

Regionalisation as a learning process



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Regionalisation

Hydrological prediction is very often concerned with non-stationary conditions

- changing land-use
- changing boundary conditions (e.g., climate)
- changing catchments (i.e. regionalisation)

When making predictions in non-stationary conditions, we expect effective model parameters to change.

Strategies for changing parameters in a regionalisation context

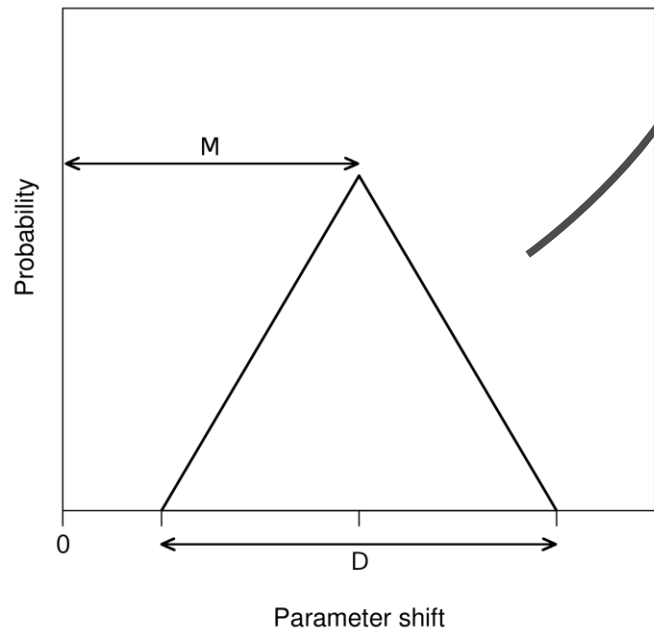
