The influence of event and catchment characteristics on heavy-tail behaviour of flood peak distributions

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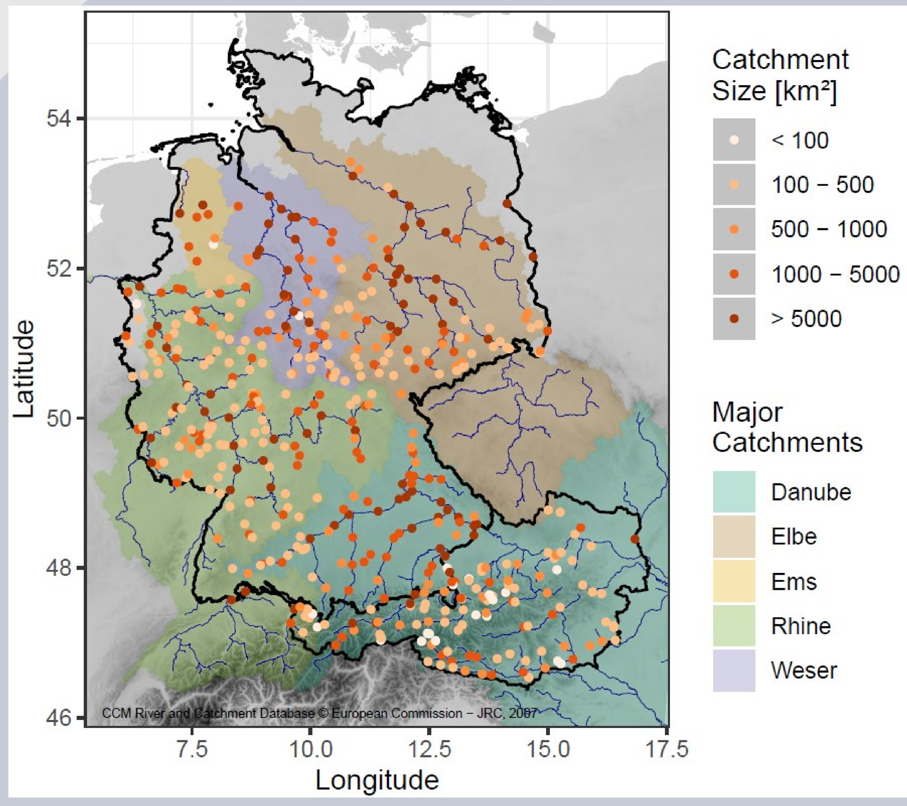
Motivation

- With heavy-tailed flood peak distributions, the occurrence of extreme events has a relatively high probability.
- Reliable estimation of heavy-tail behavior is crucial, for instance, for robust flood design or insurance appraisal.
- Literature discusses a multitude of potential controls on flood tail behaviour with partly contradictory results (e.g. Gaume, 2006; Rogger et al., 2012; Smith et al., 2018).

Objectives

- A multivariate analysis of an extensive set of event and catchment characteristics to explore the causes of heavy tails of flood distributions
- Analysing German and Austrian basins covering a large range of flood-generating processes to be able to draw general conclusions

Study Area and Data



- Mean daily discharge series for 1951-2010 from 480 gauges across Germany and Austria
- Hydrometeorological time series: catchment-averaged daily series of potential evapotranspiration, precipitation, snowmelt, soil moisture, soil pore space, convective available potential energy, and convective inhibition

Figure 1: Locations of the 480 stream gauges used for analysis. The gauges are coloured according to the catchment size. Depicted river networks are from Vogt et al. (2007).

