CLIMXTREME
Climate Change and Extreme Events
Freie Universität Berlin

Extreme Precipitation in the past and future

Change of IDF relations over Central Europe

Felix S. Fauer
Henning W. Rust

In the news: Trump | JD Vance | Kamala Harris | Covid

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ENVIRONMENT | JULY 21, 2023

The Problem With Calling Vermont's Storms a "100-Year-Flood"

Thanks to climate change, these deluges are occurring much more often.

JACKIE FLYNN MOGENSEN
Reporter
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Tyler Jovic, of Montpelier, carries his neighbor's dog to dry ground on July 11, 2023
Washington Post/Getty

THE LOCAL dk

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Weather | For Members

'100 year-event': Denmark braced for extreme torrential rain this weekend

Michael Barrett - michael@thelocal.dk
Published: 12 Jul, 2024 CET. Updated: Fri 12 Jul 2024 11:35 CET

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nformation. Also, the new model enables insights into the

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Rain storm shatters records in N.S., called a "one-in-100 year event"

By Mark Hodgins
Posted Jul 23, 2023 12:32:49 PM. Last Updated Jul 24, 2023 02:16:35 PM.

100-year-event

- stationary climate?
- changing climate?

Motivation

to project small-scale extremes
(extreme precipitation)
difficult

vs.

to project large-scale average variables
(NAO, temperature, blocking, humidity)
easy

---

1. Find relation:

Precipitation Intensity

Frequency

Large-scale average variable

2. Use future projection of large-scale variables (MPI-ESM)

2020 to 2100

3. Estimate future extremes

Use relation from the past

+

And future projection

To estimate future extremes

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Goal: estimate future extremes with down-scaling

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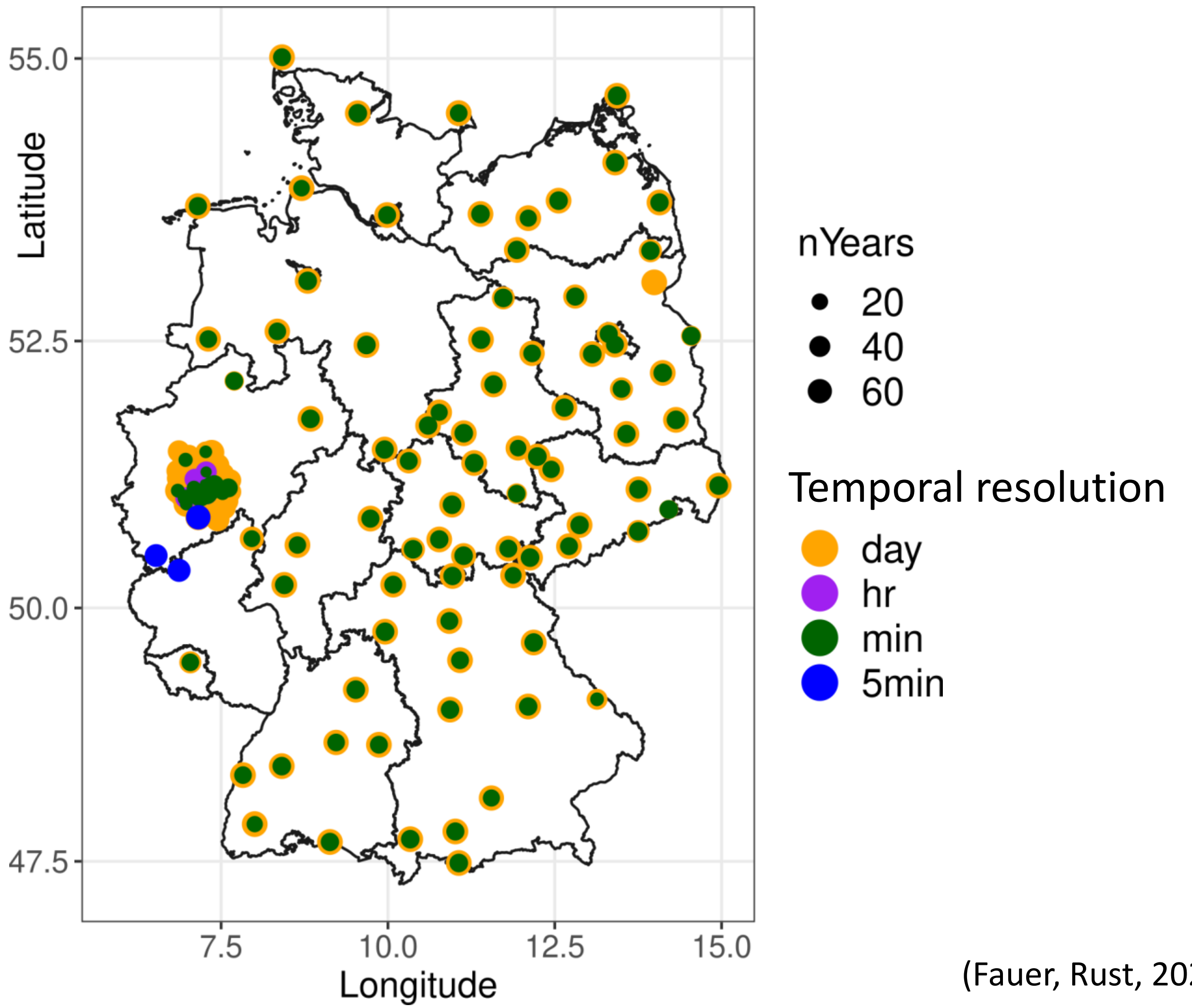
Goal: estimate future extremes with down-scaling

New: more data and different covariates reveal new patterns

Data

Precipitation

- station-based data
- Temporal resolution: 1 min to 24 h



(Fauer, Rust, 2023)

