

Motivation

How can gridded datasets be combined to improve IDF analysis for remote locations?
How will extreme precipitation change in the future, based on large-scale patterns in the past?
Different perspectives on Intensity-Duration-Frequency (IDF) relations.

Precipitation Data and Methods

Stations

2727 DWD stations

- Temporal resolution: 1 min to 24 h
- Up to 95 years (1931-2025)

Gridded data

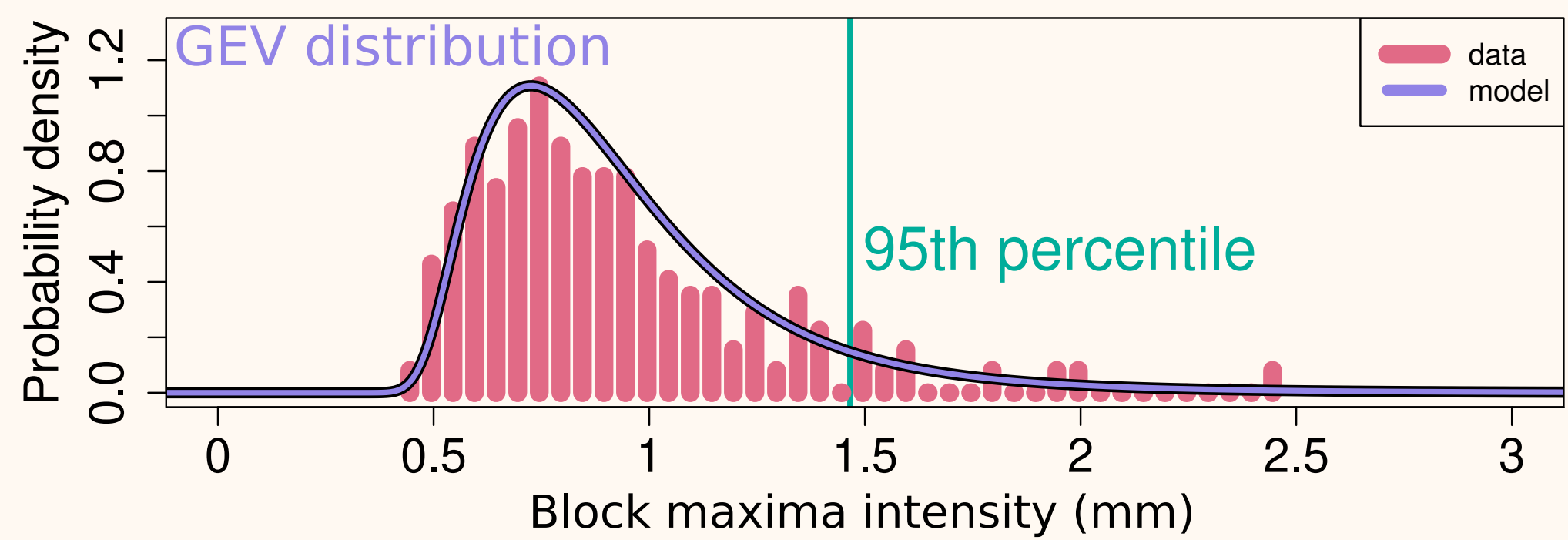
Hyras (1 km)

- 95 years (1931-2025)
- Temporal res.: 24h

Radklim (1 km) :

- 20 years (2001- 2025)
- Temporal res.: 1h

Example Grid Berlin



GEV distribution

$$G(z) = \exp \left\{ - \left[1 + \xi \left(\frac{z - \mu}{\sigma} \right) \right]^{-1/\xi} \right\}$$
$$\mu(d) = \tilde{\mu}(\sigma_0(d + \theta)^{-\eta} + \tau)$$
$$\sigma(d) = \sigma_0(d + \theta)^{-(\eta + \eta_2)} + \tau$$
$$\xi = \text{const.}$$

