Experimenting on simple and flexible top-down approaches for hydrological modelling

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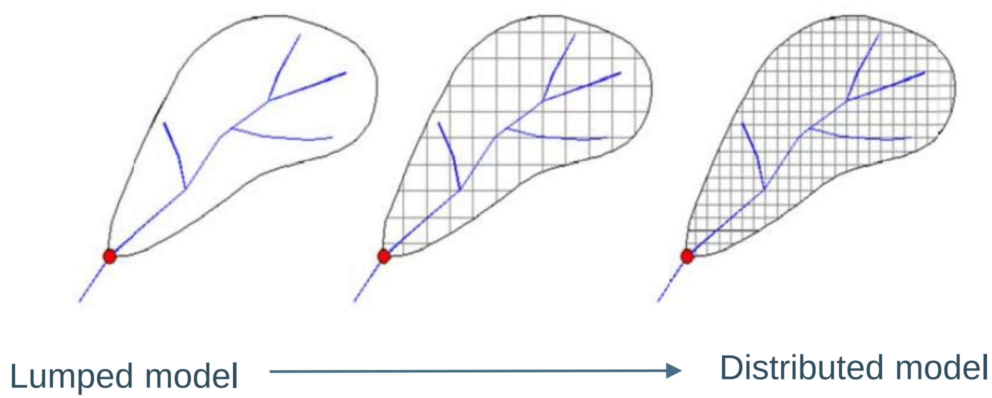
Introduction

- Nowadays, a plethora of hydrological models is available. Model-based studies are becoming more and more frequent in literature (Burt and McDonnell, 2015).

- To account for the complexity and spatial heterogeneity of physical processes, many of those models employ physically-based formulations, which may require a large amount of data. However, the available data are often insufficient and/or of questionable quality. Moreover, an increasing model complexity also gives rise to high computational requirements.

- A simple and flexible top-down approach for distributed rainfall-runoff (RR) modelling developed and demonstrated by Tran et al. (2018) poses as a step towards addressing the above. The distributed RR model can be built starting from a lumped or uniform distributed model (calibrated at the catchment outlet), whose parameters are then spatially disaggregated. Disaggregation is carried out using conceptual links between model parameters and natural catchment characteristics.



Research questions

1) How well does the approach performs with respect to the internal gauging stations (internal flow dynamics)?

   - The concept is tested for a catchment (see later) with a lot of gauging stations (see later). Out of those, 11 (including the outlet) with sufficient data quality have been selected. The results are compared against those of the rescaled lumped model (drainage-area ratio method) or the uniform distributed model.

2) Is it preferable to start disaggregation from a calibrated lumped model (as Tran et al., 2018) or from a distributed model calibrated with a uniform parameterset (same parameter values for the entire domain)?

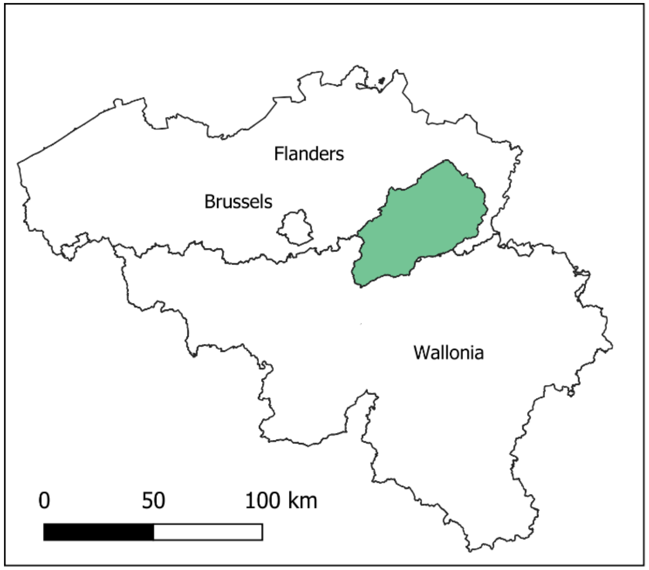
   - Modelling performance is evaluated for both configurations.

3) How well do the resulting distributed models perform with respect to modelling shallow, phreatic groundwater (GW) levels?