Data

Precipitation

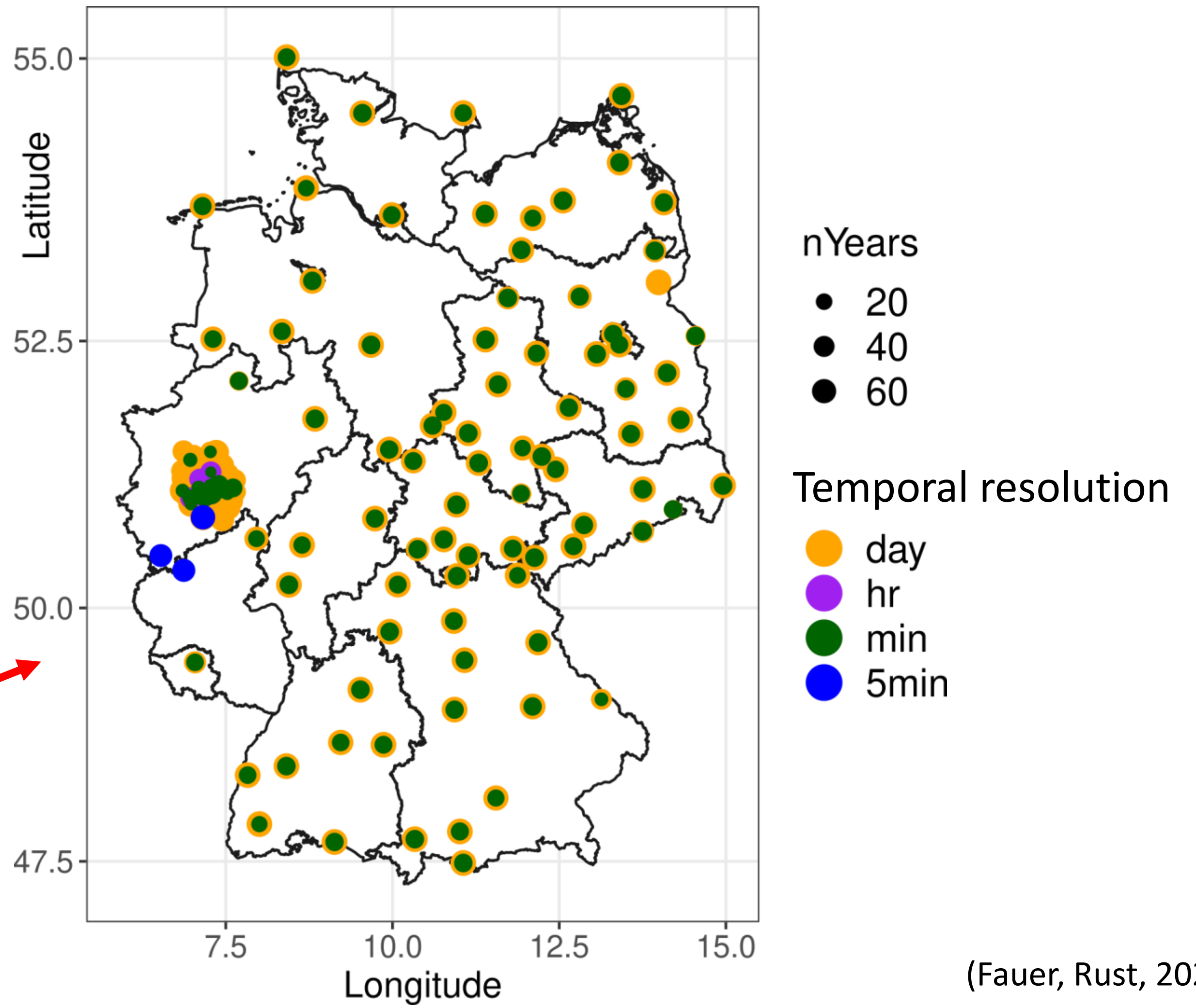
- station-based data
- Temporal resolution: 1 min to 24 h

Large-Scale variables

- North Atlantic Oscillation NAO (NOAA)
- Temperature and humidity,
  Binary Blocking-Index (ERA5)

