

Precipitation forecasting through an analog sorting technique: a comparative study

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Abstract. This study aims at comparing two quantitative precipitation forecasting techniques based on the meteorological analogy concept. Method A considers first a selection of analogous situations at synoptic scale. Second a subset of the most similar situations in terms of hygrometry is extracted. Method B extends method A by two innovative ways, which are restricting the search for analogues with temperature information instead of the common season criterion, and exploiting the information about vertical motion considering vertical velocity. Forecasts are evaluated in a perfect prognosis context and in operational conditions as well, by mean of verification measures (Continuous Ranked Probability Skill Score and scores computed from contingency tables). Results of the case study in France show that: (1) there is an increase in forecast skill when temperature and vertical velocity are included in the procedure, (2) it is possible to anticipate rainfall events up to one week ahead and (3) the introduction of new variables such as vertical velocity may be useless beyond few days ahead if the forecast of the weather model is not reliable.

1 Introduction

Many water-related stakeholders, especially operational flood forecasting services and hydroelectricity power producers, need quantitative precipitation forecasts (QPFs) as reliable as possible to anticipate discharges in river basins several hours or days ahead. Probabilistic QPFs provide multiple forecasts that represent the possible future states of the atmosphere, the uncertainty related to meteorological predictions and the risk of extreme events. At least, two approaches for producing probabilistic QPFs are commonly used: (i)



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regional ensemble weather forecasts based on dynamical approaches (e.g. COSMO-LEPS, Marsigli et al., 2005; PEARP, Thirel et al., 2008), (ii) statistical approaches based on a search for analogues (Obled et al., 2002).

The specific objectives of this study are to present two examples of probabilistic QPFs based on an analog sorting technique and recently developed and to compare their efficiency on a French large river basin. Both methods are described in the next section. Section 3 presents the study area, data and the skill scores used in the evaluation of probabilistic forecasts. The main results of the comparison are analysed in the fourth section. The last section draws general conclusions.

2 Methods

The analog method (AM) assumes that similar meteorological situations lead to similar local effects (e.g. rainfall amount) as suggested by Lorenz (1963). Since the development of numerical weather prediction (NWP) modelling, AM has been used as a statistical adaptation of model outputs (Obled et al., 2002). For a given target situation forecasted by a NWP model, the general principle of the AM consists in searching for the most similar meteorological situations observed in an historical archive using similarity criteria. Precipitation amounts observed during the analogous situations are collected to derive the empirical predictive distribution function, i.e. the probabilistic estimation of the precipitation amount expected for the target day.

Duband (1970) initiated the development of the AM in France. Improvements were later suggested by Guilbaud (1997), Obled et al. (2002), Bontron (2004), Gibergans-Báguena and Llasat (2007), Bliefernicht and Bardossy (2007).

The first method (referred hereafter as method A) is the procedure suggested by Bontron (2004). This method is

dedicated to small basins located in South-Eastern France and runs operationally at the forecasting service of the hydroelectricity power company Compagnie Nationale du Rhône. For a target day, a preliminary step (step 1-A) consists in collecting past situations the dates of which are within a temporal window of 4 months centred on the calendar day of interest. This step models the seasonal effect in precipitation: for a given meteorological situation, one assumes that rainfall amount will not be the same whether the situation is observed in winter or in summer. The second step (step 2-A) enables to choose, among this large sample, the most similar situations in terms of general circulation, based on geopotential height fields (considered at 1000 hPa and 500 hPa) at synoptic scale compared with a shape similarity criterion. Finally (step 3-A), only the most analogous situations at local scale in terms of hygrometry are kept, considering both the precipitable water amount in the air column and the relative humidity (850 hPa).

For improving AM performances, Ben Daoud (2010) addressed two important issues: can we question the restriction of the search for analogues, and are there further useful predictors for characterising frontal precipitation systems?

Thus a modified version of method A was proposed (referred hereafter as method B). In order to take the seasonal effect into account, the first step of method A was modified by replacing the commonly used fixed calendar criterion by an analogues searching in terms of temperature (step 1-B). Step 2-B, relative to general circulation analogy, is identical to step 2-A. Then, in order to characterise frontal precipitation systems, a new step (step 3-B) considering similarities in terms of vertical motion was added. Different approaches based on different variables were tested to perform this step, to finally keep a comparison with vertical velocity in the low troposphere (850 hPa). Lastly, step 4-B relative to hygrometry analogy, is similar to step 3-A (relative humidity is considered both at 925 hPa and 700 hPa instead of 850 hPa).

3 Materials

3.1 Study area and data

The study area covers three sub-catchments of the Saône river basin located in eastern France (Fig. 1), with a response time of about 12 to 24 h. This basin is under oceanic influences and westerly fluxes generating rainfall when large fronts pass. This area can be also affected by heavy rainfall events coming from the Mediterranean Sea.

