Rainfall–runoff modelling as a tool for constraining the reanalysis of daily precipitation and temperature fields in mountainous regions

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Abstract Hydrological modelling in mountainous regions, where catchment hydrology is heavily influenced by snow (and possibly ice) processes, is a challenging task. The intrinsic complexity of local processes is added to the difficulty of estimating spatially-distributed inputs such as rainfall and temperature, which often exhibit a high spatial heterogeneity that cannot be fully captured by the measurement network. Hence, an interpolation step is often required prior to the hydrological modelling step. In most cases, the reconstruction of meteorological forcings and the calibration of the hydrological model are done sequentially. The outputs of the hydrological model (discharge estimates) may give some insight on the quality of the reconstructed forcings used to feed it, but in this two-step approach it is not possible to easily feed the interpolation scheme back with the discrepancies between observed and simulated discharges. Yet, despite having undergone the rainfall–runoff (or snow-runoff) transformation, discharge at the outlet of a (sub)catchment is still an interesting integrator (spatial low-pass filter) of the forcing fields and is an ancillary areal information complementing the direct, point-scale data collected at raingauges. In this perspective, choosing the best interpolation scheme partly becomes an inverse hydrological problem. In this study, we present a one-step calibration strategy where the parameters of both the interpolation model (i.e. reconstruction procedure of meteorological forcings) and of the hydrological model (i.e. snow cover evolution, soil moisture accounting, and flow routing schemes) are jointly inferred in a multi-site and multi-variable approach, using a multi-objective evolutionary algorithm. Interpolated fields are daily rainfall and temperature, whereas hydrological prognostic variables consist in discharge and snow water equivalent (SWE) time series at several locations in the 3600 km^2 Upper Durance River catchment (French Alps).

Key words rainfall reanalysis; temperature reanalysis; geotatistics; rainfall–runoff modelling; multiobjective calibration; assimilation

INTRODUCTION AND AIM OF THE STUDY

Bardossy & Pegram (2012) recall that spatial interpolation of rainfall over different time and spatial scales "is necessary in many applications of hydrometeorology including (i) catchment modelling, (ii) blending/conditioning of radar-rainfall images and (iii) correction of remote sensing estimates of rainfall". Though the standards may differ according to local specificities, the World Meteorological Organization typically recommends a minimum density of 250 km^2 per raingauge in mountain regions (WMO, 2008). Given the fact that the section of a typical raingauge is a few 1000 cm^2 (200–400), this still means that even in these "ideal" conditions the area on which we actually measure the rainfall is in the order of 0.00000001% of the catchment surface. What is more, in mountain catchments the elevation at which raingauges are located is rarely representative of the overall elevation distribution (hypsometry) of the catchment due to accessibility constraints. According to Bardossy & Pegram (2012), some of the problems encountered in precipitation interpolation are "the quantification of the influence of topography, usually the most influential of exogenous variables", and the difficulty of dealing with a large range of spatial scales: these issues become particularly important in mountain areas.

These facts have been known for a long time by hydrologists working in the field of mountain hydrology, who are fully aware of the possibly strong lack of spatial representativeness of point-scale precipitation measurements. As a result, any re-analysis of mountain precipitation fields requires both *interpolating* between scarcely distributed gauges and *extrapolating* along elevation z (i.e. specifying a deterministic model for the dependence on z). If the former problem is a rather classical one in geostatistics and can be relatively well constrained with appropriate variography, the latter is much more difficult to constrain in the lack of any data at high elevations. The calibration and evaluation of precipitation re-analyses is often performed on the basis of point-scale criteria (e.g. jackknife or cross-validation at independent raingauges, see e.g. Gottardi, 2009), although they may well turn out to be very insensitive to the deterministic drift model for the dependence on z. In this study we propose a strategy that aims to broaden the amount of information for constraining this problem.