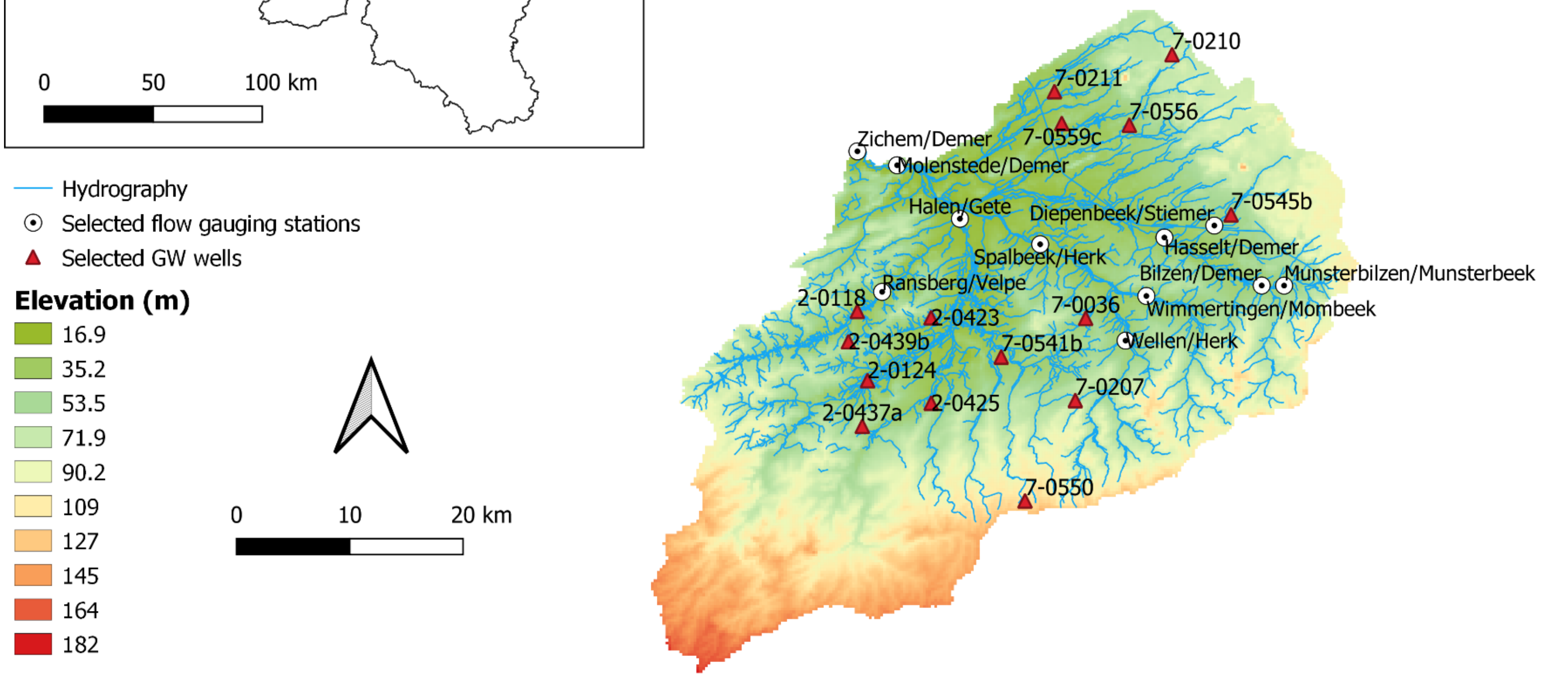
   - We experiment on the potential of simple methods for GW level modelling. We approach this challenge by trying to identify links between a) the variations and b) the reference levels of the modelled groundwater storages and observed groundwater levels.

   - For testing the concepts, we selected 15 GW filters, which involve phreatic aquifers with average GW depths of less than 10 m and do not present proclaimed trends due to pumping.

Study case: Demer catchment, Belgium



- Upstream of station at Zichem: 1969 km^2
- Croplands: 67%, Urban environment: 22%
- Silt: 50%, Silt loam: 20%, Sand:18%
- 01/01/2008-12/09/2019 (daily timestep, 2 years as warmup)
- Mean discharge at Zichem (study period): 11.9 m^3/s
- Resolution used for distributed models: 250 m



Parameter disaggregation

- For the current tests, the following form of disaggregation relationship was used:

$$C_{S,g} = C_U * \frac{\rho_g^a}{\overline{\rho^a}}$$

g : index referring to a grid cell

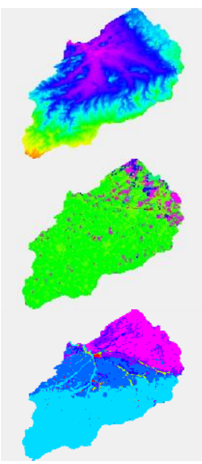
$C_{S,g}$: parameter value at the grid cell

C_U : lumped/uniform model parameter value

ρ_g : grid cell physical property

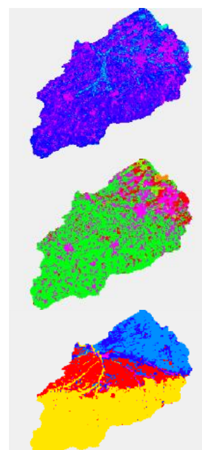
a : parameter to be calibrated

$\overline{\rho^a}$: average ρ^a for the whole catchment



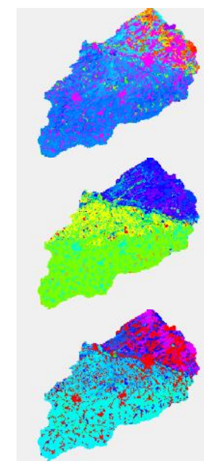
- Topography (DEM)
- Land cover
- Soil texture

Lookup tables (e.g. Rawls et al., 1982)



