Hydrologically-constrained estimation of daily rainfall and temperature fields in a meso-scale Alpine catchment

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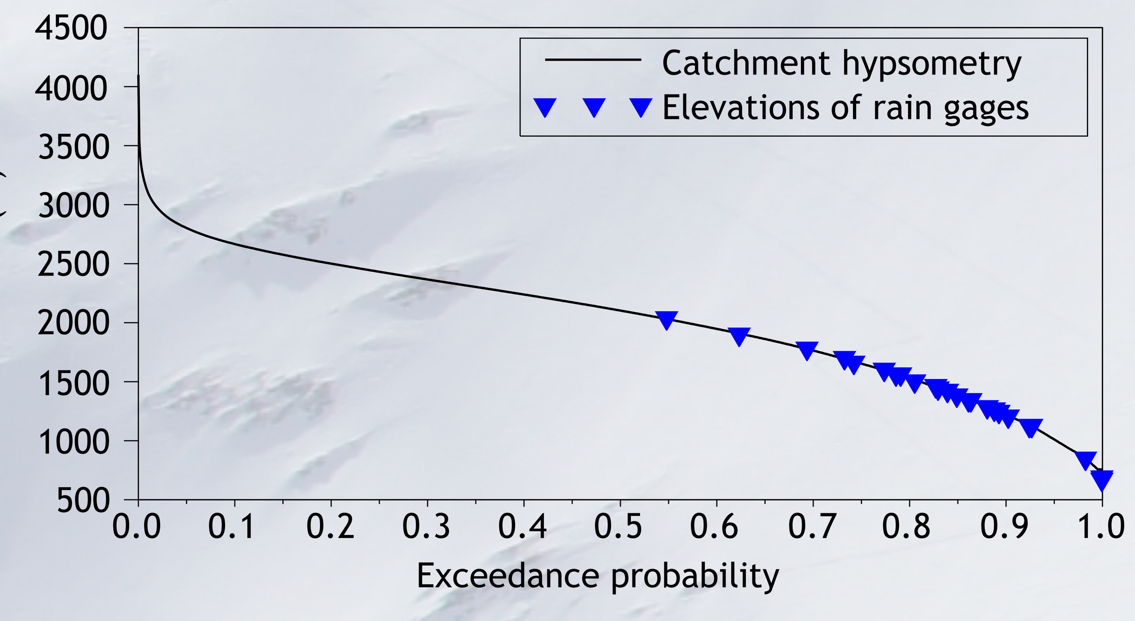
AGU FALL MEETING
San Francisco | 9–13 December 2013

