H21C-0690: Adaptive parameter optimization of a grid-based conceptual hydrological model

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1. Introduction

Any spatially explicit hydrological model at the mesoscale is a conceptual approximation of the hydrological cycle and its dominant process occurring at this scale. Manual-expert calibration of this type of models may become quite tedious —if not impossible— taking into account the enormous amount of data required by these kind of models and the intrinsic uncertainty of both the data (input-output) and the model structure.

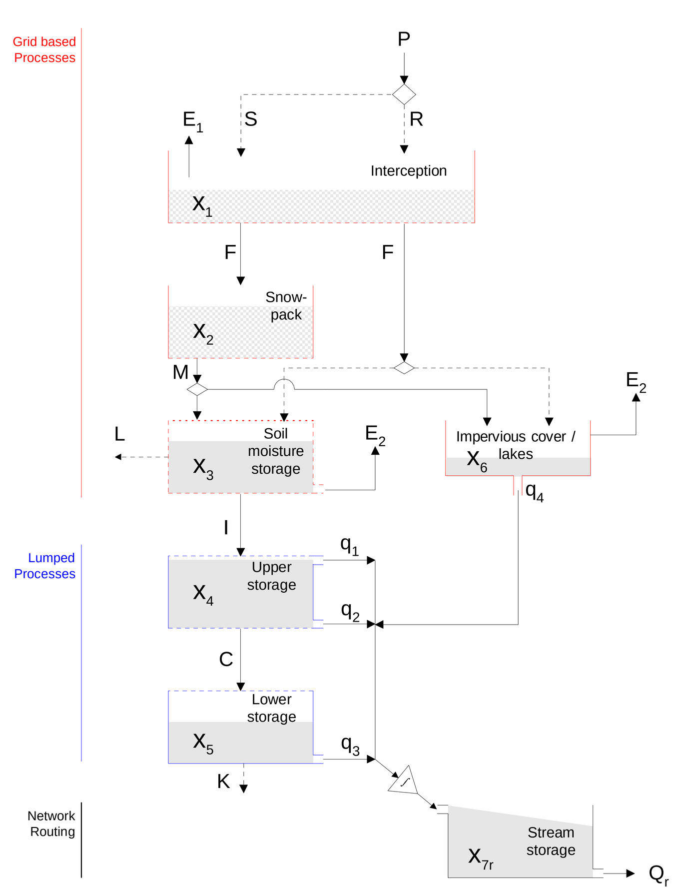
⇒ Some degree of automatic calibration is required to find ''good'' 'solutions, each one constituting a trade-off among all calibration criteria.

2. Research questions

1. How to avoid overparameterization and still have a adequate model performance? How to assess the model complexity?
2. How to find a "good solution" with a relatively low computational burden?

3. Mesoscale Hydrological Model

In the present study, a grid-based conceptual hydrological model (denoted as HBV-UFZ) based on some of the original HBV concepts was employed.



Grid based HBV-UFZ

State equations: cell (i), t:

$$\dot{x}_1 = P - F - E_1$$
$$\dot{x}_2 = F - M$$
$$\dot{x}_3 = F + M - E_2 - I - L$$
$$\dot{x}_4 = I - q_1 - q_2 - C$$
$$\dot{x}_5 = C - K - q_3$$
$$\dot{x}_6 = F + M - E_2 - q_4$$
$$\dot{x}_{7r} = \hat{Q}_{0r} - \hat{Q}_{1r}$$

Output: Runoff Q(t):

$$\hat{Q}(t) = \langle \hat{Q}_r(t) \rangle = g(\mathbf{x}, \mathbf{v}, \boldsymbol{\beta}) + \epsilon(t)$$

