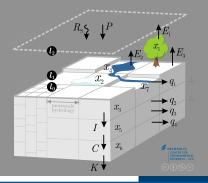
The mesoscale hydrological model (mHM); & Improving the realism of hydrologic model functioning



presented by Oldrich Rakovec

In collaboration with R. Kumar, J. Mai, S. Thober, M. Zink, ..., and L. Samaniego

KVHEM seminar FŽP ČZU, 4 October 2016



Outline

1. CV

- 2. State-of-the-art hydrology topics (Gupta et al. 2014, HESS)
- 3. Intro on mHM structure and the Multiscale Parameter Regionalization (MPR)
- 4. Improving the realism of hydrologic model functioning through multivariate parameter estimation (*Rakovec et al., 2016, WRR*)

CV

- Bc: Applied Ecology (FŽP): Ivan Landa
- Ing: Environmental modelling (FŽP): Standa Horáček, Petr Máca

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- MSc: Hydrology and Quantitative Water Management (Wageningen): Anne Van Loon, Henny van Lanen
- PhD: Improving operational flood forecasting using data assimilation (Wageningen, DELTARES): *Remko Uijlenhoet, Albrecht Weerts*



Research Interests: PhD thesis

- Rakovec, O., Hazenberg, P., Torfs, P. J. J. F., Weerts, A. H., and Uijlenhoet, R. (2012): Generating spatial precipitation ensembles: impact of temporal correlation structure, *Hydrol. Earth Syst. Sci.*, 16, 3419–3434, doi:10.5194/hess-16-3419-2012.
- Rakovec, O., Weerts, A. H., Hazenberg, P., Torfs, P. J. J. F., and Uijlenhoet, R. (2012): State updating of a distributed hydrological model with Ensemble Kalman Filtering: effects of updating frequency and observation network density on forecast accuracy, *Hydrol. Earth Syst. Sci.*, 16, 3435–3449, doi:hess-16-3435-2012.
- Rakovec, O., Weerts, A. H., Sumihar, J., and Uijlenhoet, R. (2015):
 Operational aspects of asynchronous filtering for flood forecasting, *Hydrol. Earth Syst. Sci.*, **19**, 2911–2924, doi:10.5194/hess-19-2911-2015.
- Rakovec, O., Hill, M. C., Clark, M. P., Weerts, A. H., Teuling, A. J., Uijlenhoet, R. (2014): Distributed Evaluation of Local Sensitivity Analysis (DELSA), with application to hydrologic models, *Water Resour. Res.*, 50, 409–426, doi:10.1002/2013WR014063

PostDoc @ Helmholtz Centre for Environmental Research - UFZ; Computational Hydrosystems

Stochastic and Land Surface Hydrology

Team



PostDoc @ Helmholtz Centre for Environmental Research - UFZ; Computational Hydrosystems

Research Focus

Our main focus is on understanding and modeling the complex interaction of landsurface hydrologic processes and their spatial and temporal variability at meso- to macro-scale. Research focus is laid on drought reproduction and prediction, multiscale data assimilation and evaluation, and Multiscale Parameter Regionalisation:

- Drought reproduction and prediction
- Multiscale data assimilation and evaluation
- Multiscale parameter regionalization

The need to get the right answers for the right reasons (Kirchner, 2006)

State-of-the-art hydrology topics

Hydrol. Earth Syst. Sci., 18, 463–477, 2014 www.hydrol-earth-syst-sci.net/18/463/2014/ doi:10.5194/hess-18-463-2014 © Author(s) 2014. CC Attribution 3.0 License.





Large-sample hydrology: a need to balance depth with breadth

H. V. Gupta¹, C. Perrin², G. Blöschl³, A. Montanari⁴, R. Kumar⁵, M. Clark⁶, and V. Andréassian²

¹Department of Hydrology and Water Resources, The University of Arizona, Tucson, AZ, USA ²Irstea, Hydrosystems and bioprocesses Research Unit (HBAN), Antony, France ³Institute of Hydraulic Engineering and Water Resources Management, Vienna University of Technology, Vienna, Austria ⁴Department DICAM, University of Bologna, Bologna, Italy ⁵UFZ – Helmholtz Centre for Environmental Research, Leipzig, Germany ⁶Hydrometeorological Applications Program, Research Applications Laboratory, Boulder, CO, USA

State-of-the-art hydrology topics

Gupta et al (2014), HESS:

The context of much current hydrological practice is a focus on depth rather than breadth (with several notable exceptions), wherein detailed process investigation and model development/refinement are conducted at only one or a limited number of catchments. The typical goal is to (a) learn more about a specific catchment by improving upon some prior concept, or (b) establish a basis for prediction and decisionmaking at that specific location. This might be called placebased learning. By contrast, the scientific aspiration is to generalize from the study of specific cases, so that we can discover and establish general hydrological principles, thereby advancing hydrological understanding.