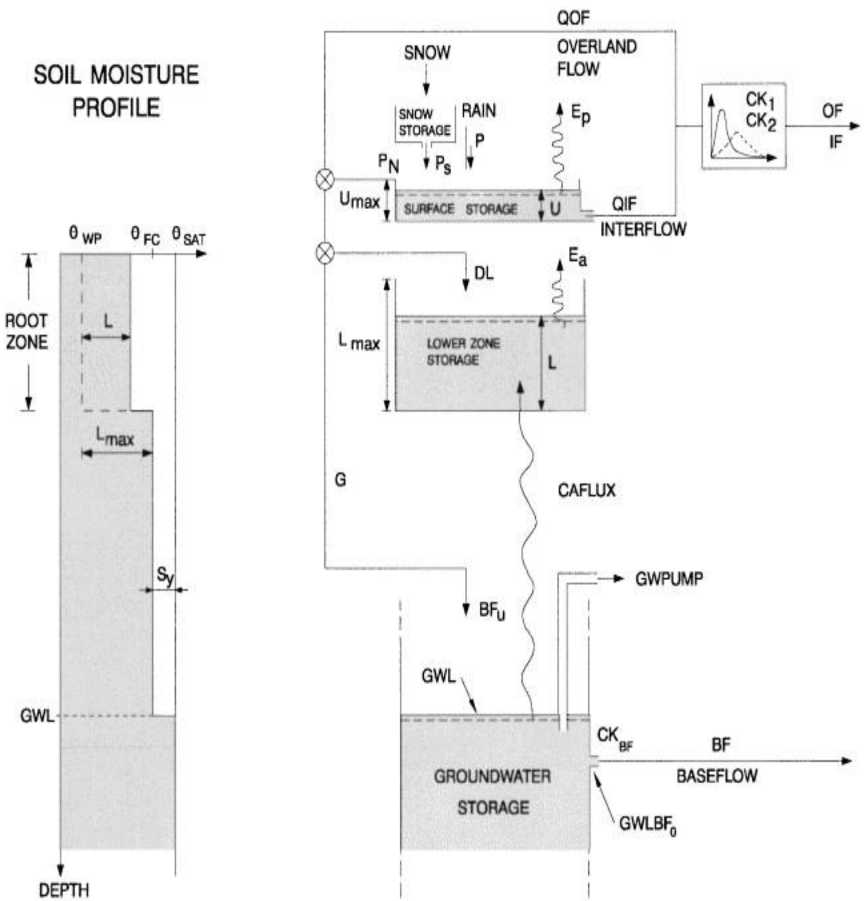
- Manning coeff.
- Porosity
- …

Lumped model parameters + Disaggregation relationships



Distributed model parameters

Lumped RR model structure: NAM (Nedbør-Afstrømnings-Model)



NAM model structure (DHI, 2011)

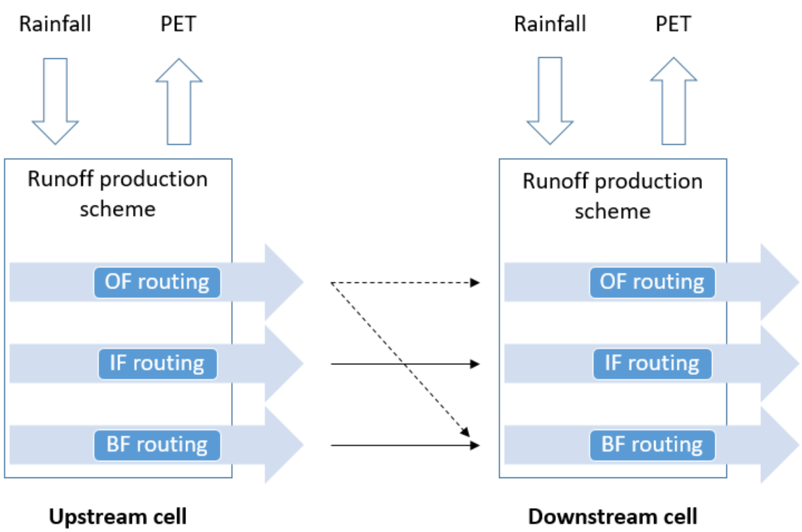
Parameters	Description
Umax	Maximum water content in surface storage (mm)
CQOF	Overland flow runoff coefficient (-)
TOF	Root zone moisture threshold for overland flow (-)
TIF	Root zone moisture threshold for interflow (-)
TG	Root zone moisture threshold for ground water recharge (-)
CKBF	Baseflow time constant (hours)
CKIF	Interflow time constant (hours)
CKOF	Overland flow time constant (hours)
Lmax	Soil storage capacity (hours)

- As opposed to Tran et al. (2018), all NAM model parameters are now linked to physical properties (and, thus, can be disaggregated).

