Assimilation of streamflow data for constraining meteorological reanalyses in mountain environment

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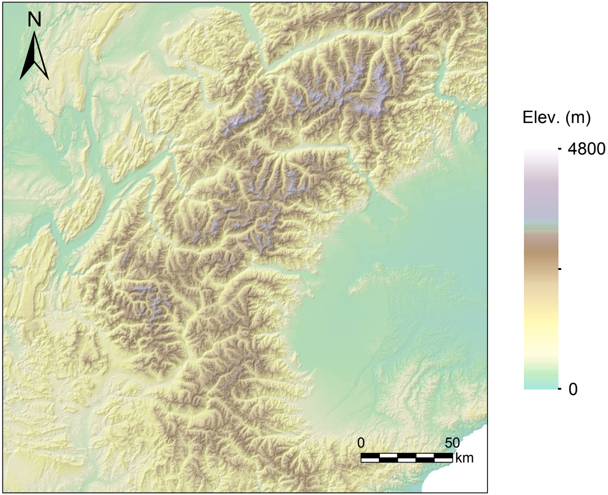
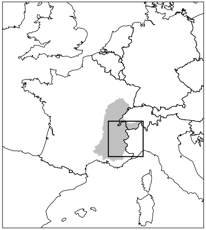
Mountain catchment hydrology

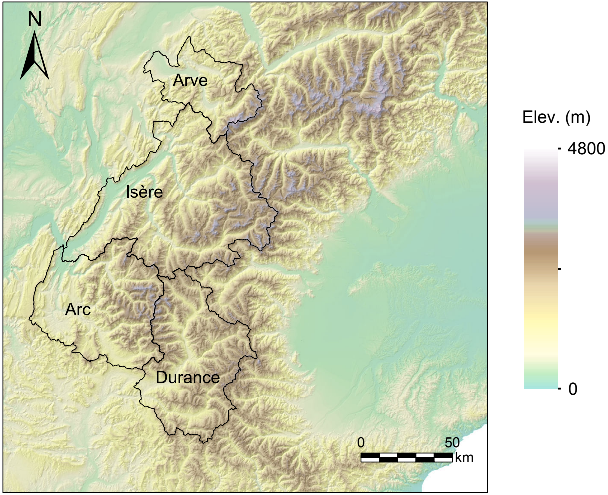
- Headwater mountain catchments are the ‘water towers’ of many populations around the globe
- It is crucial to have a good quantitative knowledge of this resource both in present and future climate
- However, hydro-meteorological measurement networks are usually **scarce** in these regions