State-of-the-art hydrology topics

Gupta et al (2014), HESS:

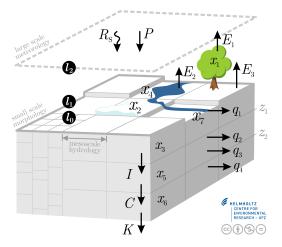
This move has deep roots (see Linsley, 1982), but has become considerably stronger since the 1999 IAHS meeting in Birmingham where the idea was extensively discussed. It has helped drive the search for improved understanding of the hydrological cycle, and for modeling approaches that

a. achieve the three R's (reliability, robustness and realism);

b. have greater generality and transposability; and for which

c. the parameters can be more easily specified from data.

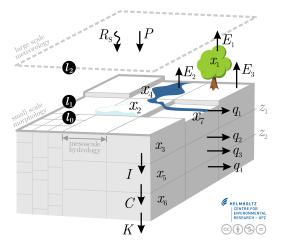
mesoscale Hydrologic Model (mHM)





www.ufz.de/mhm mhm-admin@ufz.de

mesoscale Hydrologic Model (mHM)

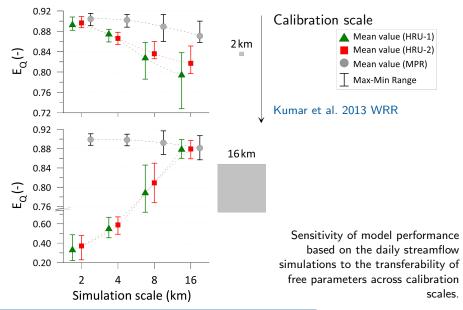




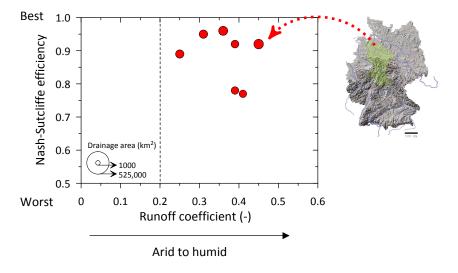
- Fotran code;
- doxygen documentation;
- regular releases;
- svn, netcdf;
- multiple optimiz. meth.;
- OpenMP, MPI, ...

www.ufz.de/mhm mhm-admin@ufz.de

Scale invariance of global "parameters" γ

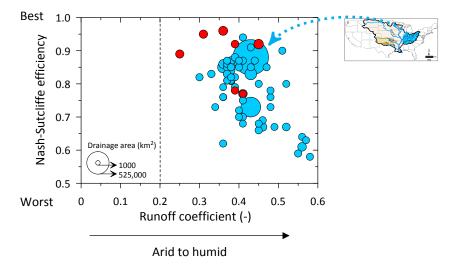


Transferability: mHM on German basins



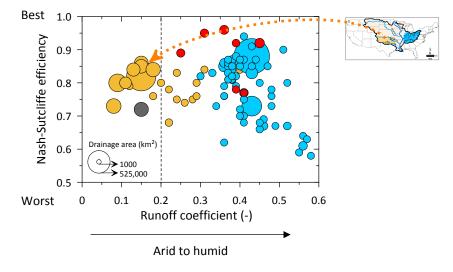
Kumar et al., WRR 2013

Transferability: mHM on US basins



Kumar et al., WRR 2013

Transferability: mHM on US basins



Kumar et al., WRR 2013

Water Resources Research

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Highlights

Improving the realism of hydrologic model functioning through multivariate parameter estimation

Editors' Highlight-

This paper is the most recent in a series of modeling studies demonstrating improved ability to do spatially distributed modeling by careful assimilation of relevant spatially-distributed and point data. In particular, it demonstrates how use of satellite-based soil moisture relevant data can constrain the calibration of a model to provide more robust model simulations/predictions.

