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Modeling extreme streamflow events in river networks for stochastic simulation and climate-change projection

– Research project –

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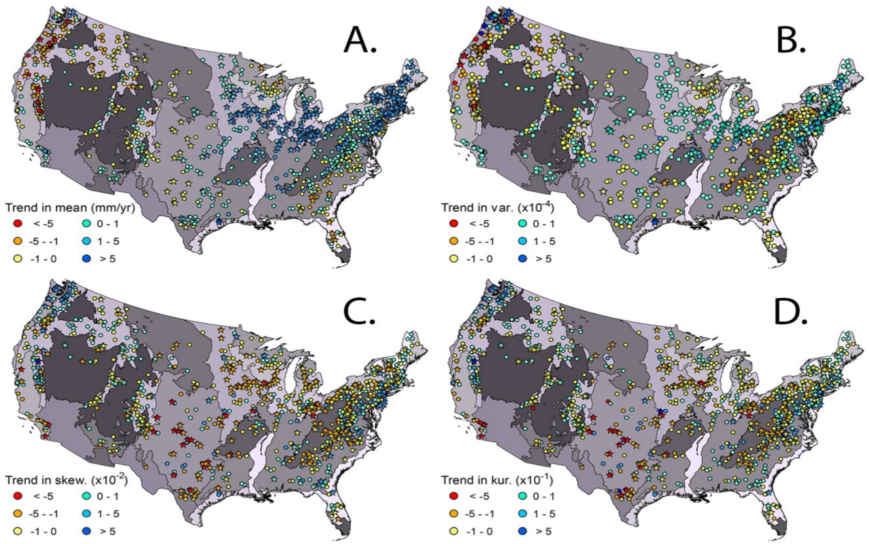
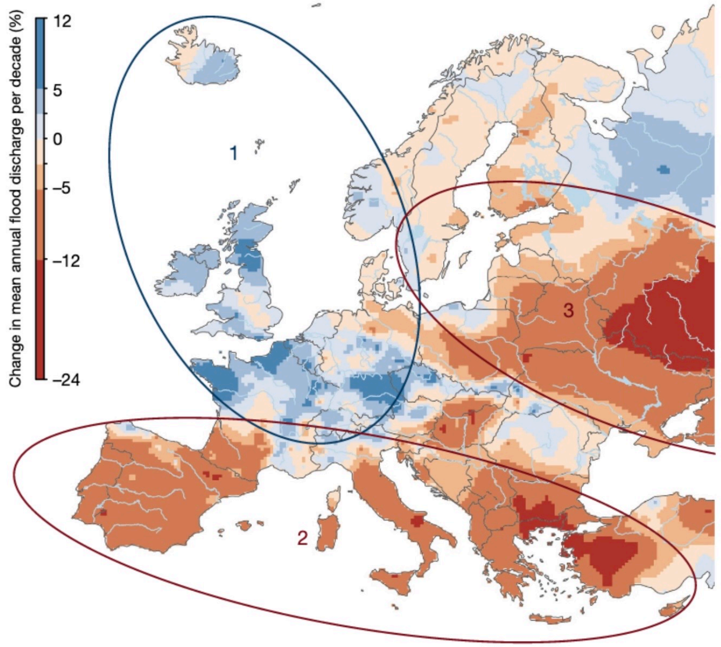
River flood risk

- Not a recent phenomenon,
  but **modified by changes in land use and climate**
- Intensively investigated,
  in fundamental and operational research
- Past and present **streamflow trends**:
  - **More heterogeneous and noisy** than large-scale climate
  - Possibly different trends in means and **extremes**



