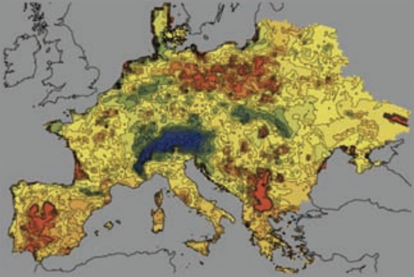
Calibration in hydrology

- Parameter estimation and multiscale verification in the Pan-EU -

Luis Samaniego, R. Kumar, O. Rakovec, M. Zink,
S. Attinger, M. Cuntz, J. Mai, D. Schäfer, S. Thober

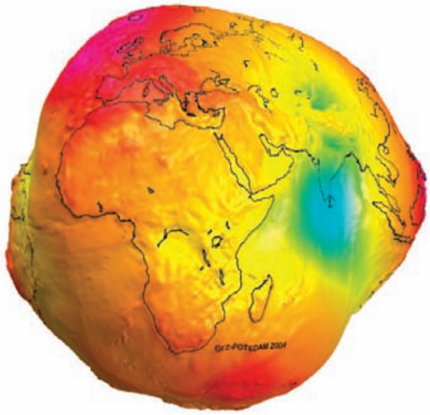


H-SAF and HEPEX Workshops on Coupled Hydrology

Reading, 6 November 2014

HELMHOLTZ CENTRE FOR ENVIRONMENTAL RESEARCH - UFZ

The “Grand Challenge” in hydro-meteorology



GRACE anomalies, Reigber et al., GFZ

To develop the ability to globally **monitor** and predict the movement of water on the landscape at resolutions of 4 km or less

Wood et al. WRR 2011

Bierkens et al. 2014 HP (in press)

The “Grand Challenge” in hydro-meteorology

EC-Tower Hohes Holz, TERENO-UFZ (Künzelmann)

To develop the ability to globally **monitor** and **predict** the movement of water on the landscape at resolutions of 4 km or less

Wood et al. WRR 2011

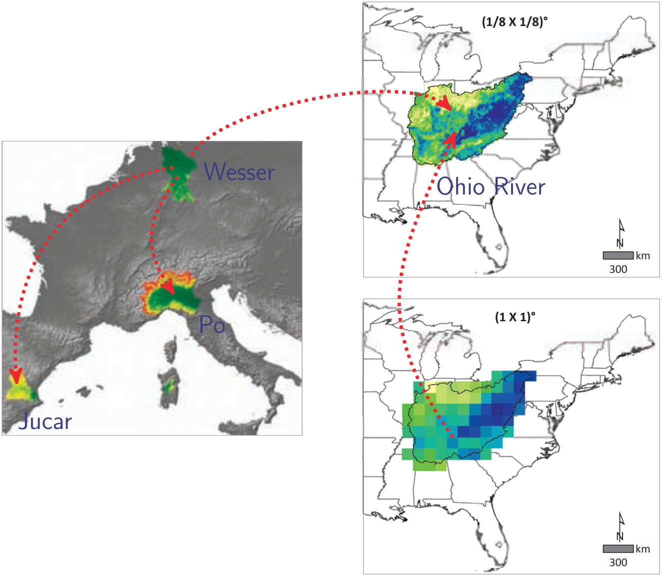
Bierkens et al. 2014 HP (in press)

Challenges in distributed hydrologic modeling

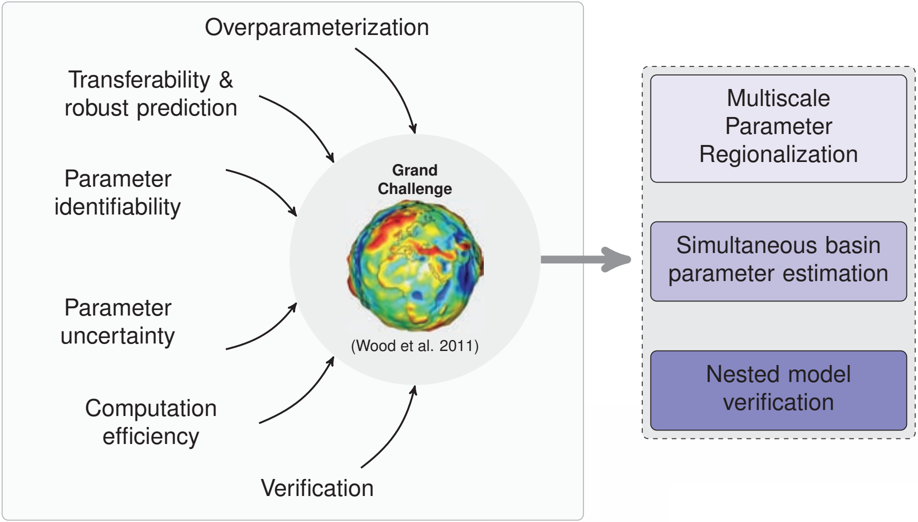
Models

should perform well across

- locations
- scales



Holistic framework

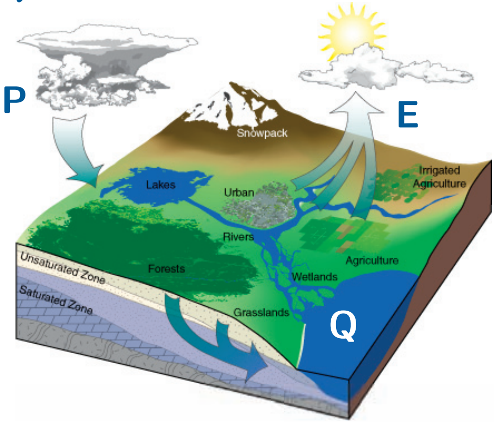


Distributed Modeling and Parameterization with

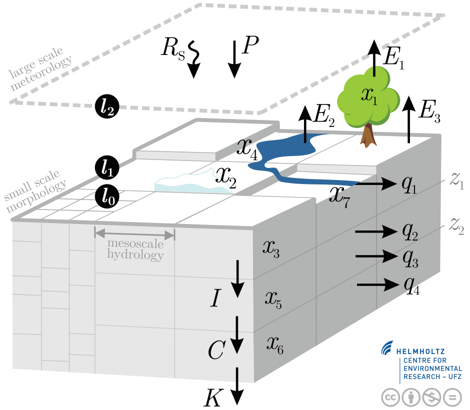
mHM & MPR

Modeling the water cycle

$\frac{\partial S}{\partial t} = P - E - Q$



mesoscale Hydrological Model (mHM)



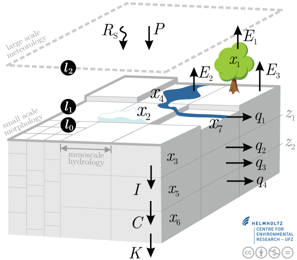
www.ufz.de/mhm
mhm-admin@ufz.de

Parameterization of a Hydrologic Model

State equations

$$\frac{d}{dt}\mathbf{x}_{it} = \mathbf{g}(\mathbf{x}_{it}, \mathbf{u}_{it}, \beta_{it}) + \eta_{it}$$

$$\mathbf{y}_{it} = \mathbf{f}(\mathbf{x}_{it}, \mathbf{u}_{it}, \beta_{it}) + \epsilon_{it}$$



Cell i, time t

$\mathbf{x}$	model states, fluxes
$\mathbf{y}$	observations
$\hat{\mathbf{y}}$	model outputs
$\mathbf{u}$	scaled input data
$\mathbf{g}(\bullet)$	dominant processes
$\mathbf{f}(\bullet)$	transformation functions
η	structural error
ϵ	observation error
β	effective parameters **?**