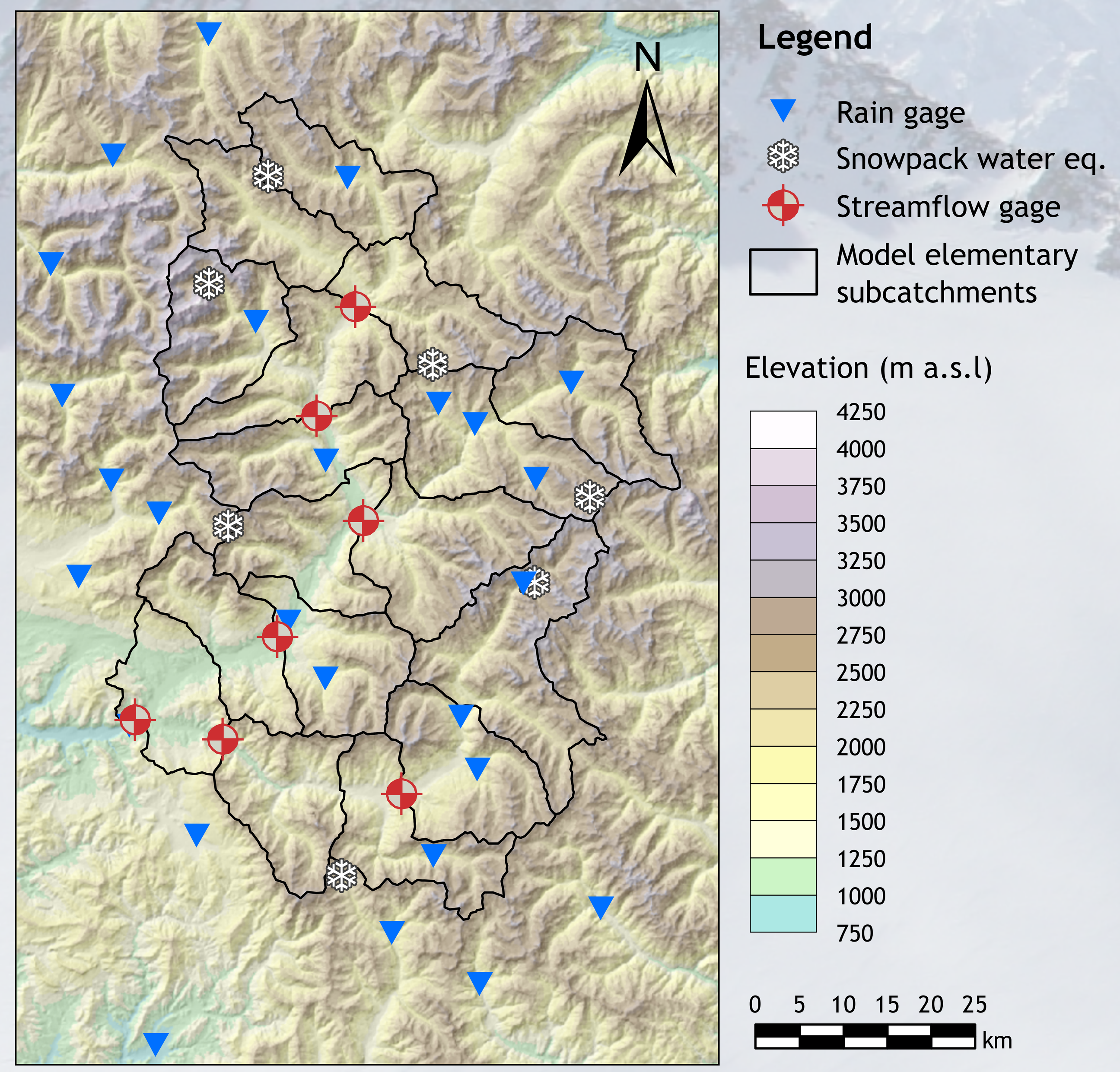
1. Research question

- Closing the water balance in mountain areas is difficult due to the **scarcity** and lack of **spatial representativeness** of point-scale rainfall measurements (typically 1 gage for each 100 km²).

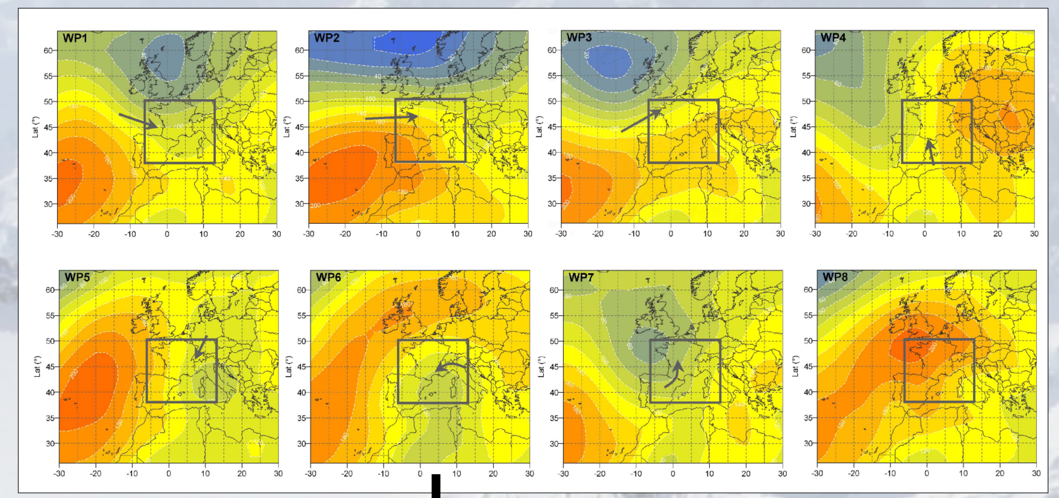
- No rainfall measurements available above ~2000 m, which means typically no information in the upper 50% of a meso-scale catchment in the Alps. Nonetheless we need **areal rainfall estimates** in order to force hydrological models.

