(0.07)	0.01(0.00)	0.08(0.03)	0.13	0.37
Mediterranean	0.23(0.11)	-0.08(0.01)	-0.45(0.08)		0.12(0.02)	0.14	0.55

Table A.3. Measure for general dominance (additional contributions) for MAF – indicating general dominance. For each row: highest value indicates most important variable in terms of improvement of the model fit for the given regression, second highest indicates second most important, lowest indicates least important. Summing over measures gives R^2 of regression.

Log_{10} MAF	Log_{10} A	Log_{10} P95	TWin	AI	R2
Europe	0.12	0.25	0.01	0.09	0.47
Northeastern	0.14	0.1	0.03	0.14	0.41
Atlantic	0.08	0.43	0		0.51
Central-Eastern	0.06	0.13	0.13	0.01	0.33
Alpine	0.15	0.07		0.06	0.27
Mediterranean	0.2	0.15	0.03	0.1	0.47

Table A.4. Measure for general dominance (additional contributions) for CV – indicating general dominance. For each row: highest value indicates most important variable in terms of improvement of the model fit for the given regression, second highest indicates second most important, lowest indicates least important. Summing over measures gives R^2 of regression.

Log_{10} CV	Log_{10} A	Log_{10} P95	TWin	AI	R2
Europe	0.03	0.04	0.01	0.21	0.29
Northeastern	0.02	0.05		0.42	0.48
Atlantic	0.04		0.05	0.19	0.28
Central-Eastern		0.03	0.14	0.44	0.61
Alpine	0.03	0.2	0.01	0.13	0.37
Mediterranean	0.09	0.2		0.26	0.55

Table A.5: Spearman-Correlation between statistical moments of flood series, including mean specific discharge MAF, mean specific discharge normalized to a catchment area MAF_α of α=100km^2, the coefficient of variation CV, the coefficient of skewness CS, and catchment attributes. Statistically significant estimates (at the 5% level) are printed in bold.