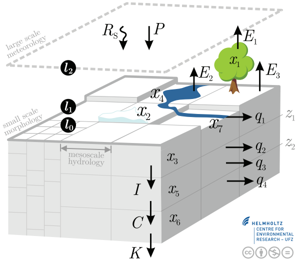
Parameterization of a Hydrologic Model

State equations

$$\frac{d}{dt}\mathbf{x}_{it} = \mathbf{g}(\mathbf{x}_{it}, \mathbf{u}_{it}, \beta_{it}) + \eta_{it}$$

$$\mathbf{y}_{it} = \mathbf{f}(\mathbf{x}_{it}, \mathbf{u}_{it}, \beta_{it}) + \epsilon_{it}$$

$$\min_{\hat{\beta}} = \|\mathbf{y} - \hat{\mathbf{y}}\|$$



Cell i, time t

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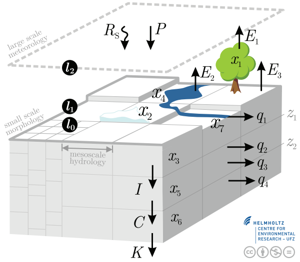
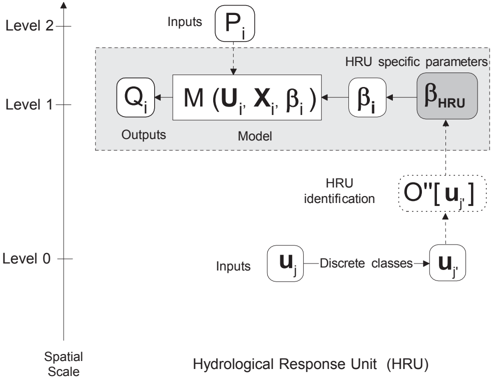
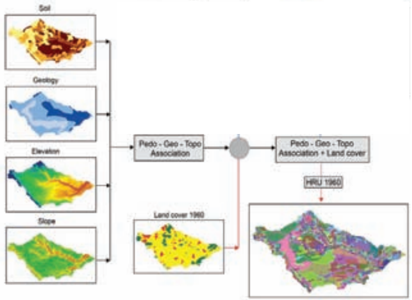


Cell i, time t

How to take into account the subgrid variability of $\mathbf{u}^0$ and β^0?

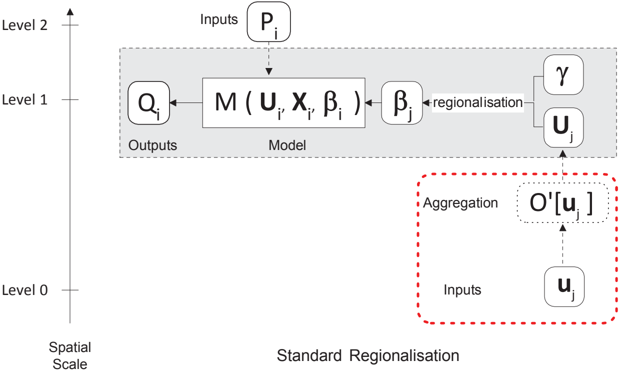
Parameterization schemes





- Leavesley et al. 1983
- Flügel, 1995
- Beldring et al., 2003
- Tolson and Shoemaker, 2007
- Blöschl et al., 2008
- Das et al., 2008
- Viviroli et al., 2009
- Kumar et al., 2010,12

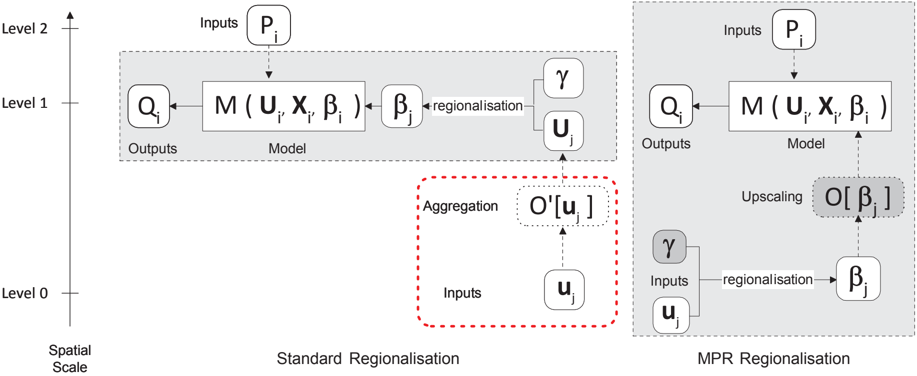
Parameterization schemes



Standard Regionalisation

- Fernandez et al., 2000
- Hundecha & Bárdossy, 2004
- Götzinger & Bárdossy, 2007
- Pokhrel et al., 2008
- Kling and Gupta, 2009

Parameterization schemes



- Fernandez et al., 2000
- Hundecha & Bárdossy, 2004
- Götzinger & Bárdossy, 2007
- Pokhrel et al., 2008
- Kling and Gupta, 2009

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

Multiscale Parameter Regionalization in mHM

State equations

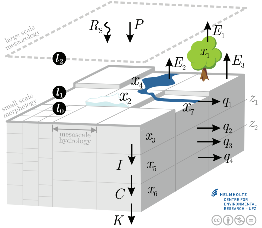
$$\dot{\mathbf{x}}_{it} = \mathbf{g}(\mathbf{x}_{it}, \mathbf{u}_{it}, \beta_{it}) + \eta_{it}$$

$$\Longleftarrow$$

Regionalization

$$\beta = \langle \beta^0 \rangle$$

$$\beta^0 = f(\mathbf{u}^0, \gamma)$$



Cell i, time t

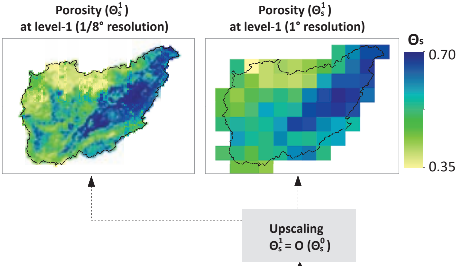
γ	calibration coefficients
$\mathbf{u}^0$	input physiographic data
$f(\bullet)$	regionalization functions
β^0	sub-grid regionalized parameters
β	effective parameters

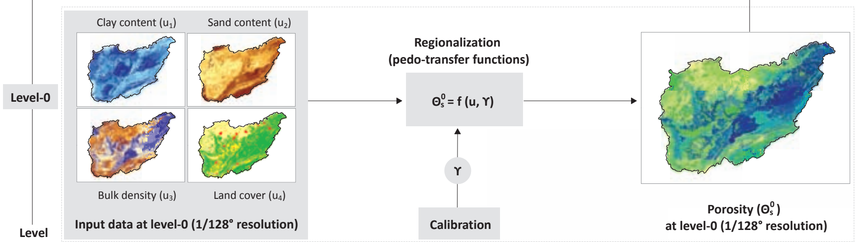
Samaniego et al. WRR, 2010a*, 2010b
Kumar et al. JoH, 2010
* WRR Editor's Choice Award 2010

Multiscale Parameter Regionalization in mHM

Provided that:

$$|\mathrm{NSE}(Q,\hat{Q})_{1/8} - \mathrm{NSE}(Q,\hat{Q})_1| < \epsilon$$



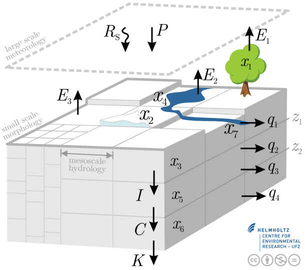


Kumar et al. 2013b WRR

Multiscale Parameter Regionalization in mHM

State equations

$$\dot{\mathbf{x}}_{it} = \mathbf{g}(\mathbf{x}_{it}, \mathbf{u}_{it}, \beta_{it}) + \eta_{it}$$



Cell i, time t

Does parameterization technique affect simulations of water fluxes?