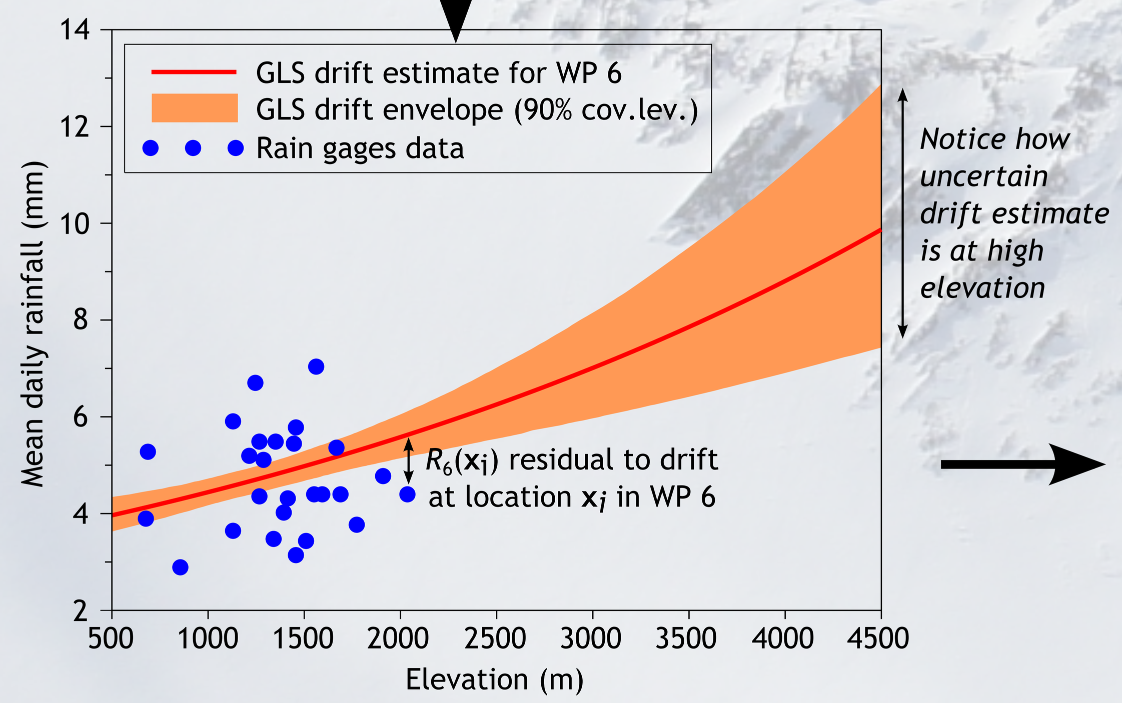
- We investigate this issue on the **Durance River** catchment in the Southern Alps of France (3600 km² at Espinasses).





2. Geostatistical model for rainfall estimation





- We use a geostatistical approach based on a **weather pattern** (WP) classification in order to estimate daily rainfall and temperature fields from a set of conditioning gages. This classification consists in 8 WPs defined according to the pattern of geopotential height at 1000 hPa at the synoptic scale (Paquet *et al.*, 2006).

- The geostatistical model aims at reproducing the variability in the 2D geographic plane as well as the **orographic effects** in the *z*-dimension.

- For each weather pattern *k*, we define a **scale height** H_k accounting for the increase of precipitation with elevation and a **lapse rate** c_k for the decrease of temperature (here we present only the model for rainfall).