- changing parameters by linking them to catchment properties
- reconstitution of parameter sets from one or more donor catchments

Here, we combine both approaches using within a learning framework:

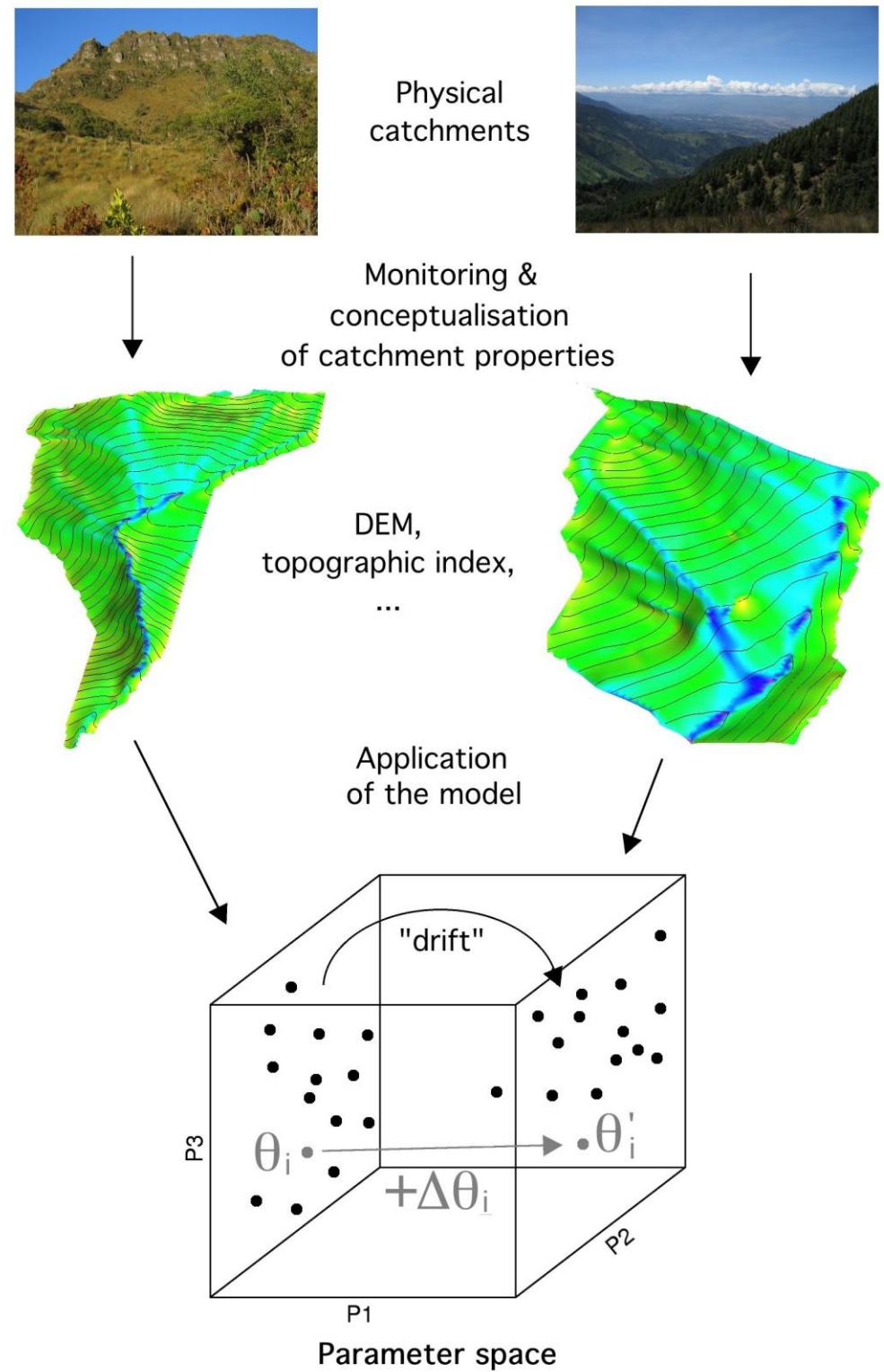
- Can parameter modifications improve the predictions of an ungauged basin in an ensemble approach?
- If so, how much uncertainty is involved in this process?
- Is it possible to characterize this uncertainty, and use it for future predictions?

