Automatic Estimation of Parameter Transfer Functions for Distributed Hydrological Models - Function Space Optimization Applied on the mHM Model

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Abstract

FSO is a symbolic regression method that allows for automatic estimation of the structure and parameterization of transfer functions from catchment data. The FSO method transforms the search for an optimal transfer function into a continuous optimization problem using a text generating neural network (variational autoencoder). mHM is a widely applied distributed hydrological model, which uses transfer functions for all its parameters. For this study, we estimate transfer functions for the parameters saturated hydraulic conductivity and field capacity. To avoid the influence of parameter equifinality, the remaining mHM parameter values are optimized simultaneously. The study domain consists of 229 basins, including 7 major basins for Training and 222 smaller basins for validation, distributed across Germany. 5 years of data are used for training und 35 years for validation. By validating the estimated transfer functions in a set of validation basins in a different time period, we can examine the FSO estimated transfer functions influence on model performance, scalability and transferability. We find that transfer functions estimated by FSO lead to a robust performance when being applied in an ungauged setting. The median KGE of the validation basins in the validation time period is 0.73, while the median KGE of the 7 training basins in training time is 0.8. These results look promising, especially since we are only using 5 years of training data, and show the general applicability of FSO for distributed hydrological models.

AUTOMATIC ESTIMATION OF PARAMETER TRANSFER FUNCTIONS FOR DISTRIBUTED HYDROLOGICAL MODELS

FUNCTION SPACE OPTIMIZATION APPLIED TO THE mHM MODEL

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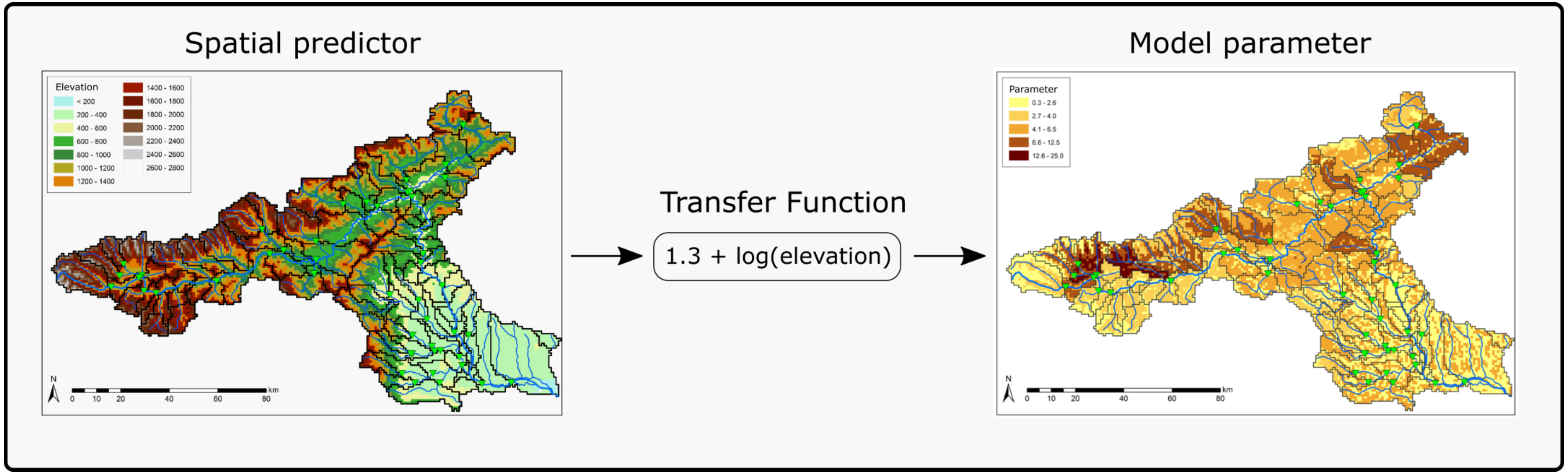
Transfer Functions

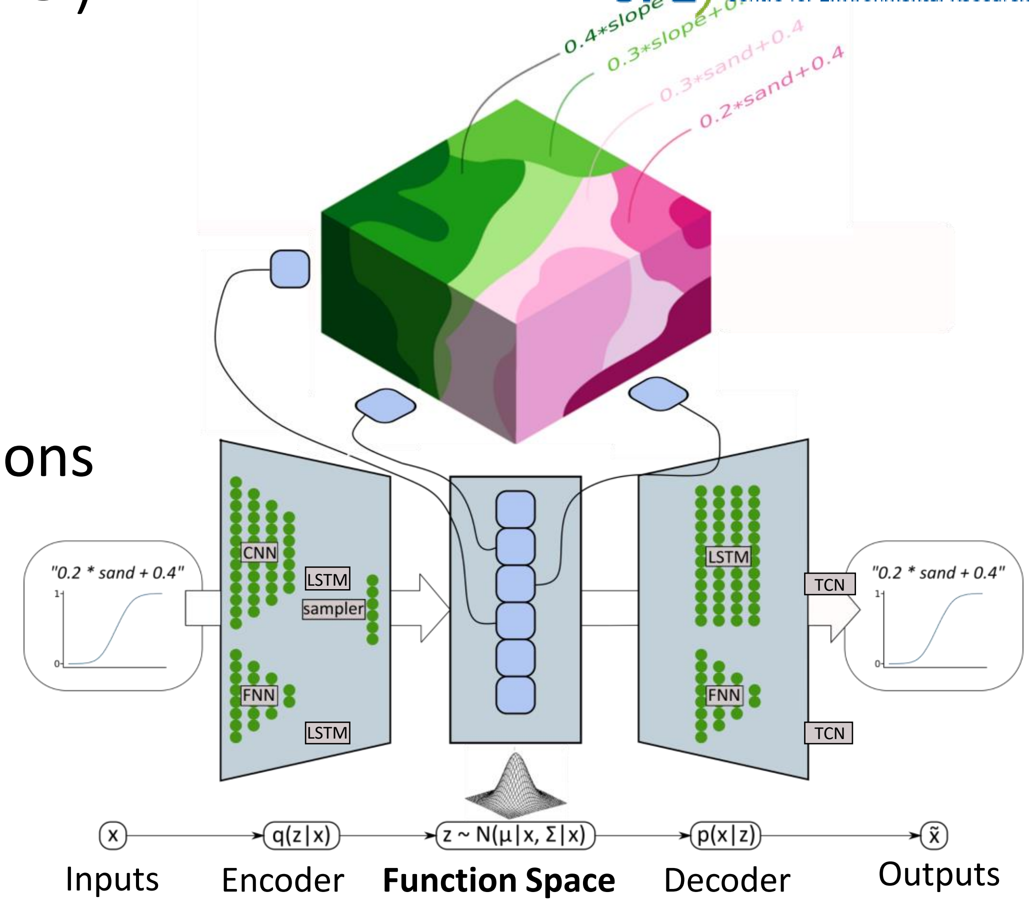


Transfer functions map geophysical catchment properties to distributed model parameters