→ 1950-2015
→ averaged over one year
→ averaged over Germany

new

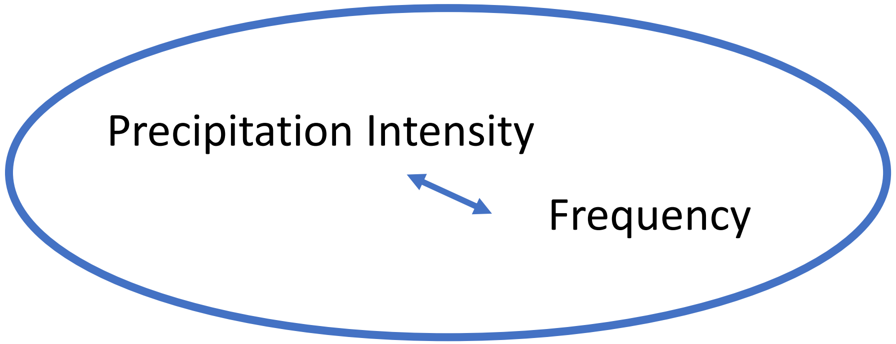


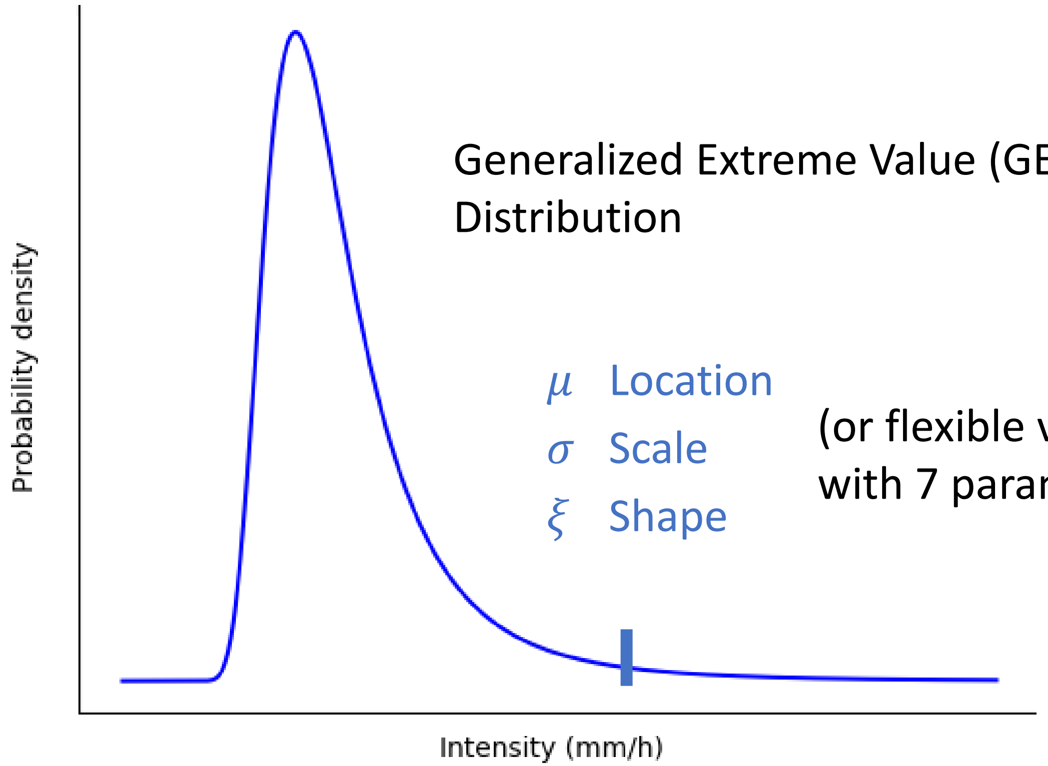
(Fauer, Rust, 2023)

Methods   Distribution of Block Maxima

Rain intensity daily time series

Annual max. intensity: M_{2009} M_{2010} M_{2011} ...





Generalized Extreme Value (GEV) Distribution

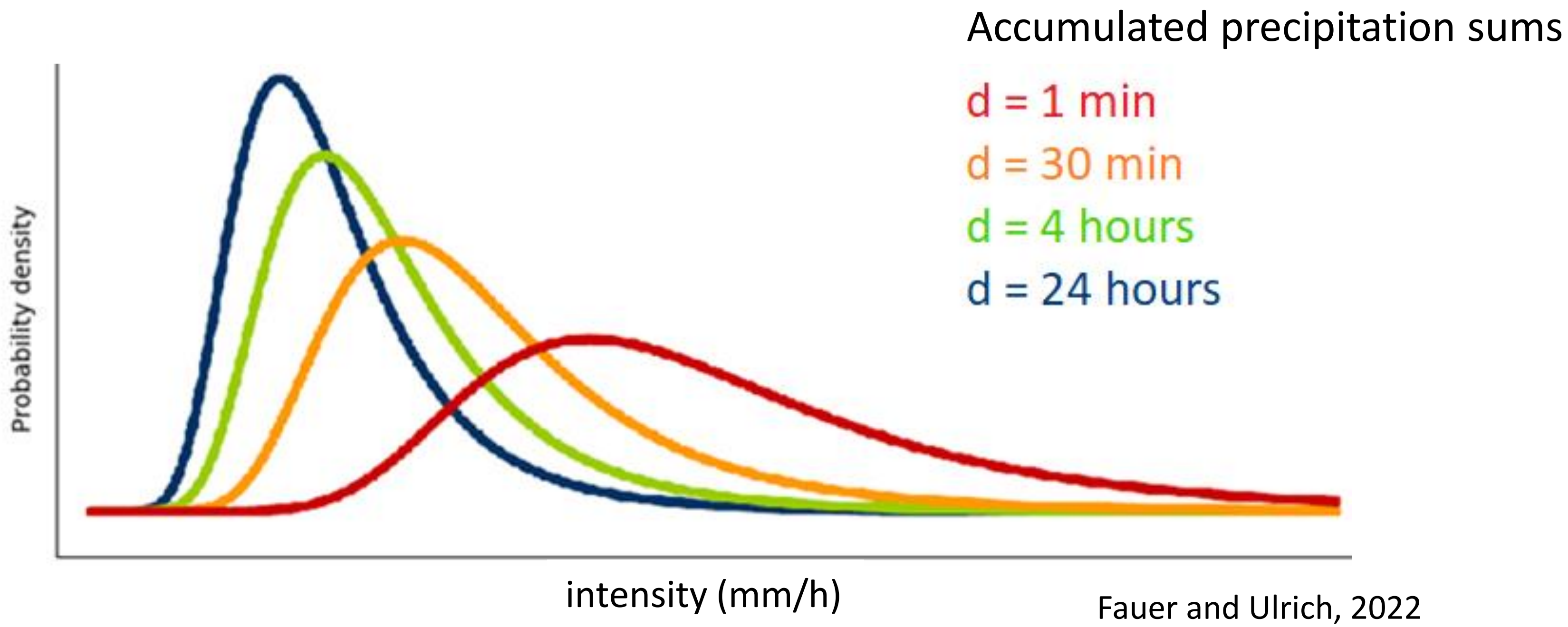
μ Location
σ Scale
ξ Shape

(or flexible version with 7 parameters)