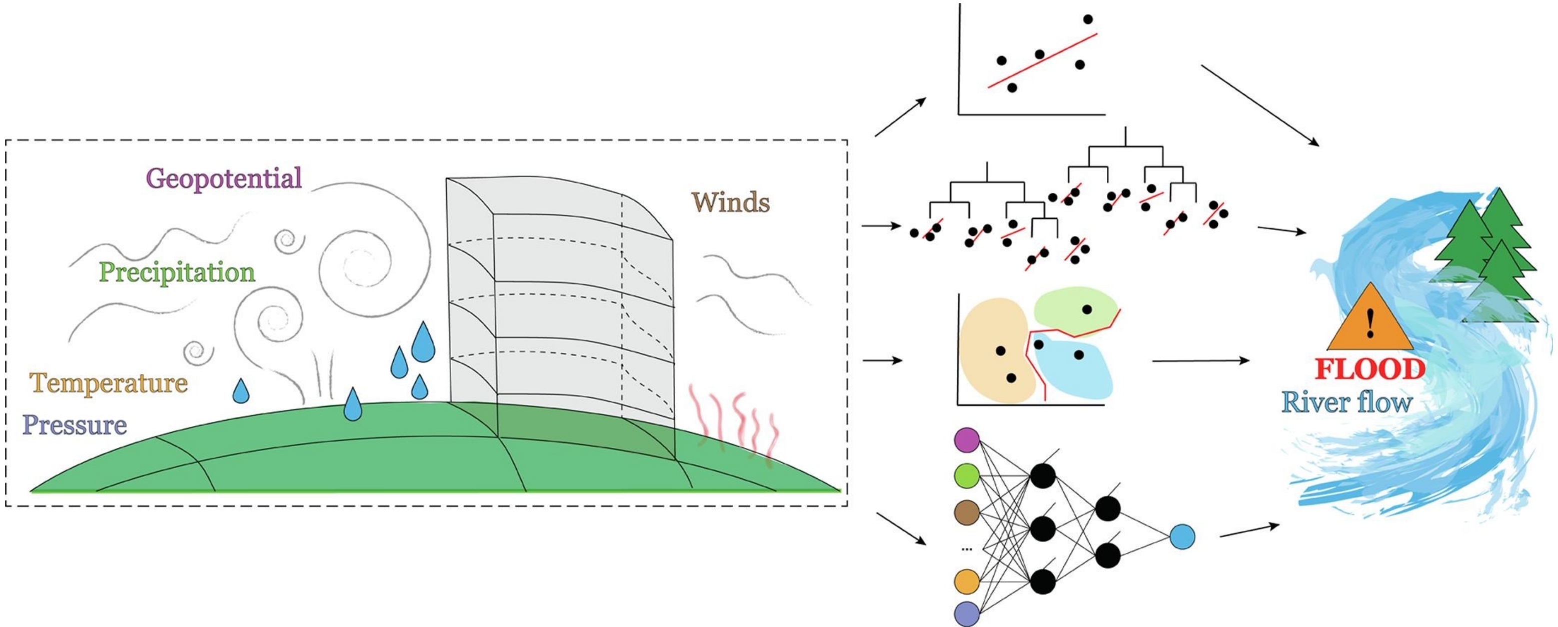
Rice et al (2015, WRR)



Blöschl et al (2019, Nature)

How can we learn about future floods?

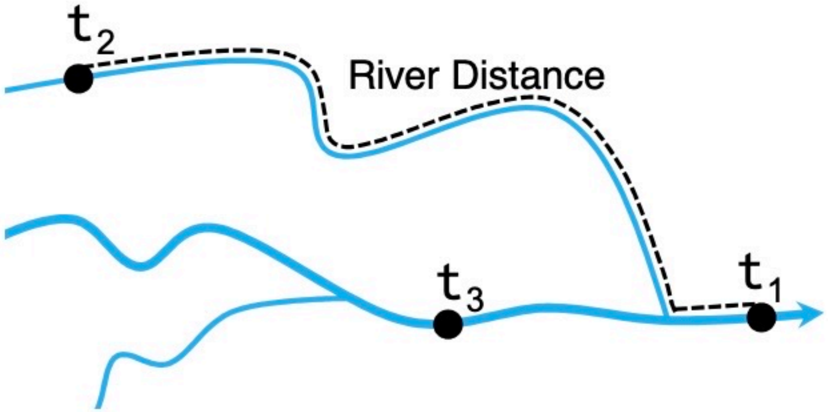
- **Climate-model simulations** of large-scale variables
  (Coupling of Global Circulation Models and Regional Climate Models)
- **Downscaling** to local scale of streamflows
  - Dynamical downscaling: large-scale variables as „boundary conditions“ in physical models
  - **Statistical downscaling** (our approach) :
    Learn statistical relationships to predict local-scale distribution
  - Include features of local topography, especially of the river catchment
- So far, relatively little work on **spatiotemporal dependence** along the river network



Hagen et al (2021, J Hydrol)

Dependence models should be aware of river topology

- No classical „Euclidean“ geometry and autocorrelation models
- Locations connected along the **1D river network**
- Direction of flow
- Space-time autocorrelation depends on **river distance**