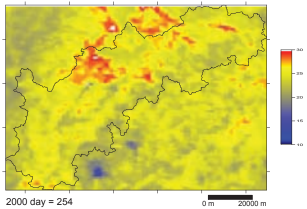
Kumar et al. WRR, 2013a

→ WRR Feature article

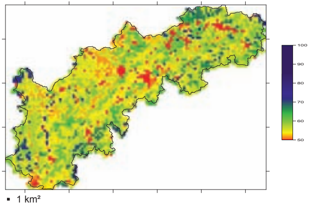
→ Eos Research Spotlight

Soil moisture and streamflow: HRU vs. MPR

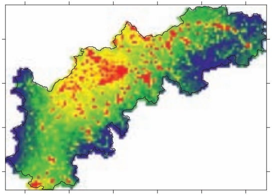
MODIS LST [°C]

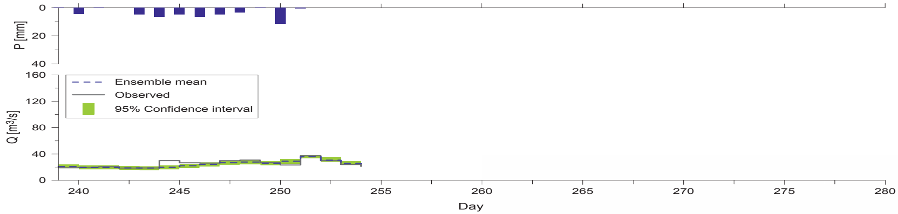


HRU: θ/θ_s



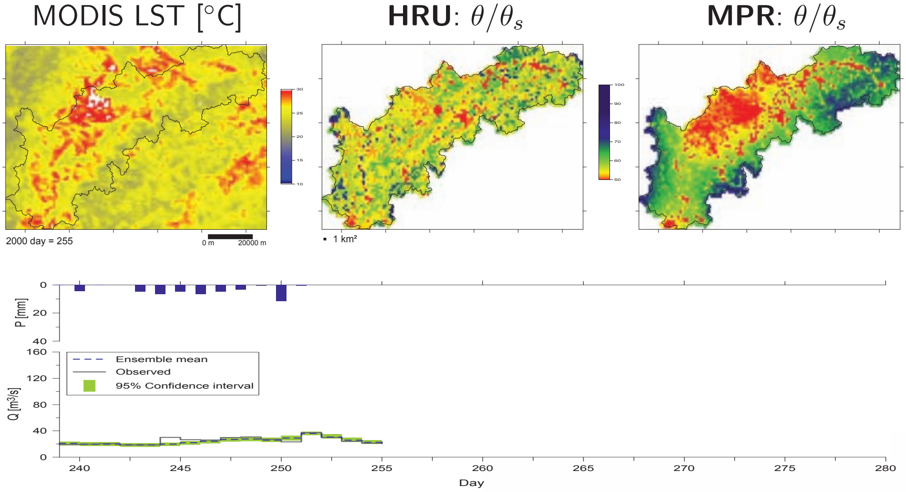
MPR: θ/θ_s





Samaniego et al. 2010, WRR

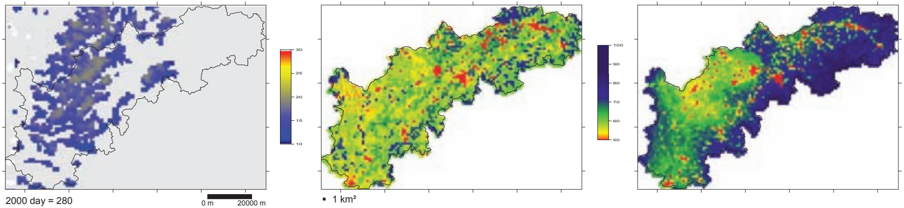
Soil moisture and streamflow: HRU vs. MPR

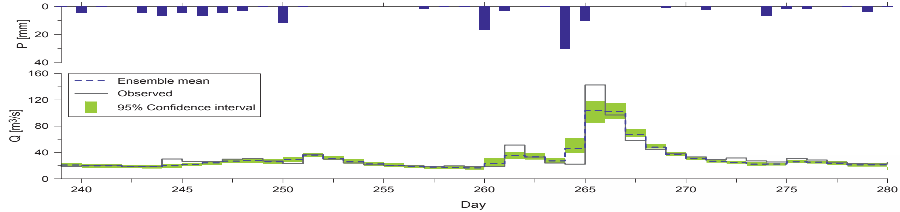


Samaniego et al. 2010, WRR

Soil moisture and streamflow: HRU vs. MPR

MODIS LST [°C] | **HRU**: θ/θ_s | **MPR**: θ/θ_s

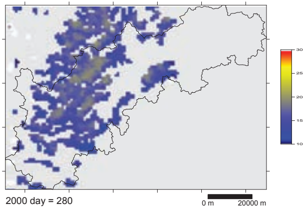




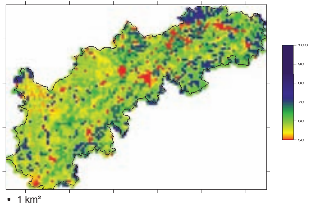
Samaniego et al. 2010, WRR

Soil moisture and streamflow: HRU vs. MPR

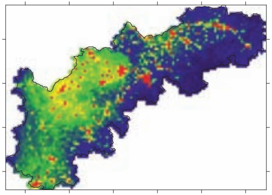
MODIS LST [°C]



HRU: θ/θ_s

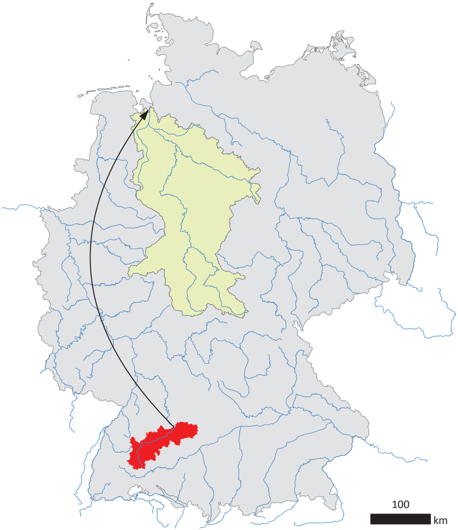


MPR: θ/θ_s



$$\left.\begin{array}{lcr@{\;}r} \text{All parameters} & \Rightarrow & \#\{\beta\} = & 212\,000 \\ \text{20 HRU, LC static} & \Rightarrow & \#\{\beta\} = & 1\,040 \\ \text{MPR} & \Rightarrow & \#\{\gamma\} = & 52 \end{array}\right\}\text{unknowns!}$$

Transferability within German basins



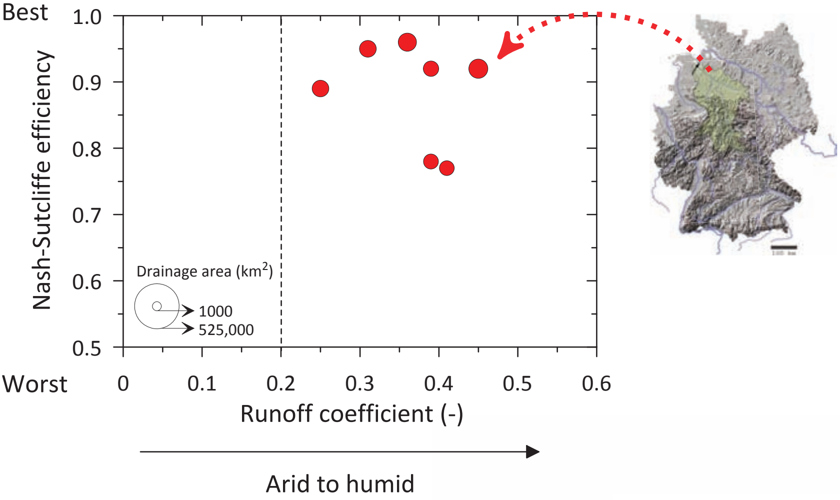
Basin	NSE-trans	NSE-cal
Main	0.92	0.95
Danube	0.87	0.90
Weser	0.91	0.94
Ems*	0.67	0.88
Saale**	0.60	0.84

Daily discharge evaluation: 1965-2005

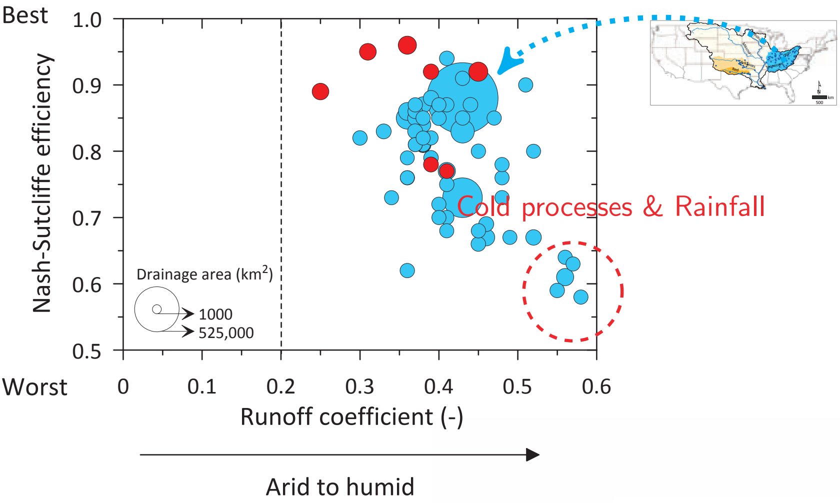
* Precipitation undercatch ** Rappbode Dam