Mountain catchment hydrology



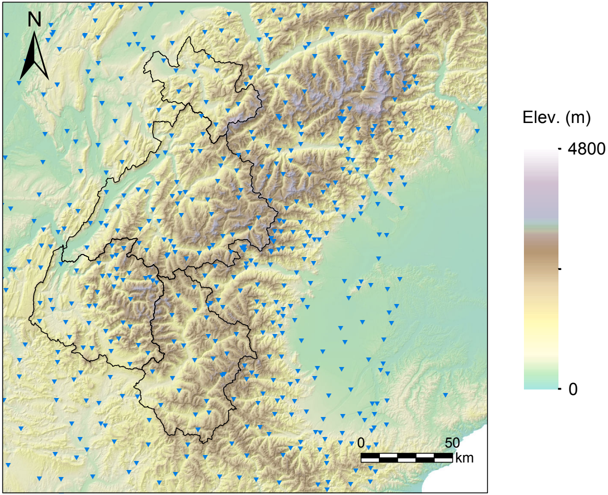


Mountain catchment hydrology



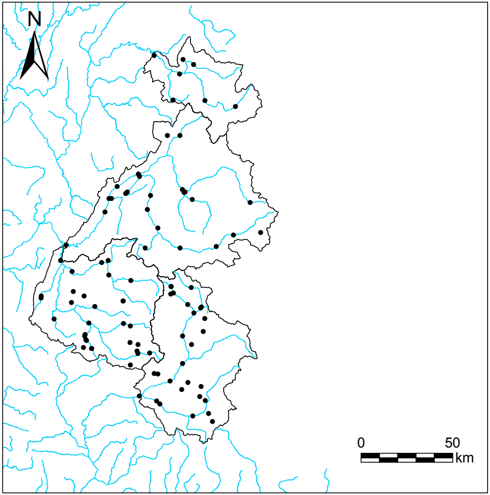
14600 km^2

Mountain catchment hydrology



14600 km^2
139 rain gauges

Mountain catchment hydrology

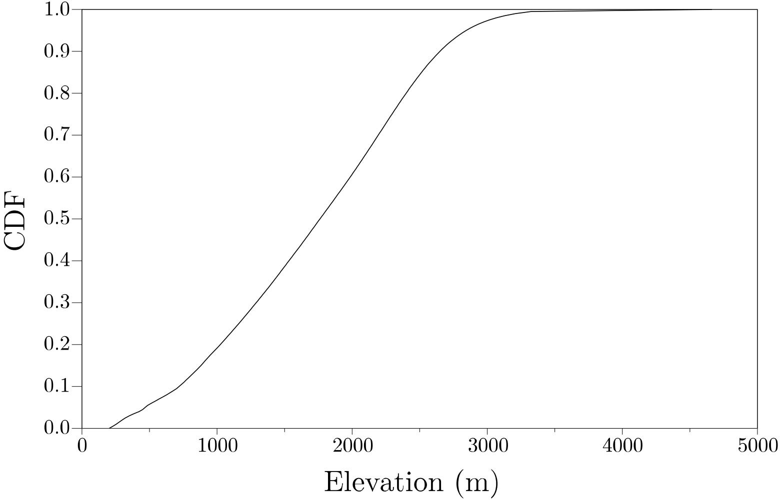


$14600\ km^2$
139 rain gauges
89 stream gauges

Meso-scale hydrological modeling

- Hydrometeorological resolution: $\sim$ **100 km^2**
- Typical size of elementary subcatchments in topographically-based (semi-distributed) hydrological models
- Issues:
  - Subgrid heterogeneity
  - Lack of data at high elevations

Insufficient sampling at high elevations



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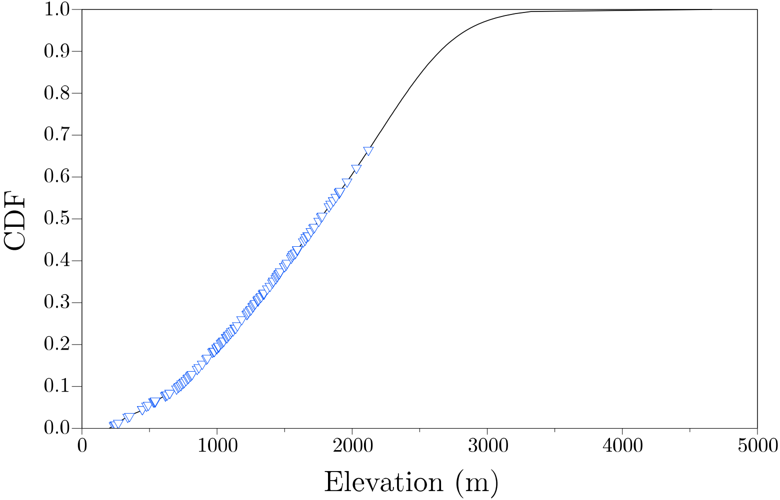


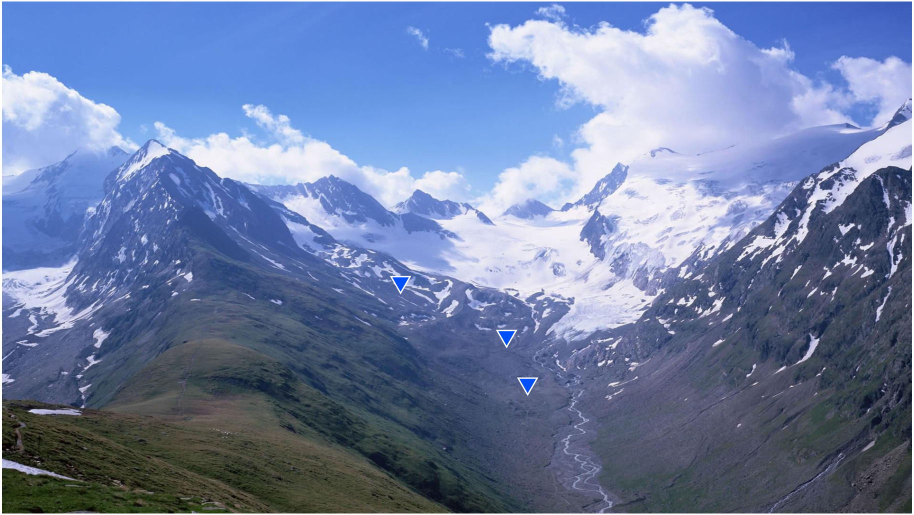
Meso-scale hydrological modeling

- Hydrometeorological resolution: $\sim$ **100 km^2**

- Typical size of elementary subcatchments in topographically-based (semi-distributed) hydrological models

- Issues:
  - Subgrid heterogeneity $\Rightarrow$ INTERPOLATION in (x, y)
  - Lack of data at high elevations $\Rightarrow$ EXTRAPOLATION in z

"Doing hydrology backwards"...