From a hydrological perspective, a gauged catchment (i.e. a streamgauge collecting the runoff produced in an area within a topographic drainage divide) is by construction a huge raingauge. Just as a regular raingauge, this device may exhibit several meterological problems: its leaking (both by evapotranspiration and groundwater flow), and its concentration time may be quite long, so that what we observe at the streamgauge is the catchment-scale precipitation signal convoluted with some nonlinear, non-conservative transfer function. In this paper, we show that using a rainfall–runoff model in order to invert this signal (hydrological "deconvolution") is an interesting way of adding constraints to the re-analysis of precipitation and temperature field in scarcely-instrumented regions such as mountain areas (Valéry *et al*, 2009). In particular, we show that:

– For a given structure of the precipitation and temperature forcing fields, the parameters of the transfer function (snow/rainfall–runoff model) are relatively easy to identify (this is a classical problem of hydrological model calibration with fixed inputs);
– Conversely, for a given parameterization of hydrological model, the discharge response is very sensitive to the drift parameters, because all elevation ranges are involved in the response to areal estimates;
– As a result, the combination of the drift parameters and the rainfall–runoff parameters is more easily identified on the basis of streamflow measurements, than the sole drift parameters on the sole basis of raingauges measurements.

This result is also important from a climate change modelling point of view, since in this joint calibration procedure we reduce the risks of biasing the estimation of the system's behavioural (snow/rainfall–runoff) parameters. Indeed, calibrating the rainfall–runoff parameters with biased forcings could lead to a loss of robustness in non-stationary conditions, and a biased evaluation of climate change impacts on hydrological regimes in mountain regions.

MODEL FORMULATION FOR PRECIPITATION AND TEMPERATURE FIELDS

Weather typing

In order to interpolate daily precipitation and temperature field, we use a weather typing approach in which each day is treated according to its atmospheric circulation pattern. We use the weather pattern classification designed at Electricite de France – DTG, which consists in eight patterns. The reader is referred to Paquet *et al*. (2006) for more details, since our methodology can be used with any alternative classification.

Precipitation model

On a given day j belonging to weather pattern WP(j), we write the precipitation amount at location $\mathbf{x}$ as:

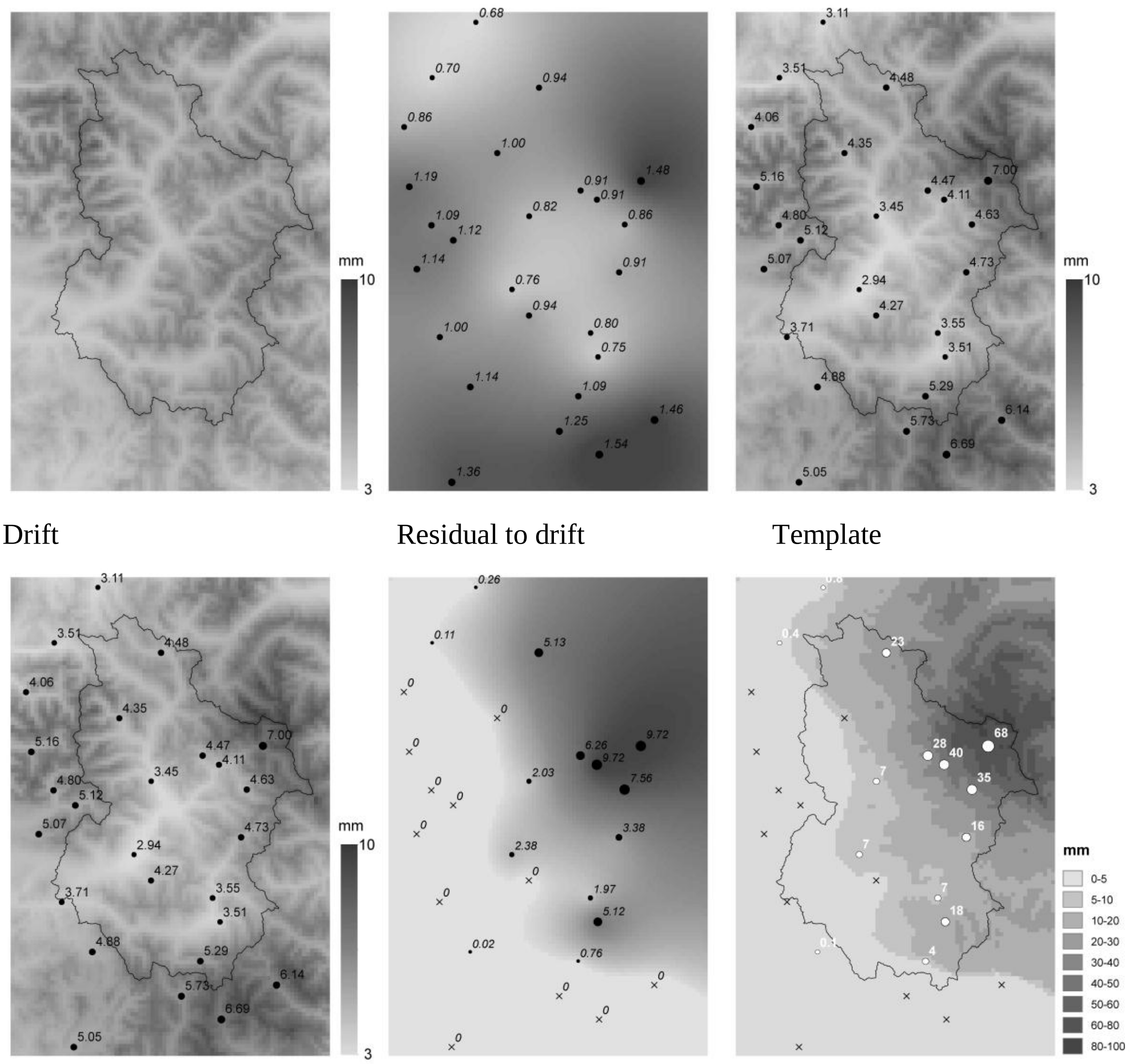
$$p(\mathbf{x}, j) = p^*_{\mathrm{WP}(j)}(\mathbf{x}) \cdot \lambda(\mathbf{x}, j) \quad (1)$$