26 September 2016

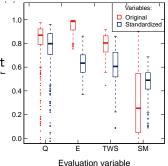
RESEARCH ARTICLE

Improving the realism of hydrologic model functioning through multivariate parameter estimation

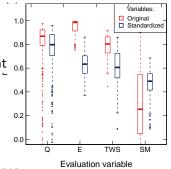
O. Rakovec, R. Kumar, S. Attinger, L. Samaniego

 Large domain hydrological models are used for predicting SM, ET and other water states and fluxes. They are usually properly constrained against river discharge (Q);

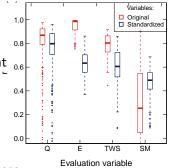
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- Constraining parameters against river discharge is necessary, but not a sufficient condition (Rakovec et al., 2016, JHM);
- We aim at scrutinizing appropriate 0.2 incorporation of available real-world 0.0 information into a hydrological model, to improve realism of hydrological processes;

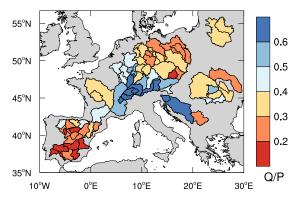


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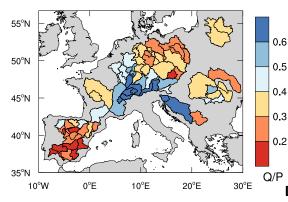
 Two distinct methods of constraining model parameters (against Q only and Q + TWS anomaly) are compared.

Modelling domain and data



- Consists of 80 EU basins;
- Wide range of distinct physiographic and regional climate characteristics;
 - Area > 10 000 $\rm km^2$;
 - First-order data quality check to eliminate heavily human influenced basins.

Modelling domain and data

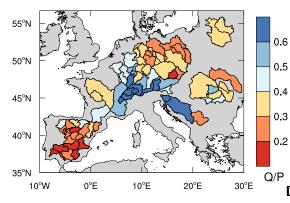


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Data:

- Streamflow (Q);
- Total water storage (TWS) anomaly from GRACE;
- FLUXNET gridded evapotranspiration (ET).

Modelling domain and data



2 objective functions ϕ to be minimazed:

- Q only:
 - $\phi = 1 \mathrm{KGE}(Q);$
- **Q** + **TWS** anomaly: $\phi = \text{RMSE}(\text{TWS}_{SA}) * (1 - \text{KGE}(Q)).$

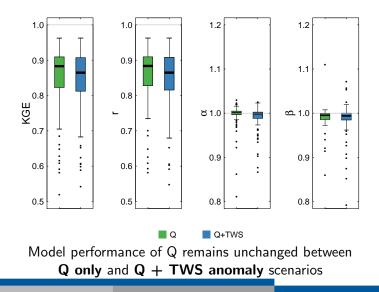
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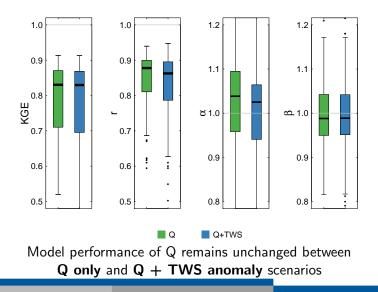
Model performance for streamflow (daily)

Calibration period

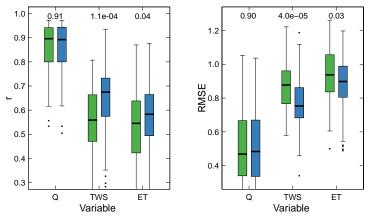


Model performance for streamflow (daily)

Evaluation period



Verification of monthly TWS and ET

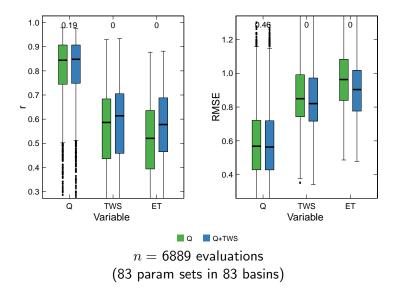


Q Q+TWS

On-site model performance (in 83 basins): TWS GRACE data and the (independent) gridded ET data show consistent improvements of using Q + TWS anomaly over Q only, with statistically significant means.

