H23C-0981: Multiscale Parameter Regionalization of a Grid-based Hydrologic Model

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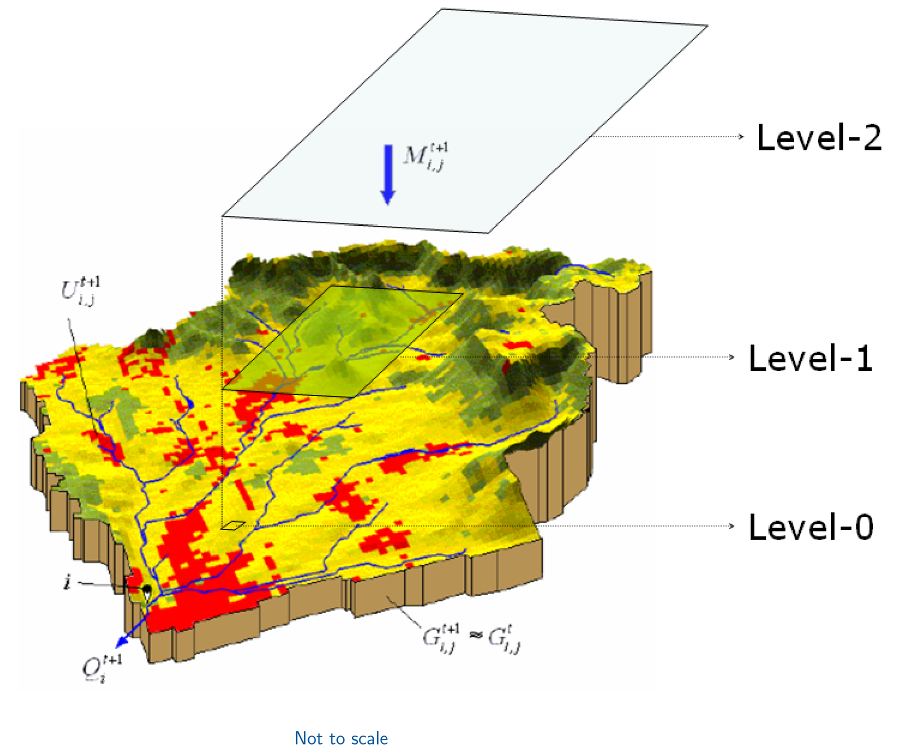
1. Abstract

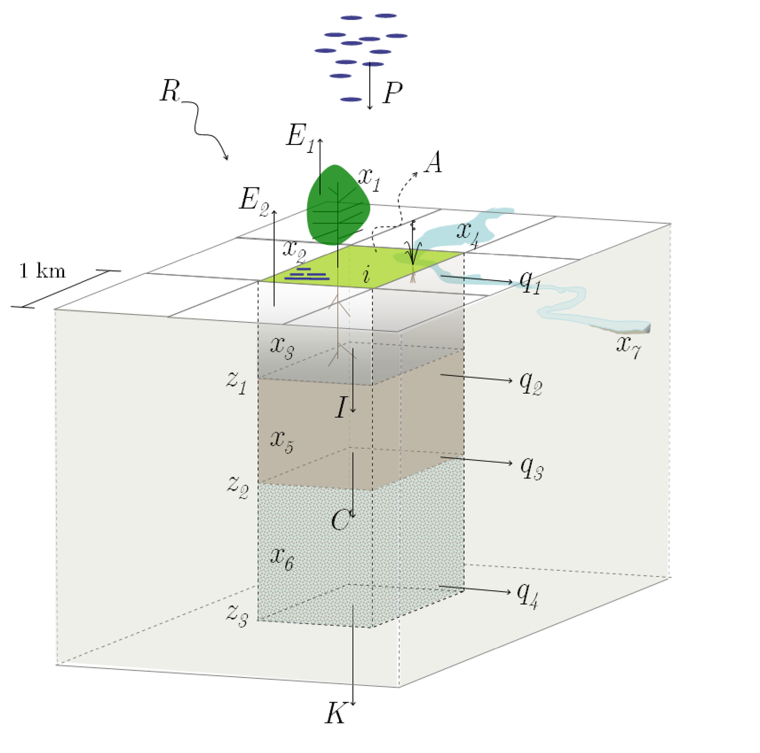
The main goal of this study is to validate a multiscale regionalization technique (MPR) integrated into a grid-based mesoscale hydrologic model (mHM). This model should be able to reproduce not only the discharge hydrograph at any gauged or ungauged location but also the spatio-temporal distribution of state variables such as soil moisture. mHM is based on accepted hydrological conceptualizations and require three levels of spatial information: level-2 for the climatic information, level-1 for the state variables of the model, and level-0 for physiographic input data such as soil textures, land cover, elevation, and geological formations. Model parameters at level-1 are location and time dependent. They are estimated through upscaling operators that link level-0 information with global transfer-function parameters, which in turn are found through optimization. mHM results were compared against that obtained with the HBV model whose parameters were regionalized based on the Homogeneous Response Units (HRU) approach.