Function Space Optimization (FSO)

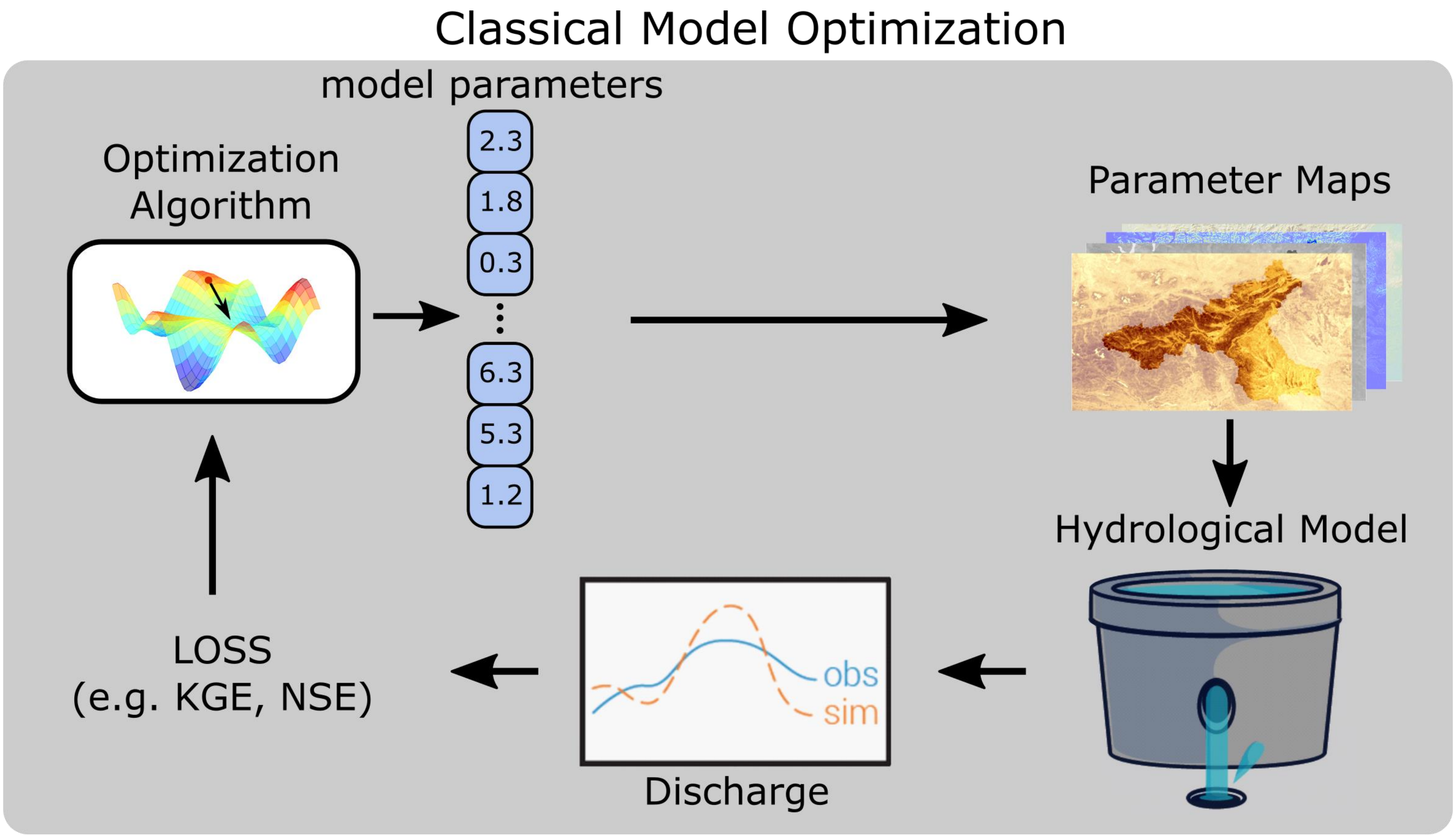
Feigl et al., 2020

- FSO: optimization method for transfer functions
- Uses a text generating Neural Network
- Transforms search into continuous problem
- Successfully tested on a single catchment