- A **template** field for WP *k*, i.e. the mean daily rainfall amount at location **x** in WP *k* is defined by:

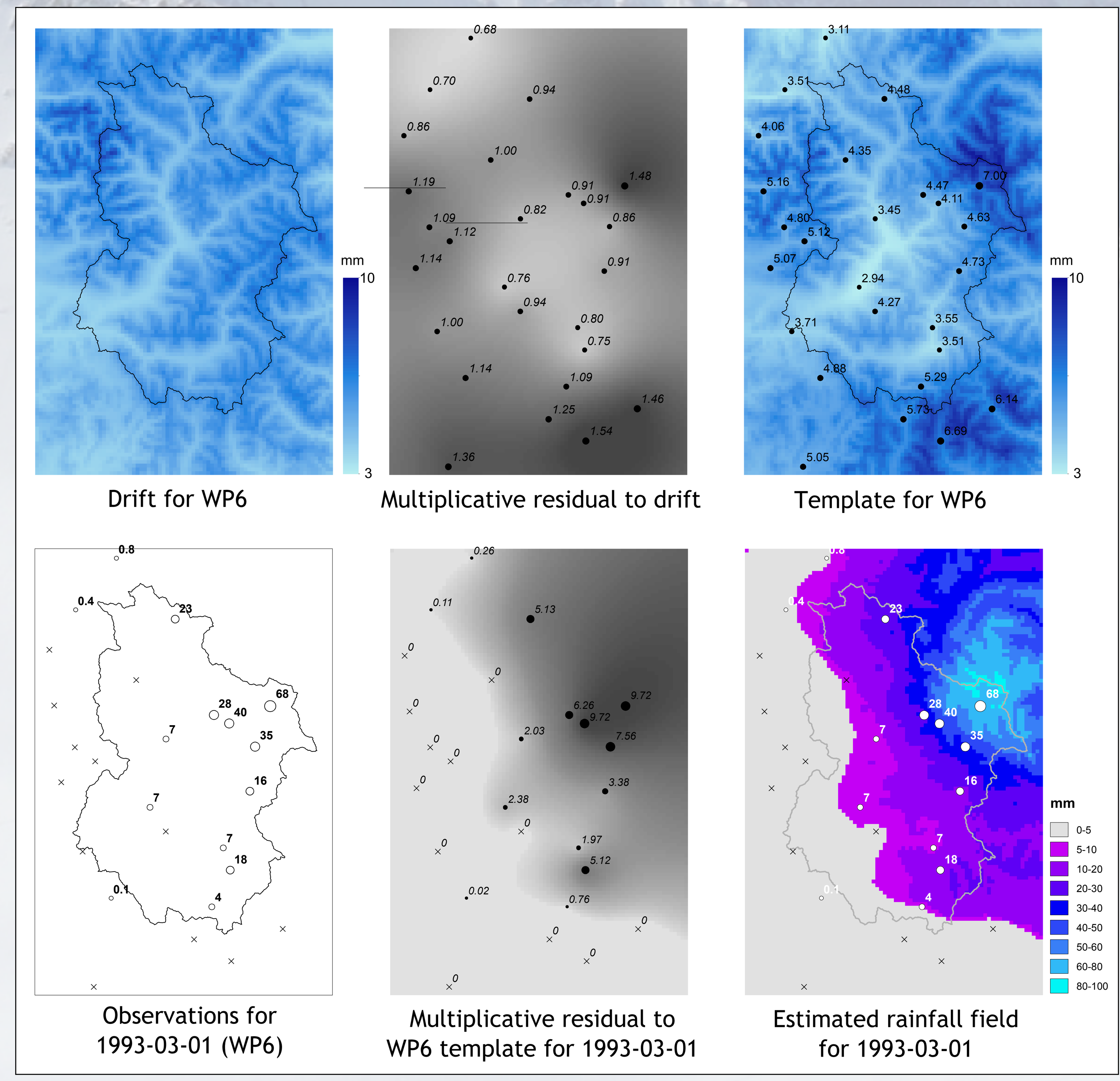
$$\overline{P}_k(\mathbf{x}) = \frac{1}{n_k} \cdot \sum_{j/\mathrm{wp}(j)=k} P(\mathbf{x},j) = R_k(\mathbf{x}) \cdot \exp\left(\frac{z(\mathbf{x})}{H_k}\right)$$

- Multiplicative residual $R_k(\mathbf{x})$ is assumed to be log-normally distributed and is obtained by log-normal ordinary kriging.