Transfer functions:

$$\begin{Bmatrix} \beta_1 \\ \vdots \\ \beta_n \end{Bmatrix}_{(i,t)} = f\left[\begin{Bmatrix} \gamma_1 \\ \vdots \\ \gamma_m \end{Bmatrix}, \begin{Bmatrix} v_1 \\ \vdots \\ v_k \end{Bmatrix}_{(i,t)} \right] \quad n \times N \times T \gg m$$

where

- $\dot{x}_i \equiv \frac{\partial x_i}{\partial t} \quad \forall i$
- i, t Indexes for cell and time respectively
- N Number of cells
- T Number time intervals
- n Number model parameters
- m Number transfer function parameters

v_1	$[1]$	Land cover
v_2	$[mm]$	Soil properties: field capacity, porosity...
v_3	$[m]$	Elevation
v_4	$[1]$	Slope
v_5	$[^\circ]$	Aspect
v_6	$[ms^{-1}]$	Permeability of the geological formation
v_7	$[1]$	Mean slope river reaches
v_8	$[1]$	Fraction of impervious areas in floodplains

4. Characteristics of the optimization algorithm

- It is an adaptive constrained optimization algorithm based on a parallel implementation of simulated annealing (SA)
- Parameter search routine uses adaptive heuristic rules to improve its efficiency.
- The efficiency of the model is evaluated with four objective functions:
  - Φ_1: Nash-Sutcliffe efficiency coefficient at node 1 with discharge Q
  - Φ_2: Nash-Sutcliffe efficiency coefficient at node 1 with $\ln Q$
  - Φ_3: Nash-Sutcliffe efficiency coefficient at node 3 with discharge Q
  - Φ_4: Nash-Sutcliffe efficiency coefficient at node 3 with $\ln Q$
- The overall objective function is given by

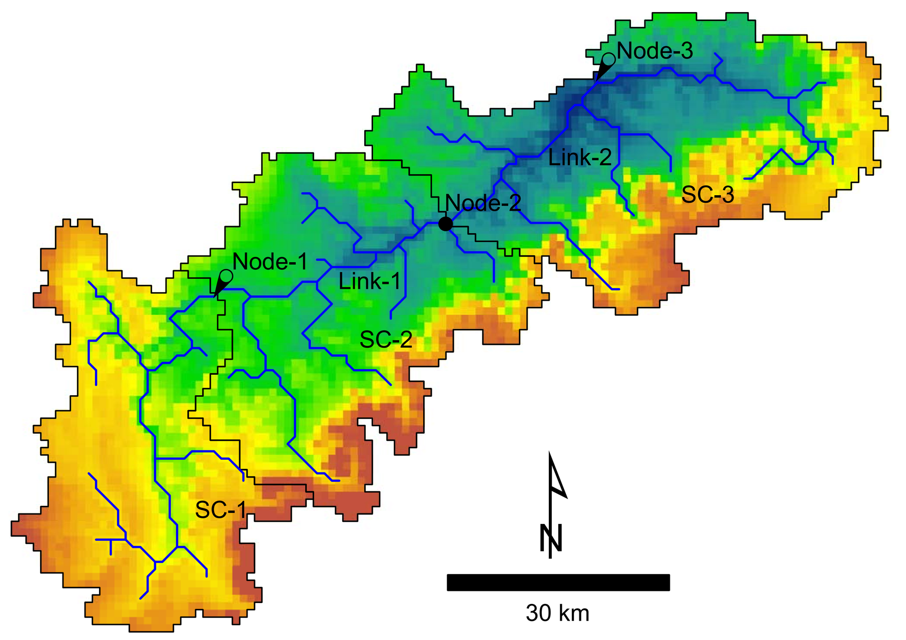
$$\Phi = \left(\sum w_i^p \Phi_i^p \right)^{1/p} \quad \sum w_i = 1 \quad p \geq 6$$

- The adaptive search algorithm is activated when any of the objective functions is less than a given threshold value $\tau \leq 1$.