Samaniego et al. JHM, 2013

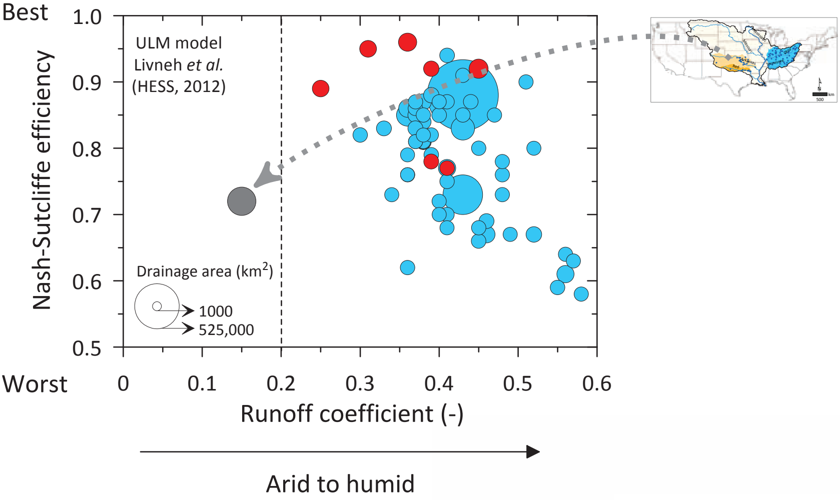
Transferability to US basins



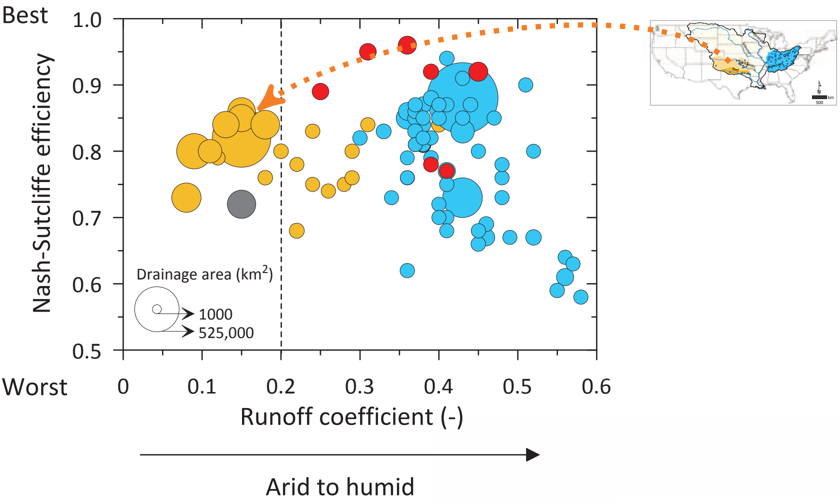
Transferability to US basins



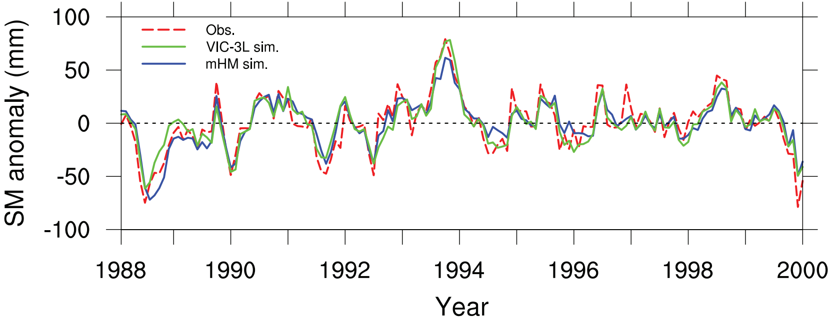
Transferability to US basins



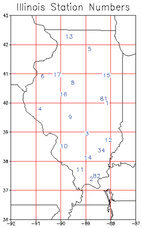
Transferability to US basins



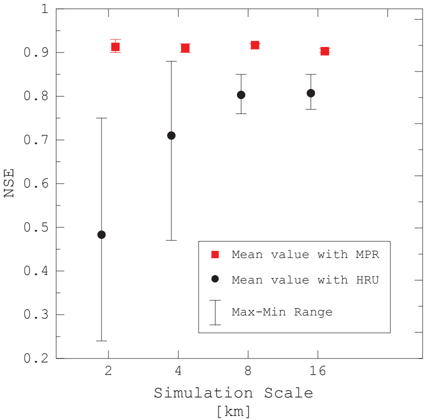
mHM Evaluation at Illinois SM network



VIC simulation by Roads et al. 2003, JGR

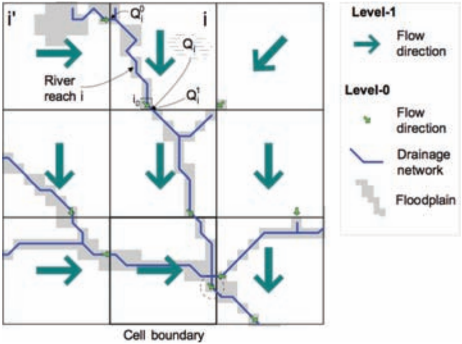


Scale invariance of global "parameters" γ



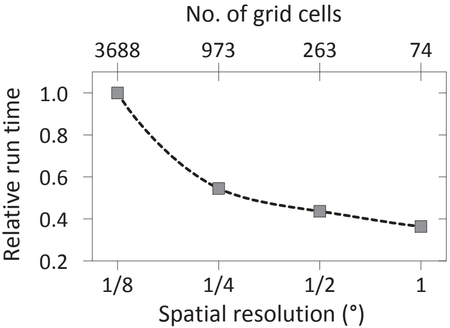
Samaniego et al. 2010, WRR

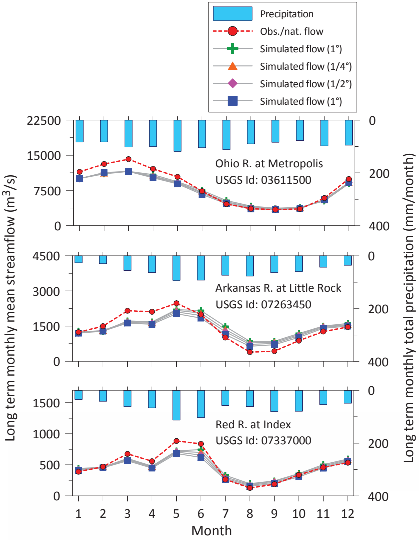
Kumar et al. 2013a, WRR



Scaling the river network

Reduction of the computational load

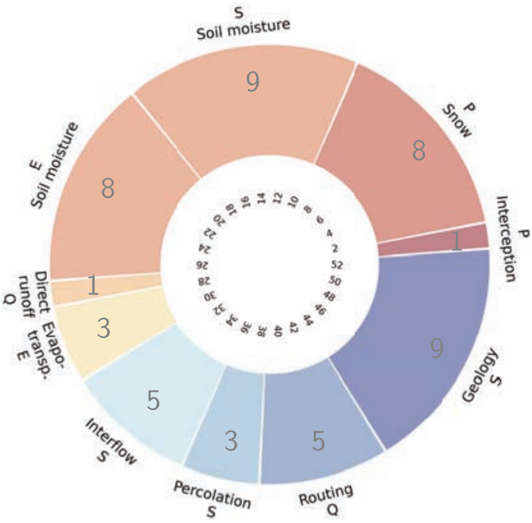




Kumar et al. 2013b, WRR

Parameter identifiability

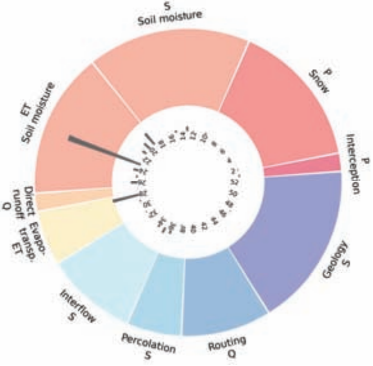
mHM parameter space

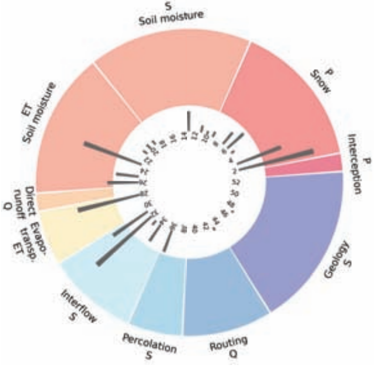


1. Which parameters can be identified by SA?
2. Which parameters are important during calibration?

Derivative vs. variance-based SA[1]