Methods

Duration Dependency

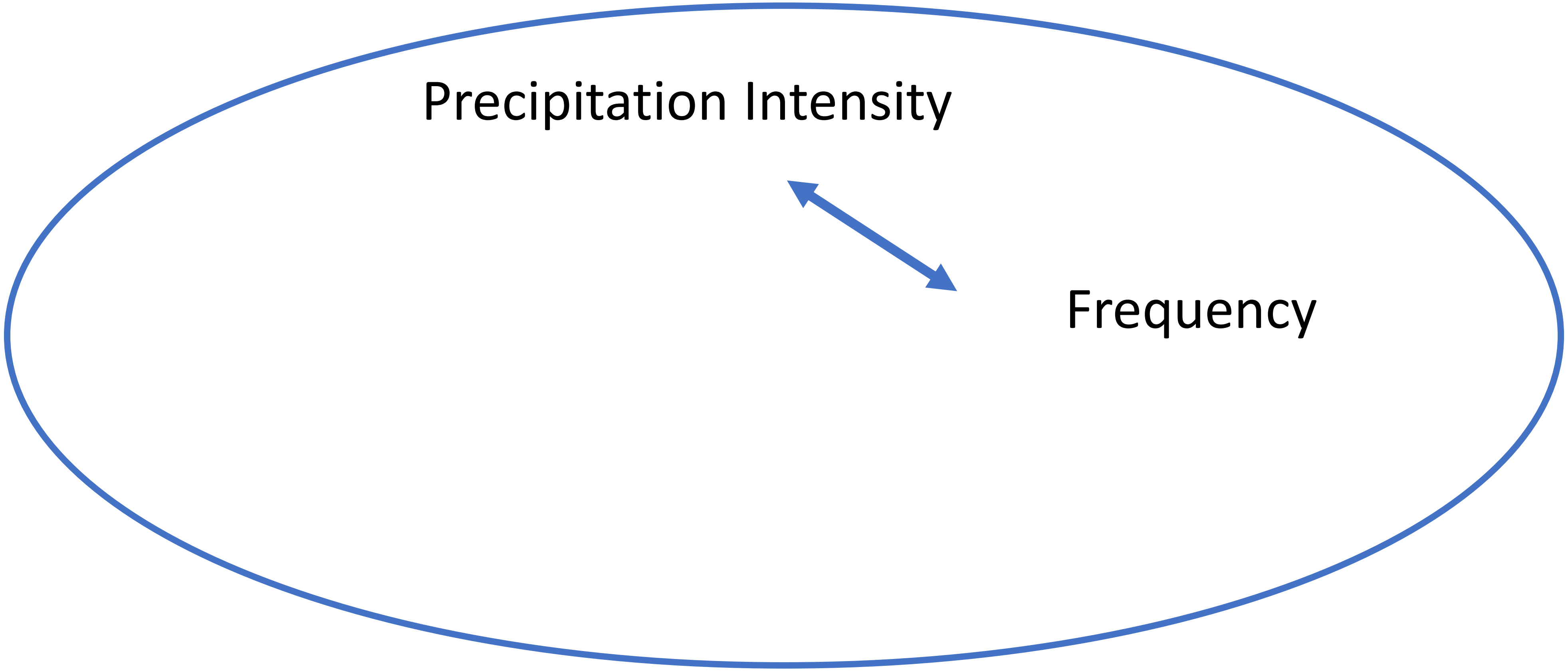
GEV - curves



Fauer and Ulrich, 2022

d-GEV: see Blanchet et al., 2016

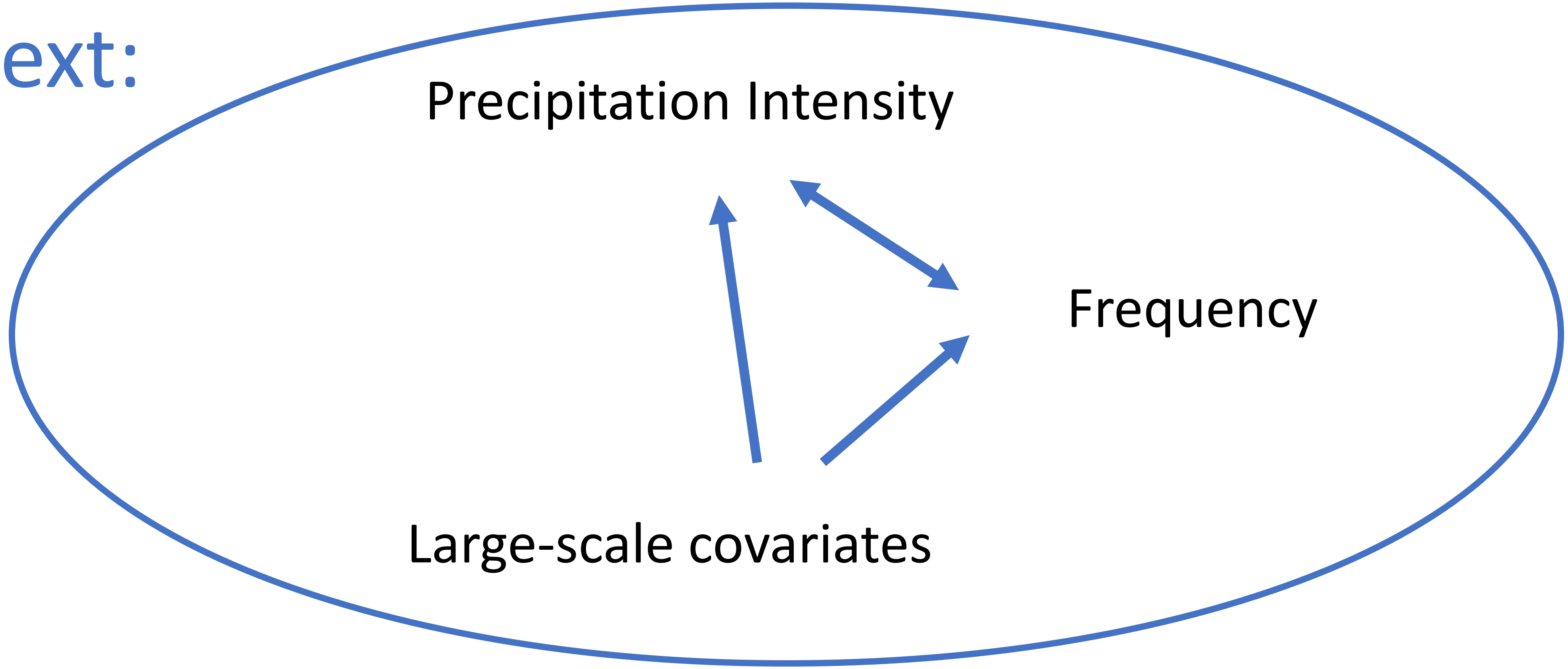
Methods



Methods

Distribution parameters: function of large-scale variable

Next:



→ see Ouarda et al, 2019

Methods

Distribution parameters: function of large-scale variable

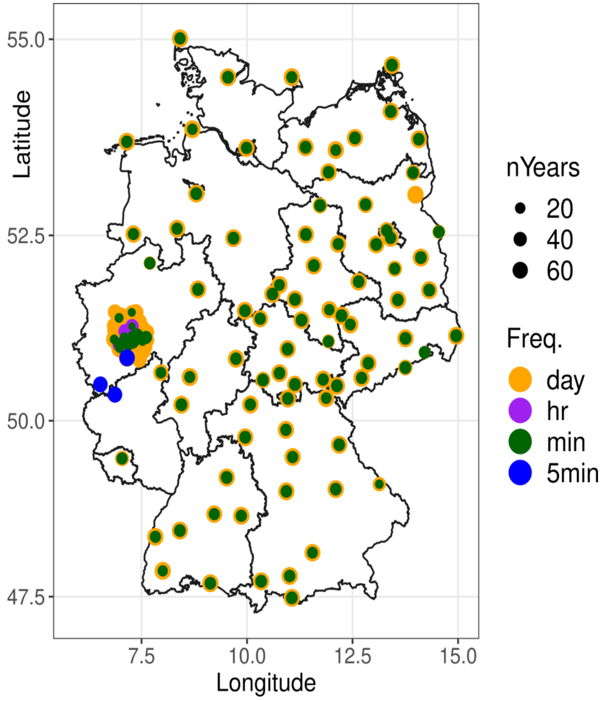
→ Example for dependency of location-parameter:

$$\tilde{\mu} = \beta_0 + \beta_1 \text{ NAO} + \beta_2 \text{ temperature}^2$$

- d-GEV parameters: linear model of large-scale covariates
- Up to 4th order
- Stepwise BIC model selection
- Cross-validated (2-fold)

Methods

Distribution parameters: function of large-scale variable



→ Individual model for every station

→ Example for dependency of location-parameter:

$$\tilde{\mu} = \beta_0 + \beta_1 \text{ NAO} + \beta_2 \text{ temperature}^2$$

- d-GEV parameters: linear model of large-scale covariates
- Up to 4th order
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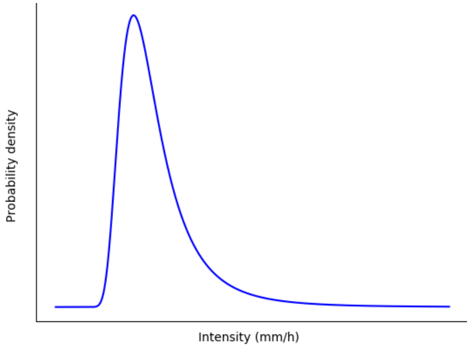
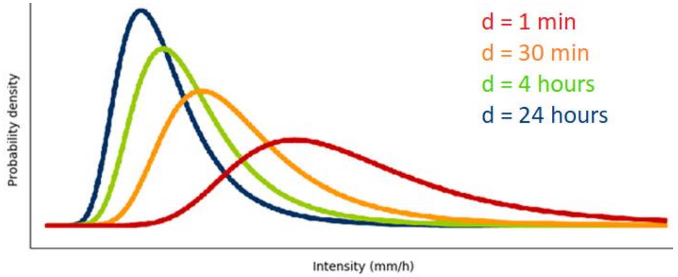
Summary of methods

1. Model distribution of extremes (GEV)



2. Include duration dependency of GEV – parameters (→ d-GEV)



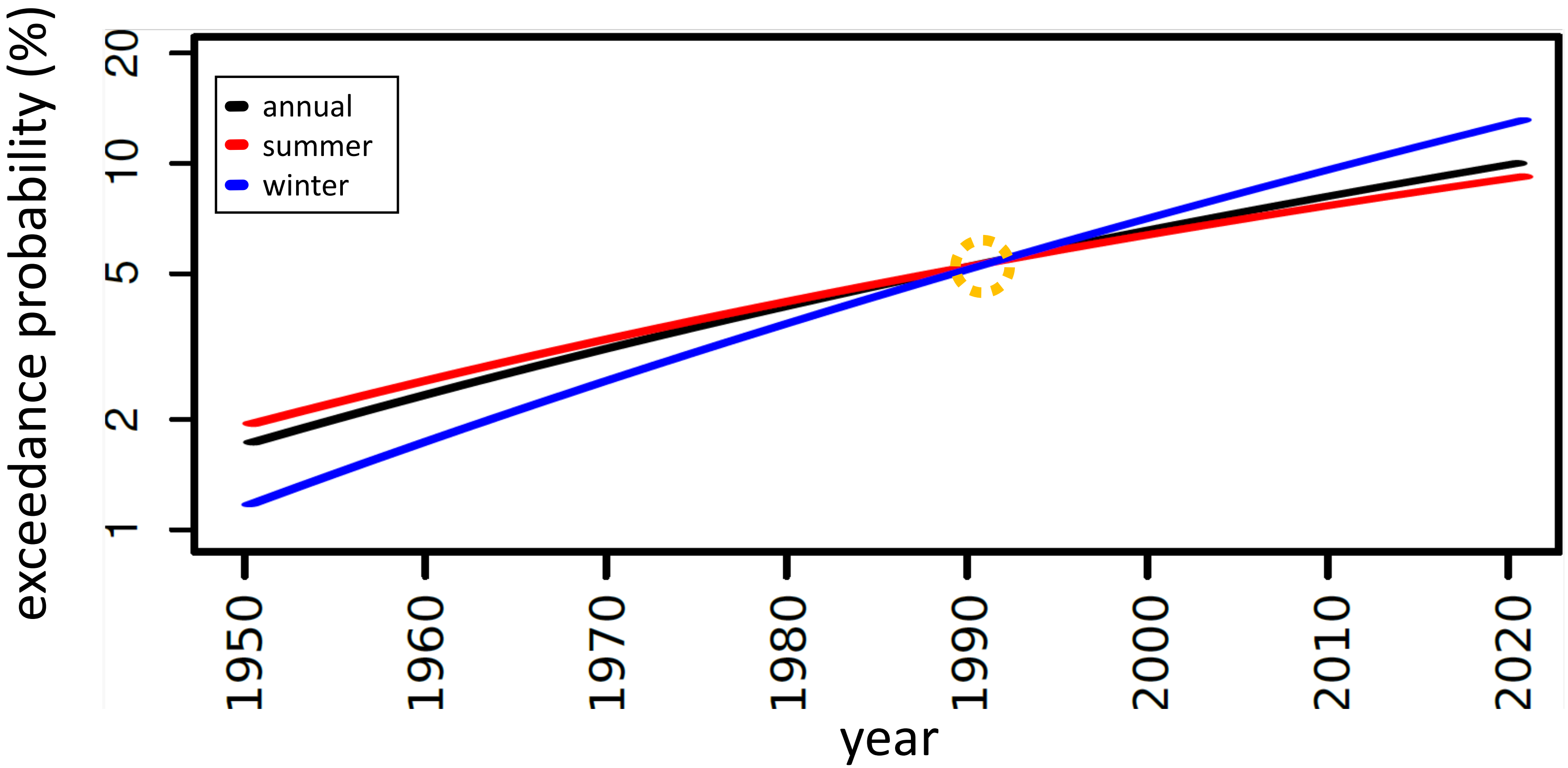
3. Include large-scale dependence of d-GEV parameters