Table 1: Potential predictors for heavy-tail behaviour of flood flows

EVENT CHARACTERISTICS	
Event precipitation	Precipitation volume *Pvol*
	Event duration *Pdur*
	Maximum precipitation intensity *Pmax*
Antecedent catchment state	Flow at event start *Qbegin*
	Soil moisture at event start *SM*
	Precipitation before event start *P10d*
Event catchment response	Runoff coefficient *RC*
	Event time scale *ETS*
Event timing	Flood seasonality *FS*
	Event unseasonality *EUnS*
Event types	Event types of top 5 *Type_top5*
	Event type share *Type_share*

CATCHMENT CHARACTERISTICS	
Catchment area	Catchment area *A*
Catchment wetness	Mean annual precipitation *MAP*
	Aridity index *AI*
Tail heaviness of rainfall	Shape parameter of the maximum precipitation in the flood season *MP_shape*
Nonlinearity of catchment response	Flashiness index *FI*
	Ratio of low to median flow *Q10Q50*
Synchronicity of precipitation and catchment state	Phase correlation between P and SM *P_SM_cor*
	Phase correlation between P and Q *P_Q_cor*

Methods

Automated identification of flood event hydrographs for annual maximum series (AMS) peaks (adjusted from Guse et al., 2020)

Characterisation of upper-tail behaviour of AMS distributions with the GEV shape parameter (ξ_{AMS})

Compilation of an extensive dataset of potential heavy-tail predictors (Table 1)

Catchment characteristics

Event characteristics

Aggregation to catchment-specific indicators (Table 2)

Assessment of indicators

Predictor sets with different indicators of event-based variables

Multivariate analysis

Multiple linear regression (MLR) with 5-fold cross-validation

Random forests (RF) with conditional inference trees

Table 2: Assumptions regarding the association between a variable and the tail-heaviness of flood distributions based on which five indicators for event-based variables were calculated

ASSUMPTION	INDICATOR
A larger variability of the variable favours heavier flood tails	Coefficient of variation *CV*
A heavier tail of the variable favours heavier flood tails	GEV shape parameter *shape*
A close association between (the upper tail of) the variable and the flood magnitude favours heavier flood tails	Spearman rank correlation *rho*
	Upper tail dependence coefficient *UTD*
	Novel slope indicator *slope* (Figure 2)