$\frac{\partial S}{\partial t} = P - E - Q$





Parameter Importance index

Optimization (all)

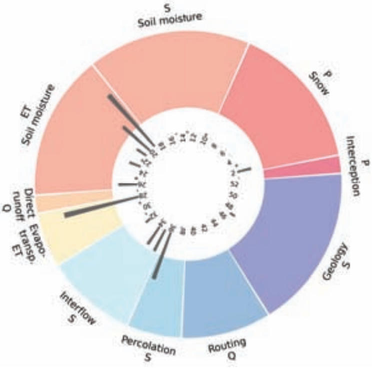
≈ 100,000 model evaluations

≈ 16,000 model evaluations

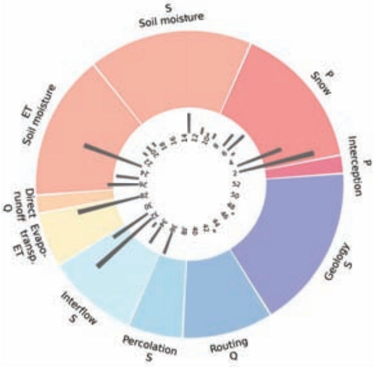
[1] Göhler et al. JGR 2013, Cuntz et al. WRR 2014 (draft)

Derivative vs. variance-based SA[1]

$\frac{\partial S}{\partial t} = P - E - Q$



Sobol index



Optimization (all)

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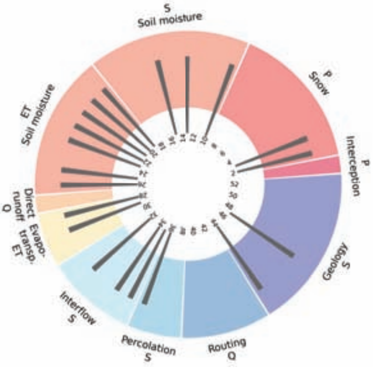
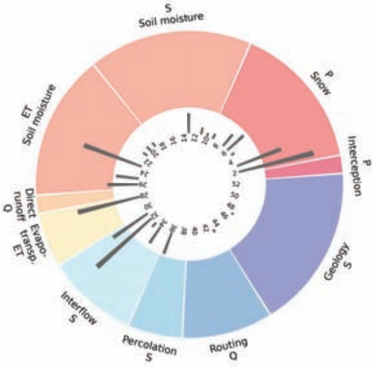
[1] Göhler et al. JGR 2013, Cuntz et al. WRR 2014 (draft)

Derivative vs. variance-based SA[1]

$\frac{\partial S}{\partial t} = P - E - Q$



Efficient Elementary Effects



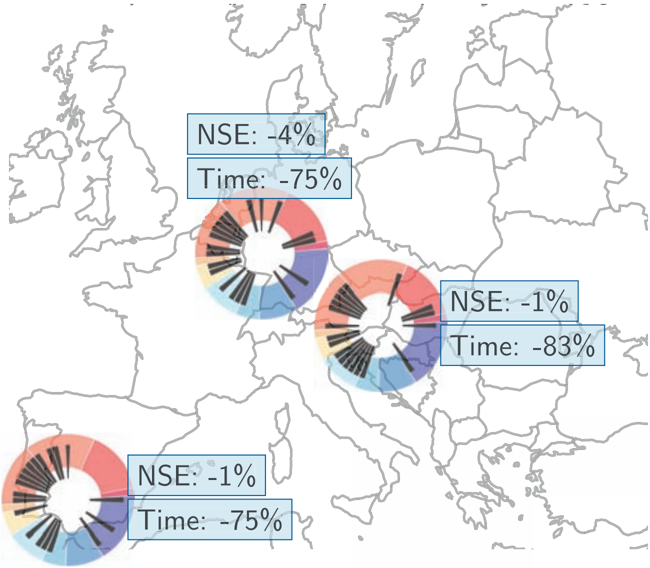
Optim. (20 informative)

≈ 600 model evaluations

≈ 4,000 model evaluations

[1]Göhler et al. JGR 2013, Cuntz et al. WRR 2014 (draft)

Model calibration with informative parameters



Multiscale verification of Pan EU simulations

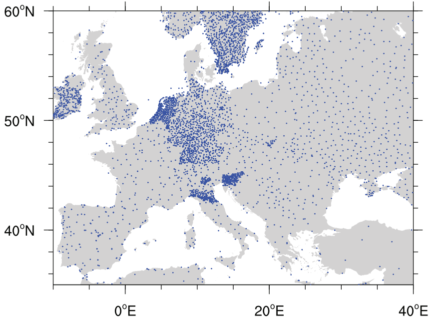
Research goals and hypothesis

- To estimate uncalibrated water fluxes and states at multiple scales
- To investigate potential benefits of conditioning a model with multiple scale data sets.

Parameter inference based **only** on streamflow data
→ Necessary but not a sufficient condition
→ Potentially leading to biased states and fluxes

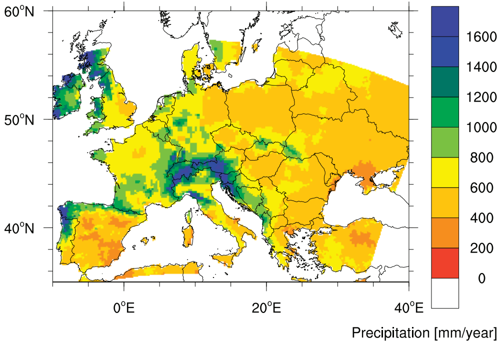
Pan-EU data

ECA&D Rain gauge Network



cib.knmi.nl

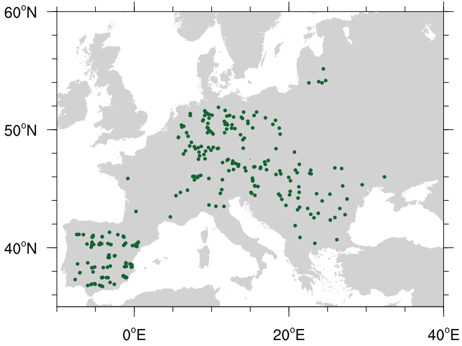
EOBS 24×24 km^2



Period: 1950 - 2012

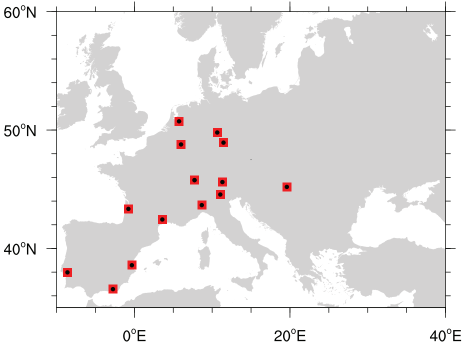
Pan-EU data

Streamflow gauges



GRDC, EURO-FRIEND

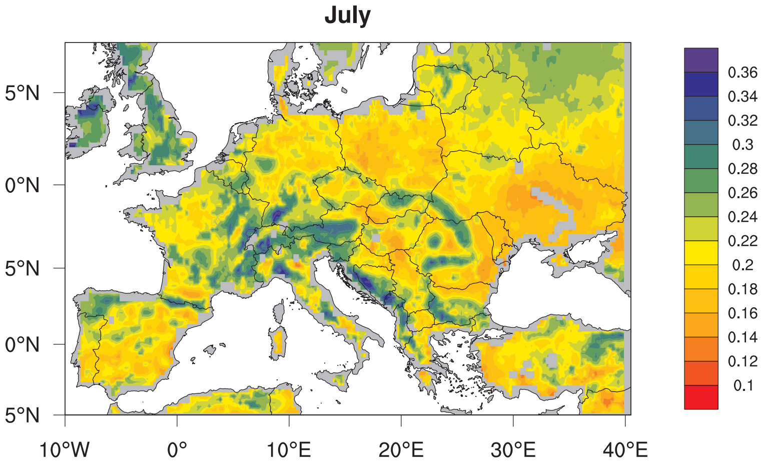
Latent heat



FLUXNET and LandFlux-EVAL[2]