2. Spatial Resolution

- **Level-2**: (1000-10 000) m
  - Meteorologic forcings
- **Level-1**: (500-5000) m
  - Dominant hydrologic processes
- **Level-0**: (50-100) m
  - DEM, land cover, soils, geology
  - SVAT processes



3. Mesoscale Hydrologic Model (mHM)



State variable at cell i, time t

State equations: cell i, time t:

$$\dot{\mathbf{x}}_i(t) = \mathbf{f}(\mathbf{x}_i, \mathbf{u}_i, \boldsymbol{\beta}_i) + \boldsymbol{\eta}_i(t) \quad \forall i \in \Omega$$

Output: Runoff:

$$\mathbf{q}_l(t) = \mathbf{g}(\mathbf{x}, \mathbf{u}, \boldsymbol{\beta}) + \boldsymbol{\epsilon}_l(t)$$

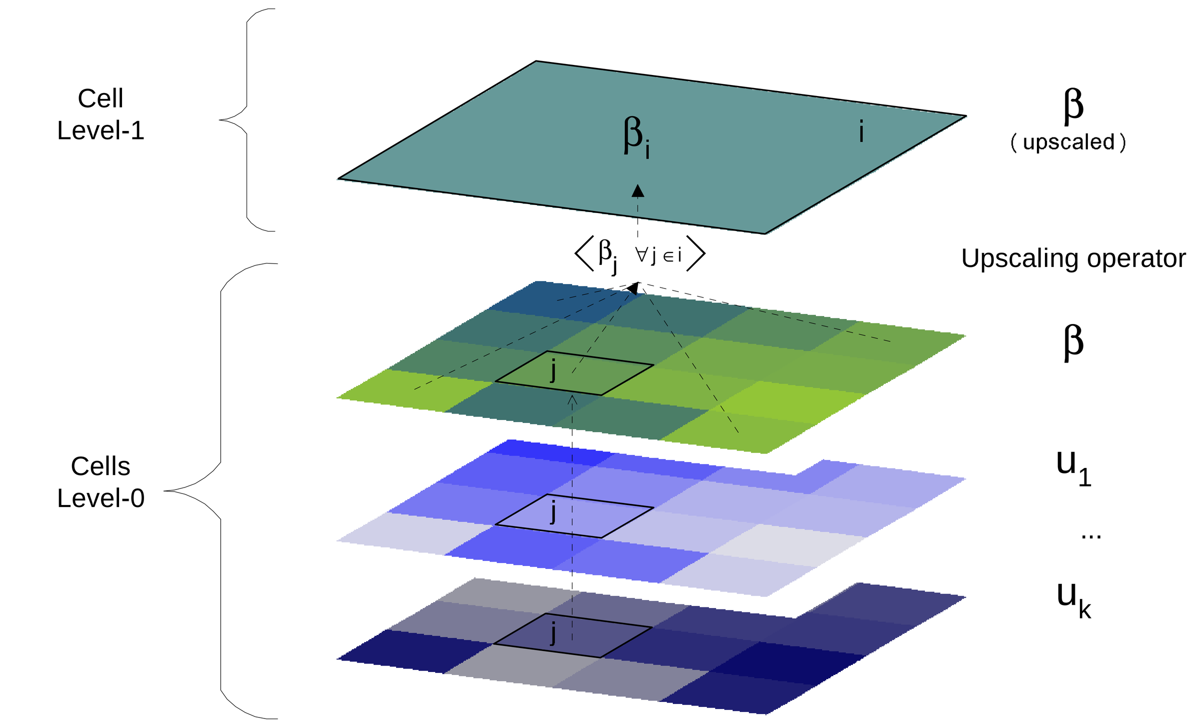
Upscaling Operator[3]:

$$\beta_{ki}(t) = \mathrm{O}_k \left\langle \boldsymbol{u}_j(t), \boldsymbol{\gamma} \quad \forall j \in i \right\rangle_i$$

where

f, g	system and output functional relationships	$\boldsymbol{\beta}$	location specific parameters
$\mathbf{q}$	l-dimensional (measurable) output vector	$\boldsymbol{\gamma}$	s-dimensional global transfer function parameters (to be calibrated).
$\mathbf{u}$	fields (grids) representing land cover states, physiographical and meteorological variables	$\mathrm{O}_k\langle\bullet\rangle_i$	upscaling operator
$\mathbf{x}$	state variables	Ω	control volume (e.g. river basin)
$\boldsymbol{\eta}$	unmeasurable stochastic inputs	t, k	time and parameter indexes
$\boldsymbol{\epsilon}$	system's uncertainty due to measurements defects	i	cell location index at level-1

4. Multiscale Parameter Regionalization (MPR)



5. Example

Upscaling van Genuchten saturated volumetric water content θ_s

Variable	Function	Ref.
Saturated volumetric water content, cell i	$\theta_{si}(t) = \mathcal{H}\langle\, \theta_{sj}(t)\, \rangle_i = \frac{n}{\sum_{\forall j\in i}\theta_{sj}(t)}$	[5]
Saturated volumetric water content cell i	$\theta_{sj}(t) = \begin{cases} \gamma_1 + \gamma_2 u_{1j} + \gamma_3 \varrho_j(t) & u_{2j} < \tau_s \\ \gamma_4 + \gamma_5 u_{1j} + \gamma_6 \varrho_j(t) & \text{otherwise} \end{cases}$	[4]
Soil bulk density, cell j	$\varrho_j(t) = \frac{1}{\frac{o_j(t)}{\varrho_O} + \frac{1-o_j(t)}{u_{3j}}}$	[2]
Fraction organic matter, cell j	$o_j(t) = \begin{cases} \gamma_7 & u_{4j}(t) \equiv \text{Forest} \\ \gamma_8 & u_{4j}(t) \equiv \text{Impervios cover} \\ \gamma_9 & u_{4j}(t) \equiv \text{Permeable cover} \end{cases}$	[3]

where

j	cell index at level-0	$\gamma_1,\dots,\gamma_9$	pedo-transfer parameters (calibration)
n	number of cells j contained in cell i	u_1	Mean fraction of clay at level-0.
o	Fraction of organic matter	u_2	Mean fraction of sand at level-0.
ϱ_o	Average organic matter bulk density (= 0.224 g/cm^3)	u_3	Mineral bulk density based on clay and sand contents [2].
τ_s	Sand fraction threshold according to [4] (= 66.5%).	u_4	Land cover.

References

[1] NASA, http://modis-land.gsfc.nasa.gov/.