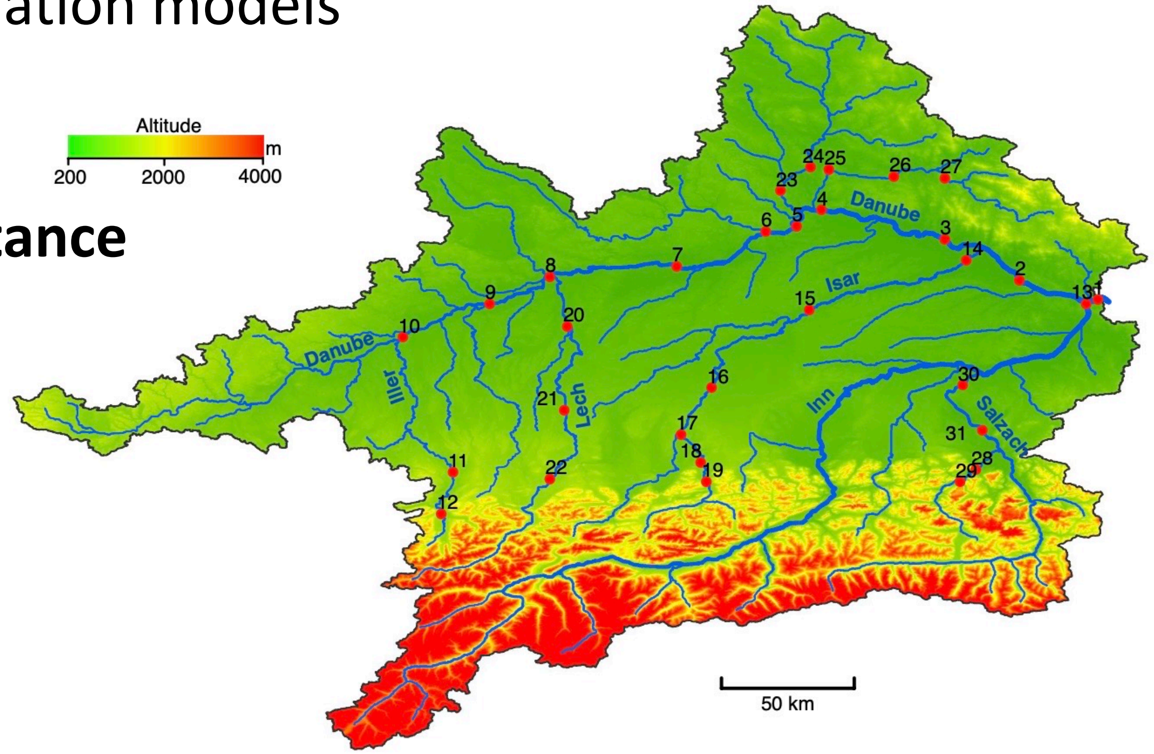


FIGURE 1. Topographic map of the upper Danube basin, showing sites of 31 gauging stations (red blobs) along the Danube and its tributaries. Water flows broadly from left to right.

Asadi et al (2015, AOAS)

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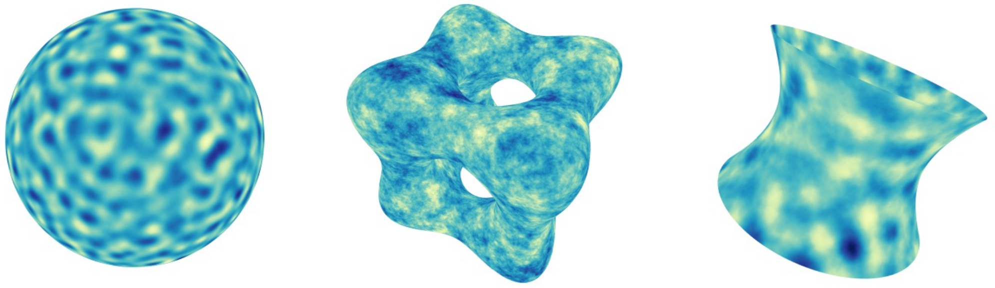
Random field models from Stochastic Partial Differential Equations