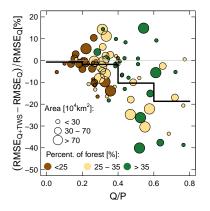
13

Crossvalidation (monthly values)



Why we observe improvements for ET? I

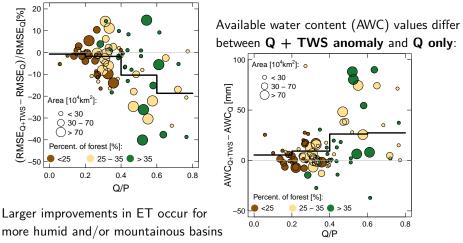
Reasoning due to parameter values



Larger improvements in ET occur for more humid and/or mountainous basins (i.e., larger Q/P values)

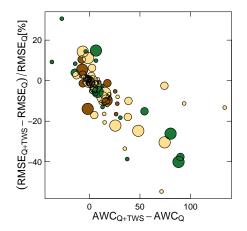
Why we observe improvements for ET? I

Reasoning due to parameter values



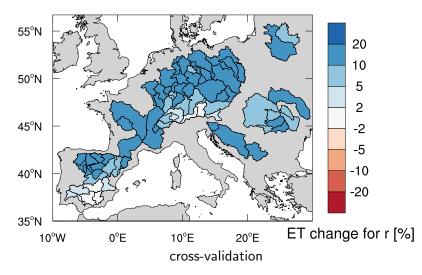
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Why we observe improvements for ET? II

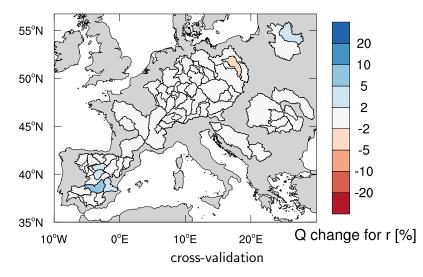


Improvements in model ET are positively affected by increased dynamic range of soil water from Q only to Q + TWS anomaly.

ET Improvements

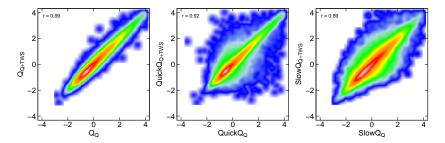


ET Improvements with no deterioration in Q



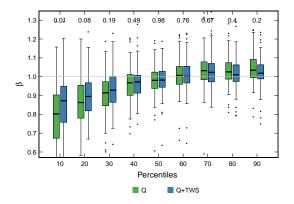
Decomposition of discharge into slow and fast components (model vs. model z-score)

Choice of objective function to constrain model leads to changes in partitioning P into runoff components, while maintaining total runoff:



Scatter of standardized anomalies for daily runoff components between **Q** only and $\mathbf{Q} + \mathbf{TWS}$ anomaly calibration approaches lumped over 80 basins.

TWS: reduce the bias of the low-flows



Ratios between mod. and obs. Q percentiles

- Bias between model and observation across individual percentiles of flow duration curves for daily values and its monthly aggregates;
- Q model underestimation gets reduced when TWS data are employed

Conclusions (Rakovec et al., 2016 WRR)

- Constraining mHM with the TWS anomaly (GRACE):
 - \rightarrow no significant reduction on streamflow efficiency (Q)
 - \rightarrow significant improvements
 - Iow-flow prediction
 - ET estimates
- Choice of the objective function:
 - \rightarrow considerable changes in the partitioning of P into runoff components
 - \rightarrow maintaining total runoff estimate unaltered
- A cross-validation at independent locations:

 \rightarrow (Q + TWS anomaly) is superior to (Q only)



- Collaboration with Martyn Clark (NCAR): Model intercomparison over CONUS (mHM, SAC, VIC, Noah-MP): 600 basins
- Multi-basin parameter estimation: European domain using new/updated 5km resolution
- Improved hydrological forecasting of mHM via particle filtering and

Thank you!