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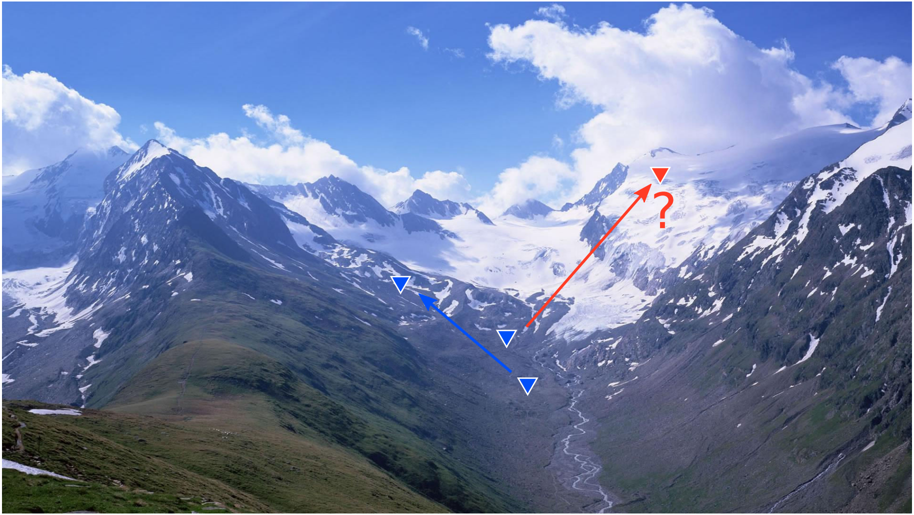
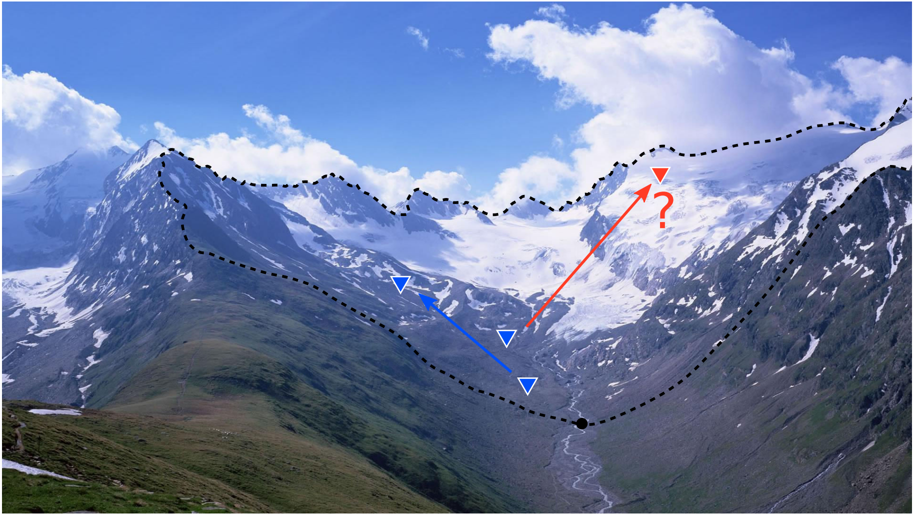


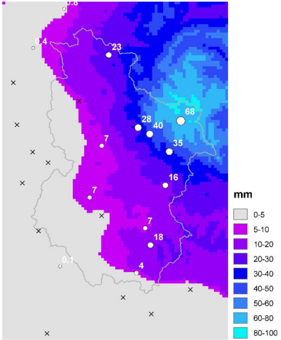
"Doing hydrology backwards"...



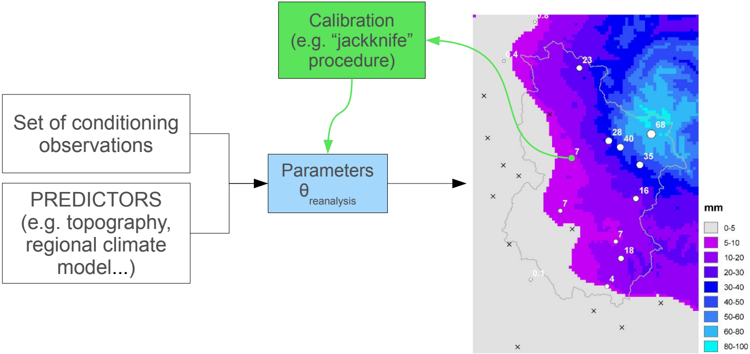
Set of conditioning observations

PREDICTORS (e.g. topography, regional climate model...)