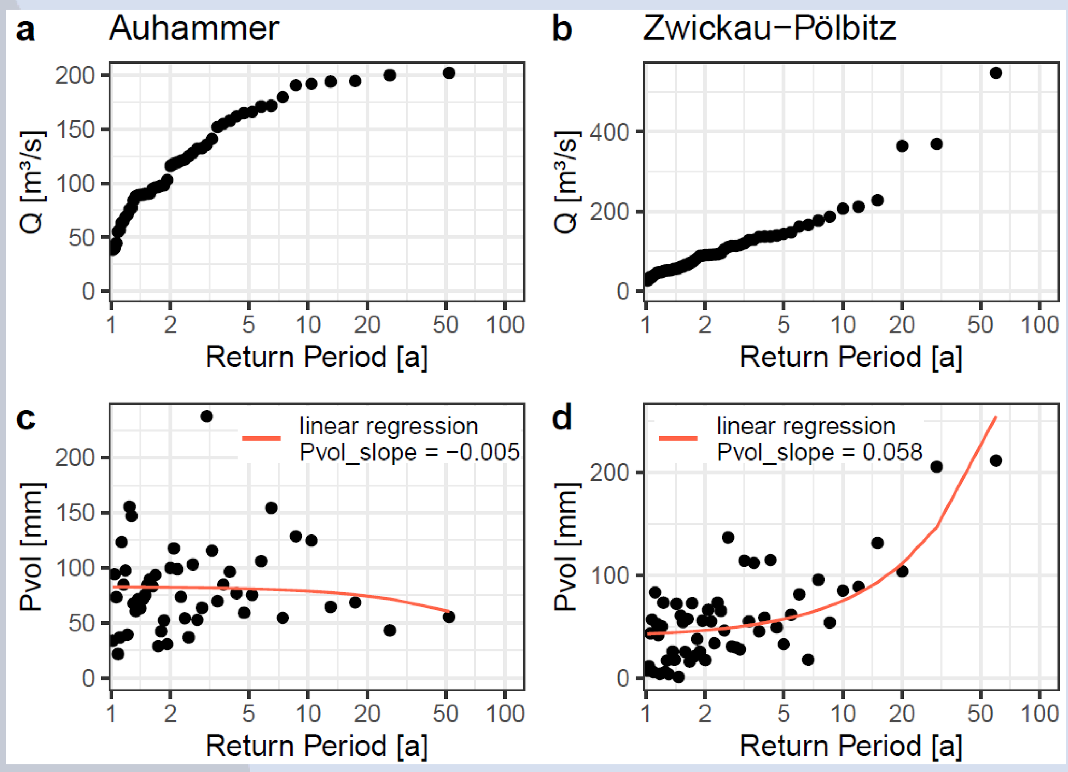


*Figure 2: Two examples of the association of a variable, here event rainfall volume (Pvol), with the return period of the associated flood events (Q). (**a**, **c**) Pvol values associated with the largest flood events are slightly below average, resulting in a negative slope. (**b**, **d**) The highest Pvol values are associated with the largest flood events, resulting in a positive slope. Note the logarithmic scale on the x-axes.*

Results

Indicators for event-based variables

- Predictor sets containing the novel *slope* indicator result in distinctively higher values of R^2 for both MLR models and RF models.
- In the best-performing MLR (RF) models, most (all) selected event-based predictors are *slope* indicators.

Linear models

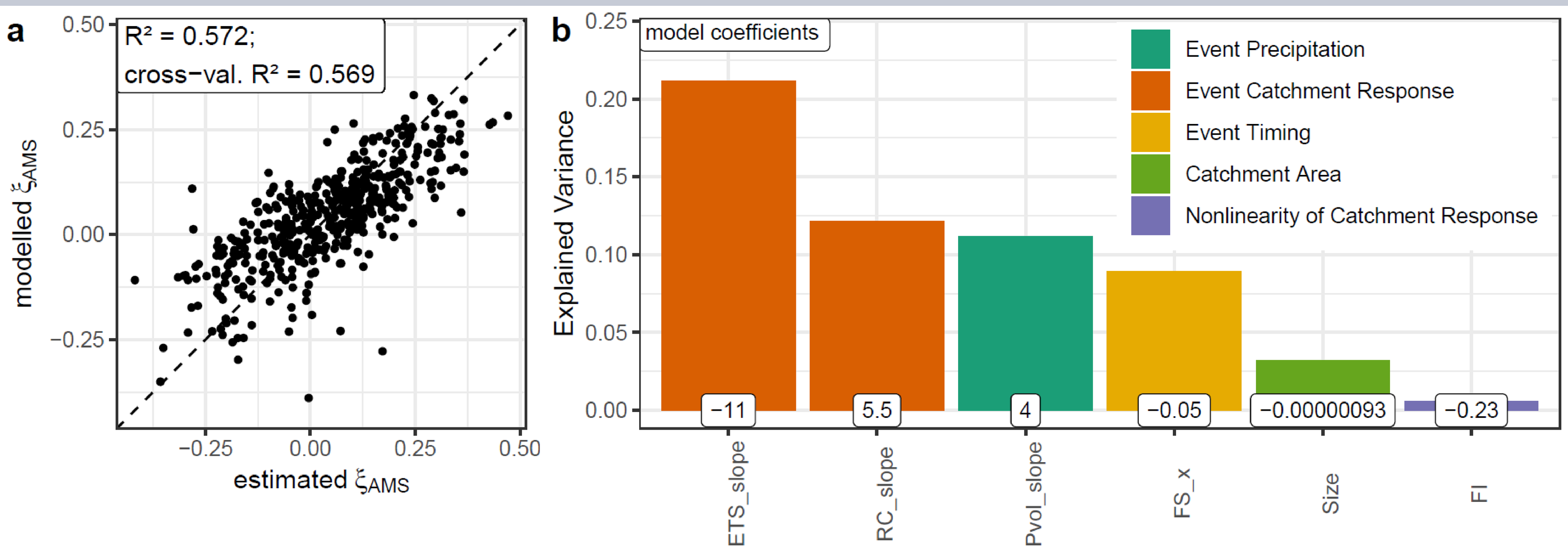


*Figure 3: Results from the multiple linear regression model based on a predictor set with only slope indicators for event-based variables. (**a**) Modelled GEV shape parameters of AMS flood flows (ξ_{AMS}) against ξ_{AMS} estimated from time series. (**b**) Selected predictors along with their model coefficients and their relative importance for the model output. Event characteristics are found to be of greater importance for the heavy-tail behaviour of flood flows than catchment characteristics. Predictors representing event catchment response (ETS_slope, RC_slope), event precipitation (Pvol_slope) and event timing (FS_x) have the highest explained variance.*