Distributed RR modelling

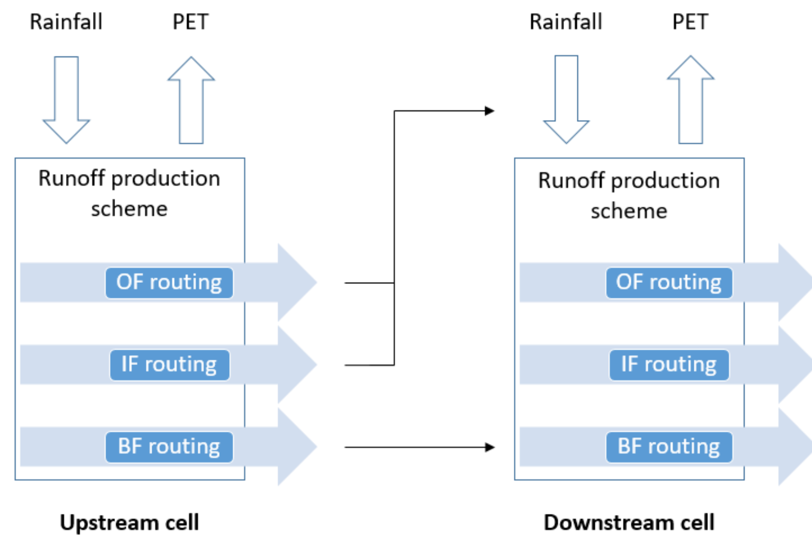
Config. C1

- Disaggregation starts from a calibrated lumped model (original approach).
- To account for vertical re-distribution of water as it moves downstream, a part of the overland flow (OF) from each upstream grid cell enters the groundwater storage of the corresponding downstream grid cell.
- To compensate for the extra water entering the groundwater storages, the OF flow produced by the model is multiplied by a factor (larger than 1.0) and baseflow (BF) reduced by the corresponding quantity.



Config. C2

- Disaggregation starts from a distributed model calibrated with a uniform parameterset (same parameters for the entire domain).
- Overland flow (OF) and interflow (IF) from each upstream grid cell are added to rainfall inputs for the corresponding downstream grid cell. Thus, the model structure itself determines the vertical water re-distribution.
- As opposed to the previous configuration (C1), no additional parameters are needed.



RR models: Calibration methodology

- Half the period was used for (automatic) calibration. To mitigate the danger of over-parameterization, an integrated objective function (to be minimized) was used for the lumped and uniform models:

$$f = (1 - KGE) + \left(1 - KGE_{H,ranked}\right) + (1 - KGE_{L,ranked}) + \mathrm{relVol}$$

$$relVol = \begin{cases} \frac{\left|\sum model - obs\right|}{\sum obs}, & if \ \frac{\left|\sum model - obs\right|}{\sum obs} \geq 10\% \\ 0 & ,if \ \frac{\left|\sum model - obs\right|}{\sum obs} < 10\% \end{cases}$$

KGE : Kling-Gupta Efficiency (Gupta et al., 2009)
$KGE_{H, ranked}$: KGE on “nearly-independent” ranked extreme high flows
$KGE_{L, ranked}$: KGE on “nearly-independent” ranked extreme low flows

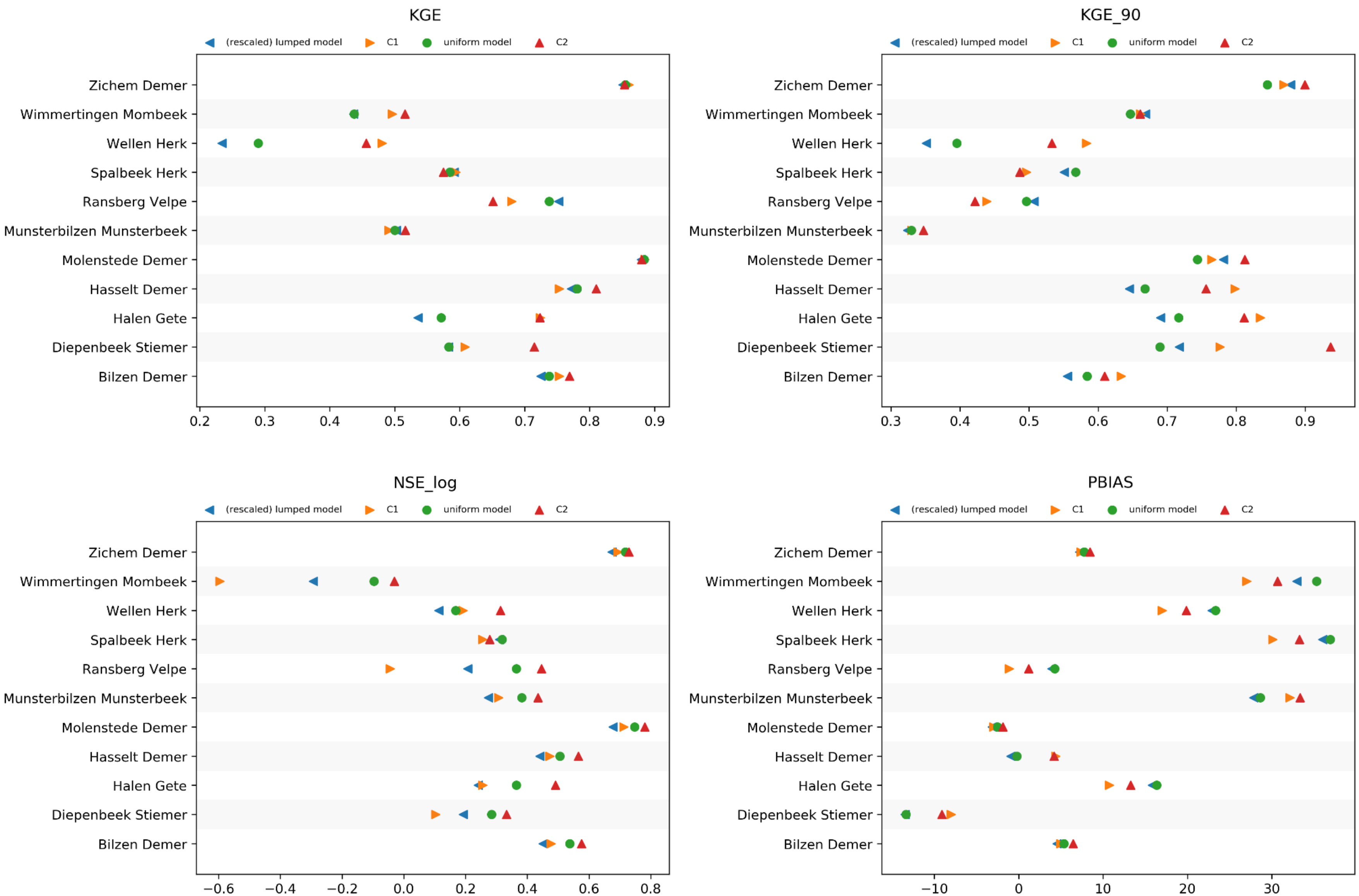
- “Nearly-independent” extreme flows were extracted using WETSPRO tool (Willems, 2009).