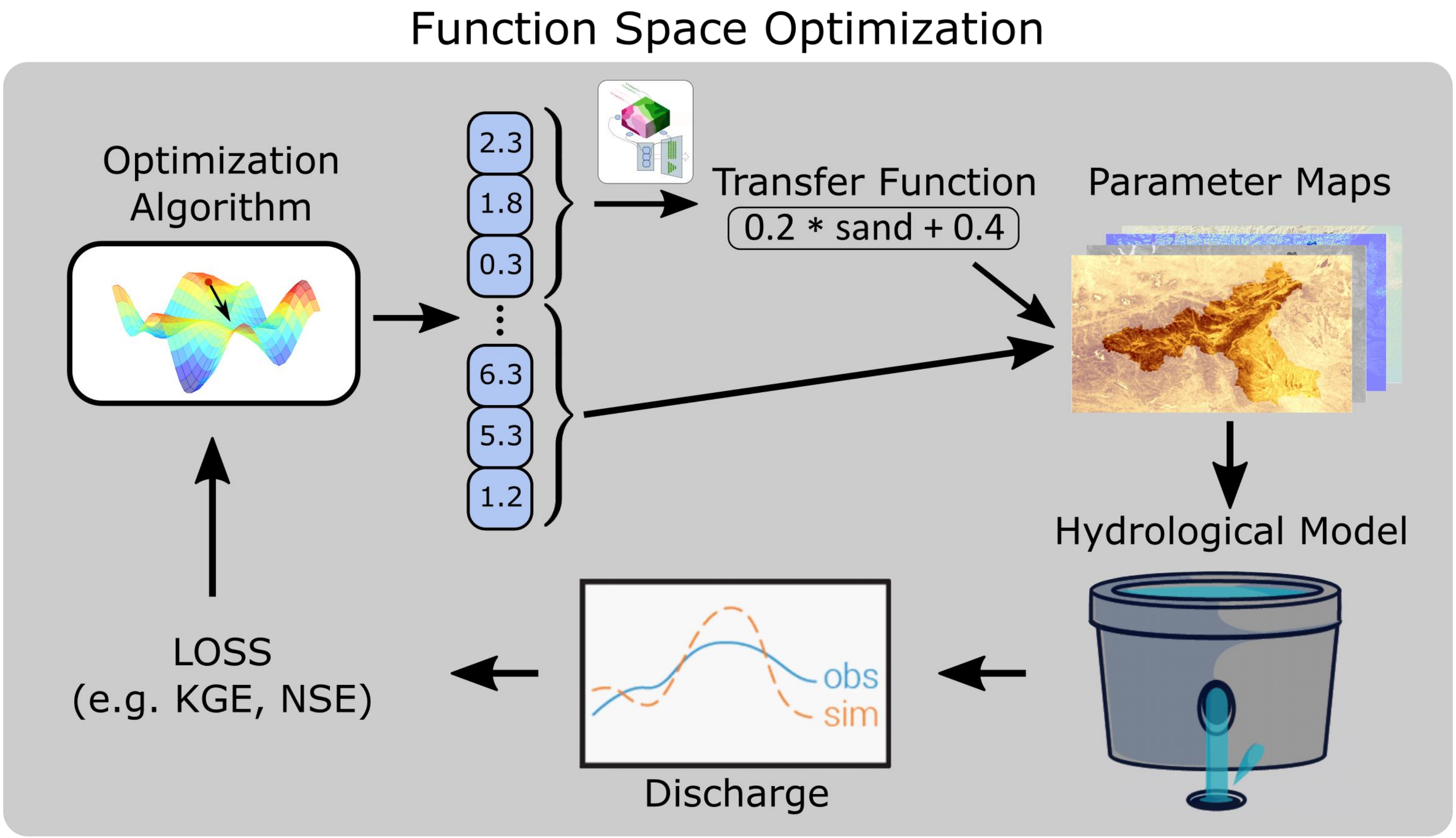


FSO variational autoencoder
Feigl et al. (2020)

Function Space Optimization (FSO)

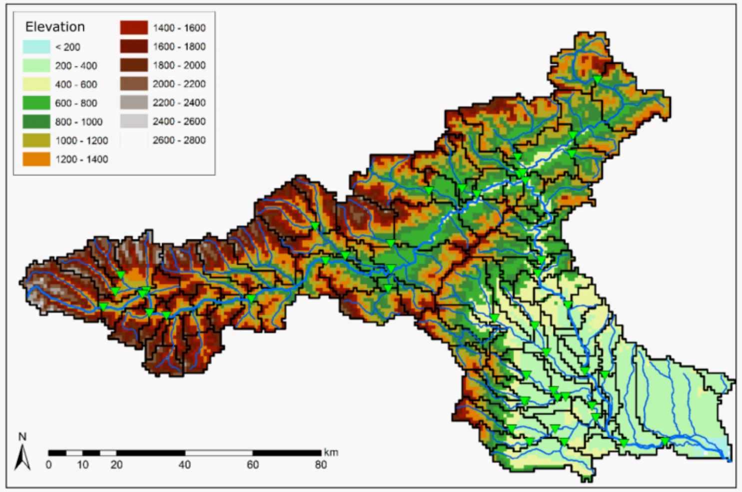


Function Space Optimization (FSO)



FSO parameter scaling

Spatial predictor

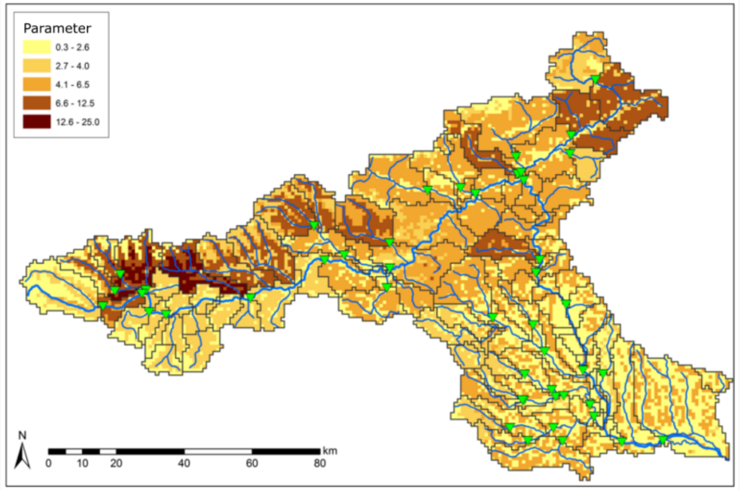


value range: e.g. elevation [0, 3000]