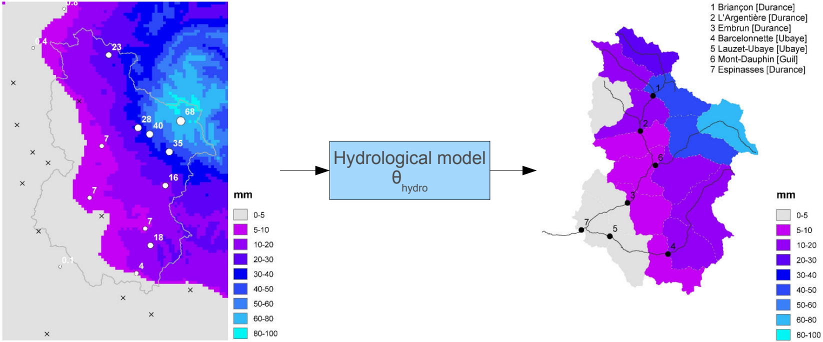
Parameters $\theta_{\text{reanalysis}}$



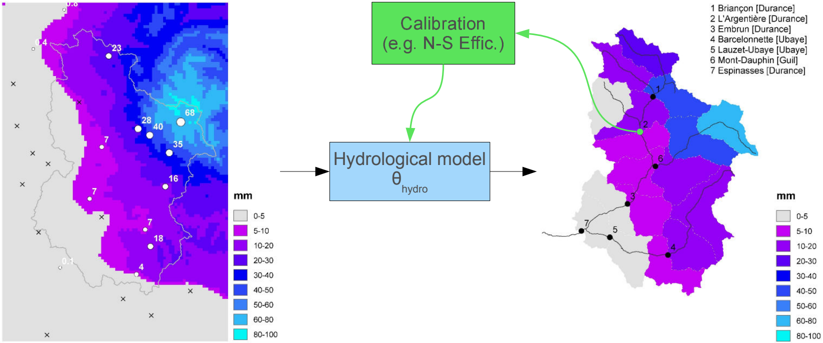
Two-step approach / Step 1 : meteorological reanalysis



Two-step approach / Step 2 : hydrological modeling



Two-step approach / Step 2 : hydrological modeling



One-step approach

Set of conditioning observations

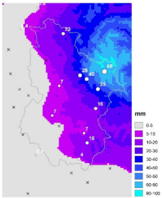
PREDICTORS (e.g. topography, regional climate model...)

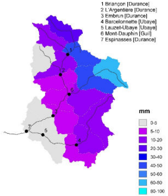
→

Hydro-meteorological model

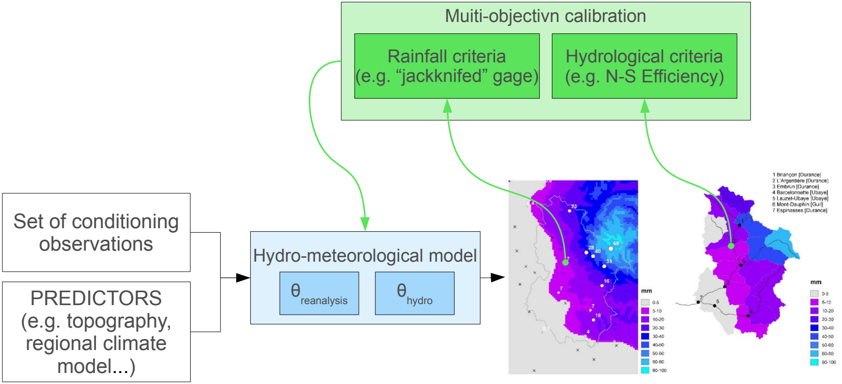
$\theta_{\text{reanalysis}}$ θ_{hydro}

→

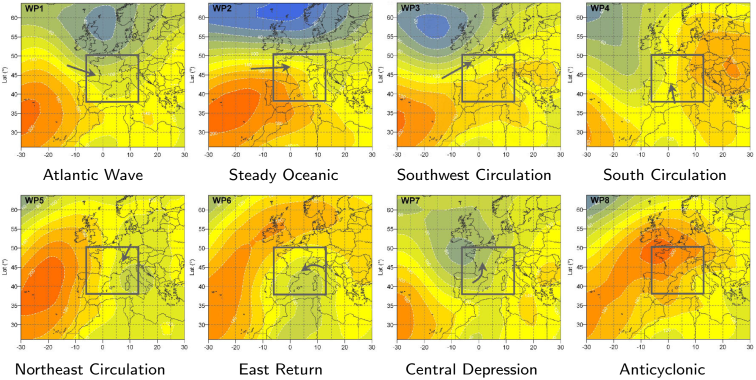




One-step approach



- Each day is attributed to one of **8 weather types**, according to its pattern of geopotential height at 1000 hPa at the synoptic scale (*Paquet* et al., 2006 ; *Garavaglia* et al., 2010)



Geostatistical model for daily rainfall estimation

- On each day, the rainfall field is modelled as the product of a **template** and a **scaling factor**

$$p(\mathbf{x}, j) = \lambda(\mathbf{x}, j) \cdot p^{*}_{\mathrm{wp}(j)}(\mathbf{x})$$