- Effluents (from WWTPs and/or industry) were considered in the modelling process.

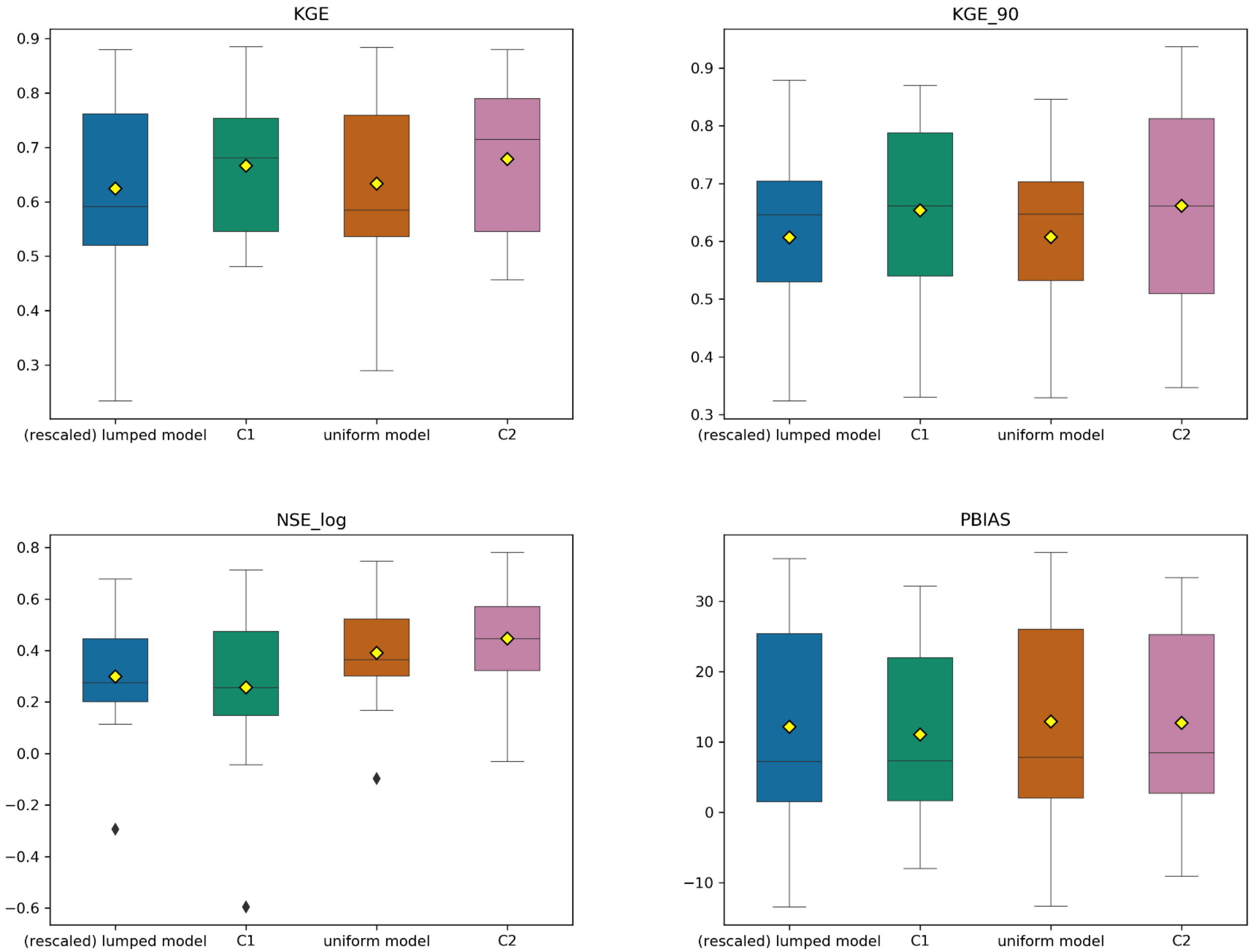
- The disaggregated models (configurations C1, C2) were calibrated using the average KGE on the internal gauging stations. To avoid a proclaimed deterioration on the performance at the catchment outlet, a strong penalty was enabled if KGE at the outlet fell below a certain threshold.