Transfer Function

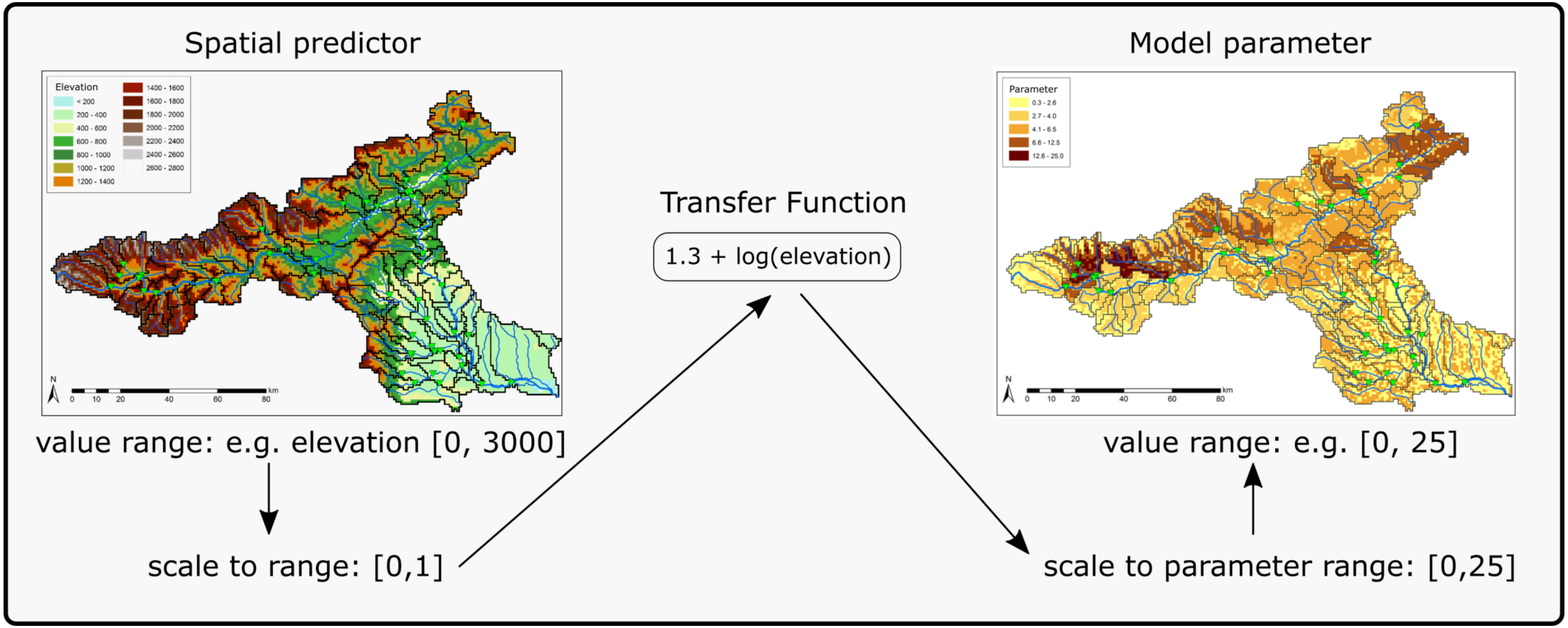
→ 1.3 + log(elevation) ? →

Model parameter

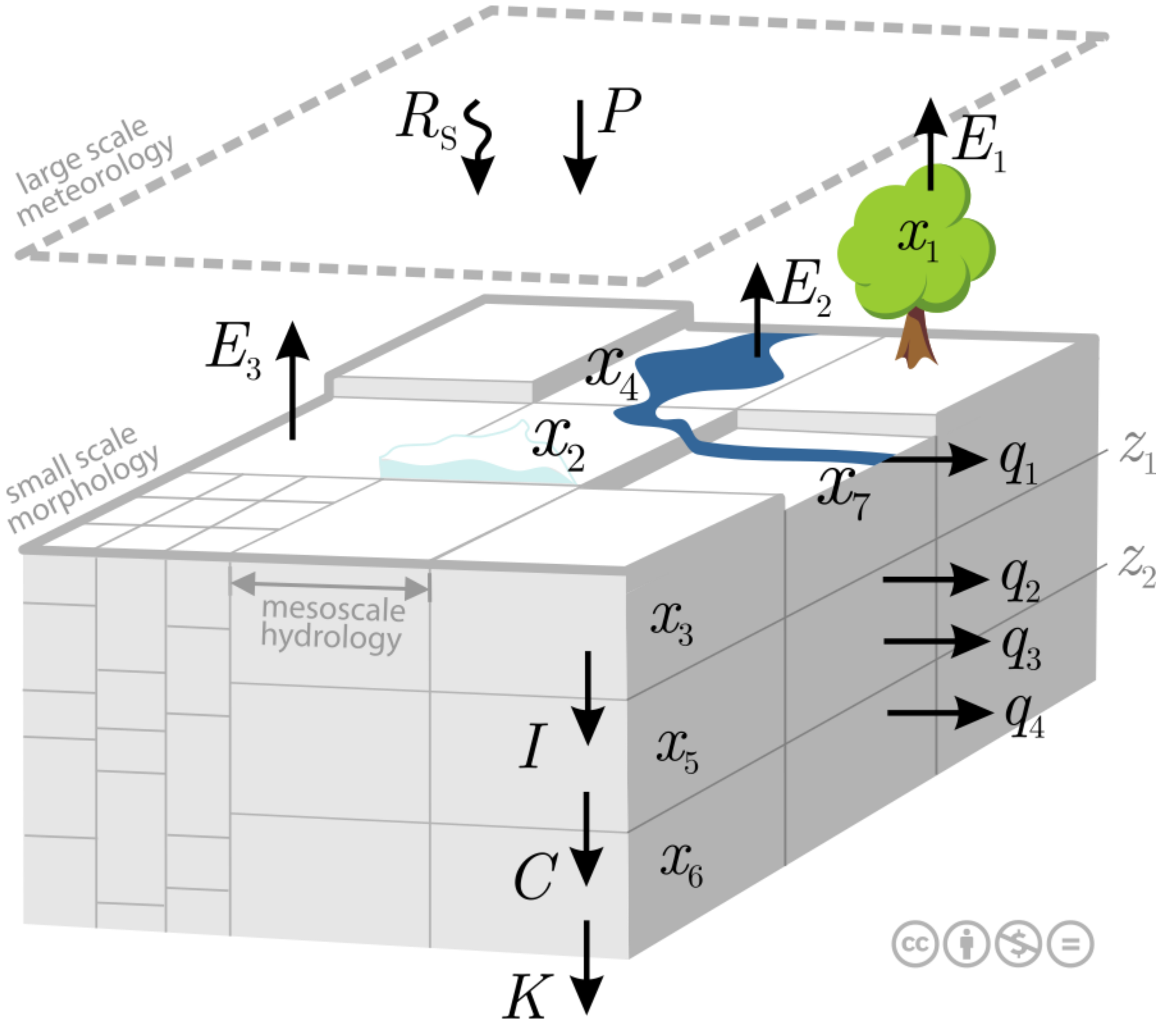


value range: e.g. [0, 25]

FSO parameter scaling

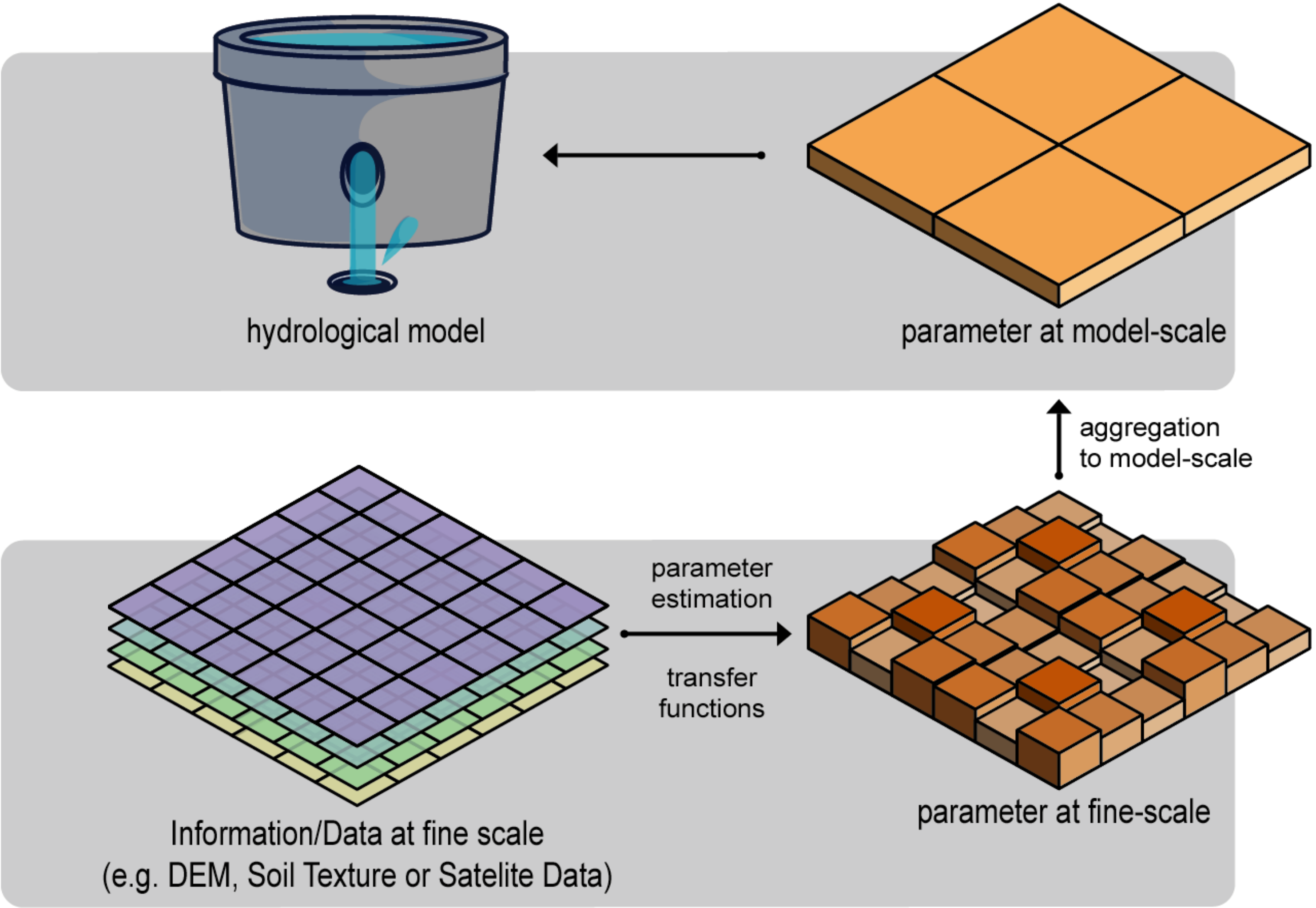


The mesoscale Hydrological Model (mHM)