Looking for uncertain parameter transformations...

$$\theta'_i = \theta_i + \Delta\theta_i$$



sampling



Physical catchments

Monitoring & conceptualisation of catchment properties

DEM, topographic index, ...


Application of the model

"drift"

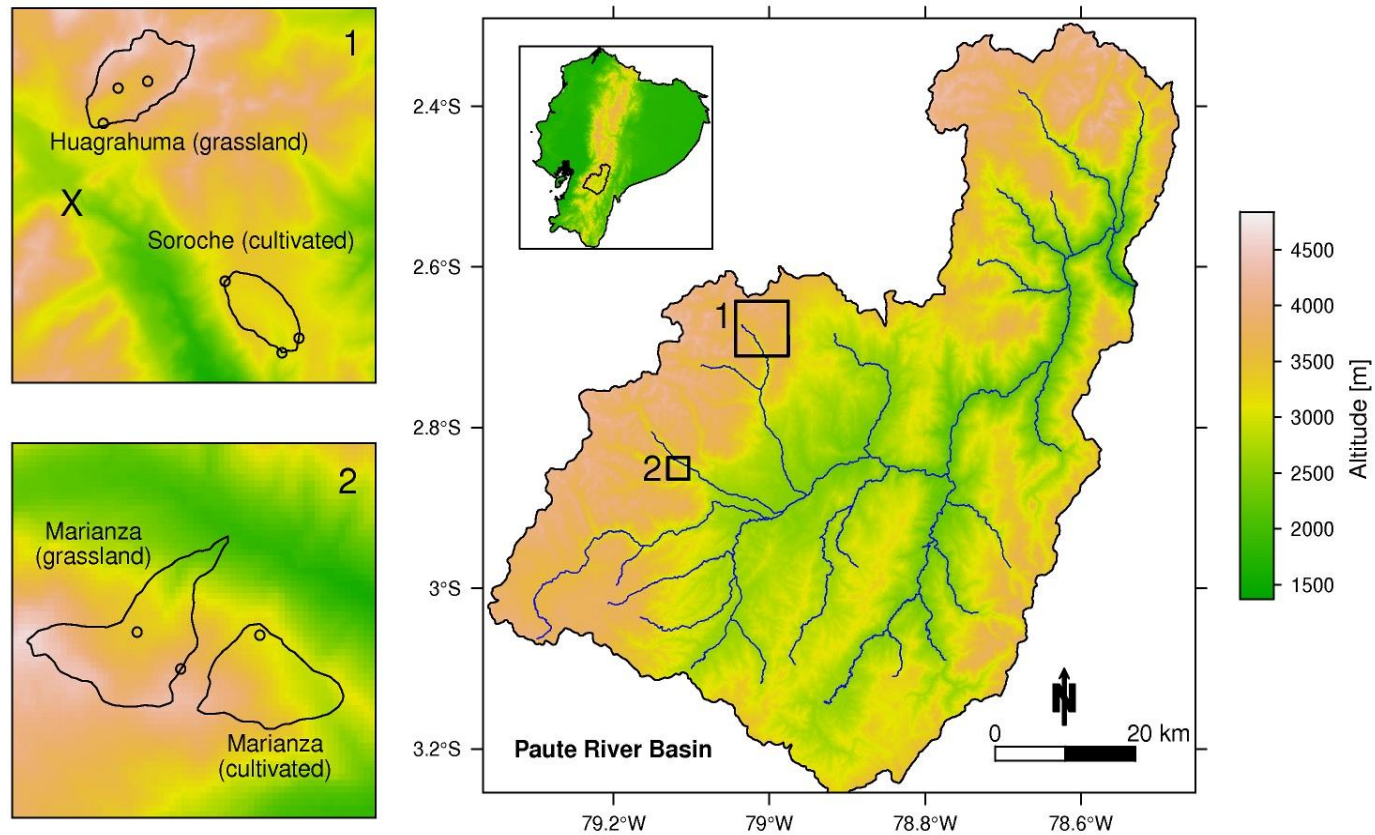
Parameter space

The learning framework

The learning process can be summarised as follows:

- **Derivation** of parameter sets for one or more donor catchments with similar characteristics;
 - Construction of **priors** for the stochastic modifications needed for the predictor catchment;
 - **Updating** the parameter sets of the donor catchments with the modification to get prior parameters for the predictor catchment;
 - **Evaluation and improvement** of the modifications of step 2 when more information becomes available.
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Case study: forestation in the Andes