The daily precipitation field is thus seen as a "mean" realization (or template field) for the weather pattern WP(j), $p^*_{\mathrm{WP}(j)}(\mathbf{x})$, deformed by a local scaling factor $\lambda(\mathbf{x}, j)$. The template is a rather smooth field (it does not have the variance of an actual daily precipitation field) without spatial intermittence and is meant to embed as many deterministic effects as possible (such as orographic forcing). In contrary, the field $\lambda(\mathbf{x}, j)$ may exhibit spatial intermittence, as illustrated in Fig. 1.

Given the properties mentioned above, we chose a log-linear model to represent the template field for weather pattern k. We perform a kriging with an external drift (KED) with elevation $z(\mathbf{x})$ as an auxiliary variable in order to get an estimation of $\ln P^*_k(\mathbf{x_0})$ at an ungauged location $\mathbf{x_0}$, given the values $p^*_k(\mathbf{x_1})$, ..., $p^*_k(\mathbf{x_n})$ and $z(\mathbf{x_1})$, ..., $z(\mathbf{x_n})$ at the n conditioning raingauges. As a result, the value of the template at location is given by the expectation:

$$\begin{aligned} \tilde{p}^*_k(\mathbf{x_0}) &= E\left[P^*_k\left(\mathbf{x_0} \,|\, p^*_k(\mathbf{x_1}), \ldots\, p^*_k(\mathbf{x_n})\right)\right] \\ &= \exp\left(a_k + \frac{z(\mathbf{x_0})}{h_k} + \mu_{\mathrm{KED},k}(\mathbf{x_0})\right)\exp\left(\frac{1}{2}\sigma_{\mathrm{KED},k}(\mathbf{x_0})\right) \end{aligned} \tag{2}$$

where h_k is the precipitation scale height for weather pattern k (in m), $\mu_{\mathrm{KED},k}$ and $\sigma^2_{\mathrm{KED},k}$ the kriging estimate and kriging variance of the residual to the drift.



Drift — Residual to drift — Template

Template — Residual to template — Daily precipitation field

Fig. 1 Construction of a daily rainfall field: example of 1 March 1993, belonging to Weather Pattern 6 (East Return). The procedure consists in five steps: (i) construction of the drift for Weather Pattern 6 (top left, here with scale height parameter h_6 = 3600 m); (ii) log-normal kriging of the residuals to the drift (top centre); (iii) construction of the template for Weather Pattern 6 (top right); (iv) kriging of the anamorphosed, daily residuals to the template (bottom centre); (v) obtaining the daily field. Grid size is 1 x 1 km, and the domain shown is 80 × 120 km (9600 grid points).