- Developed by Samaniego et al. (2010)
- Spatially explicit distributed model
- Uses grid cells as primary units
- Defines parameter fields with the Multiscale Parameter Regionalzation method (MPR)

Multiscale Parameter Regionalization (MPR)



Regionalization method by Samaniego et al. (2010)

Benchmark Study – Zink et al. (2017)

Hydrol. Earth Syst. Sci., 21, 1769–1790, 2017
www.hydrol-earth-syst-sci.net/21/1769/2017/
doi:10.5194/hess-21-1769-2017

Hydrology and Earth System Sciences
Open Access

A high-resolution dataset of water fluxes and states for Germany accounting for parametric uncertainty

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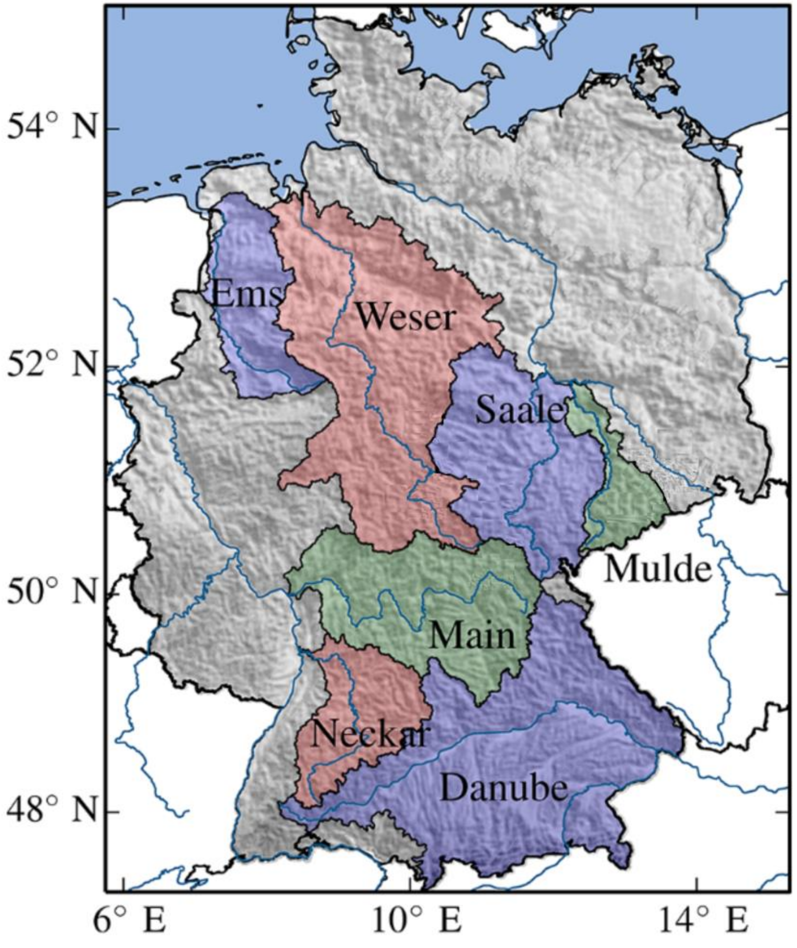
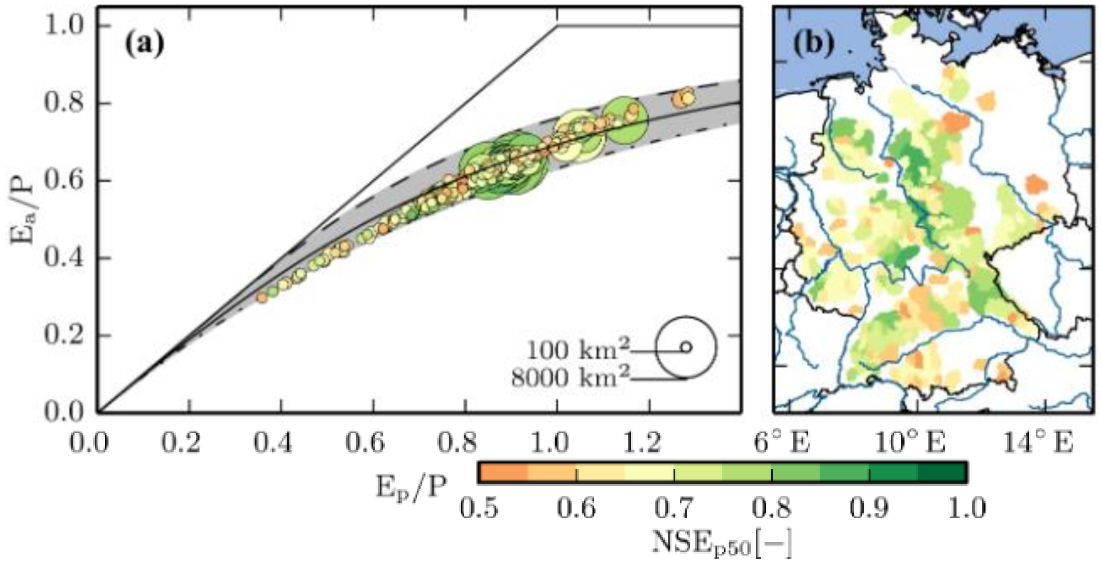
Benchmark Study – Zink et al. (2017)

- Optimizing mHM 100 times with 2000 iterations
- Using 7 gauging stations
- Validate 100 parameter sets on 220 Basins



Training basins

(Zink et al., 2017)



Validation basins

(Zink et al., 2017)

Study Objectives

1. Apply FSO using a wide range of catchments
2. Simultaneously optimize 2 transfer functions and all other numerical parameters
3. Optimize: Saturated Hydraulic Conductivity, Field Capacity
4. Analyze performance and transferability in a prediction in ungauged basins (PUB) setting
5. Compare original mHM tranfer functions with FSO estimates

Case study – study basins

7 Training basins, 220 Validation Basins

Resolution:

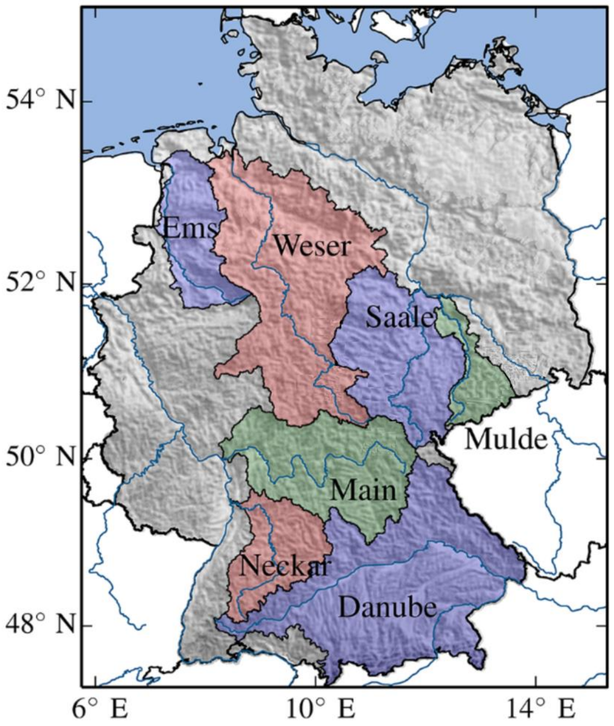
Spatial predictors: 100 x 100 m
Model grid: 4 x 4 km

Spatial predictors:

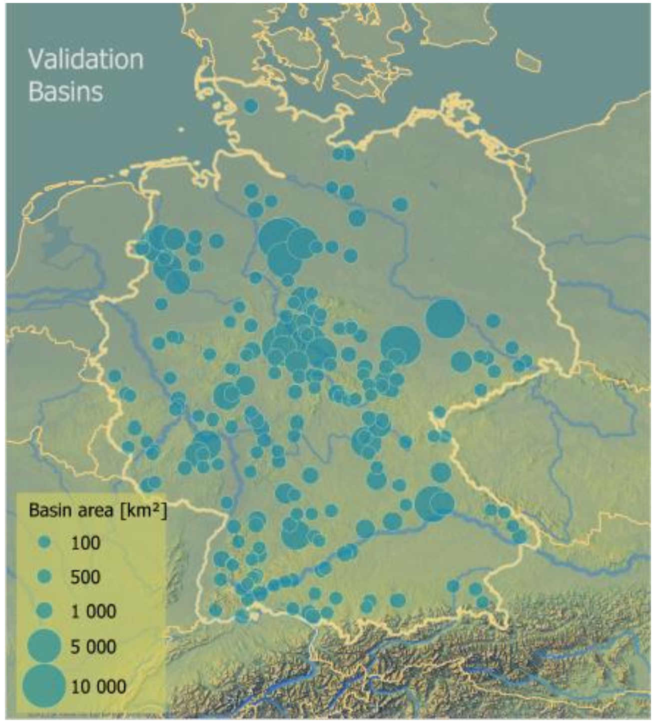
Mean sand percentage (sand)
Mean clay percentage (clay)
Mineral bulk density
Aspect
Terrain slope
Elevation

Time series:

7 & 220 gauging stations
Calibration: 2000-2004
Validation: 1965-1999
Spin-up: 5 years

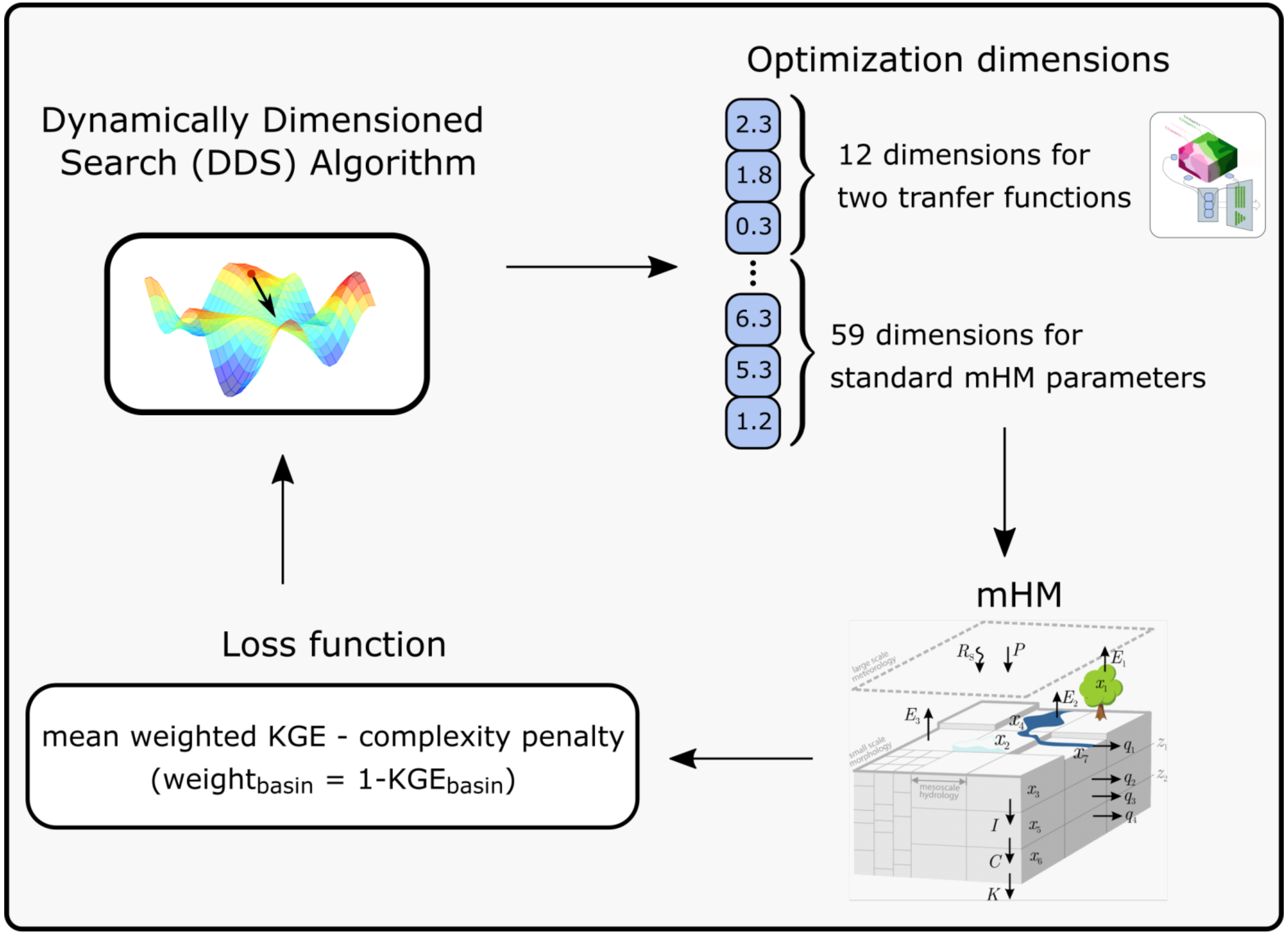


7 Training basins
(Zink et al., 2017)



220 Validation basins

Case study – Optimization



FSO optimization using the DDS algorithm (Tolson & Shoemaker, 2007)

