Soil moisture parameter regionalization in a mesoscale hydrologic model

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1. Introduction

Regional climate modeling and integrated water resources management require, among other things, of a robust, distributed, and parsimonious hydrologic model able to estimate the magnitude of the hydrologic consequences of the land cover and climatic changes on a mesoscale river. This model should also provide reasonable estimates of a number of state variables required for other related processes. Soil moisture is one of these state variables. Current state-of-the-art in estimating and validating soil moisture is not quite satisfactory though. This study presents a comparison of two regionalization approaches that may help improving the estimation of daily estimates made with the distributed hydrologic model HBV-UFZ. Plausibility tests were carried out with a proxy obtained from MODIS images.

2. Facts and research questions

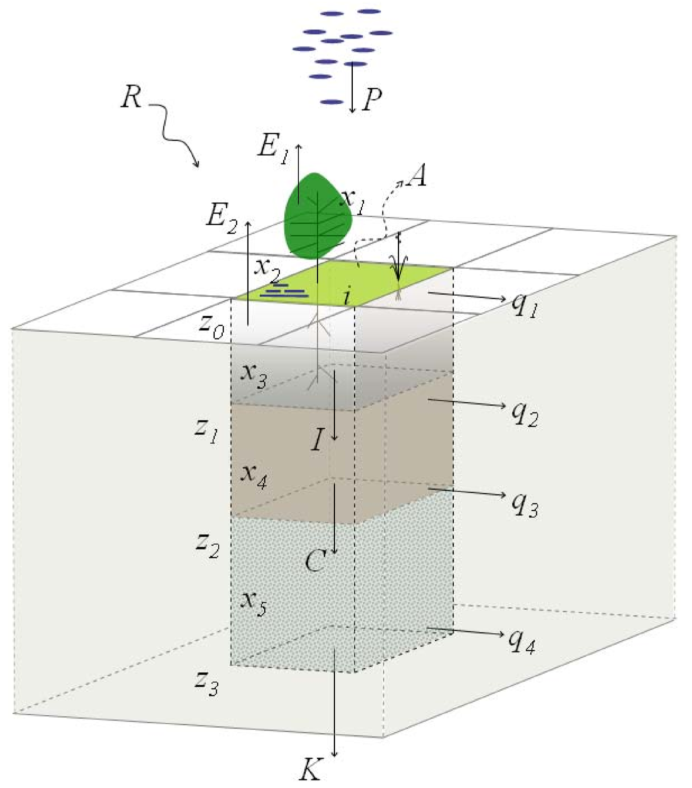
The spatial-temporal distribution of the soil moisture plays a crucial role on:

- Lateral flows and streamflow generation
- Evapotranspiration and plant growth dynamics
- Response (feedbacks) of the regional climate models

⇒ How to better regionalize the parameters of the soil infiltration model?

⇒ How to constrain its parameters during calibration?

3. Mesoscale hydrological model



Grid based HBV-UFZ

State equations: cell (i), t:

$$\dot{x}_1 = P - F - E_1$$
$$\dot{x}_2 = F - M$$
$$\dot{x}_3 = R + M - E_2 - I - q_1$$
$$\dot{x}_4 = I - q_2 - q_3 - C$$
$$\dot{x}_5 = C - K - q_4$$

Output: Runoff Q(t):

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

Transfer functions:

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

where

$\dot{x}_i$		$\equiv \frac{\partial x_i}{\partial t} \quad \forall i$	v_3	[1]	Fraction of impervious areas in floodplains.
i, t		Indexes for cell and time respectively	v_4	[1]	Fraction of clay content.
N		Number of cells	v_5	[1]	Fraction of sand content.
T		Number time intervals	v_6	$[kgm^{-3}]$	Bulk density.
n		Number model parameters	Θ	[1]	Modeled soil moisture.
m		Number transfer function parameters	Θ_s	[1]	Saturated soil moisture.
q_k		Surface runoff component, $k = 1, \ldots, 4$	z_k	$[m]$	Depth of the horizon k.
v_1	[1]	Land cover	β		regionalized model parameters.
v_2	$[mm]$	Soil texture class	γ		transfer function parameters (to be calibrated).

4. Soil moisture process

Assuming only vertical flows and Brook & Corey (1964) parametrization of the soil hydraulic conductivity.

$$\dot{x}_3 = F + M - E_2 - I$$

$$E_2 = \begin{cases} \inf\{x_3, (V - E_1)\} & x_3 > \beta_2 \\ \inf\left\{x_3, \frac{x_3}{\beta_2 - \beta_1}(V - E_1)\right\} & \beta_1 < x_3 \leq \beta_2 \\ 0 & \text{otherwise} \end{cases}$$

$$\frac{I}{R + M} = \left(\frac{x_3}{\beta_3}\right)^{\beta_4} \approx \left(\frac{\Theta}{\Theta_s}\right)^{\frac{2}{\lambda}+3}$$

5. Regionalization approaches

R1: Based on land cover and soil classes: It discriminates land cover classes and soil texture types into subsets, each of then exhibiting unique parameters.