AM requires two archives containing predictors and predictands. Variables that describe past meteorological situations (predictors) are extracted from the 45-Year European Centre for Medium-Range Weather Forecasts (ECMWF) Re-Analysis (Uppala et al., 2005), at 2.5° resolution, available from September 1957 to August 2002. The hydrological database that contains past basin daily rainfall amounts

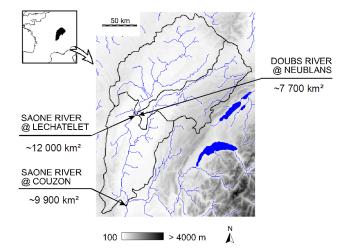


Fig. 1. Location of the Saône river basin divided into three subcatchments.

(predictand) was built from the surface variables reanalysis SAFRAN (Vidal et al., 2010), available from August 1970 to July 2008 and with an initial resolution of 8 km. Thus, the common period is from August 1970 to August 2002.

In addition, to evaluate the two methods in real conditions, a set of past weather forecasts provided by the ECMWF operational NWP model and covering the period 1 October 2001– 1 October 2004 (i.e. 3-year period) was selected in this study.

3.2 Evaluation scores

Numerous appropriate scores to evaluate probabilistic forecast performances can be found in the literature (for a complete list, see Jolliffe and Stephenson, 2003). Among them, the Continuous Ranked Probability Score (CRPS; Hersbach, 2000) is well suited for probabilistic forecast verification, especially when performances are evaluated for any kind of event (i.e. considering dry days as well as any precipitation event):

$$CRPS = \frac{1}{N} \sum_{i=1}^{N} \int_{-\infty}^{+\infty} [F(x) - H_{x_0}(x)]^2 dx$$
(1)

where *N* is the number of forecasts, *x* is the forecast variable, x_0 is the observation, *F* is the repartition function of the forecast variable, and H_{x_0} is the Heaveside function. For the interpretation of the results in terms of gain, it is widespread to use a reference forecast. Thus, the related CRPS skill score (CRPSS) was used instead:

$$CRPSS = (CRPS_{ref} - CRPS_M) / CRPS_{ref}$$
(2)

where $CRPS_M$ is the score of method M and $CRPS_{ref}$ is the score of a reference method. Here, forecasts issued from the reference method are given by the climatological distribution of the predictand. If CRPSS is 0, the method M and the reference have identical performances. If CRPSS is higher than

Table 1. Contingency table for a precipitation threshold T (A = number of hits; B = number of false alarms; C = number of misses; D = number of correct rejections).

		Observation (P_0)	
		$P_o > T$	$P_o \leq T$
Forecast (P_f)	$P_f > T$	Α	В
-	$P_f \leq T$	С	D

0, performances from M are higher than those from the reference. If CRPSS is 1, forecasts obtained with M are perfect.

In addition, another type of verification can be used with regard to end-user needs to quantify the ability of the system to detect specific rainfall events whose accumulated precipitation exceeds a given threshold T. In this application, we assume that such an event is expected for day D if the 60% quantile extracted from the empirical predicted distribution function for day D is above T (i.e. $P_f > T$). An event occurs if rainfall amount for day D exceeds T (i.e. $P_o > T$).

By filling a contingency table (Table 1), different scores may be calculated. In this study, two scores were derived from contingency tables: the probability of detection (POD) and the false alarm rate (FAR), defined by Eq. (3):

$$POD = A/(A+C)$$
 and $FAR = B/(A+B)$ (3)

where A, B, C are integer numbers obtained through the contingency table (see Table 1). Thus, for a perfect forecast system, POD is 1 and FAR is 0.

4 Results

The evaluation of forecast and the comparison of methods A and B performances were carried out in two contexts. In a "perfect prognosis" context, predictors are extracted from a reanalysis whereas in an operational forecast context, predictors are provided by a NWP model and the AM runs in real conditions (i.e. forecasts include modelling errors and biases of the NWP). The parameters for both methods were optimised in a perfect prognosis context over the common archive period (1 August 1970 to 30 August 2002) except five non-contiguous years used for validation of the parameters calibration.