- Apart from KGE, the following criteria were used to evaluate model results: KGE on the ranked flows larger than the 90th percentile (KGE_90), NSE (Nash and Sutcliffe, 1970) on log-transformed flows (NSE_log), percent bias (PBIAS).

Results: RR modelling



Results: RR modelling (2)



GW level modelling: methodology

- For modelling groundwater levels (shallow, phreatic aquifers), we test the following equation:

$$GWL = \mathrm{a} + \mathrm{b} * \mathrm{elevation} + \left(\frac{\mathrm{GW_{stor}}}{UPS_{overland} * 1000}\right) * \frac{\mathrm{c}}{Sy}$$

GWL : groundwater levels (m)
Elevation : soil surface elevation (from DEM) (m)
GW_{stor} : groundwater storage from NAM model (mm)
$UPS_{overland}$: nr. of upstream non-river cells
S_y : specific yield (sometimes also called effective porosity) (-).
a, b, c : parameters to calibrate (-)

Specific yield (S_y) was estimated as follows (Bear, 1979):

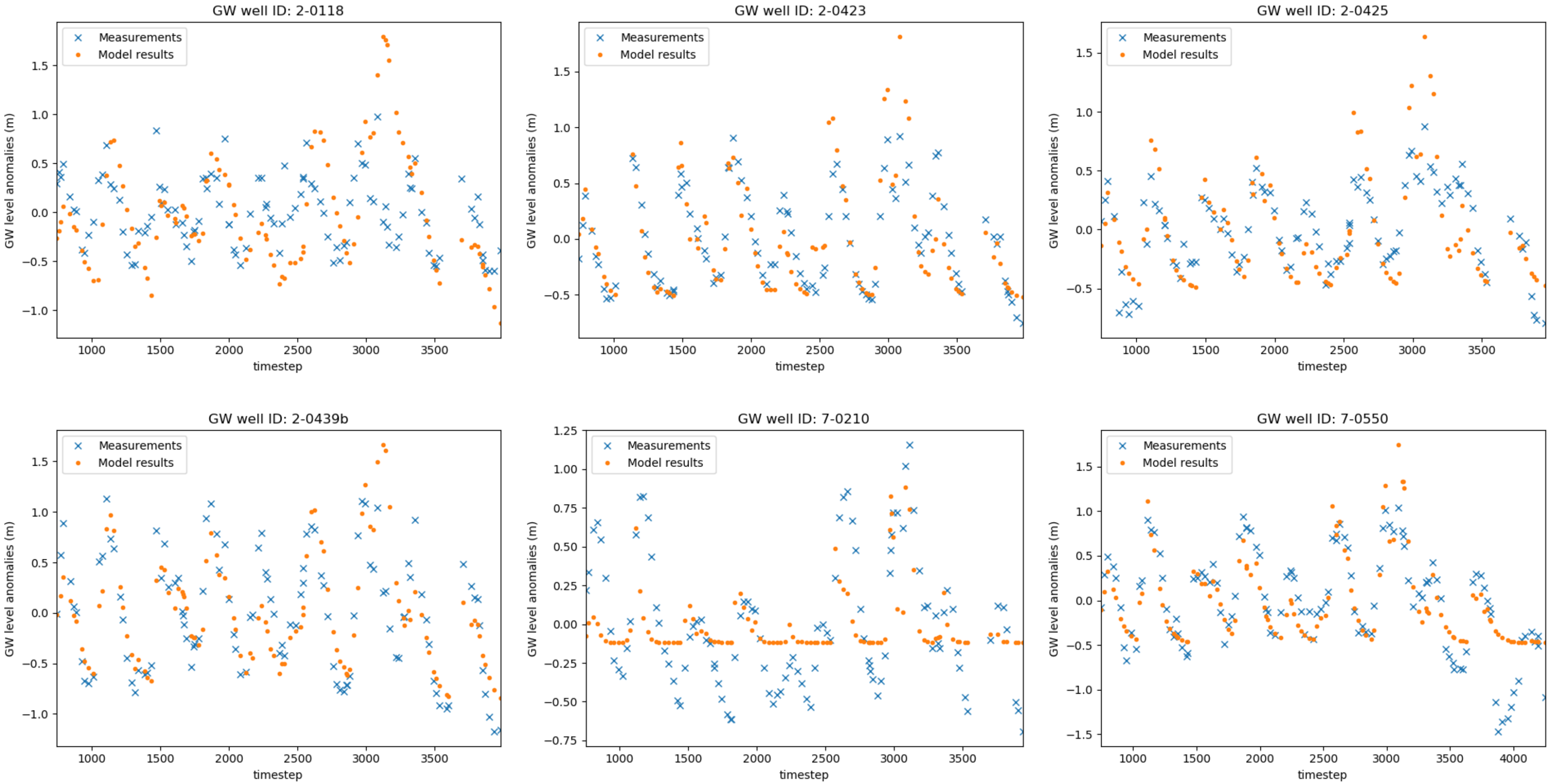
$$S_y = n - S_r$$

n : porosity (-), can be estimated from soil texture
S_r : specific retention (-), can be estimated from soil texture (e.g. see Rawls et al., 1983)