	Europe				Northeastern				Atlantic				Central-Eastern				Alpine				Mediterranean			
	MAF	MAF_α	CV	CS	MAF	MAF_α	CV	CS	MAF	MAF_α	CV	CS	MAF	MAF_α	CV	CS	MAF	MAF_α	CV	CS	MAF	MAF_α	CV	CS
A	**-0.44**	**-0.12**	**-0.13**	**-0.13**	**-0.47**	0.01	**-0.16**	-0.07	**-0.31**	0.01	**-0.19**	**-0.08**	**-0.23**	-0.01	0.09	**0.17**	**-0.40**	0.02	-0.03	**-0.15**	**-0.48**	0.03	**-0.25**	**-0.18**
MAP	**0.62**	**0.59**	**-0.33**	-0.01	**0.18**	**0.15**	**-0.23**	**0.15**	**0.64**	**0.67**	**-0.33**	-0.03	**0.25**	**0.24**	**-0.49**	**-0.38**	**0.34**	**0.26**	**-0.61**	**-0.13**	**0.42**	**0.48**	**-0.68**	**-0.35**
P95	**0.64**	**0.60**	**-0.22**	0.02	**0.21**	0.02	-0.10	**0.17**	**0.67**	**0.66**	**-0.22**	0.00	**0.39**	**0.31**	**-0.19**	**-0.26**	**0.32**	**0.24**	**-0.58**	**-0.14**	**0.49**	**0.52**	**-0.59**	**-0.34**
Pmax	**0.61**	**0.55**	**-0.05**	**0.12**	**0.19**	-0.04	-0.09	**0.20**	**0.53**	**0.52**	**0.14**	**0.17**	**0.30**	**0.22**	**-0.18**	**-0.23**	**0.36**	**0.26**	**-0.40**	**-0.09**	**0.57**	**0.49**	**-0.36**	**-0.20**
TSpr	**-0.22**	**-0.22**	**0.26**	0.00	**-0.31**	**-0.35**	**0.58**	**0.23**	**-0.29**	**-0.29**	0.02	**-0.14**	**-0.14**	-0.11	**0.50**	**0.41**	**-0.17**	**-0.14**	**0.38**	-0.04	-0.09	**-0.12**	**0.17**	0.02
TWin	**-0.04**	**-0.07**	**0.04**	**-0.06**	-0.04	**-0.20**	**0.20**	**0.30**	-0.02	-0.03	**-0.23**	**-0.17**	**-0.28**	**-0.33**	**-0.52**	**-0.31**	**-0.11**	**-0.10**	**0.10**	**-0.12**	**0.12**	-0.04	**0.27**	**0.14**
SM	**0.58**	**0.57**	**-0.31**	-0.03	**0.17**	**0.16**	**-0.14**	**0.19**	**0.52**	**0.55**	**-0.29**	-0.05	**0.28**	**0.28**	**-0.4**	**-0.33**	**0.26**	**0.22**	**-0.56**	**-0.10**	**0.45**	**0.50**	**-0.64**	**-0.37**
PET	**-0.05**	-0.03	**0.39**	**0.14**	**-0.30**	**-0.33**	**0.60**	**0.22**	**-0.23**	**-0.22**	**0.34**	0.03	0.02	0.07	**0.68**	**0.45**	**-0.16**	**-0.11**	**0.11**	**-0.10**	**-0.11**	**-0.21**	**0.63**	**0.31**
AI	**-0.55**	**-0.53**	**0.46**	**0.07**	**-0.36**	**-0.36**	**0.62**	**0.12**	**-0.51**	**-0.53**	**0.38**	0.04	**-0.16**	-0.12	**0.63**	**0.50**	**-0.39**	**-0.31**	**0.50**	**0.08**	**-0.37**	**-0.43**	**0.69**	**0.35**
Elev	**0.53**	**0.55**	**0.08**	**0.20**	**0.35**	**0.47**	**-0.31**	0.06	**0.38**	**0.44**	**0.35**	**0.22**	**0.48**	**0.50**	**0.21**	**0.16**	**0.19**	**0.16**	**-0.47**	0.00	0.06	0.02	**0.20**	**0.20**
Slope	**0.63**	**0.65**	-0.01	**0.16**	**0.34**	**0.39**	**-0.36**	0.04	**0.58**	**0.62**	**0.17**	**0.19**	**0.29**	**0.30**	-0.01	0.02	**0.25**	**0.24**	**-0.40**	-0.01	**0.33**	**0.37**	0.06	0.06
LUF	**0.46**	**0.45**	**-0.10**	**0.06**	**0.30**	**0.28**	-0.01	0.05	**0.43**	**0.45**	**0.14**	**0.14**	0.08	0.01	**-0.39**	**-0.24**	**0.27**	**0.16**	**-0.26**	0.03	**0.40**	**0.32**	0.03	-0.03
LUW	**-0.30**	**-0.16**	**-0.27**	**-0.15**	**-0.25**	**-0.21**	**-0.22**	-0.06	**-0.19**	-0.04	**-0.20**	-0.06	**-0.55**	**-0.55**	**-0.50**	**-0.23**	**-0.16**	0.03	**-0.19**	**-0.14**	**-0.40**	-0.10	**-0.19**	-0.10
Stex	**-0.06**	**-0.06**	**0.29**	**0.11**	**-0.12**	-0.07	**0.37**	**0.25**	-0.06	-0.05	**0.17**	-0.01	**0.29**	**0.32**	**0.53**	**0.31**	-0.02	-0.06	**0.23**	0.01	**-0.22**	**-0.18**	**0.26**	**0.16**

Data Availability

The flood data used in this paper are available at https://github.com/tuwhydro/europe_floods. The authors acknowledge the E-OBS dataset from the EU-FP6 project UERRA (http://www.uerra.eu) and the Copernicus Climate Change Service, and the data providers in the ECA&D project (https://www.ecad.eu), as well as the CCM River and Catchment database (https://data.europa.eu/), the Global Aridity Index and Potential EvapoTranspiration

Climate Database (https://doi.org/10.6084/m9.figshare.7504448.v3), the CPC Soil Moisture database (https://www.cpc.ncep.noaa.gov/), the data on terrain elevation provided by the USGS (https://www.usgs.gov/), the Corine Land Cover data set (https://land.copernicus.eu/) and the European soil database (https://esdac.jrc.ec.europa.eu).

Author Contributions

DL performed the analysis and prepared the paper. GB designed the overall study. All co-authors contributed to the interpretation of the results and writing of the paper.

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Competing Interests

The authors declare that they have no conflict of interest.

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