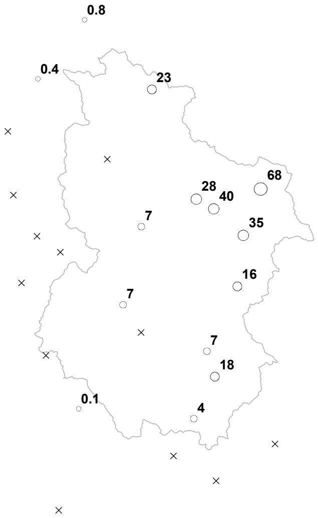
Geostatistical model for daily rainfall estimation

- On each day, the rainfall field is modelled as the product of a **template** and a **scaling factor**

- The template is itself the product of a deterministic **drift** and a **residual**

$$\overline{P}_k(\mathbf{x}) \quad = \quad \frac{1}{n_k} \cdot \sum_{j/\mathrm{wp}(j)=k} P(\mathbf{x}, j) \quad = \quad R_k(\mathbf{x}) \cdot \exp\left(\frac{z(\mathbf{x})}{H_k}\right)$$

Example: estimating rainfall field for March 1st, 1993



- Daily circulation pattern was "East Return" (wp(j) = 6)
- First step: build precipitation template

$$p_6^*(\mathbf{x}) \;=\; p_6^0 \exp\left(\frac{z(\mathbf{x})}{H_6}\right) \cdot r_6(\mathbf{x})$$

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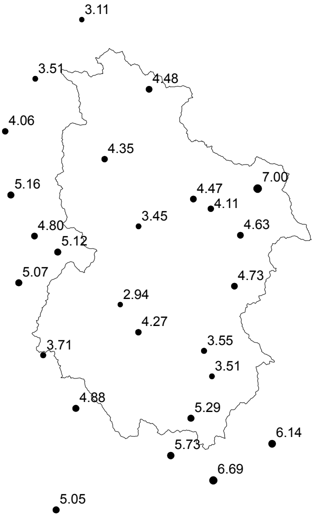

- We compute the mean rainfall amount for all days of pattern 6 at each rain gauge:

$$p_6^*(\mathbf{x_k}) = \frac{1}{N_6} \sum_{j/\mathrm{wp}(j)=6} p(\mathbf{x_k}, j)$$

- The classical way to estimate the drift and the residuals would be through iterative GLS (to account for spatial correlation) on the $\left\{ z(\mathbf{x_k}) \; ; \; \ln p_6^*(\mathbf{x_k}) \right\}$

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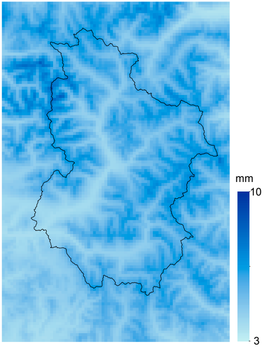

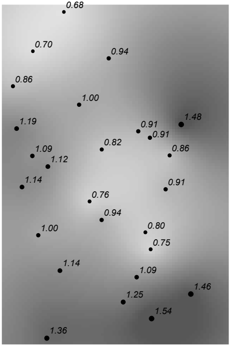

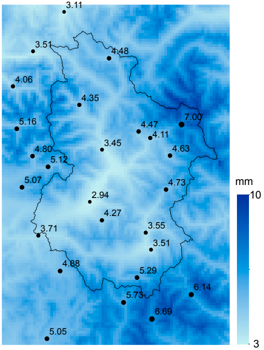

Drift

$$p^0_{\mathrm{wp}(j)} \exp\left(\frac{z(\mathbf{x})}{H_{\mathrm{wp}(j)}}\right)$$

Residual

$$r_{\mathrm{wp}(j)}(\mathbf{x})$$

Template

$$p^*_{\mathrm{wp}(j)}(\mathbf{x})$$

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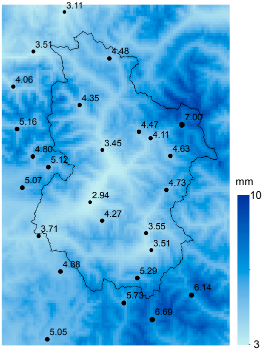
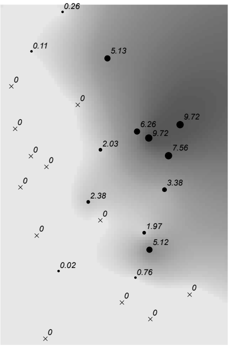
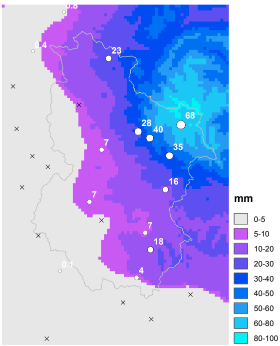