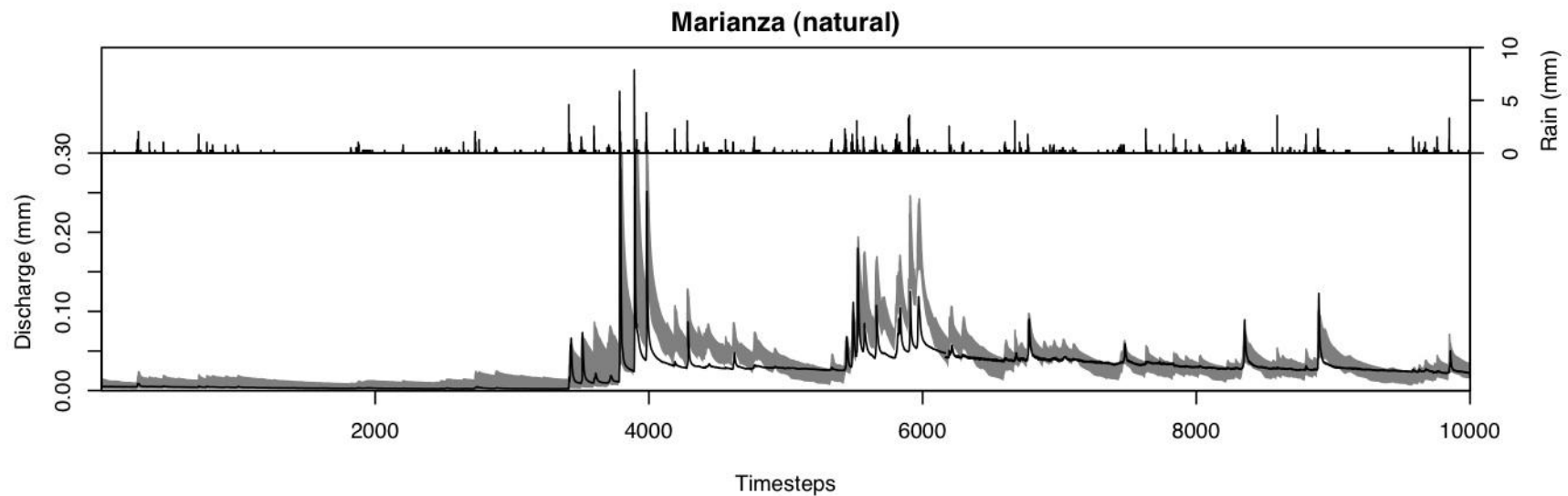


Name	Altitude (m)	Average Altitude (m)	Area (km ²)	Modeling Period	Land Use
Marianza (natural)	2980–3810	3496	0.84	06/02/07–21/05/07	Grassland and forest
Marianza (pinus)	3230–3710	3414	0.63	06/02/07–21/05/07	Pine plantation
Huagrahuma	3690–4100	3894	2.58	05/02/05–20/05/05	Grassland
Soroche	3520–3720	3650	1.59	20/05/02–01/09/02	Cultivation

Predicting proxy catchments (with uncertainty)

1. Prediction in similar conditions

- generating prior parameter sets using GLUE
- assessing prediction on **precision** and **accuracy** of prediction limits
- no transformation