GEV parameters depend on duration:
 $\Phi_d = \{ \mu, \sigma, \xi \} = \Phi_d(d)$
d-GEV parameters depend linearly on Latitude and Longitude:
 $\Phi_m = \{ \tilde{\mu}, \sigma_0 \} = f(\text{lat}, \text{lon})$

$$\tilde{\mu} \sim \beta_{\mu,0} + \beta_{\mu,1} \text{ lat} + \beta_{\mu,2} \text{ lon}$$
$$\sigma_0 \sim \beta_{\sigma,0} + \beta_{\sigma,1} \text{ lat} + \beta_{\sigma,2} \text{ lon}$$

Validation with Quantile Skill Index

I) Quantile Score

QS: compares modeled quantiles with all observations. Determine QS for model and reference

II) Quantile Skill Score

$$QSS = 1 - \frac{QS_{mod}}{QS_{ref}}$$

III) Quantile Skill Index

$$QSI = \begin{cases} 1 - \frac{QS_{mod}}{QS_{ref}} & \text{, if } QS_{mod} < QS_{ref} \\ \frac{QS_{ref}}{QS_{mod}} - 1 & \text{, else} \end{cases}$$

Quantile Skill Score vs Quantile Skill Index

Summary of phase 2 achievements

- Finalization of IDF plugin

Easy creation of IDF analyses in freva. Featuring confidence intervals, and temporal trend.
- Future IDF relations

Predict future large-scale conditions. Then, derive small-scale IDF-relations for extreme precip.
- Framework for combining gridded data sets

Improve modeling efficiency by combining long low-res records with short high-res records.

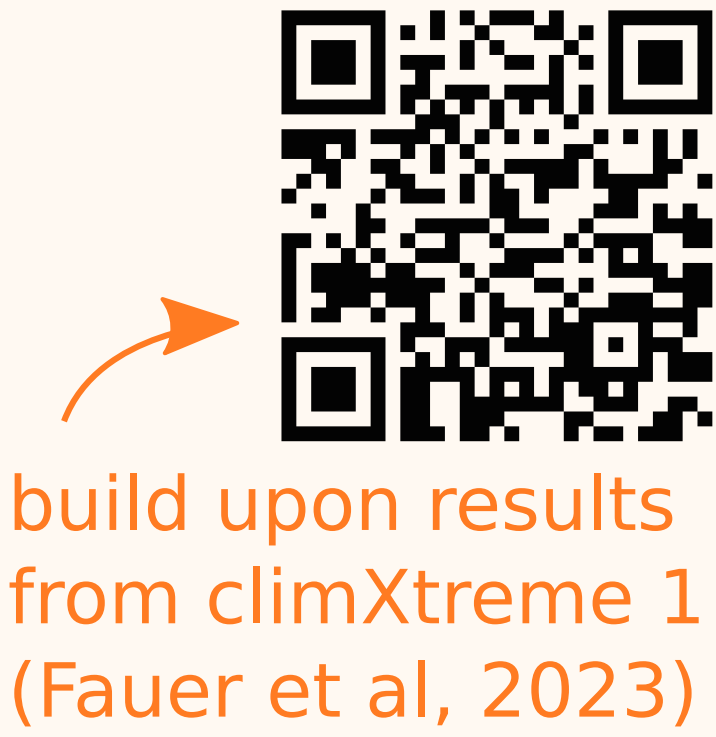
References

Fauer, F. S., Ulrich, J., Jurado, O. E., & Rust, H. W. (2021). Flexible and Consistent Quantile Estimation for Intensity-Duration-Frequency Curves, Hydrol. Earth Syst. Sci., 25, 6479–6494.
Fauer, F. S., Rust, H.W. Non-stationary large-scale statistics of precipitation extremes in central Europe. Stoch Environ Res Risk Assess 37, 4417–4429 (2023). <https://doi.org/10.1007/s00477-023-02515-z>
Fauer, F. S., Large-Scale Effects on Statistics of Extreme Precipitation Over Different Time Scales (PhD thesis, not peer-reviewed) (2025). <http://dx.doi.org/10.17169/refubium-47808>