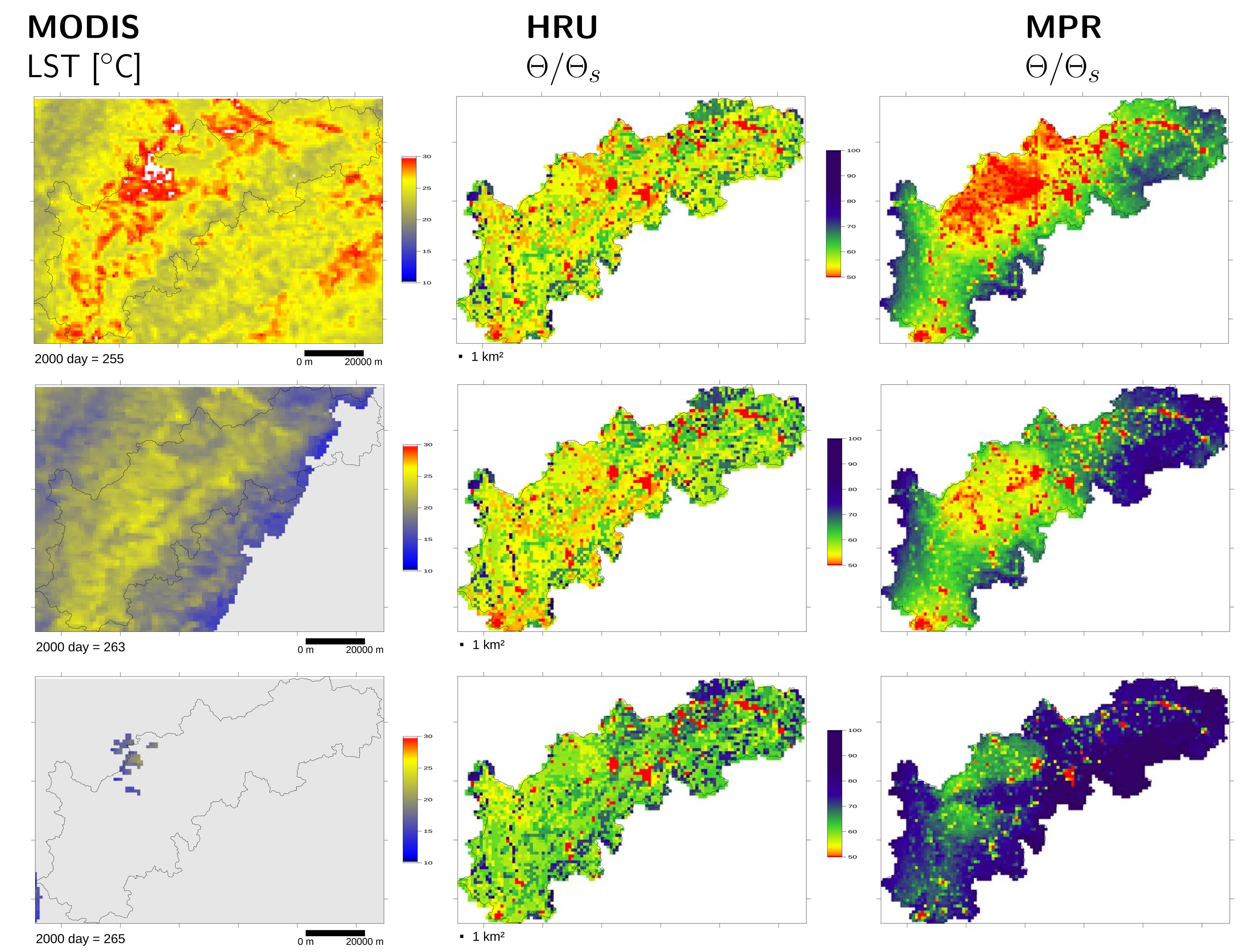
[2] W. J. Rawls, "Estimating soil bulk densiry from particle size analysis and organic matter content," *Soil Sci.*, vol. 135, pp. 123–125, 1983.

[3] L. Samaniego, R. Kumar, and S. Attinger, "Multiscale parameter regionalization of a grid-based hydrologic model at the mesoscale," *Water Resources Research*, 2008, submitted.