Nonlinear models

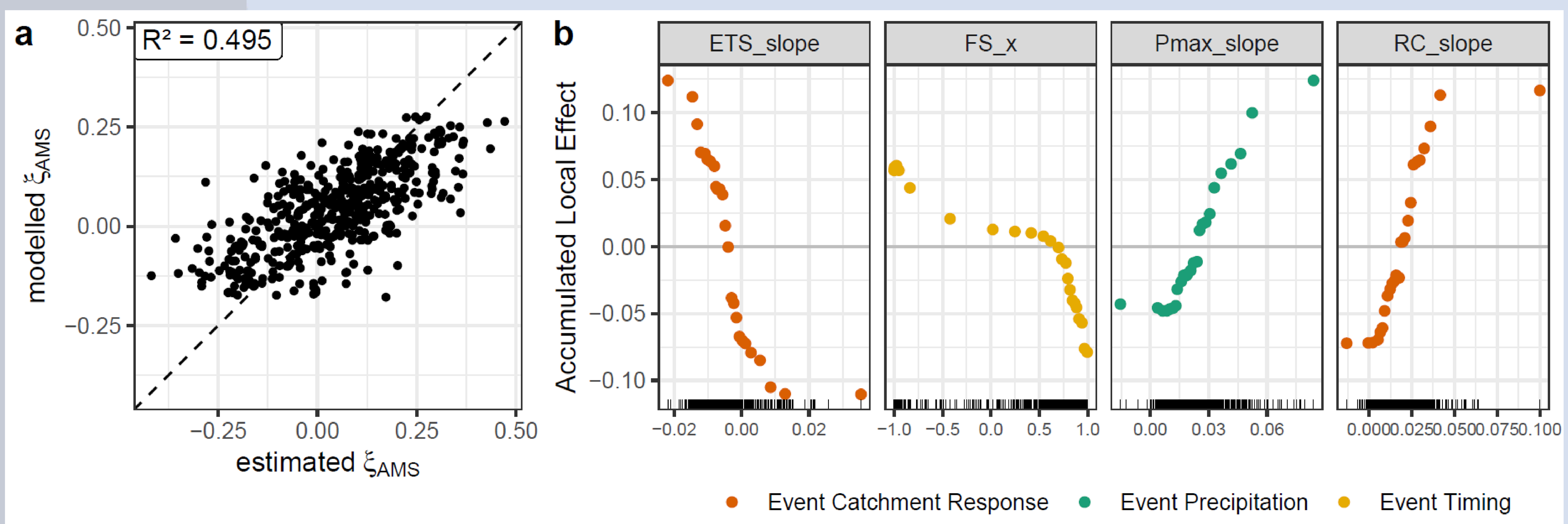


*Figure 4: Results from the best-performing random forest model. (**a**) Modelled GEV shape parameters of AMS flood flows (ξ_{AMS}) against ξ_{AMS} estimated from time series. (**b**) Accumulated local effects (ALE) for the four selected predictors. ALE plots show how over the range of a predictor the model outcome differs from the mean prediction, in units of the predictand. Here, ranges were set to encompass 20 catchments each, leading to the uneven spacing of points. High (low) values of FS_x correspond to a mean date of flood occurrence in winter (summer). The four selected predictors characterize the event catchment response, event precipitation and event timing.*

Conclusions

- The novel *slope* indicator captures well how a variable is associated with flood magnitude especially for high return periods, and is found to be of high value for the analysis of heavy-tailed flood flows.
- Both linear and non-linear models indicate that heavy-tail behaviour of flood peak distributions is mainly controlled by characteristics of the event catchment response and event precipitation, and to a lesser extent by flood seasonality and catchment area.

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Acknowledgement

The financial support of the German Research Foundation (Deutsche Forschungsgemeinschaft, DFG) for the research group FOR 2416 "Space-Time Dynamics of Extreme Floods (SPATE)" is gratefully acknowledged.