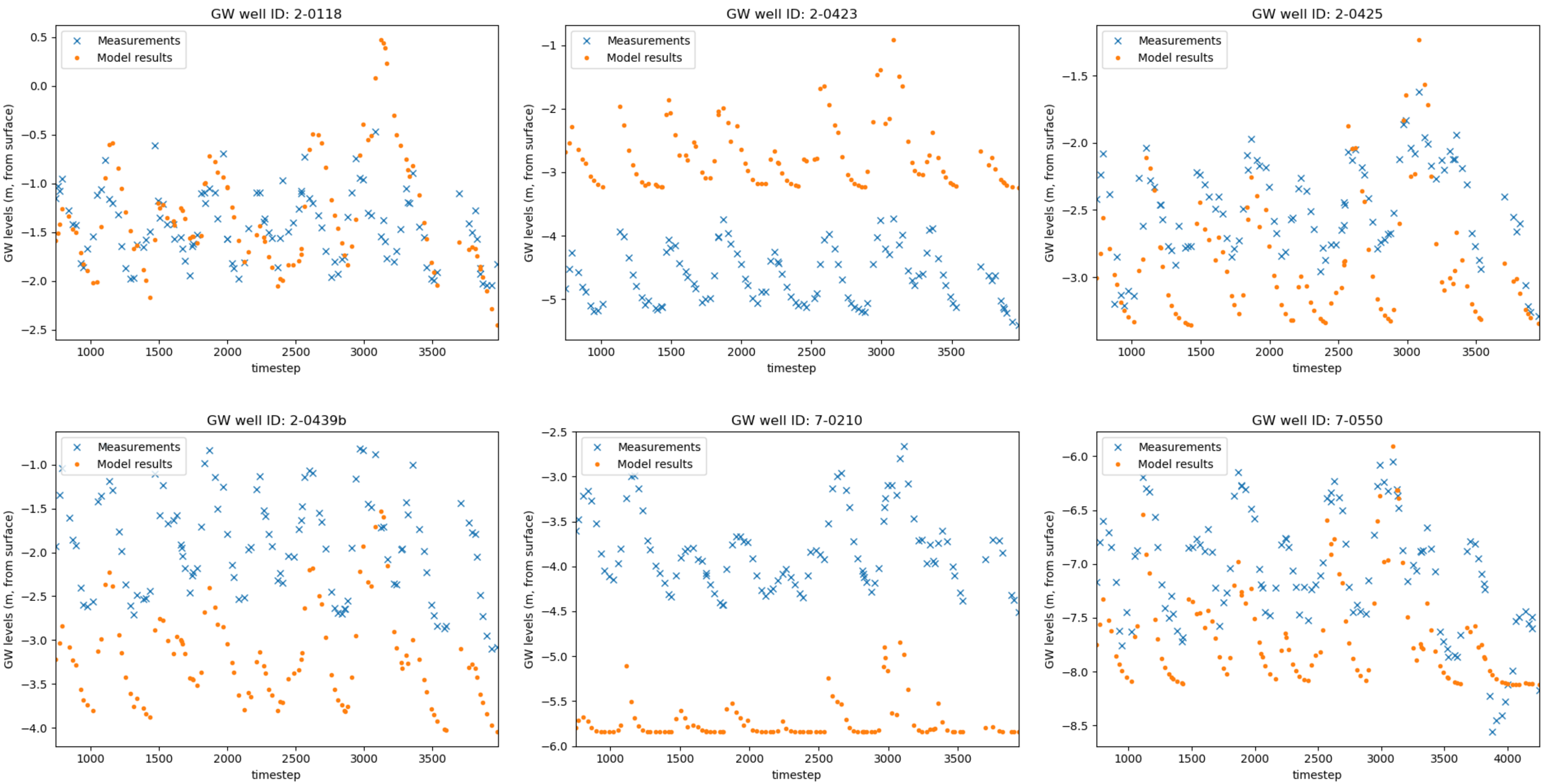
- The distributed RR modelling configuration C2 is used (C1 could have been selected as well..). Calibration was carried out (automatically) using half the modelling period based on the average Nash-Sutcliffe Efficiency (NSE) for the selected GW filters.

- We evaluate modelling performance on both GW levels and GW level anomalies.