Template
$p^*_{\mathrm{wp}(j)}(\mathbf{x})$



Daily scaling factor
$\lambda(\mathbf{x}, j)$



Daily field
$p(\mathbf{x}, j)$

Geostatistical model for daily rainfall estimation

- The model is multiplicative i.e. additive in log space
- We assume log-normal distribution for $r_{\mathrm{wp}(j)}(\mathbf{x})$ and $\lambda(\mathbf{x}, j \,|\, \lambda > 0)$
- We use Gibbs sampling to generate Gaussian samples where the daily scaling factor is zero (Gaussian anamorphosis)

Geostatistical model for daily temperature estimation

- We proceed in a similar way for temperature, except that we use an additive model

$$
\begin{aligned}
t(\mathbf{x}, j) &= \delta(\mathbf{x}, j) + t^*_{\mathrm{wp}(j)}(\mathbf{x}) \\
t(\mathbf{x}, j) &= \delta(\mathbf{x}, j) + \overbrace{\left[t^0_{\mathrm{wp}(j)} - c_{\mathrm{wp}(j)} \cdot z(\mathbf{x})\right] + \varepsilon_{\mathrm{wp}(j)}(\mathbf{x})}^{t^*_{\mathrm{wp}(j)}(\mathbf{x})}
\end{aligned}
$$

Calibration / validation protocole

- The key step is the identification of the drift parameters $H_1, \ldots, H_8$ (scale height for precipitation increase with z) and $c_1, \ldots, c_8$ (lapse rate for temperature decrease with z)

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[JK] Identification of the 16 drift parameters using Jack-Knife, then MO calibration of the hydrological model

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[2in1] Identification of the $16 + 19 = 35$ parameters using MO calibration against discharge and snow measurements

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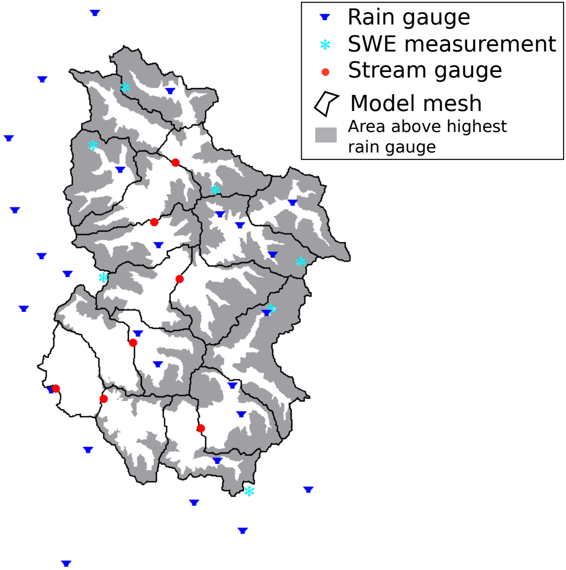
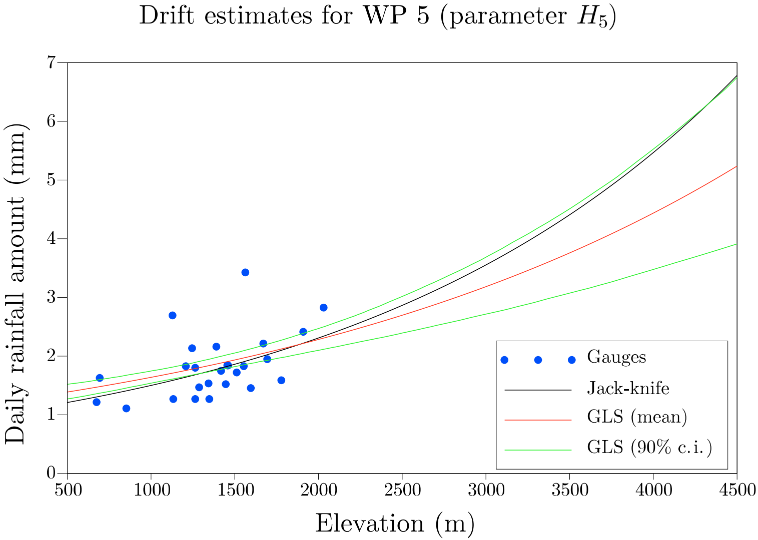
- For each solution we perform a symmetric split sample test on the periods 1983–1993 and 1994–2004