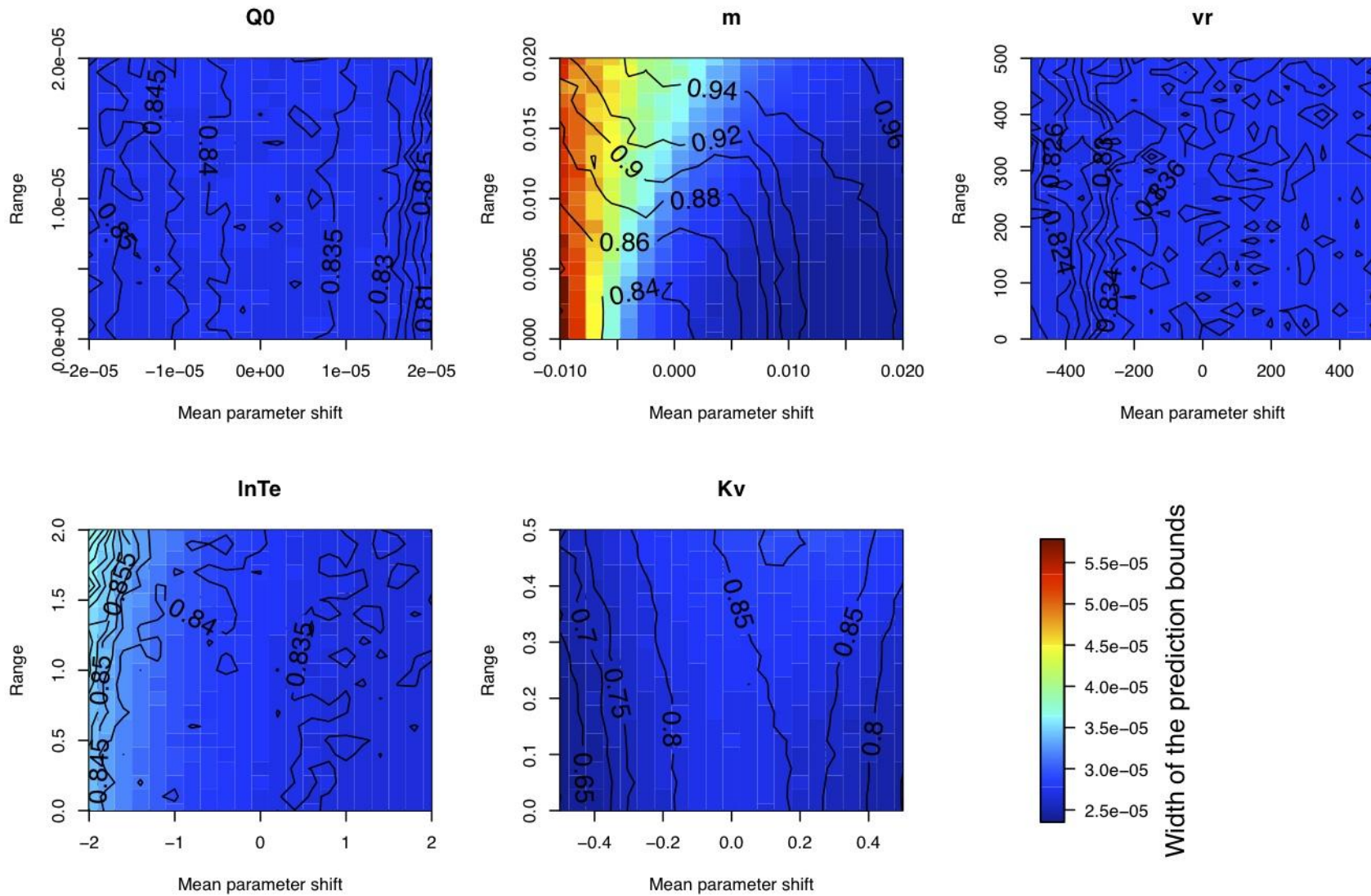


Results:

- average width of $2.5 \cdot 10^{-5}$ mm/15 min, bracketing 83.8% of the observed discharge
- accuracy lower than for the donor catchment (90%) so increased uncertainty

Predicting proxy catchments (with uncertainty)

2. Post-hoc evaluation of the parameter transformations



Predicting proxy catchments (with uncertainty)

3. Predicting the Effects of Land Use Changes

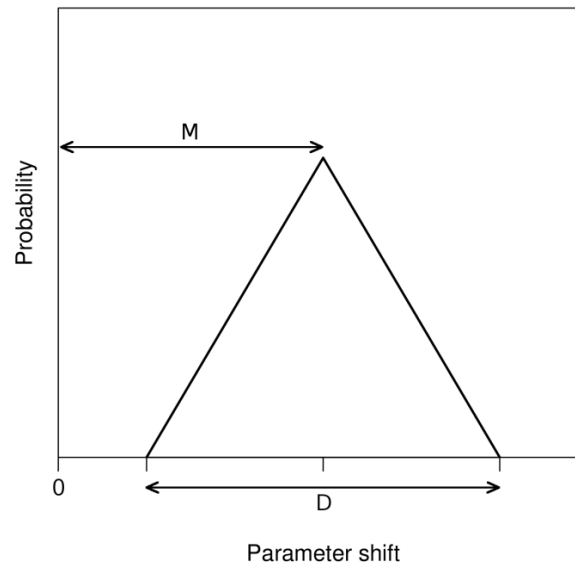
- applying fuzzy linear transformations based on physical process understanding (deforestation, land use change)

- changed parameter: vegetation coefficient for evapotranspiration (K_v):