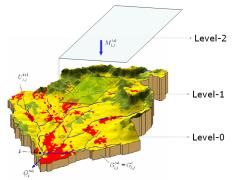
- Rakovec, O., Kumar, R., Attinger, S. and Samaniego, L. (2016): Improving the realism of hydrologic model functioning through multivariate parameter estimation. *Water Resour. Res. in press*, doi:10.1002/2016WR019430.
- Rakovec, O., Kumar, R., Mai, J., Cuntz, M., Thober, S., Zink, M., Attinger, S., Schäfer, D., Schrön, M., Samaniego, L. (2016): Multiscale and multivariate evaluation of water fluxes and states over European river basins, *J. Hydrometeorol.*, 17, 287–307, doi:10.1175/JHM-D-15-0054.1.

Data levels in mHM

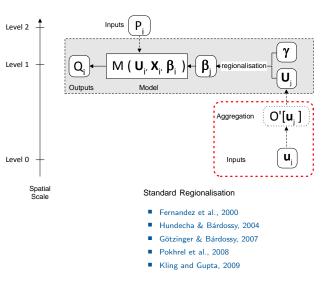
- Level-2: 1-25 km
 - Meteorological forcings DWD, E-OBS,

WATCH, NLDAS-2, TRIMM, WRF, MME

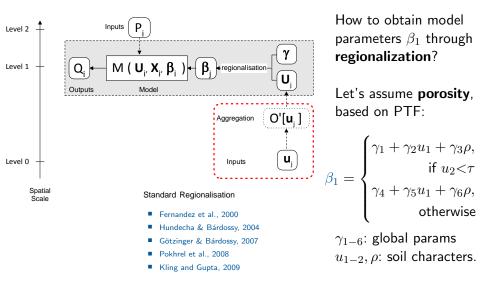
- Level-1: 1-8 km
 - Modeling states and fluxes
- Level-0: 100-1000 m
 - DEM BGK, SRTM
 - Soil texture, root zone depth вüк, whsd, statsgo
 - Hydraulic conductivity нёк
 - LAI NASA
 - □ Land cover NASA, CORINE
 - River network, gauged stations
 GRDC-EWA, EURO-FRIEND, USGS
 - Radiation, albedo, emissivity, wind LSA-SAF, NCEP-CFSR, MSG



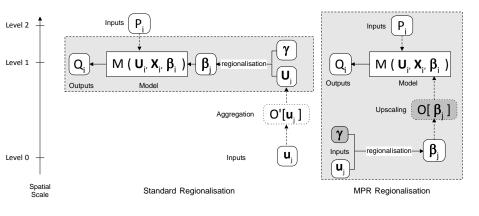
Standard regionalization scheme



Standard regionalization scheme

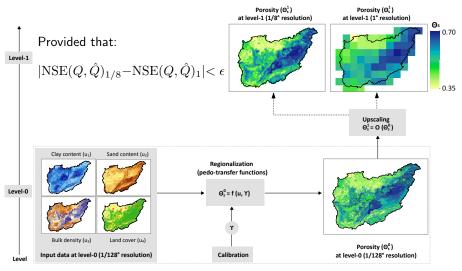


Multiscale Parameter Regionalization (MPR)



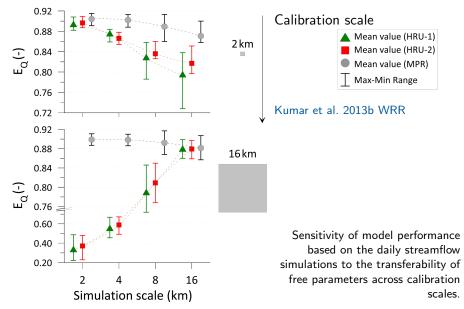
- Samaniego et al. 2010, 2011, 2012
- Kumar et al. 2010, 2012
- Wöhling et al. 2012

Application of the MPR technique

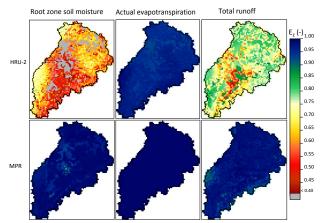


Kumar et al. 2013a WRR

Scale invariance of global "parameters" γ



Flux matching test for other model variables



Spatial pattern of the ensemble mean NSE (Ez) for selected variables. Baseline values were obtained by calibrating mHM at 2 km resolution with HRU-2 and MPR, separately. Simulated values were estimated with parameters obtained at 4, 8, and 16 km. [Kumar et al. 2013a, WRR]