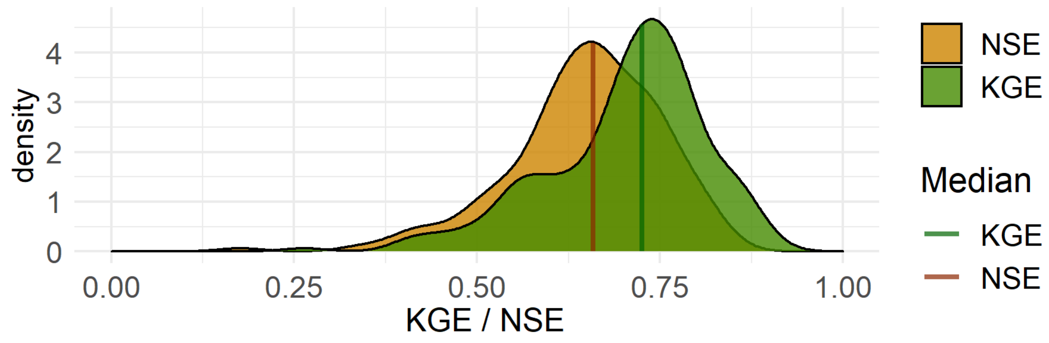
Preliminary results – 7 Training Basins

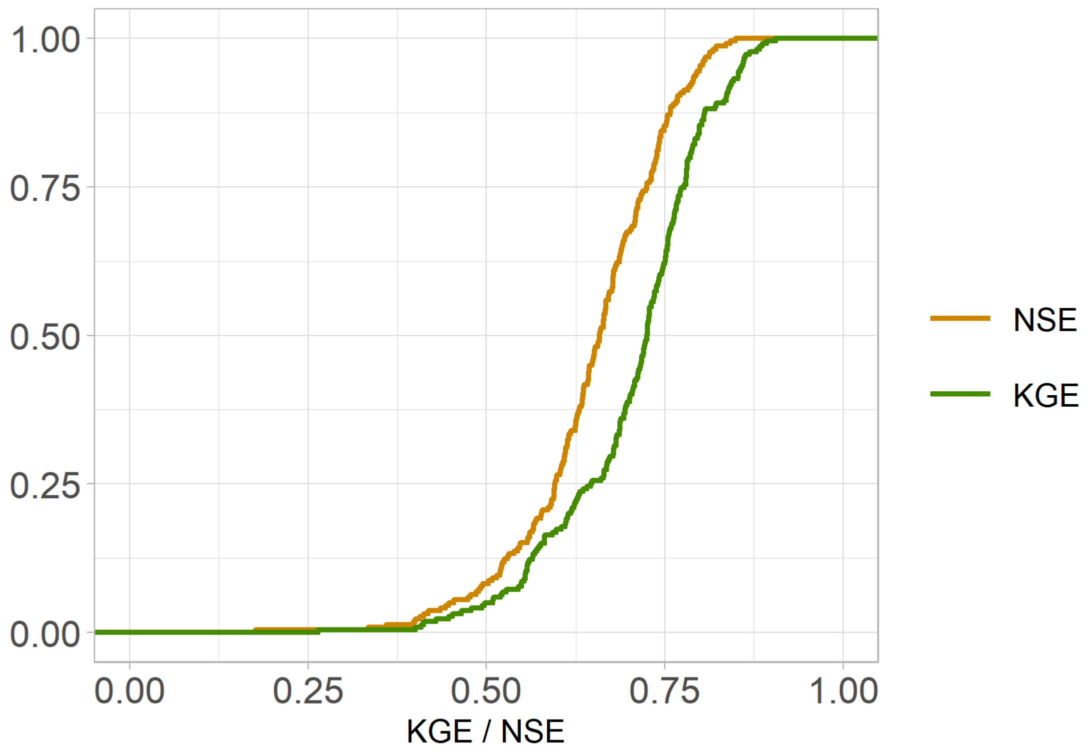
Training Basins KGE Results

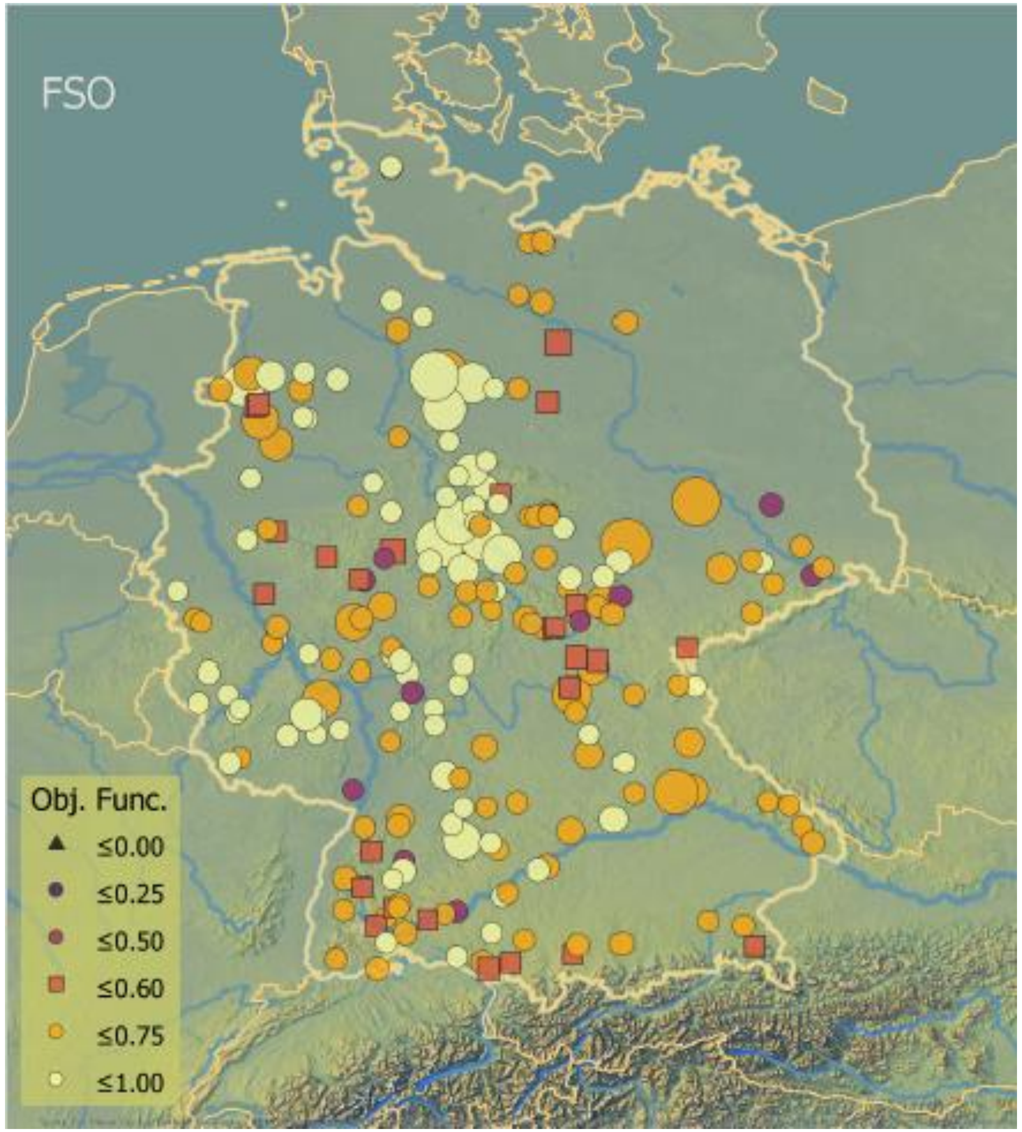
	Period	median KGE	Main	Neckar	Weser	Ems	Saale	Mulde	Donau
FSO-mHM	Calibration	0.83	0.90	0.85	0.90	0.82	0.81	0.77	0.82
	Validation	**0.80**	**0.85**	**0.83**	**0.89**	**0.80**	**0.77**	**0.65**	**0.71**