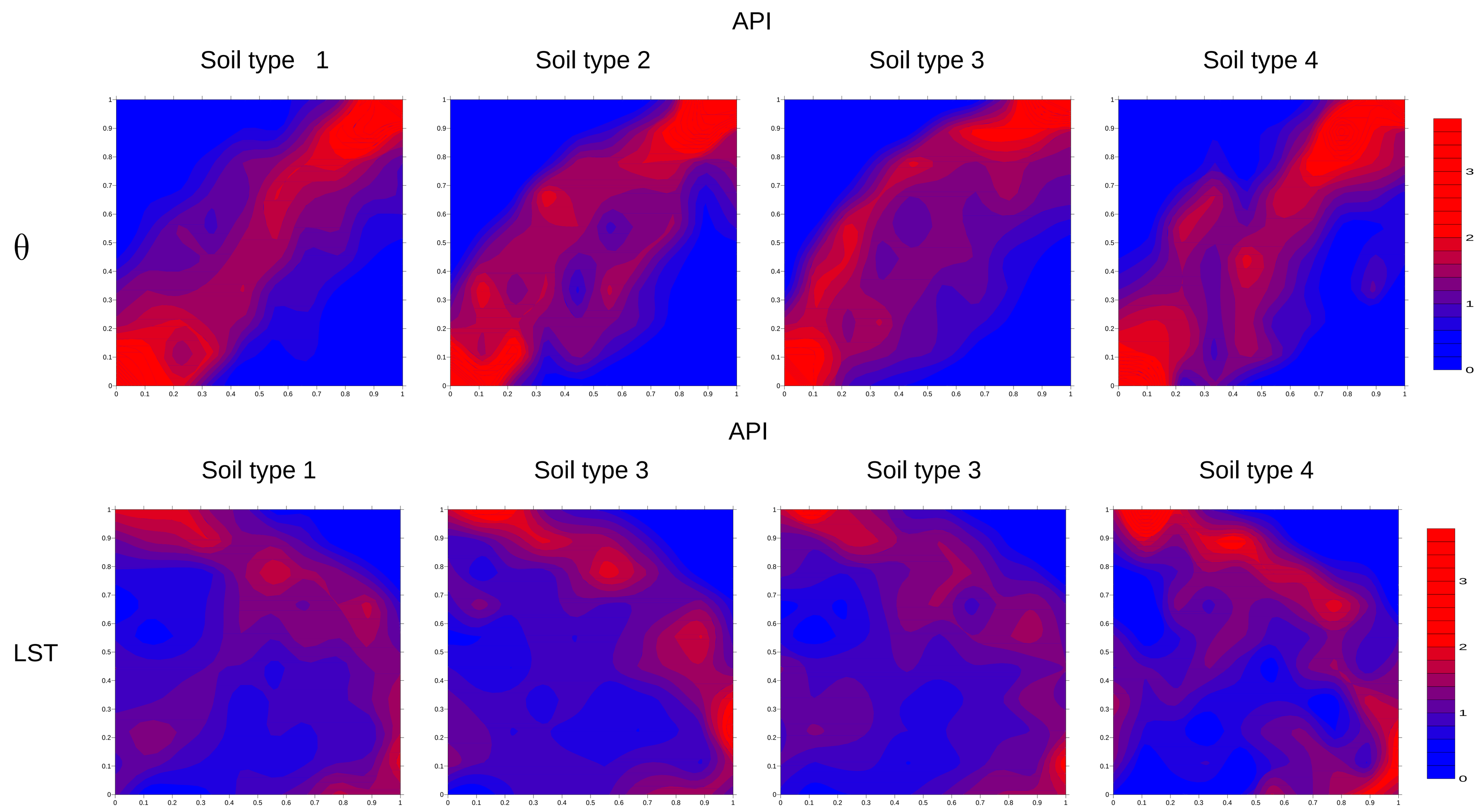
$$\beta_3 = f(v_1, v_2, \boldsymbol{\gamma})$$
$$\beta_4 = f(v_1, \boldsymbol{\gamma})$$

R2: Based on pedotransfer functions: Takes into account the fraction of clay, sand and the bulk density. The latter, in turn, depends on the organic matter content which is land cover specific.

$$\Theta_s = f(v_1, v_4, v_5, v_6, \boldsymbol{\gamma})$$
$$\lambda = f(v_1, v_6, \boldsymbol{\gamma})$$

6. Stochastic dependence using copulas

$$F(x_1, x_2) = P[X_1 \leq x_1, X_2 \leq x_2] = C\left(F_1(x_1), F_2(x_2)\right)$$