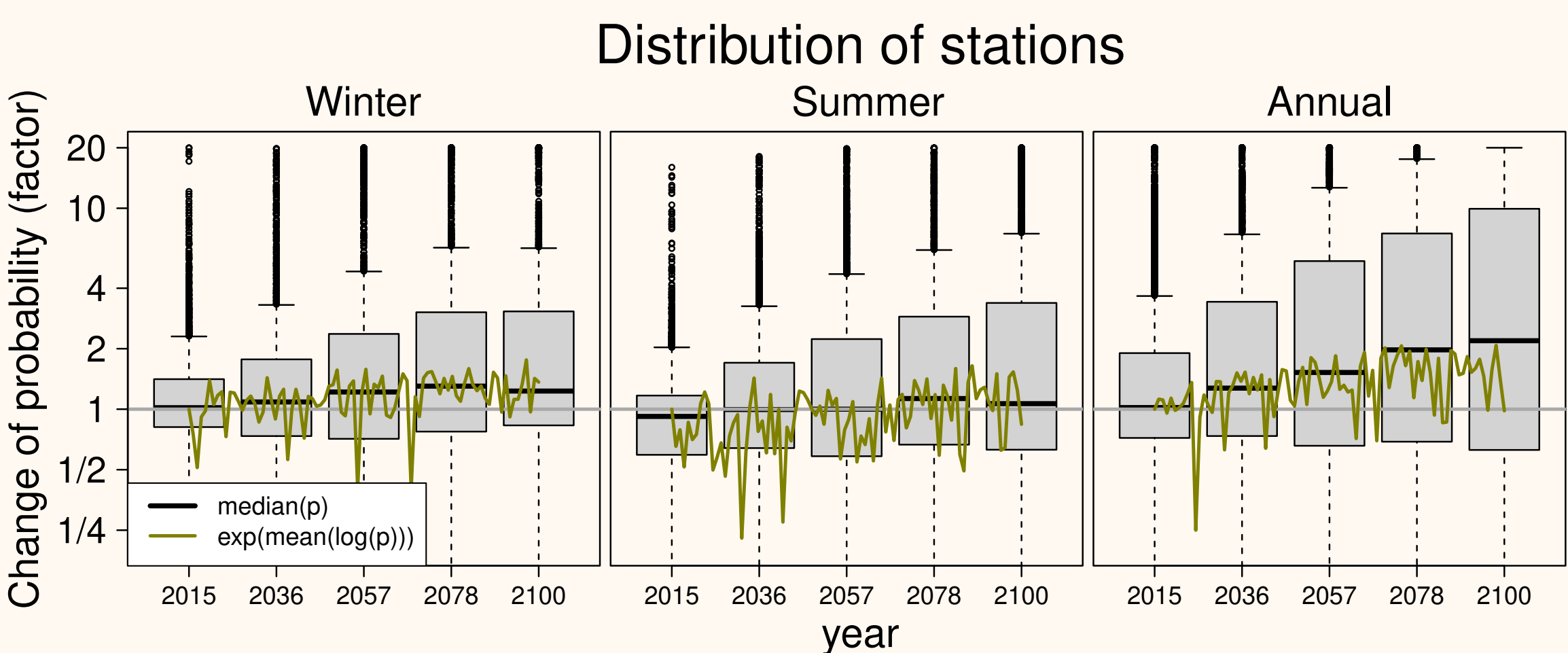
Future Projections of Extremes

to project average values **easy** vs. to project extremes **difficult**

We use the modeled relations between average **large-scale variables** and extreme **intensity** in the past to create future IDF-relations based on climate projections and the projected average large-scale values.



How does the probability of the 20-year event (p=5%) from 2015 change in the future?



Positive trend or no trend, depending on method (median or log-mean over stations)

Predictive skill (cross-validated):

All models are trained on the previous 30 years

Keywords

downscaling # perfect-prognosis

Gridded IDF



Compare spatial model to single grid point model (reference)

Mutual benefit from datasets with different record lengths:

Central grid point

Grid points within pooling radius (1.7 km)

(example)

radius = 1.7km

- Leave-out central grid point.
- "spatial cross-validation"
- Bias from gridded data

Radklim

Hyrras

Train on	Verify on	QSI (%)	Note
Radklim	Radklim	+1.49	Spatial model (one source) vs. single grid point
Hyrras	Hyrras	-0.01	
Radklim + Hyrras	Radklim + Hyrras	+3.57	Spatial model (combination) vs. single grid point
Radklim + Hyrras	Hyrras	-0.41	
Radklim + Hyrras	Radklim	+7.22	