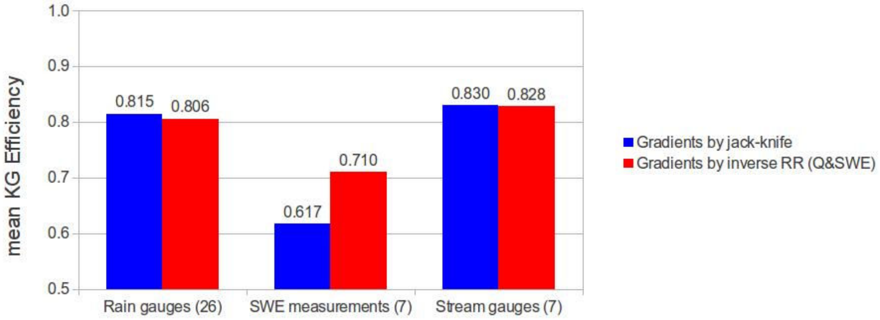
Calibration / validation protocole



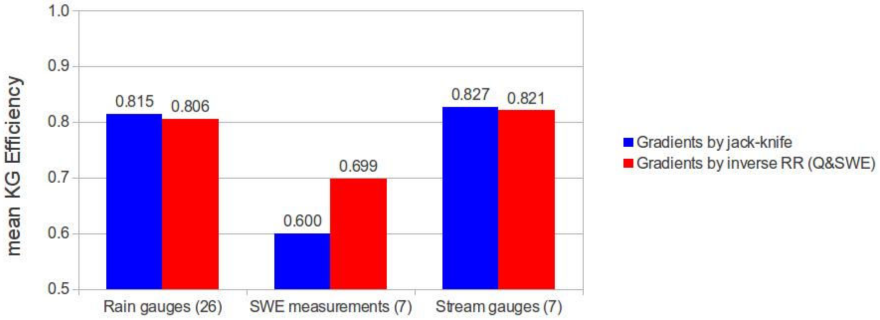
GLS vs. jack-knife in the two-step method



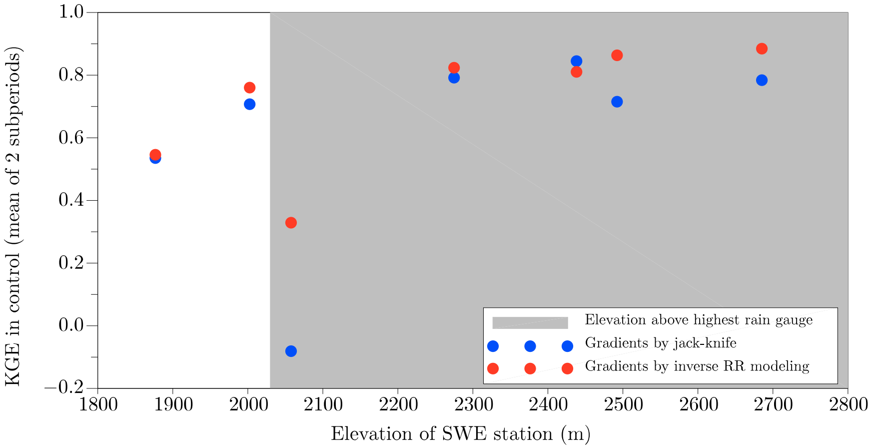
Results in calibration



Results in control



Results in control: focus on point-scale SWE measurements



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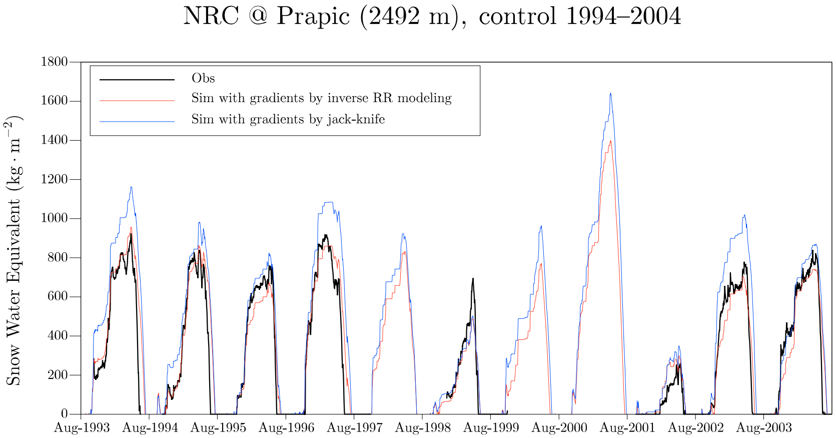

Conclusions & Perspectives

- Streamflow and SWE measurements greatly help assess orographic gradients of temperature and precipitation at the meso-scale
- This study confirms the importance (and difficulty) of building unbiased forcing fields for meso-scale hydrological modeling
- Current work: include other variables such as snow cover extent (MODIS images), glacier extent (e.g., GLIMS survey)
- Perspectives: couple the methodology with statistical downscaling approaches in climate change impact studies (e.g. analogs, etc.)