Handling the local scaling factor $\lambda(\mathbf{x}, j)$ is more complicated because of the spatial intermittence of this field (i.e., the CDF of Λ may have an atom at zero). Since the actual precipitation amount and the value of the template for day j are known at the gauging locations $\mathbf{x_1}, ..., \mathbf{x_n}$,we have the set of conditioning values $\lambda(\mathbf{x_1}, j), ..., \lambda(\mathbf{x_n}, j)$. In order to interpolate this field using ordinary kriging, we build a Gaussian anamorphosis of Λ, which relies on the following hypotheses:

– the rate of spatial intermittence f_0 can be estimated by the proportion of non-rainy gauges;
– the local scaling factor in the rainy part of the field follows a log-normal distribution;
– the location and scale parameters μ and σ of this log-normal distribution are related or, equivalently, there is a functional relation between the mean and the variance of the non-zero part of the field.

In order to generate Gaussian samples at locations where the rainfall amount is zero, we use a Gibbs sampling procedure (see e.g. Vischel *et al.*, 2009). For the sake of brevity, we do not give all the details on this step, which will be detailed in a later publication.

Temperature model

We apply a similar procedure for temperature, but we use a simpler additive model without anamorphosis: temperature is not restricted to positive values, does not span several orders of magnitude and its CDF has no atomic component. The mean daily temperature at location $\mathbf{x}$ on day j is written as the sum of a template for weather pattern k = WP(j) and a local daily offset:

$$t(\mathbf{x}, j) = t^*_{\mathrm{WP}(j)}(\mathbf{x}) + \theta(\mathbf{x}, j) \tag{3}$$

The template at an ungauged location $\mathbf{x_0}$ is again obtained by kriging with an external drift using altitude as an auxiliary variable (i.e. simple kriging of the residuals to the drift) and a parameter c_k (temperature lapse rate in °C m^{-1}) for each weather pattern k.

A TEST CASE ON THE UPPER DURANCE CATCHMENT

Data and model

In this part we present the results of the joint calibration of an interpolation scheme and a hydrological model on the Upper Durance River catchment in the Southern French Alps. The catchment is 3600 km^2 with elevation ranging between 650 m (outlet at Serre-Ponçon dam) and 4100 m (Barre des Ecrins). The hydrometeorological dataset covers the period 1961–2004 and consists in 26 raingauges, 7 temperature stations, discharge time series at the outlet (Durance at Espinasses) as well as five internal flow measurements.

The hydrological model used for simulating the rainfall–runoff relationship is a modified version of the CEQUEAU model running on a topographic mesh (Bourqui *et al.*, 2011). The snow and soil moisture accounting routines are taken from the original CEQUEAU scheme (Charbonneau *et al.*, 1977); a lumped parameter set is used for all sub-catchments of the topographic mesh (i.e. only state variables are distributed). The contribution of each mesh element is then routed to the different control nodes using a diffusive wave model with uniform, lumped celerity and diffusivity parameters (see e.g. Hayami, 1951).

Inference procedure

As mentioned in the introduction, the main objective of the procedure is to let streamflow measurements help the inference of the drift parameters controlling the precipitation and temperature templates in each weather pattern. Hence, we are dealing with three subsets of parameters:

– the first subset is the *precipitation drift parameters*: these degrees of freedom are the eight precipitation scale heights $h_1, ..., h_8$ for each weather pattern;
– the second subset is the *temperature drift parameters*, i.e. the eight lapse rates $c_1, ..., c_8$;
– the last subset consists in the 25 *rainfall–runoff model parameters* (including the snow

routine).