FSO results after approx. 900 iterations

Preliminary results –220 validation basins







Imhof-Like Background Topography by @John_M_Nelson

Preliminary results – estimated transfer functions

Saturated hydraulic conductivity (cm/d):

mHM: $\mathrm{KSat} = \gamma_1 * \exp(\gamma_2 + \gamma_3 * \mathrm{sand} - \gamma_4 * \mathrm{clay}) * \log(10)$

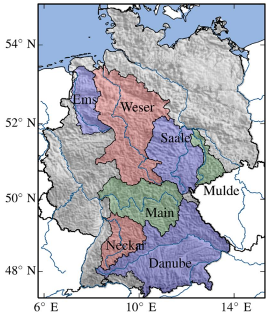
FSO-mHM: $\mathrm{KSat} = \mathrm{elevation} + \exp(\mathrm{bulk\ density}) - 3.14$

Field Capacity (-):

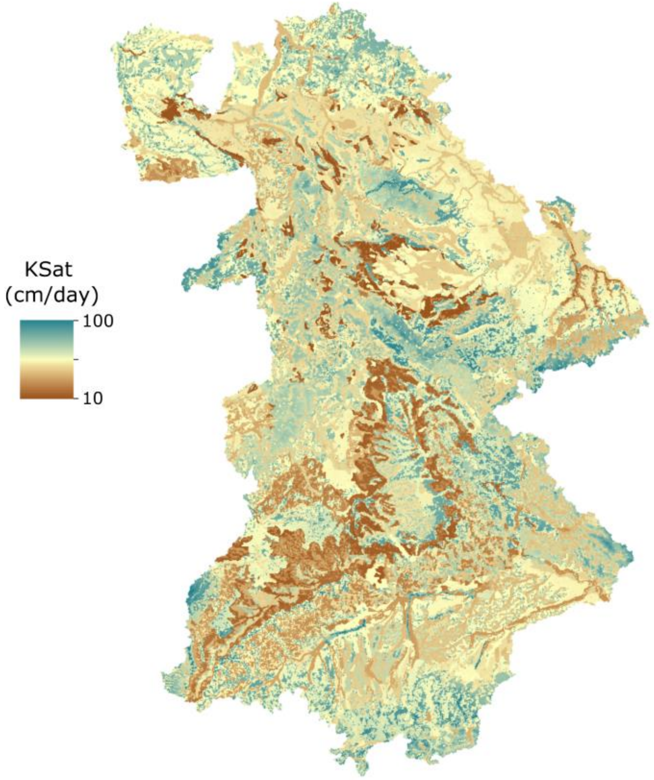
mHM: $\mathrm{FieldCap} = \mathrm{ThetaS} * \exp(\gamma_5 * (\gamma_6 + \mathrm{log10}(\mathrm{KSat})) * \log(\mathrm{vGenu\_n})$

FSO-mHM: $\mathrm{FieldCap} = -0.336^{\sqrt{0.333/\sqrt{\mathrm{bulk\ density}}}}$

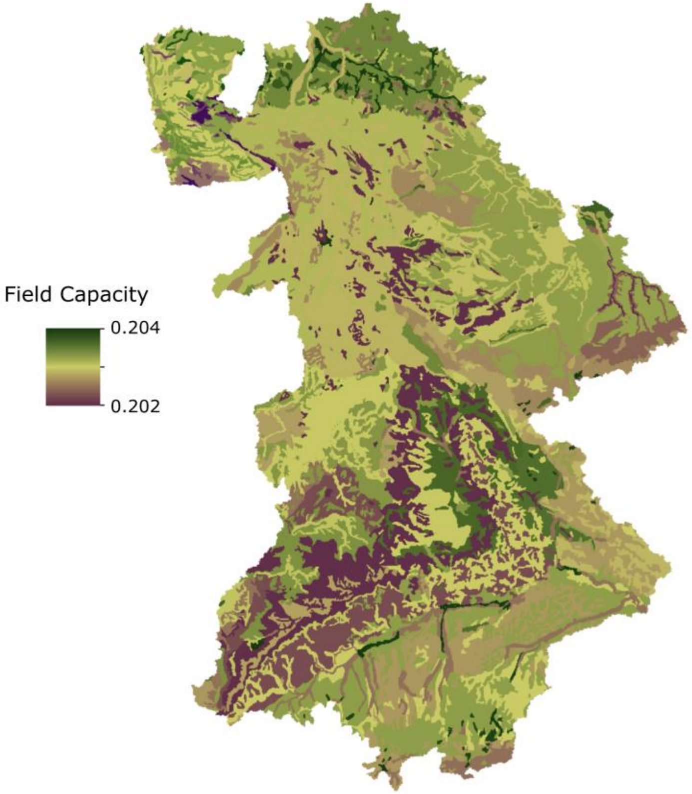
Preliminary results – estimated parameter fields



Saturated Hydraulic Conductivity (cm/day)



Field Capacity (-)



Resulting parameter fields on the 100 x 100 m grid for the top layer of the model (tillage layer, first 20 cm)

Summary, Discussion & Outlook

- FSO **trained with 5 years data of 7 gauging stations**:

  training median KGE = 0.80

  PUB median KGE = 0.73
- Preliminary results look promising → only 900 iterations
- Field Capacity is constant → most likely local minimum → continue optimization
- Multiple longer optimization runs needed for robust performance evaluation
- Compare validation basins results with performance of Zink et al. (2017)
- Comparison of final FSO parameter fields to geophysical properties

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