[2] www.iac.ethz.ch/groups/seneviratne/research/LandFlux-EVAL

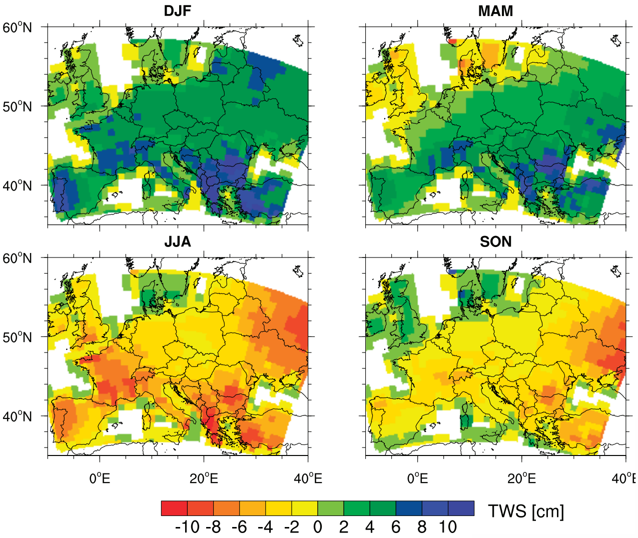
Soil moisture: ESA-CCI[3] (0.25 deg)



Period: 1978 - 2010
active and passive
microwave sensors

[3] http://www.esa-soilmoisture-cci.org

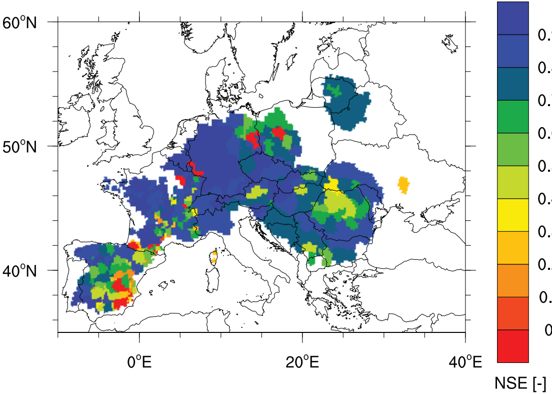
Total water storage: GRACE[4] (1 deg)



Period:
2004 - 2010

[4] Landerer and Swenson, WRR 2012 / NASA

Performance at each basin (streamflow)



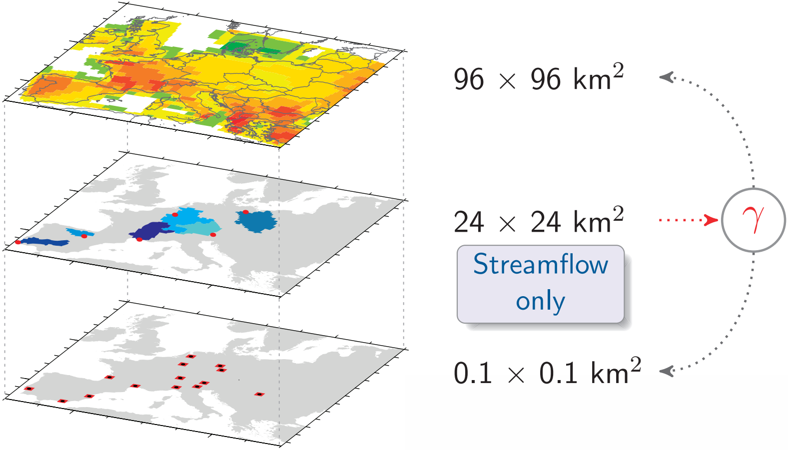
Single site

$n = 347$

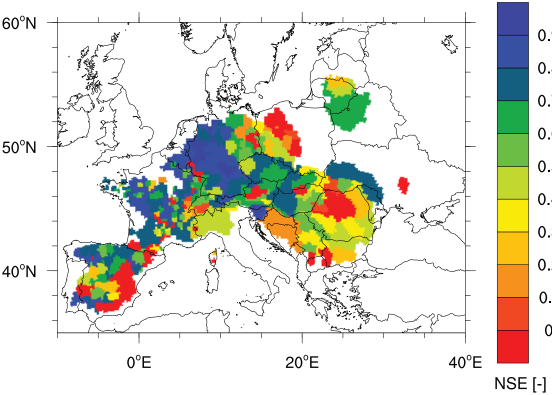
Monthly discharge

Anthropogenic influenced basins not excluded

Nested model setup for evaluation



Verification of streamflow



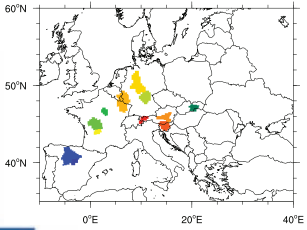
Cross-validation

$n = 347$

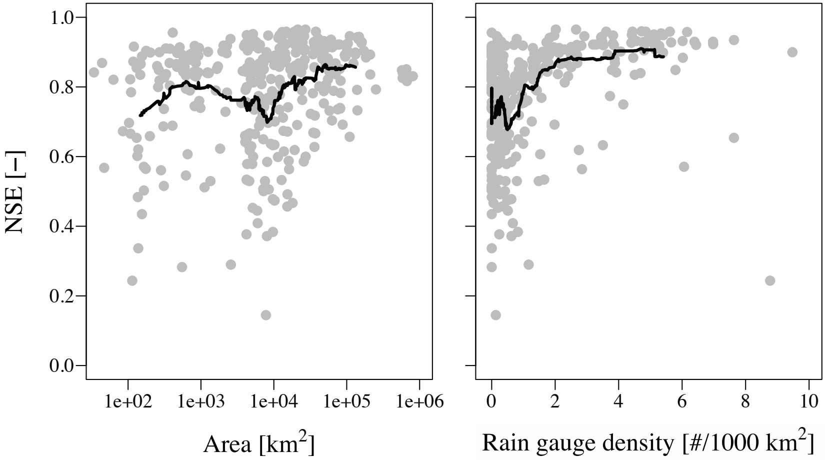
Monthly discharge

$\mathrm{NSE} < 0.5$ 25%

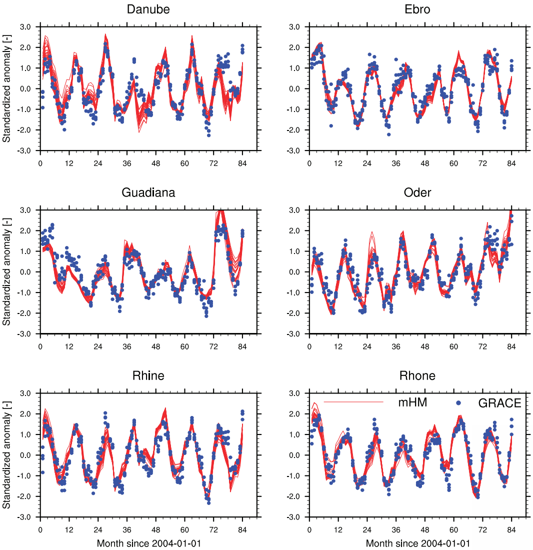
Anthropogenic influenced basins not excluded