Thank you for your attention

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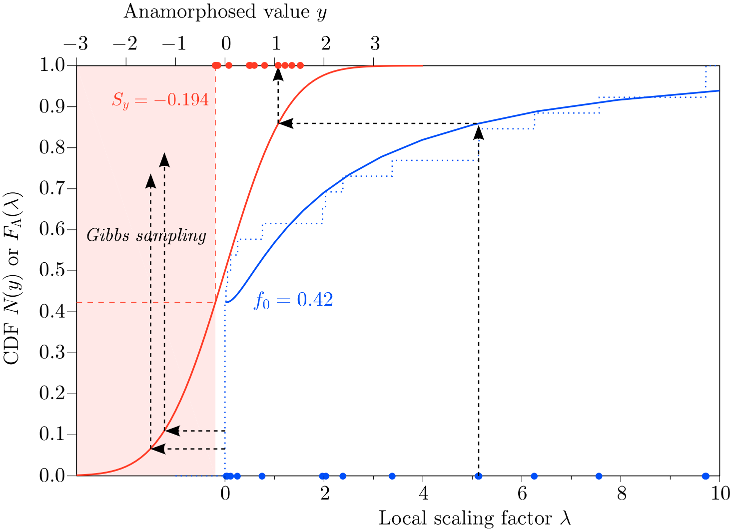
Geostatistical model for daily rainfall estimation



Snow routine

- Single-layer snowpack model with 4 state variables:

W	Snowpack water equivalent	$\mathrm{kg} \cdot \mathrm{m}^{-2}$
U	Snowpack heat content	$\mathrm{J} \cdot \mathrm{m}^{-2}$
ρ_{snow}	Snowpack bulk density	$\mathrm{kg} \cdot \mathrm{m}^{-3}$
t_{snow}	Age of snow surface	s

- Each topographical mesh element is discretized into elevation bands $\Rightarrow$ one instance of the snow routine is run on each band

Snow routine

We solve a simplified, linearized and parameterized form of surface energy balance in order to estimate (pseudo) surface temperature $T_{\text{snow,s}}$ and entering conducto-convective heat flux $Q_{\text{cc,snow}}$

$$
\begin{array}{ccccccccc}
R_{\text{sw}\downarrow} - & R_{\text{sw}\uparrow} & + & R_{\text{lw}\downarrow} & - & R_{\text{lw}\uparrow} & = & Q_{\text{cc,snow}} + \cancelto{\text{negl.}}{H} + \cancelto{\text{negl.}}{LE} \\
\bar{f}\, R_e - & \alpha_{\text{snow}} \bar{f}\, R_e & + & \sigma \bar{\epsilon}_{\text{air}} T_0^4 \left(1 + 4 \dfrac{T_{\text{air}} - T_0}{T_0}\right) & - & \sigma \epsilon_{\text{snow,s}} T_0^4 \left(1 + 4 \dfrac{T_{\text{snow,s}} - T_0}{T_0}\right) & = & k_{\text{snow}} \left(\dfrac{T_{\text{snow,s}} - T_{\text{snow}}}{2\, z_{\text{snow}}}\right)
\end{array}
$$

with

$$
\begin{cases}
\alpha_{\text{snow}} = (\alpha_{\max} - \alpha_{\min}) e^{-\frac{t_{\text{snow}}}{\tau_\alpha}} + \alpha_{\min} & \text{Age-dependent albedo} \\
k_{\text{snow}} = k_{\text{ice}} \left(\dfrac{\rho_{\text{snow}}}{\rho_{\text{ice}}}\right)^2 & \text{Density-dependent thermal conductivity}
\end{cases}
$$

Snow routine

- We want to be able to simulate snowpack density in order to validate against snow depth measurements (more commonly available than snow water equivalent measurements)
- Self-loading densification using simplified [*Pitman*, 1991] relationship without temperature dependency:

$$\frac{d\rho_{\text{snow}}}{dt} = \frac{\rho_{\text{snow}} g W}{2\eta_0} \; e^{-\frac{\rho_{\text{snow}}}{\rho_0}}$$

Snow routine

Summary of model parameters

Symbol	Parameter	Unit	Calibration
α_{max}	Maximum albedo (new snow)	—	
α_{min}	Minimum albedo (old snow)	—	
τ_α	Characteristic time for albedo decrease	s	
$\bar{f}$	Time-averaged ratio $R_{\mathrm{sw}\downarrow}/R_e$	—	•
k_{ice}	Effective thermal conductivity of ice	$\mathrm{W} \cdot \mathrm{m}^{-1} \cdot \mathrm{K}^{-1}$	
$\bar{\epsilon}_{\mathrm{air}}$	Time-averaged emissivity of the atmosphere	—	•
$\epsilon_{\mathrm{snow,s}}$	Emissivity of snow surface	—	
θ_{ret}	Maximum retention of liquid water in snowpack	$\mathrm{kg} \cdot \mathrm{kg}^{-1}$	
ρ_0	Density of new snow	$\mathrm{kg} \cdot \mathrm{m}^{-3}$	•
η_0	Compressive viscosity of new snow	$\mathrm{Pa} \cdot \mathrm{s}$	•