 - Increase (M): 0.43

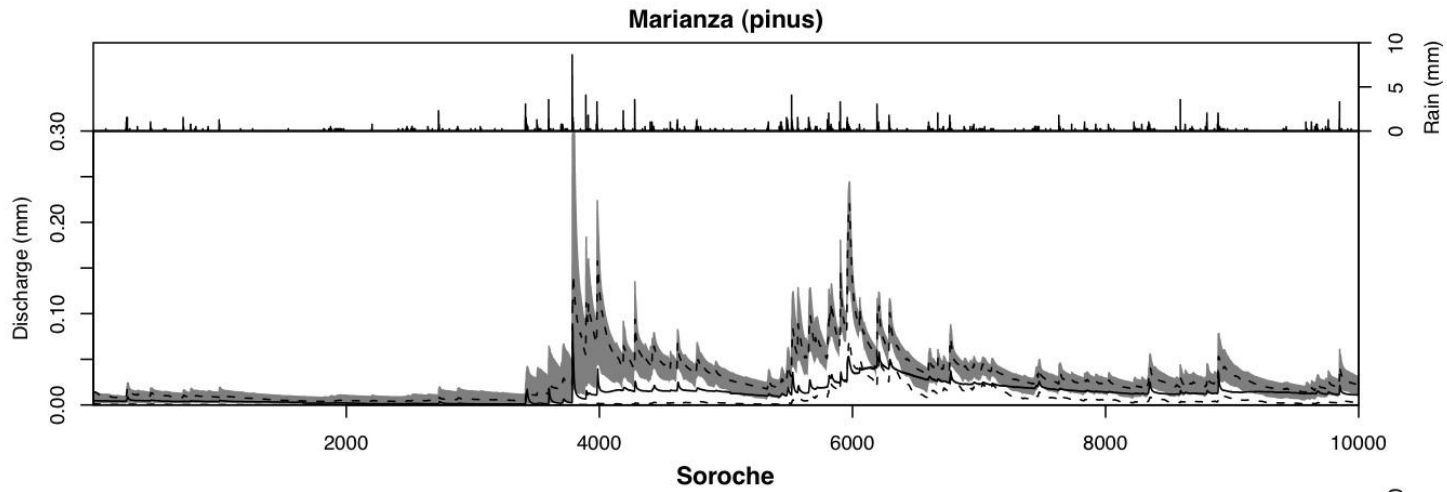
 - Dispersion (D): 0.25

- change applied randomly to parameter sets

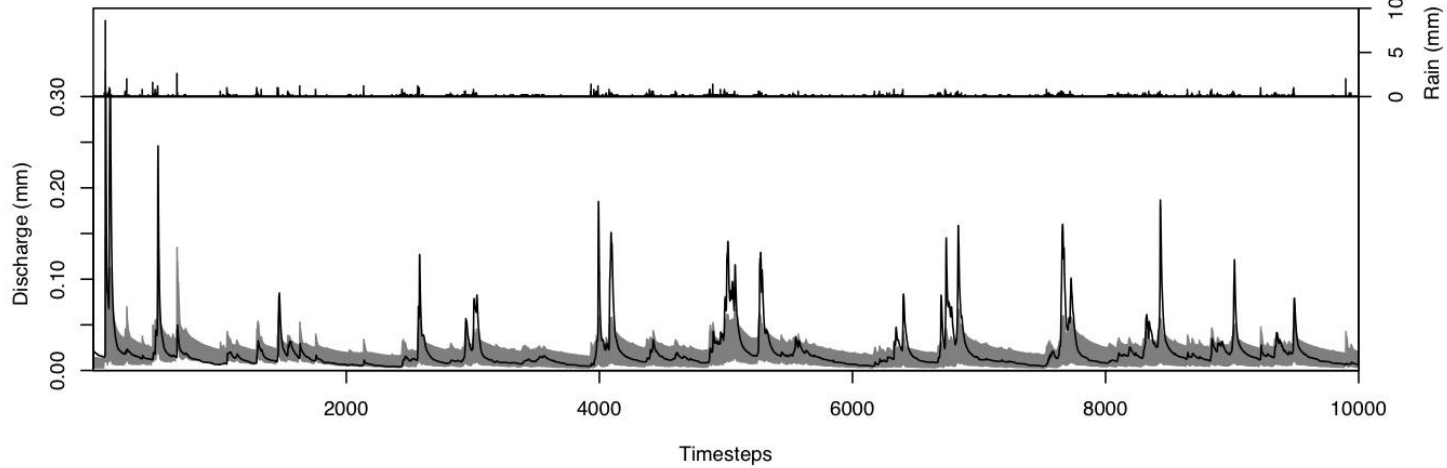




Forestation



Cultivation



(grey: without parameter transformation, dashed: with parameter transformation)

=> Possible to get accurate prediction limits using fuzzy linear parameter transformations

Conclusions

As expected, even apparently similar catchments may require **transformations of parameter sets** to obtain predictions consistent with predefined prediction limits, resulting in broader prediction bounds.

The major challenge of this approach is to choose an **appropriate transformation model**. This study explored the simplest case of linear independent dispersive shifts applied to the posterior parameter sets of the donor catchment.

In one case, the required shift is consistent with literature values and therefore identifiable. In the other case, the simulations were less successful and a post hoc analysis suggested that an **unrealistic change** in parameters was necessary.

The paper presents a general **learning framework** to analyse potential parameter transformations and to learn from parameter behaviour that allows the uncertainty in regionalisation to be analysed.