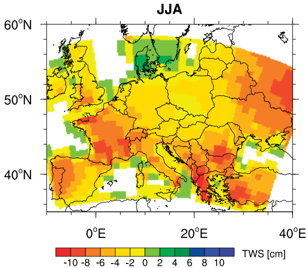


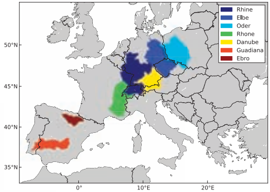
Factors affecting performance



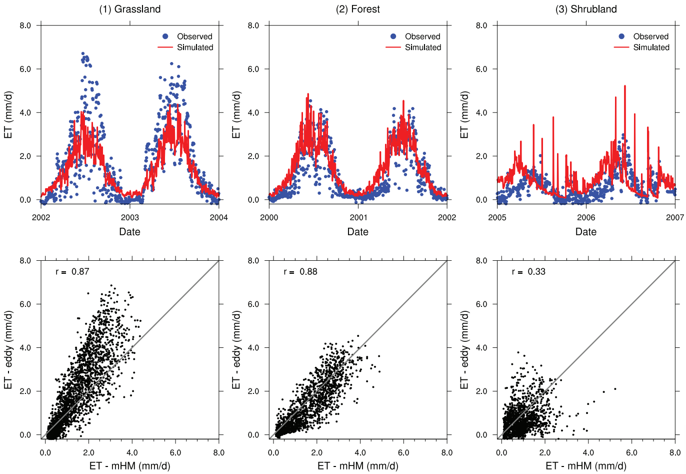
Verification of total water storage with GRACE

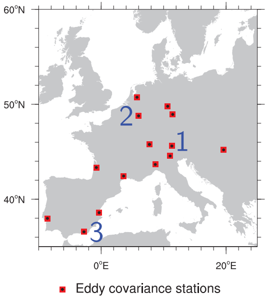




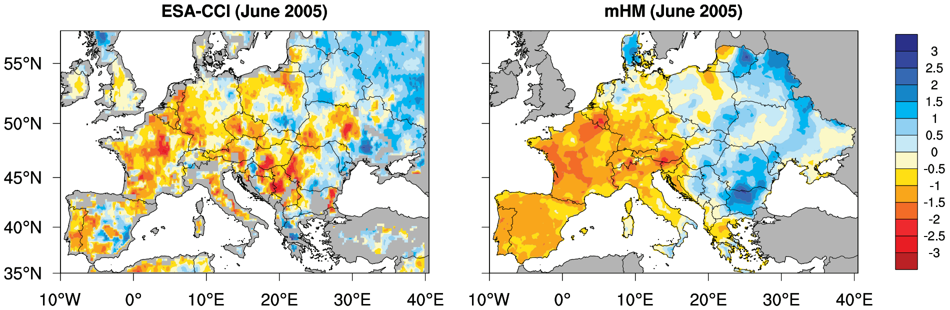


Verification of actual evapotranspiration (EC)





Verification of soil moisture (ESA-CCI)

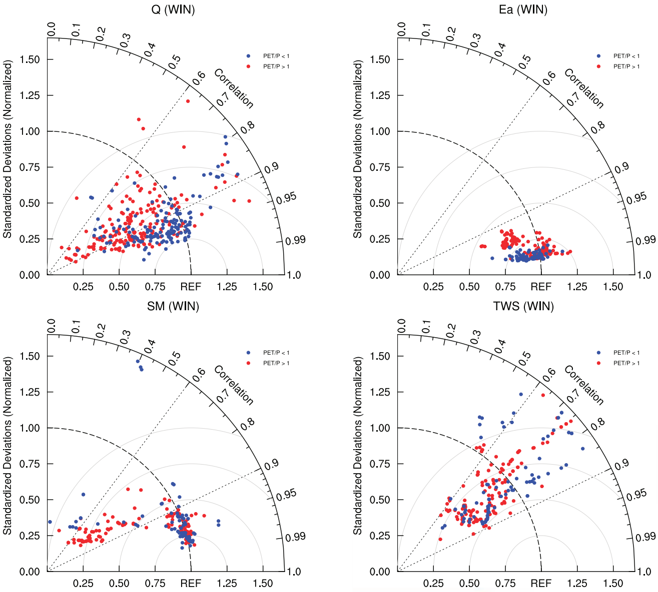


Standardized anomalies

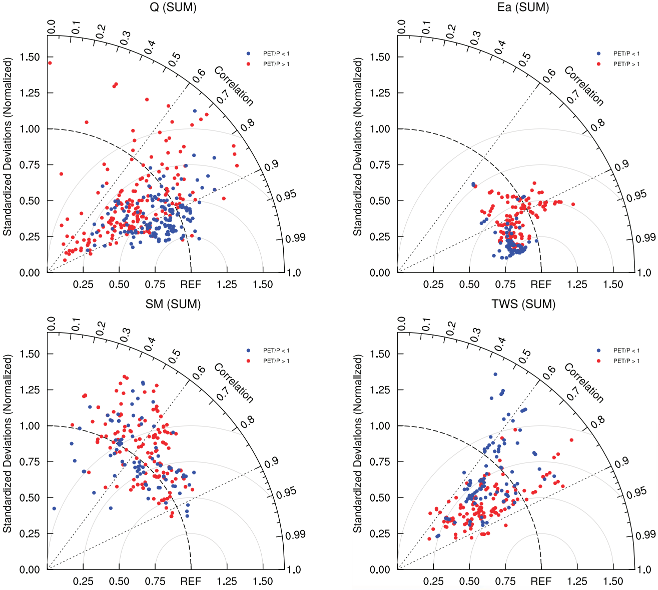
- Unknown soil depth in ESA-CCI soil moisture
- Large number of missing values

- Depth 1st soil layer = 30 cm
- PROBLEM: Droughts in Iberian Peninsula and part of France not well captured by the ESA-CCI

Evaluation summary



Evaluation summary

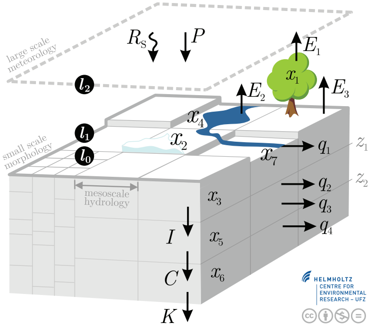


Conclusions

- Effective approach for parameter estimation:
  $\rightarrow$ parameters screening (EEE) then SCE
- Multi-basin parameter estimation
  $\rightarrow$ mHM+MPR robust for 75% of the Pan-EU basins
- Assimilation of streamflow
  $\rightarrow$ MPR leads to “good” estimation of mHM states at scales not used during parameter inference
  $\rightarrow$ Capturing high fidelity signals (anomalies) of GRACE and eddy stations was not posible
  $\rightarrow$ Nested model parameter (γ) inference framework required
- Strong to weak signals: Q, TWS, E, SM

Appendix

mHM: mesoscale Hydrological Model

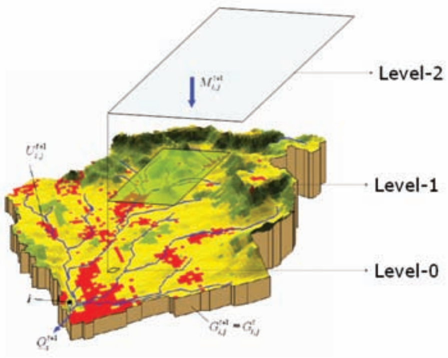


- Fortran 2003, OpenMP
- Multiscale/basin param. estimation
- Restart file
- MCMC, OPTI, SA
- Fully modular / process selection
- Python tools (pre/post proces.)
- Doxygen documentation
- SVN repository (dev. & users)
- Growing user community since release 12.2013