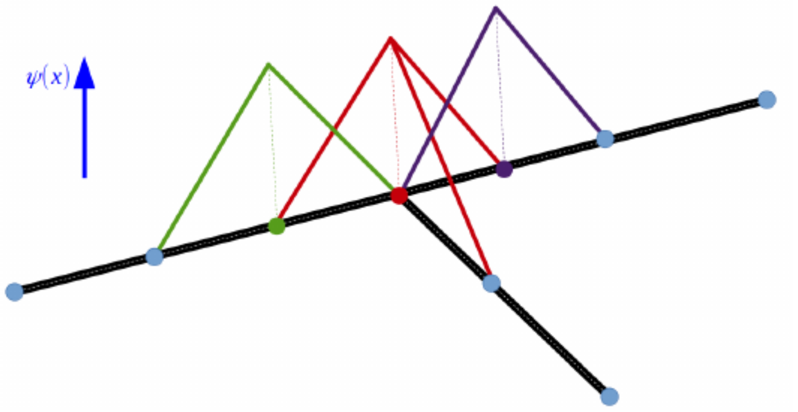
- **Space-time random field** X={X(s,t)}, here river discharge at location s, time t
- General **SPDE approach** for physically realistic and numerically tractable fields X

$$\frac{\partial}{\partial t} X(t,s) + (\kappa^2 - \Delta)^{\alpha/2} X(t,s) + \vec{\gamma} \cdot \nabla X(t,s) = \mathcal{W}(t,s), \quad t \geq 0, \quad s \in \mathcal{D}$$



- **Goal:** Adapt this approach to the topology of the **river network**
  → Finite-element discretization
  → **Flow conservation constraint**

$$\widehat{X}(s) = \sum_{i=1}^{n} \widehat{X}_i \psi_i(s)$$



Bolin et al (2022, arXiv)

Peaks-Over-Threshold for spatial extreme events

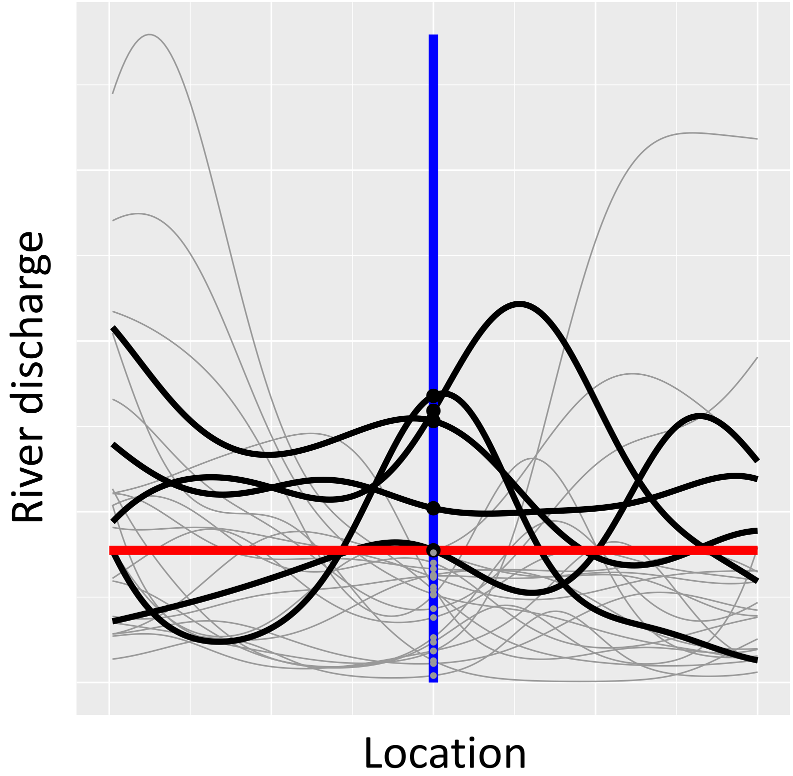
- **Risk functional** r(X), e.g. r(X) = max X(s,t) over space-time window
- Extreme episode X if **threshold exceedance** r(X) > u
- How to model X provided that r(X) > u ?

  Goal : Adapt asymptotic models from **Spatial Extreme-Value Theory**

Laurens de Haan (1987)

Example:

- r(X) = X(s0) for fixed location s0 (blue line)
- Threshold u (red line)
- Extreme episodes (black curves)
- Non-extreme episodes (grey curves)



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Expected outcomes of the project

- **Stochastic generator for space-time extreme-streamflow events**
  - Occurrence times and locations of extreme-event episodes
  - Local streamflow and space-time extent of flood events

- **Simulation of future streamflows through statistical downscaling of climate models**

- **Analysis of future extreme streamflows** at differents horizons (e.g. 2030, 2050, 2100)
  - Space-time trends
  - Sensitivity to input parameters
  - Uncertainty partitioning (climate scenario/model, downscaling, natural variability…)