5. Adaptive searching modes

Mode	Parameter	Type	Processes
1	1-16	distributed	interception, snow melt, soil moisture
2	17-24	subbasin 1	linear and nonlinear reservoirs
3	25-32	subbasin 2	"
4	33-40	subbasin 3	"
5	41-42	link 1	flow routing
6	43-44	link 2	"
7	1-44	all	all

6. Data

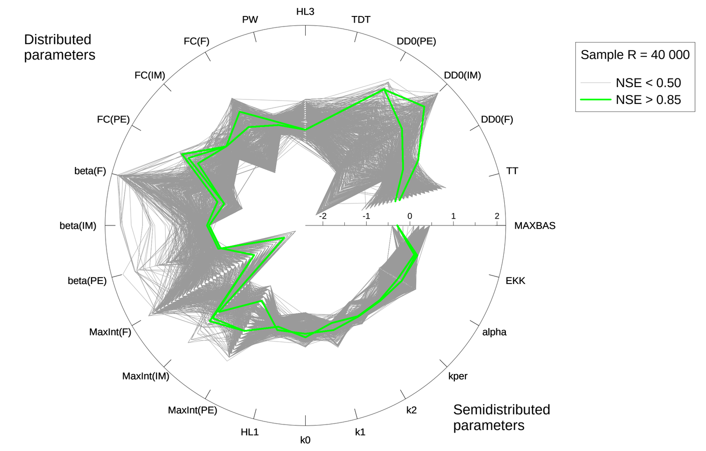


Subcatchments, nodes & links gauging stations

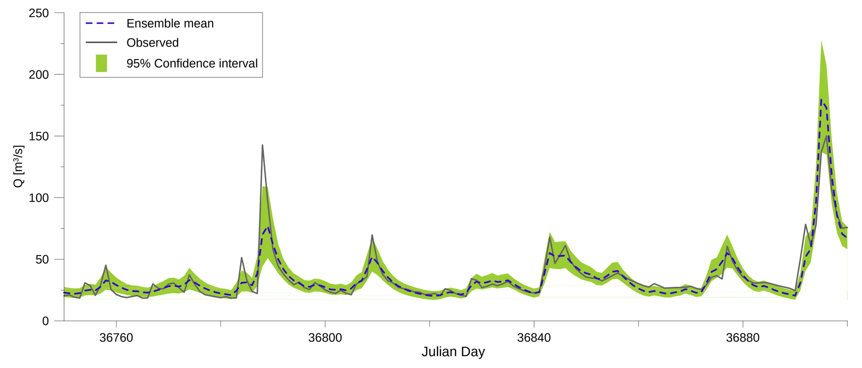
- Location: Upper Neckar Catchment, Germany
- Area: 4000 km^2.
- Elevation: ranges from 240 m to 1014 m a.s.l. with a mean of 546 m.
- Slopes: mild; 90% 0° to 15°.
- Precip.: $\approx$ 900 mm/yr.
- Grids:
  1. Climatic: (1000×1000) m
  2. Hydrologic: (500×500) m
  3. Land cover: (50×50) m

7. Results

Parameter and output uncertainties

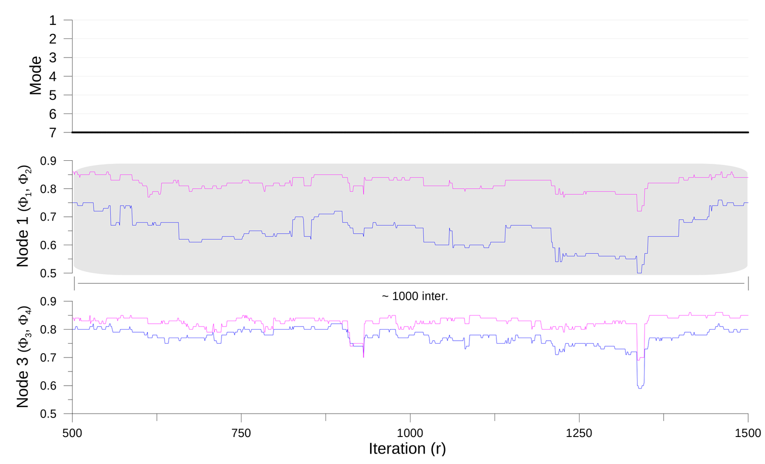


Families of parameter sets (normalized)