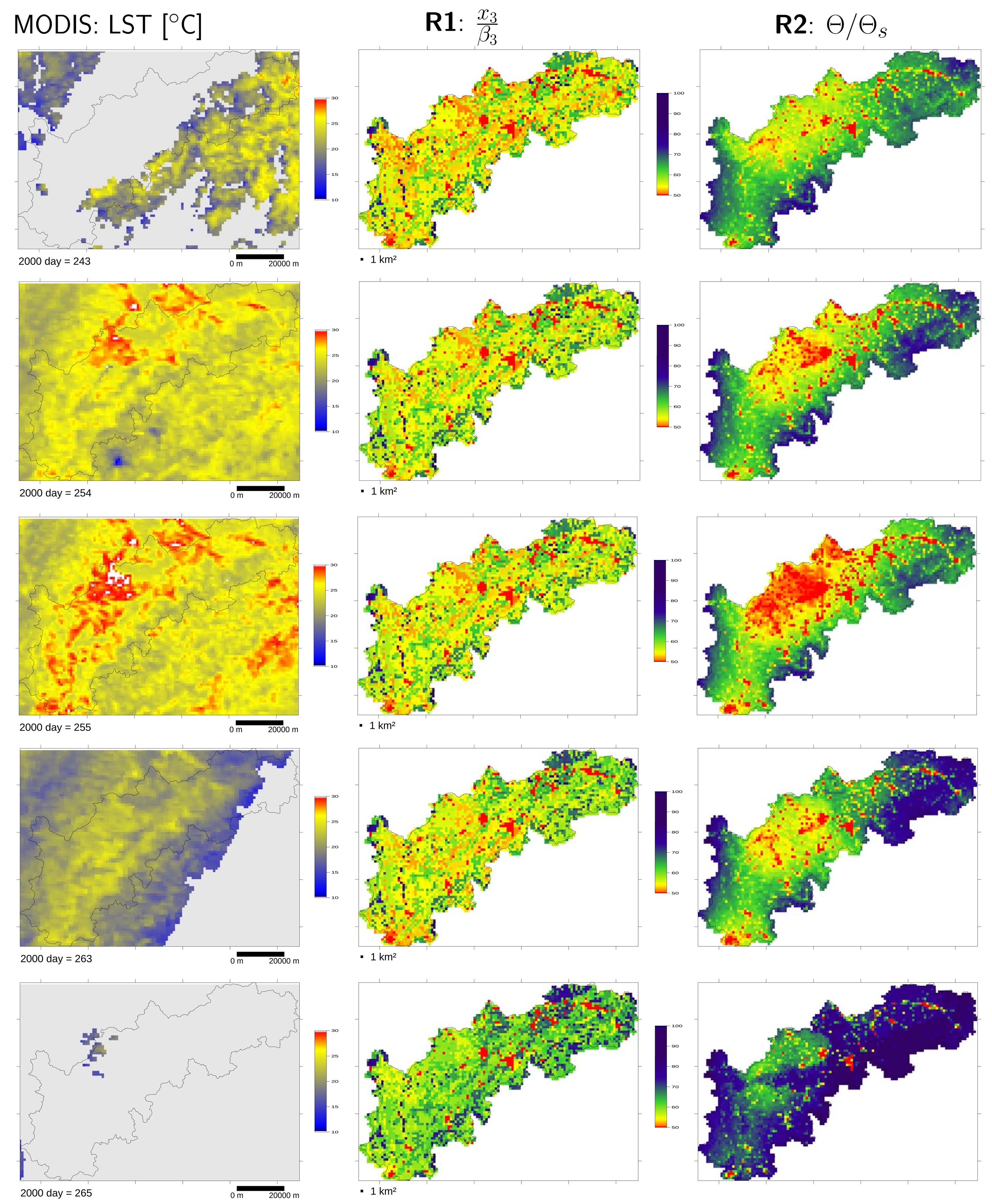


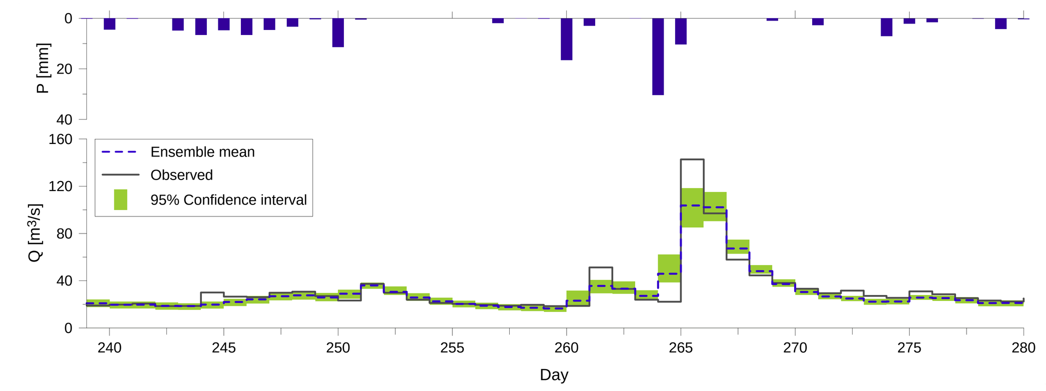
$\Theta \sim f(\mathrm{LST}, \mathrm{NVDI}, \beta)$

API = Antecedent Precipitation Index

LST = Land and Surface Temperature, http://modis.gsfc.nasa.gov/

7. Results





Ensemble prediction using 1000-best parameter sets

8. Conclusions

- Regionalization (R2) produced a significant improvement in model performance (NSE=0.90).
- R2 produced more plausible spatial patterns than the R1 approach.
- Proxies such as API and LST (see copulas) are stochastically dependent on the modeled soil moisture.

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