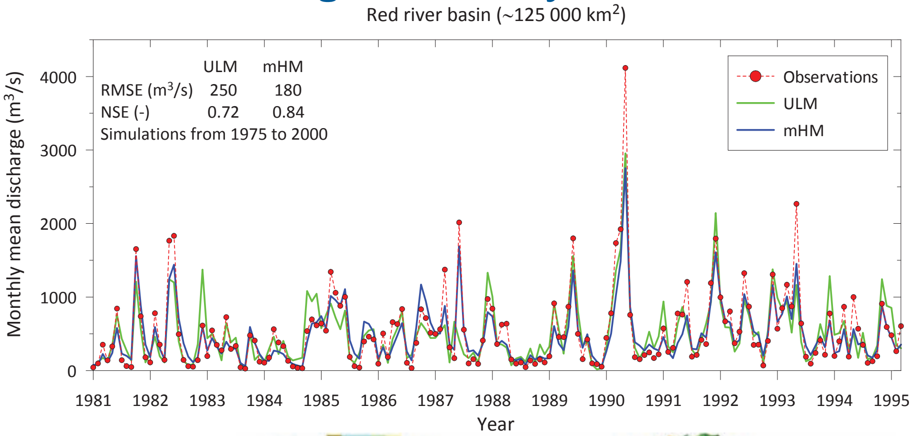
www.ufz.de/mhm
mhm-admin@ufz.de

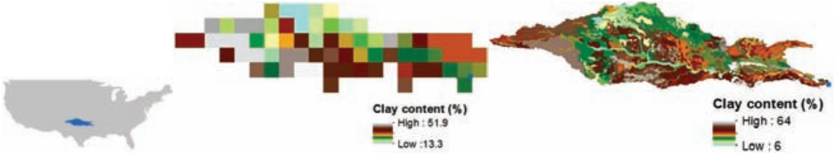
Data levels in mHM

- **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 BÜK, WHSD, STATSGO
  - Hydraulic conductivity HÜK
  - LAI NASA
  - Land cover NASA, CORINE
  - River network, gauged stations GRDC-EWA, EURO-FRIEND, USGS
  - Radiation, albedo, emissivity, wind LSA-SAF, NCEP-CFSR, MSG



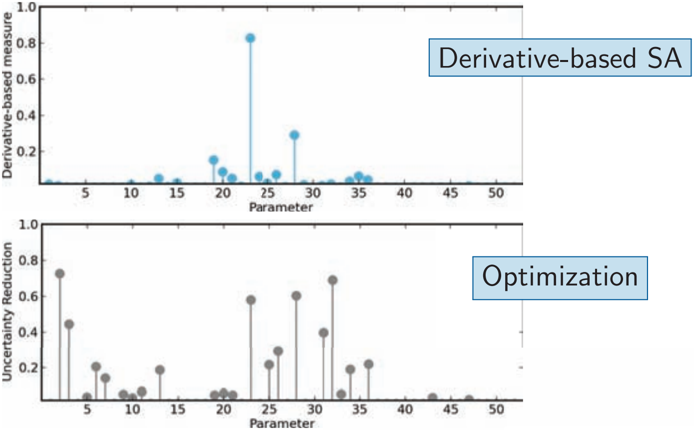
Effect of the subgrid variability





ULM runs, Livneh and Lettenmaier, HESS, 2012

Optimization & Sensitivity Analysis[5]



[5]Cuntz, Mai, et al., WRR 2014 (draft)

∂-based SA: Parameter Importance Index [6]

$$M_{i,j} = \sum_{n=1}^{N} \sum_{t=1}^{T} \left[\frac{\partial Q(p_i)}{\partial p_i} \frac{p_i}{Q(p_i)} \cdot \frac{\partial Q(p_j)}{\partial p_j} \frac{p_j}{Q(p_j)} \right]$$

Parameter Importance Index:

$$PI_k = \sum_{m=1}^{K} \lambda_m |u_{k,m}|$$

with eigenvalues λ_k and eigenvectors $u_{\cdot,k}$ of M

[6] Göhler, Mai & Cuntz (2013) JGR Biogeoscience, 118(2)

Variance-based SA: Sobol Index

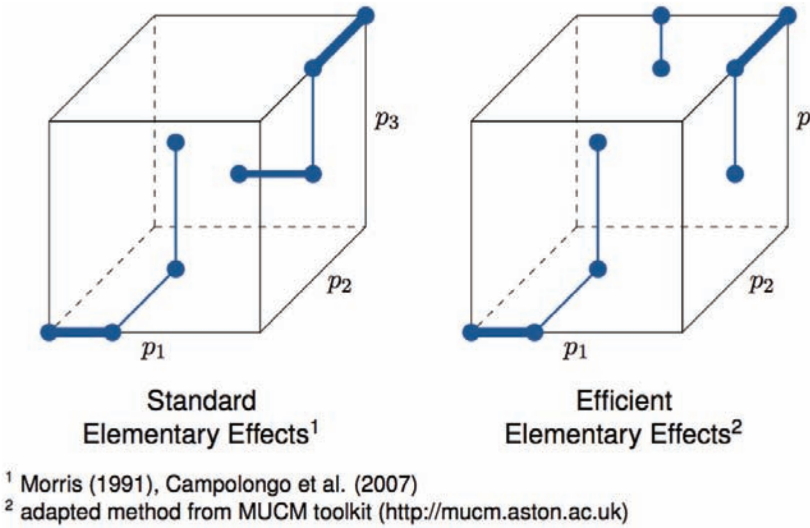
Main effect:

$$S_i = \frac{\text{Variance of Q, if } \textbf{one} \text{ parameter is variable}}{\text{Variance of Q, if } \textbf{all} \text{ parameters are variable}}$$

Total effect:

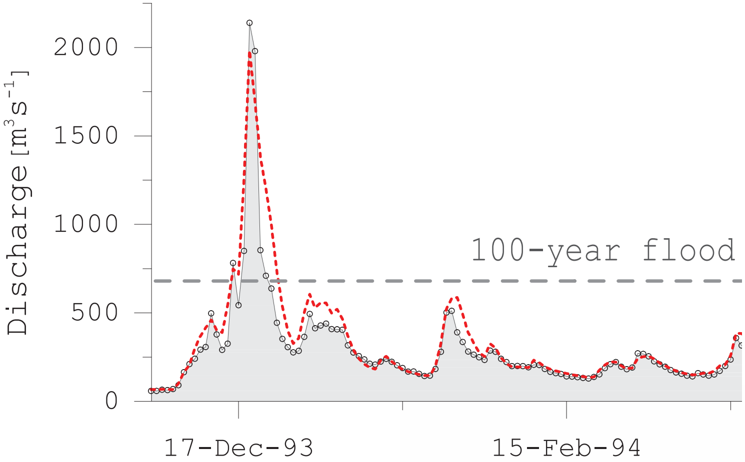
$$S_{T_i} = \frac{\text{Variance of Q, if } \textbf{all incl. one} \text{ parameters are variable}}{\text{Variance of Q, if } \textbf{all} \text{ parameters are variable}}$$

Efficient Elementary Effects [7]



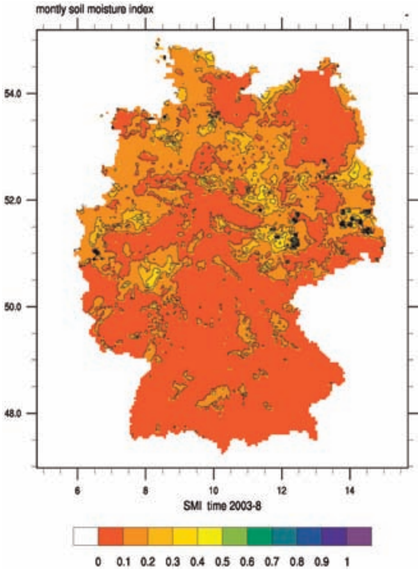
[7] Cuntz, Mai, et al. (2014) WRR (Draft)

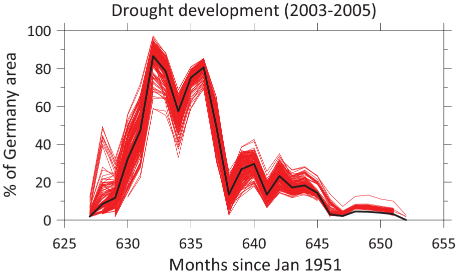
Evaluation with extremes flows (at Rockenau)



Neckar basin, 12000 km^2

Predictive uncertainty in major events





Samaniego et al., JHM, 2013

Computational efficiency and storage

Region	Cells	Δx	Δt	Run time	Storage
	$\times 10^3$	[km]	[h]	[min][8]	
DE	29	4	1	≈ 30	
US	23	12.5	3	≈ 10	
EU	8.2	24	1	≈ 15	17 GB (80 MB) [9]
Global[10]	59.6	50	1	≈ 140	
	953.6	12.5	1	≈ 300	2 TB (10 GB)

[8] Ten years run, Fortran 2003, OpenMP, EVE Linux cluster (10 cores)
[9] All variables, daily, (1 variable monthly) for 40 years simulation
[10] Extrapolated, including routing