For each trial parameterization of this whole hydrometerological model (i.e., 41 parameters), we are thus able to simulate three types of prognostic variables:

- If we put a raingauge aside, we can use it as an ungauged location for independent evaluation of the interpolation scheme (*jackknife* procedure). We can repeat this procedure for each raingauge in the network and compute a criterion (e.g. mean R^2 or RMSE between observed and reconstructed rainfall time series);
- We can do the same thing for each temperature station, and produce a goodness-of-fit criterion for temperature series;
- The rainfall–runoff model transforms the rainfall and temperature fields into discharge time series at one or several subcatchment outlets. Hence, we can compute evaluation criteria for discharge.

The first two criteria on rainfall and temperature are solely dependent on the drift parameter subsets (moreover, the search for the optimal parameter subset with respect to these criteria can be split into eight single-parameter searches). However, the third criterion on discharge is sensitive to all three subsets since the quality of the discharged simulated by the rainfall–runoff model relies not only on its own parameters, but also on the quality of the estimated forcing fields. What is more, as an example, the snowmelt on a given day *j* is of course dependent on the temperature field of that day (controlled by the lapse rate $c_{\mathrm{WP}(j)}$) but also on the whole succession of accumulation/melt episodes controlled by the parameters $h_{\mathrm{WP}(j-1)}$, $c_{\mathrm{WP}(j-1)}$, $h_{\mathrm{WP}(j-2)}$, $c_{\mathrm{WP}(j-2)}$, etc. In that step, correlation is introduced between the parameters.

For these reasons we can perform a multiobjective calibration and validation of the whole parameter set using an evolutionary (i.e. trial-and-error) scheme. We build the Pareto front for this three-criterion problem (or any combination of two of them) using the CaRaMEL multiobjective evolutionary algorithm (see e.g. Rothfuss *et al*., 2012).

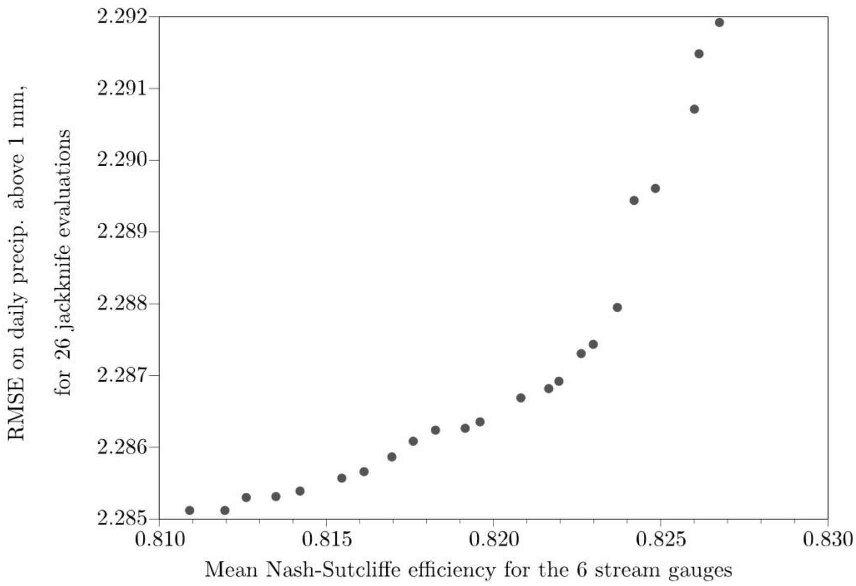


Fig. 2 Two-criterion Pareto front obtained in calibration over the period 1961–1982. The x-axis is a mean NS efficiency (increasing as the quality of the simulation increases) and the y-axis is a RMSE in mm (decreasing as the quality of the simulation increases).

RESULTS AND CONCLUSION

Figure 2 shows the Pareto front obtained when calibrating the 41 parameters (8+8+25) against the couple of criteria "Mean Nash-Sutcliffe efficiency on available streamflow series" and "RMSE on point rainfall measurements in jackknife evaluation". It appears that the latter criterion (y-axis) is much less sensitive that the criterion on discharge (x-axis). The RMSE on daily cumulates only increases from 2.285 to 2.292 across the Pareto set, whereas the mean Nash-Sutcliffe efficiency is increased by more than two points. This result shows that the precipitation drift parameters are much better identified when using streamflow measurements (i.e. assimilating an areal precipitation) than when using only point-scale (raingauges) measurements.

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