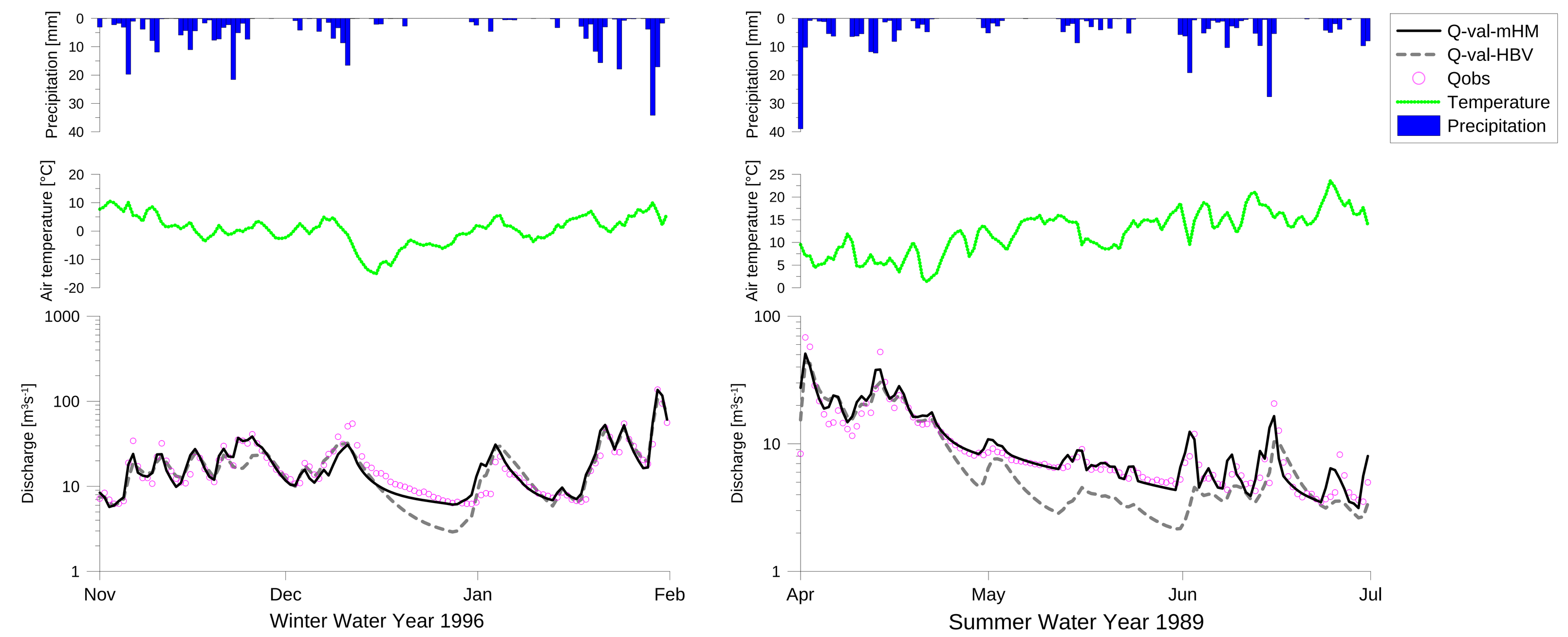
[4] S. Zacharias and G. Wessolek, "Excluding Organic Matter Content from Pedotransfer Predictors of Soil Water Retention," *Soil Sci Soc Am J*, vol. 71, no. 1, pp. 43–50, 2007.

[5] J. Zhu and B. P. Mohanty, "Spatial Averaging of van Genuchten Hydraulic Parameters for Steady-State Flow in Heterogeneous Soils: A Numerical Study," *Vadose Zone J*, vol. 1, no. 2, pp. 261–272, 2002.

6. Effect on Soil Moisture Patterns



7. Effect on Daily Streamflow Prediction



8. Conclusions

- MPR approach produced a significant improvement in model performance: NSE (mHM) $\approx$ 0.85 to 0.90 whereas NSE (HBV) $\approx$ 0.79 to 0.84.
- MPR led to more plausible spatio-temporal patterns of soil moisture than that obtained with the HRU approach. Validation with MODIS[1] LST.
- MPR induced a substantial reduction of model complexity without compromising its efficiency:
  - mHM: 64 transfer function parameters (DOF)
  - HBV: 28 HRUs $\times$ 15 parameters per HRU = 420 DOF.

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