- The rainfall field for day *j*, belonging to weather pattern wp(*j*), is obtained by deformation of the template:

$$P(\mathbf{x},j) = \Lambda(\mathbf{x},j) \cdot \overline{P}_{\mathrm{wp}(j)}(\mathbf{x})$$

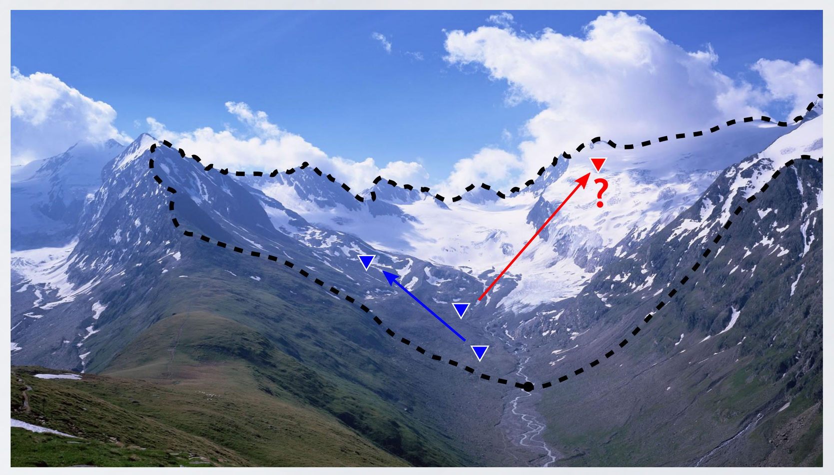
- Multiplicative residual $\Lambda(\mathbf{x},j)$ is obtained through Gaussian anamorphosis, simple kriging in the Gaussian space, and reverse anamorphosis (Le Moine *et al.*, 2013).



3. Joint calibration of geostatistical & hydrological models

- The main weakness in the geostatistical model is the lack of points-scale data at high elevations in order to constrain the **estimation of the drift parameters** (rainfall scale heights H_k and temperature lapse rates c_k).

- On the other side, a catchment can be seen as a **huge rain gage**: streamflow at the outlet is correlated with areal rainfall. Ensuring **water balance closure** at the catchment scale is thus a strong **block constraint** on the estimated rainfall fields (the rationale behind Top-Kriging, see e.g. Gottschalk, 1993).



- Paradox: In order to solve the inverse problem (rainfall from streamflow, using block-constrained geostatistics) we need to invert the model for the direct problem...

... but this is the actual hydrological model we wanted to identify in the first place!