Improvement comes mostly from combination of both datasets

RADKLIM profits from spatial model

RADKLIM profits including HYRRAS

measurement station

(example)

- Use all pixels for training
- Verify on station
- No bias from gridded data

Use for regions where not many observations are available:

Model is trained on surrounding Radklim or Hyrras (or both) pixels and verified on stations in between

Train on	Verify on	QSI (%)	Note
Radklim	Stations	-9.50	One gridded data source
Hyrras	Stations	+1.03	
Radklim + Hyrras	Stations	+0.77	Combination

Only small gains/loss compared to single-station reference

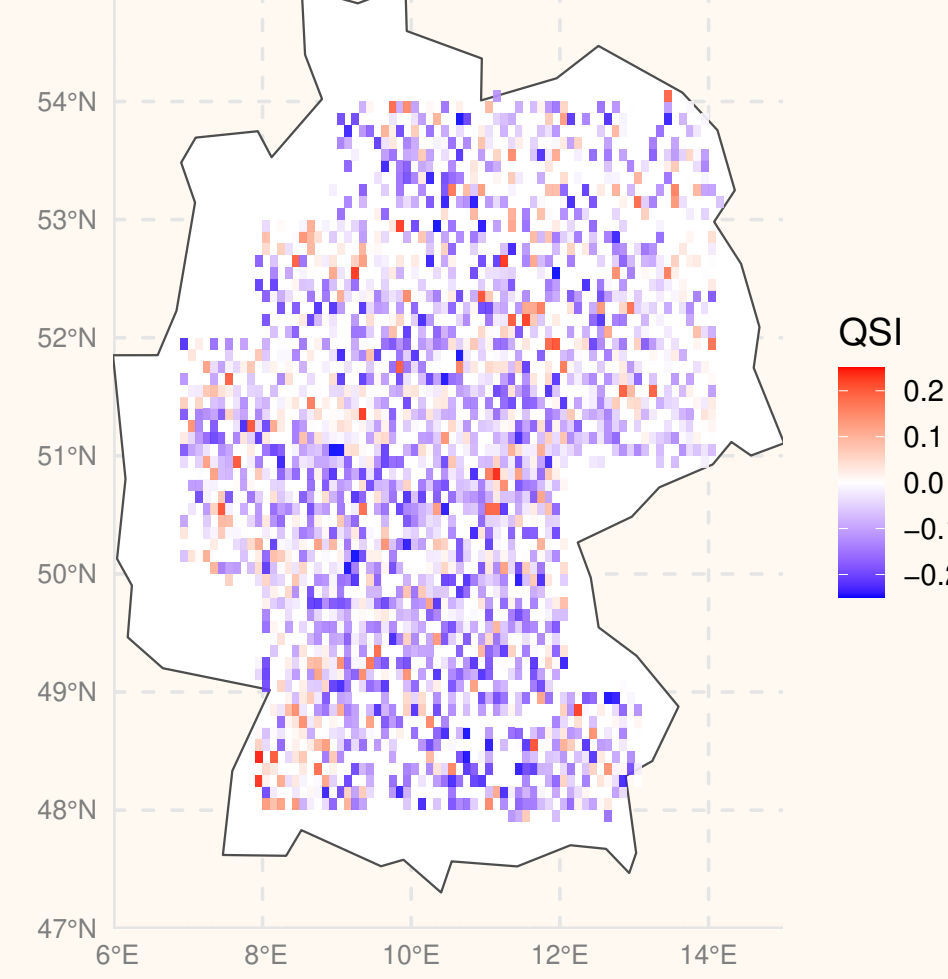
Datasets not homogenized, yet

Same procedure as in B

Train on	Verify on	QSI (%)	Note
Radklim	Stations	-9.50	One gridded data source
Hyrras	Stations	-8.69	
Radklim + Hyrras	Stations	-8.00	Combination

- > gridded data cannot replace station-based data, if stations are available (negative QSI), BUT
- > combining gridded datasets reduces the loss, when gridded data is necessary (see A)

Spatial distribution of QSI, trained on both



Detailed analysis for Berlin

Less detail for Germany