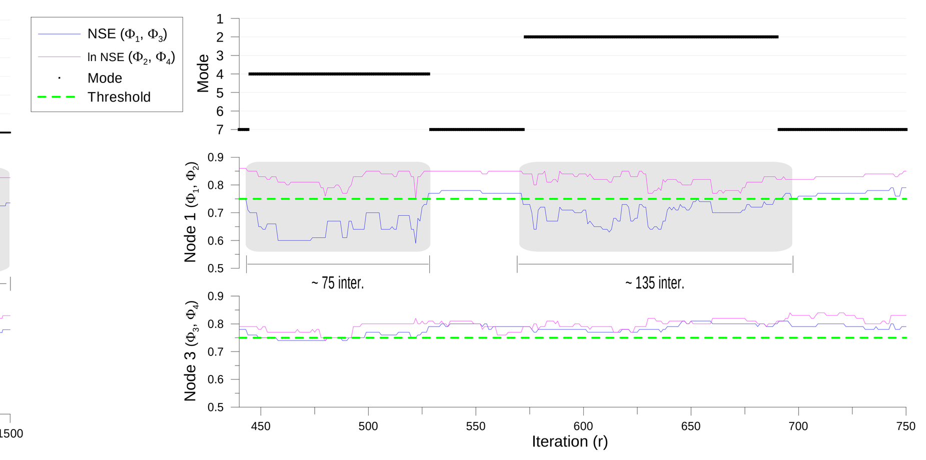


Ensemble of discharge predictions and uncertainty bands (NSE ≈ 0.83)

Evolution of the objective functions

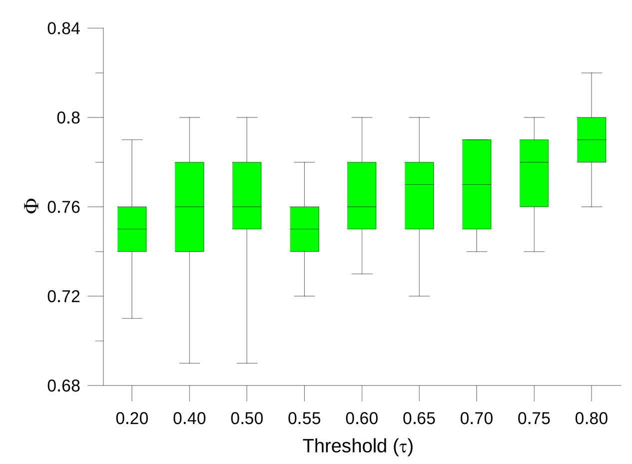


Standard simulated annealing (always in mode 7)

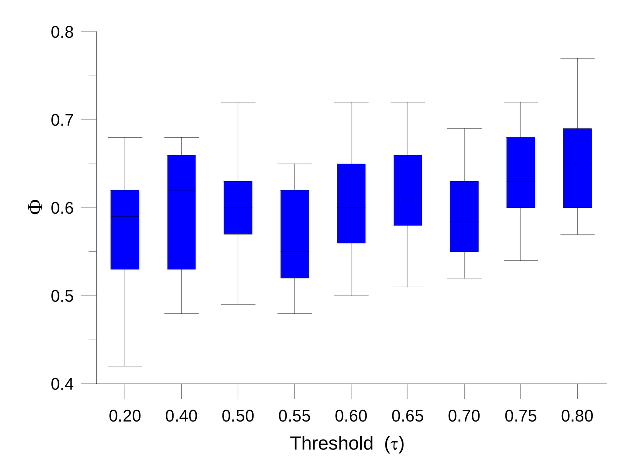


Adaptive simulated annealing (varying modes)

Statistics of the overall objective function



Average optimum value



Minimum optimum value

8. Conclusions

The results of the study indicate a:

- significant improvement in model performance:
  - at least 5% increase of the overall objective function Φ.
  - at least 50% reduction of the variance of Φ.
- at least 25% reduction in computational burden.

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