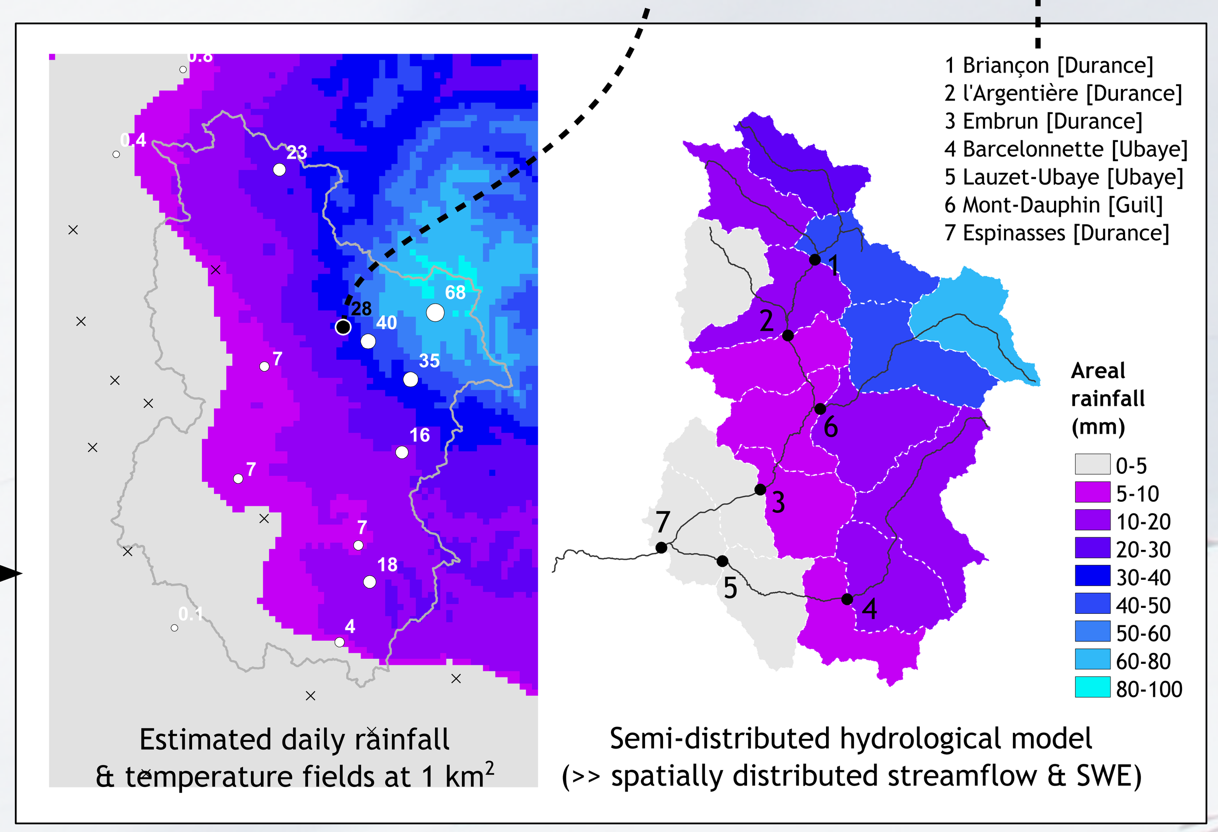
- A solution is to calibrate the geostatistical model (drift parameters) and the hydrological model **jointly** in order to find the parameter sets that best satisfy all constraints (both point-scale and block). We use a **multi-objective calibration** against all available measurements (streamflow, validation rain gages, and SWE measurements).

Multi-objective calibration
- Criteria on validation rain gages
- Hydrological criteria (Q, SWE, SCF, ...)

Set of conditioning observations

Set of auxiliary predictors (e.g. topography, coarse-grid climate model...)

Hydro-meteorological parameters
- $\theta_{\mathrm{geostat}}$ (16 parameters)
- θ_{hydro} (19 parameters)



Estimated daily rainfall & temperature fields at 1 km²

Semi-distributed hydrological model (>> spatially distributed streamflow & SWE)

4. Key results

- We use different metrics to evaluate model outputs:

C_P : Mean Kling-Gupta efficiency (KGE, Gupta *et al.*, 2009) in jack-knife (leave-one-out) validation for the **26 rain gages**
C_Q : Mean KGE on daily flows at the **7 streamflow gages**
C_{SWE} : Mean KGE on daily measurements at the **7 SWE stations**

- We compare 2 calibration approaches for the 16+19 parameters:

[2-step] **First, mono-objective** calibration of the 16 drift parameters $\theta_{\mathrm{geostat}}$ by maximizing C_P ; **Then bi-objective calibration** of the 19 hydrological parameters θ_{hydro} using $\{C_Q ; C_{SWE}\}$

[1-step] **Joint, tri-objective** calibration of all 35 parameters using $\{C_P ; C_Q ; C_{SWE}\}$

- Because hydrological criteria C_Q and C_{SWE} are **much more responsive** to changes in the drift parameters than C_P, the 1-step approach **greatly improves robustness** in the identification of $\theta_{\mathrm{geostat}}$.