$$\tilde{\mu} = f(NAO, \dots)$$
$$\sigma_0 = f(time, \dots)$$

Results

Large-scale dependencies in the **past**

- define a reference event
- simulate changes of probability ↕ in changing large scale conditions ↔
- other parameters are fixed



Reference event at

- Probability $p = 5\%$
- Year $y = 1990$
- NAO $n = 0$
- Temperature $T = 10°C$
- Blocking $b = 0$
- Humidity $h = 75\%$

One station (Bever-Talsperre)

(Fauer, Rust, 2023)

Results

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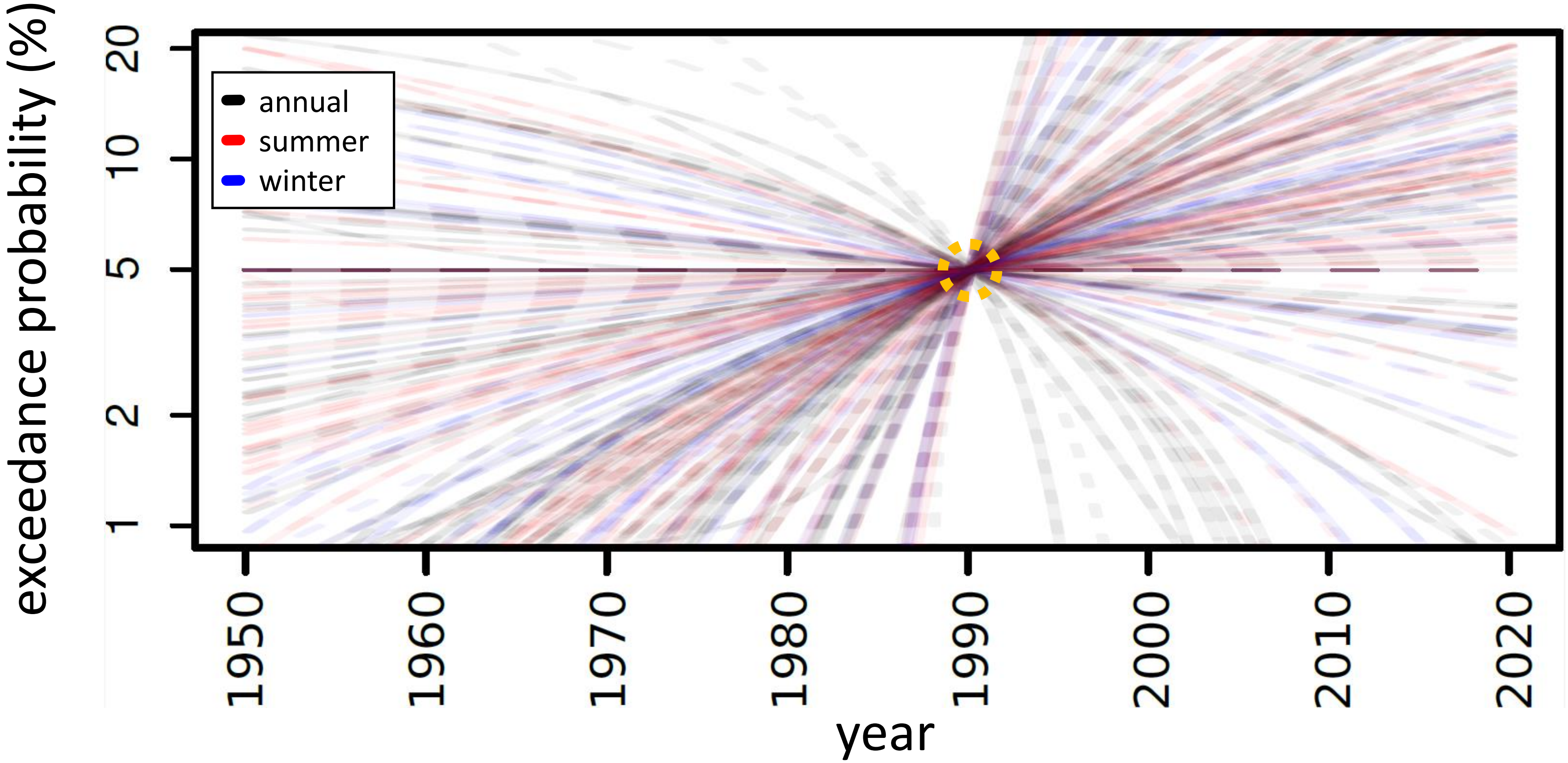

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all stations

(Fauer, Rust, 2023)