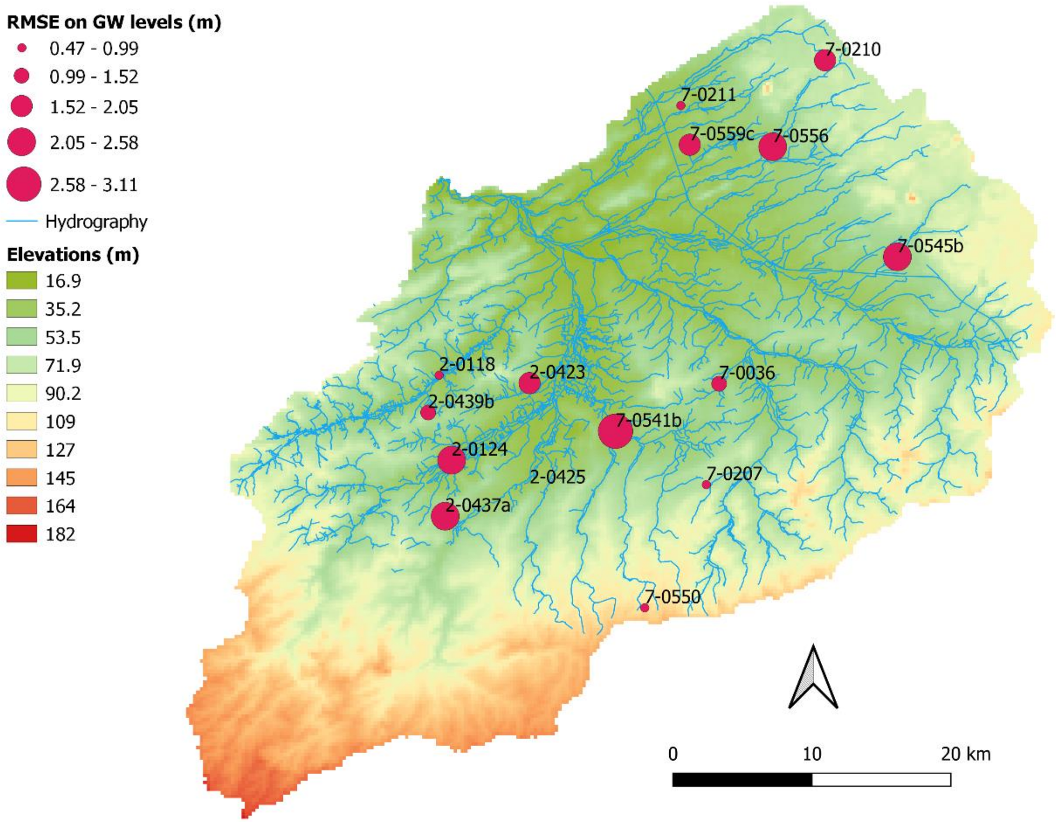
Results: GW level anomalies

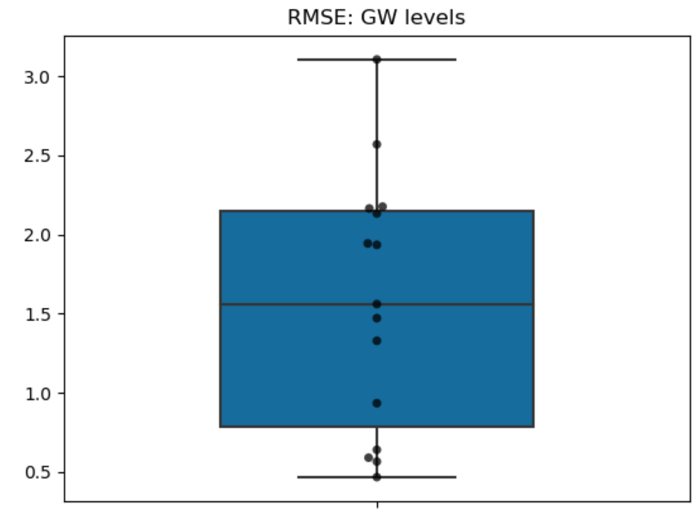


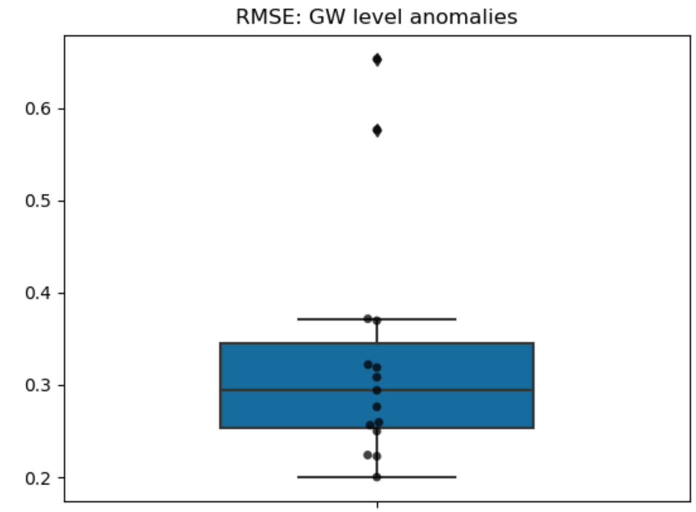
Results: GW levels



Results: GW level modelling







Conclusions & discussion

- We tested 2 versions (C1, C2) of a simple top-down approach for setting-up distributed RR models. Compared to the original (rescaled lumped or uniform distributed) models, the new models (developed via parameter disaggregation) improved the performance metrics for most of the internal stations while maintaining a similar performance (based on KGE) at the catchment outlet.

- Configuration C2 performed better than C1 with respect to most criteria.

- The tested simplified methodology for modelling GW level dynamics seems promising, but clearly needs further improvement and testing.

- For 3 out of 15 GW filters (e.g. 7-0210), the modelled GW storage is close to zero (0) for large time periods, which results in a poor performance with respect to modelling GW level anomalies. This is one of the points in need of improvement.

- RMSE for GW levels is considerably larger than RMSE for GW level anomalies. Thus, a better way to represent the reference levels of the modelled groundwater storages is needed.

- Taking into account GW abstractions could be another way for improving performance.

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