In the perfect prognosis context, forecasts were run for every day and evaluated over the entire common archive period. The CRPSS averaged on the three sub-catchments equals to 49.8% for method A and to 56.0% for method B. This result shows that a gain of performances is obtained when method B is applied instead of method A. In addition, Fig. 2 displays POD and FAR scores obtained with methods A and B for different precipitation thresholds defined by percentiles of the climatological empirical distribution. Only slight differences

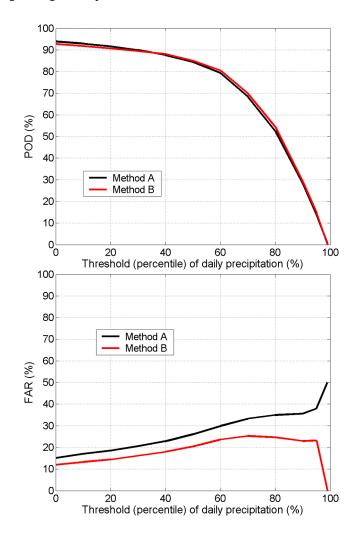


Fig. 2. POD and FAR scores obtained in perfect prognosis with methods A and B for different precipitation thresholds defined by percentiles of the climatological empirical distribution. The forecast value is represented by the 60% quantile of the distribution.

are observed for POD scores: both methods forecast heavy rainfalls with difficulty. FAR scores show that higher CRPSS scores obtained with method B are mainly due to fewer false alarms. One should note that above the 95% quantile, the puzzling behaviour of FAR score is due to the sampling.

In an operational context, the same scores were computed over the 3-year period, function of the lead-time (in days). Figure 3 shows the evolution of CRPSS, POD and FAR scores with the lead-time, computed for the Doubs River basin (Fig. 1). POD and FAR scores were obtained for a threshold *T* corresponding to 9.1 mm day⁻¹ (observed basin average daily precipitation amount value which is exceeded on 20% of the wet days). Both methods have more skill than climatology (CRPSS>0 up to t = D + 6). Method B starts with higher CRPSS scores than method A, but its skill drops as the forecast lead-time increases. At the third, the two curves merge, indicating the skill of method B has decreased to the same level as method A. The better efficiency due to the introduction of additional predictors is neutralised by the inability of the Numerical Weather Prediction models to forecast correctly these predictors. According to Fig. 3, whatever the lead-time, method A is better than method B in terms of POD scores. Conversely, method B leads to fewer false alarms, in accordance with the results obtained in a perfect prognosis context.

5 Conclusions

The objective of this study was to compare the performances of two precipitation forecasting methods based on an analog sorting technique. The first one, which was optimised essentially for small to medium sized mountain catchments, enables to select analogous situations to the target one in two steps, among a large sample of dates taken from the same 4months temporal window. The second technique, which was developed more recently to adapt the first one to larger river basins, includes a novel additional selection step based on the forecast temperature for the target day, instead of the seasonal criterion. Besides it allows characterising the vertical motions at large scale, by searching for analogues in terms of vertical velocity fields. Indeed, precipitations observed over large river basins in France are mainly associated to largescale fronts, which induce the vertical motion. This lifting differs from the one that occurs in mountain catchments, linked with fixed topography. Hence in this application, considering that the topography representation is poor, this kind of lifting is not taken into account in this application.

The area for this application was the Saône river basin $(30\,000\,\text{km}^2)$ located in eastern France. The results show a noticeable increase in forecast skill, which could be explained by the choice of predictors in accordance with the main precipitation types observed within the area of interest.

We should keep in mind that there are still many ways to improve the analog method, especially for areas where other factors are controlling precipitation events (e.g. in mountains where convection plays a major role). Various applications in France show that it is possible to anticipate rainfall events up to one week ahead using both methods here presented. When AM runs in an operational forecasting context (as opposed to the perfect prognosis context, where predictors are observations), the forecast skill of the analog methods depends on the ability of the NWP model to predict the variables used to define similarity. However, as verified in the past, AM performances will probably increase in parallel with the improvement of NWP models.

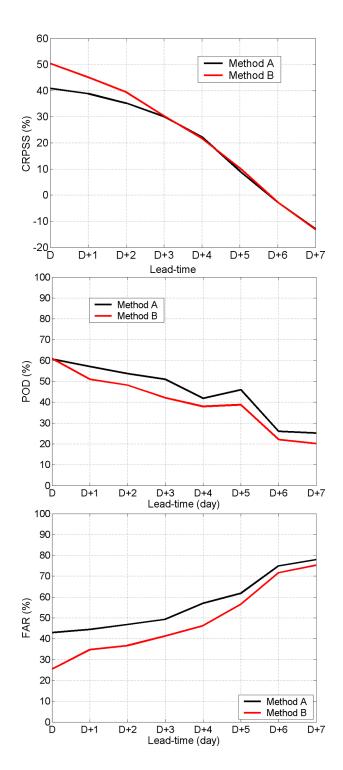


Fig. 3. CRPSS, POD and FAR scores as function of the leadtime, obtained in operational context for the Doubs River basin. POD and FAR scores are computed with a forecast value represented by the 60% quantile of the distribution and for the threshold T = 9.1 mm day⁻¹. We refer to the first day of forecast as t = D.

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