Results

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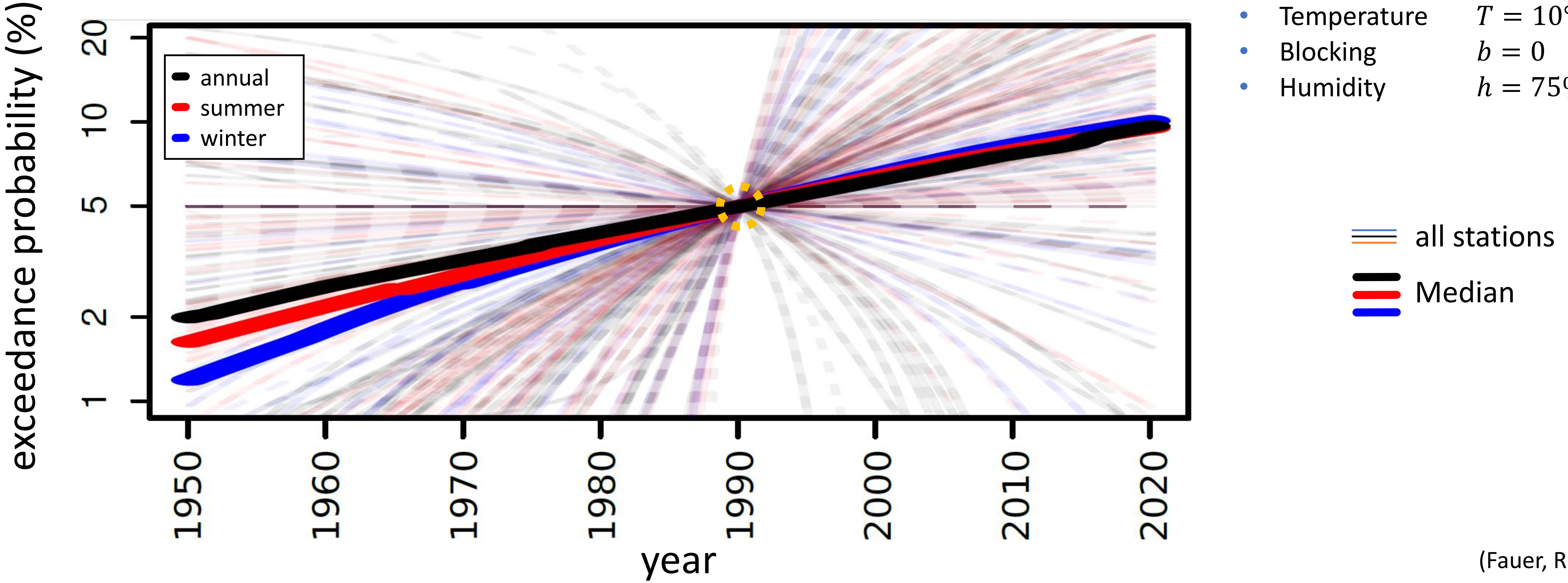

(Fauer, Rust, 2023)

Results

Large-scale dependencies in the **past**

Key result

- define a reference event
- simulate changes of probability ↕ in changing large scale conditions ↔
- other parameters are fixed

Reference event at

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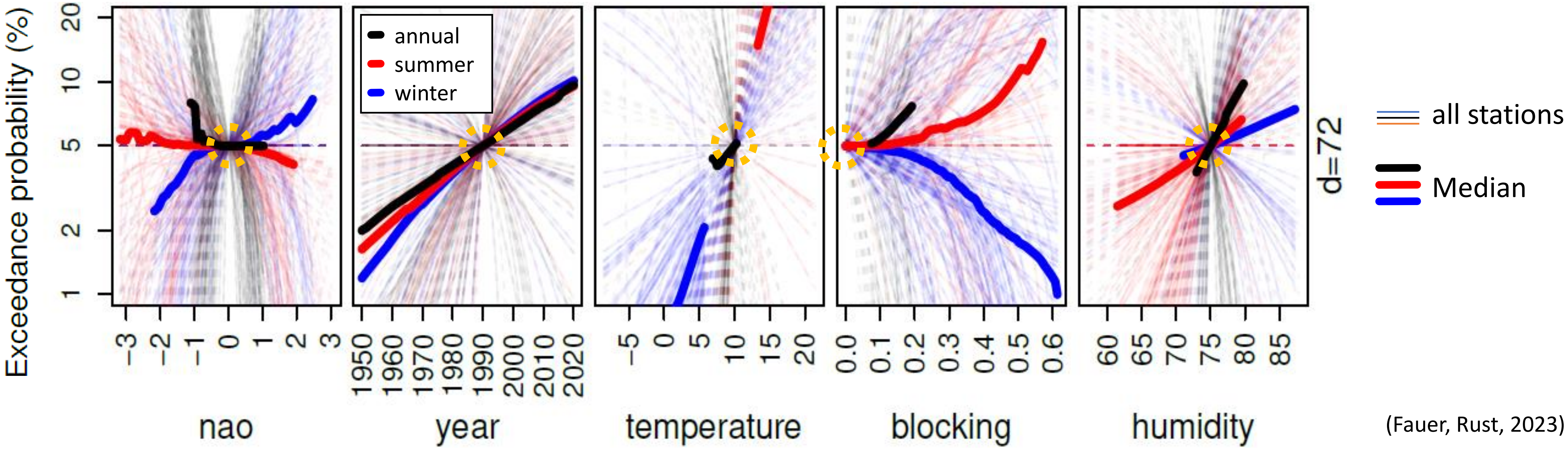
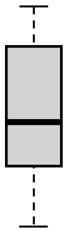


(Fauer, Rust, 2023)

Results

Large-scale dependencies – Future projections

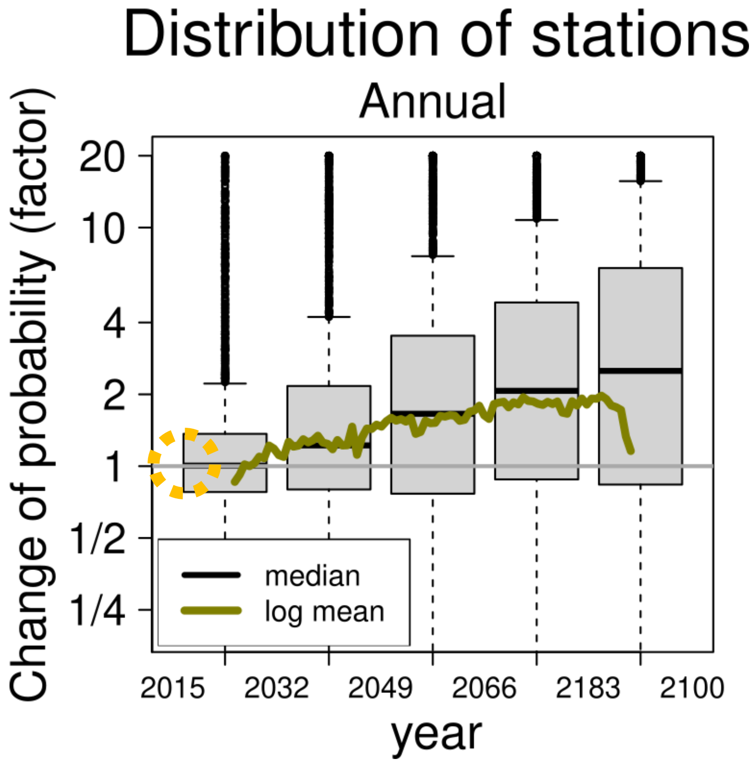
Key result



Distribution of 197 stations

- Reference event 2015: 5%-probability (factor 1)
- Simulate changes of probability ↕ in changing large-scale conditions ↔

- Training: historical station-wise block maxima
- Prediction: use projections from MPI-ESM for large-scale temperature, humidity, blocking, year



Fauer, 2024

Use our R library *IDF* 😊

available on CRAN

```
library(IDF)

# aggregate precip sums
block_maxima = IDF.agg(data, c(1, 6, 12, 24))

# estimate d-GEV parameters
fit = gev.d.fit(block_maxima$xdat, block_maxima$ds)

# plot IDF-curves
IDF.plot(ds, gev.d.parameters(fit), lwd=3)
```

- convenient aggregation
- Parallelize processes
- Easy inclusion of covariates
- Extract parameters
- Plot IDF curves
- Customize your plots

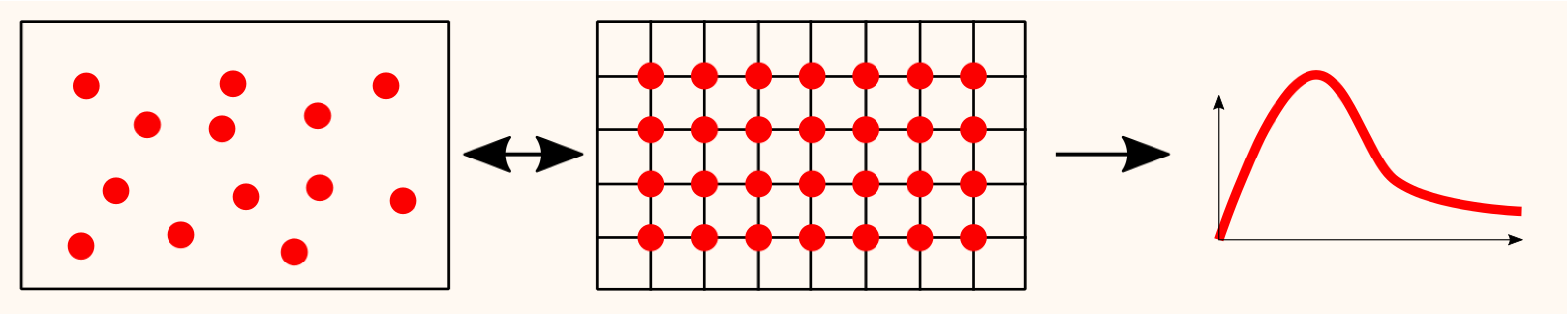
Find more information about d-GEV parameters:
Fauer et al, 2021

Future Plans - Outlook

Plans

Large-scale dependencies – **Gridded Data**

- Develop approaches to combine gridded data sets (high spatial resolution) and station-based data (long time records)
  for training



Stations

Grid-based model or reanalysis

Distribution of extremes

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Non-stationary large-scale statistics of precipitation extremes in central Europe

Original Paper | Open access | Published: 23 July 2023

Volume 37, pages 4417–4429, (2023) Cite this article

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Felix S. Fauer & Henning W. Rust

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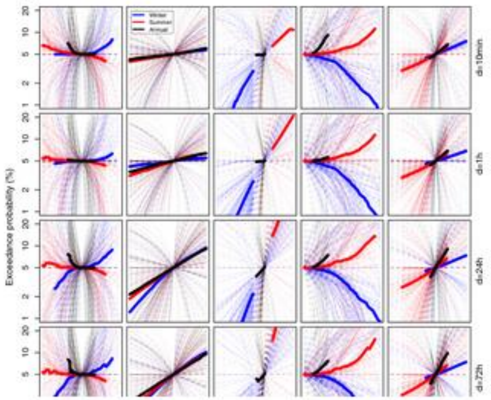
Abstract

Extreme precipitation shows non-stationarity, meaning that its distribution can change with time or other large-scale variables. For a classical frequency-intensity analysis this effect is often neglected. Here, we propose a model including the influence of North Atlantic Oscillation, time, surface temperature and a blocking index. The model features flexibility to use annual maxima as well as seasonal maxima to be fitted in a generalized extreme value setting. To further increase the efficiency of data usage, maxima from different accumulation durations are aggregated so that information for extremes on different time scales can be provided. Our model is trained to individual station data with temporal resolutions ranging from one minute to one day across Germany. Models are chosen with a stepwise BIC model selection and verified with a cross-validated quantile skill index. The verification shows that the new model performs better than a reference model without large-scale information. Also, the new model enables insights into the

Sections | Figures | References

Fig. 6



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Freie Universität Berlin

Thank you for Listening 😊

Sharing is encouraged

this slide only

You find more references on the next slide and in the supplementary material

References

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