Can discharge assimilation methods be used to improve flood forecasting when few data are available?

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Abstract Forecasting floods is a major issue for public safety all over the world. Due to the difficulties inherent in the flood forecasting exercise, data assimilation techniques have been developed to cope with model errors. Unfortunately, these techniques require recent (real or near real-time) observations which may not be readily available in regions lacking automatic measurements networks. This paper investigates the impact of data assimilation techniques on discharge forecasts and model performance when few (but not zero) discharge measurements are available for the data assimilation. A parsimonious rainfall–runoff model is applied to a set of 178 French catchments. We explore the time properties of different discharge data assimilation schemes. Life times of the updates and model performance are assessed as a function of the time between the last available discharge observation and the forecast. State updating proves to have an added value to the forecasting system, even when data availability is limited.

Key words flood forecasting; data availability; rainfall–runoff modelling; data assimilation

INTRODUCTION

A wide range of modelling strategies is available for flood forecasting. Among them, rainfall–runoff (RR) modelling has demonstrated good performance and potential for flood forecasting. Nonetheless, RR models are far from being perfect tools. They often need to integrate additional updating techniques to be kept "on track" when used in real-time operational forecasting.

Depending on the modelling approach, different updating techniques can be used (Refsgaard, 1997). They can be applied to update model inputs, internal states, parameters or outputs. Algorithms commonly used in flood forecasting are: Kalman filtering (see e.g. Da Ros & Borga, 1997; Aubert *et al*., 2003; Evensen, 2003), autoregressive models (ARIMA, see Box & Jenkins, 1976), and artificial neural networks (ANN, Maier & Dandy, 2000; Anctil *et al*., 2003). These techniques are based on real-time data assimilation. Their use implies that additional data are provided to the RR model beyond its usual input (i.e. mainly precipitation) to improve the forecasts. In most flood forecasting real-time contexts, these additional data can only be discharge observations. Operationally, as discharge measurements become available, they are introduced into the model to adjust it and/or correct forecast errors.

A need for robust and long-memory data assimilation approaches

Updating can significantly improve the accuracy of the forecasts, but it also increases the complexity of the system. Different studies have compared the potential of different data assimilation schemes for flood forecasting (see e.g. WMO, 1992; Madsen *et al*., 2000; Moore, 2007). One of the main difficulties arises from the availability of real-time or near real-time data at appropriate modelling space–time scales (data scarcity problems), as well as from the retrieving and quality-controlling of field data in real time (processing and management of data sets). Under these conditions, forecasting RR-based models require robust updating procedures, i.e. the models have to remain efficient when the operational conditions are far from "ideal" laboratory conditions. The way streamflow information is incorporated in flood forecasting models must remain coherent with the characteristics of such additional information.

In continuous model simulation, it is well known that initial states tend to dissipate after some time of simulation. Similarly, the effects of updating in forecasting models are limited in time. One can therefore say that any update is characterized by a "life time", defined as the time beyond which the additional information used at the start of the forecasts no longer has a significant impact on the forecasts issued. The impact of an updating procedure progressively declines from "High", immediately after the updating to "Low" (Fig. 1) for some delay after the updating. This delay may depend on various factors, among them the modelling approach and the physical characteristics of the catchment being modelled. If this life time is lower than the operational forecast length $\Delta t = N + L$ (where N is the lag time, expressed as a number of time steps, between the last available discharge observation and the time step at which the forecast is issued, and L is the lead time), the update is no longer effective.

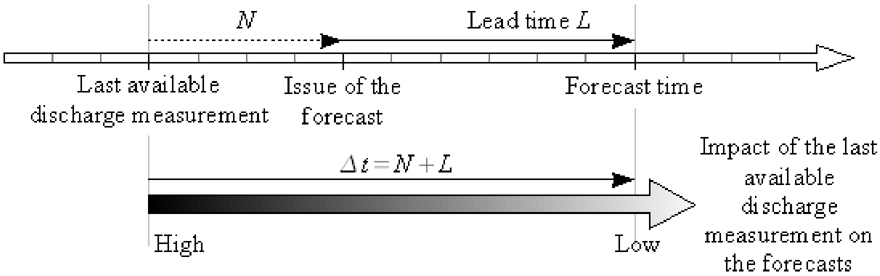

Fig. 1 Impact of an updating procedure: life times of updates are compared to the operational forecast length (i.e. duration between the last available discharge measurement and the forecast time step).

Scope of the paper

In this study, we address the following question: What is the maximum delay for which the performance of a given updating procedure still has a significant positive impact on the forecast? In other terms, at which minimum rate should discharge measurements be available to guarantee a real improvement of forecasting performances through flow data assimilation?

A two-step methodology was adopted. First, a preliminary assessment of the "life times" of an updated routing store, when considering variable updating lengths (theoretical evaluation), and of auto-regressive updated outputs (empirical evaluation) was performed. Second, we evaluate model performance when forecasts are issued on the basis of updating techniques that assimilate discharge observations available at different time steps before the forecast is issued. Data and methods are presented in the next sections, followed by results and conclusions.

DATA AND MODEL

Catchment set and hydrological data

The study is carried out on a set of 178 French unregulated catchments (Fig. 2). The set is representative of the hydroclimatic variability encountered in the country: from catchments experiencing Mediterranean flash floods to much slower catchments. Catchments in high-elevation zones are not considered, since the RR model used does not include a snow-accounting module. Catchment areas range from 10 to 5940 km^2 (354 km^2 on average). Working on various catchments ensures more general and robust conclusions to our study (Andréassian *et al.*, 2006).

Available data consist of hourly areal precipitation, potential evapotranspiration (PE) and discharge from 1995 to 2005. PE values were computed using the formula proposed by Oudin *et al*. (2005), based on temperature and extraterrestrial radiation.

The GRP forecasting rainfall–runoff model and its updating techniques

The GRP model is a continuous, lumped, hybrid metric-conceptual model, designed specifically for flood forecasting (Tangara, 2005). It is one of the operational models used to forecast river flows in real time on French catchments, including the Seine River basin upstream of Paris.

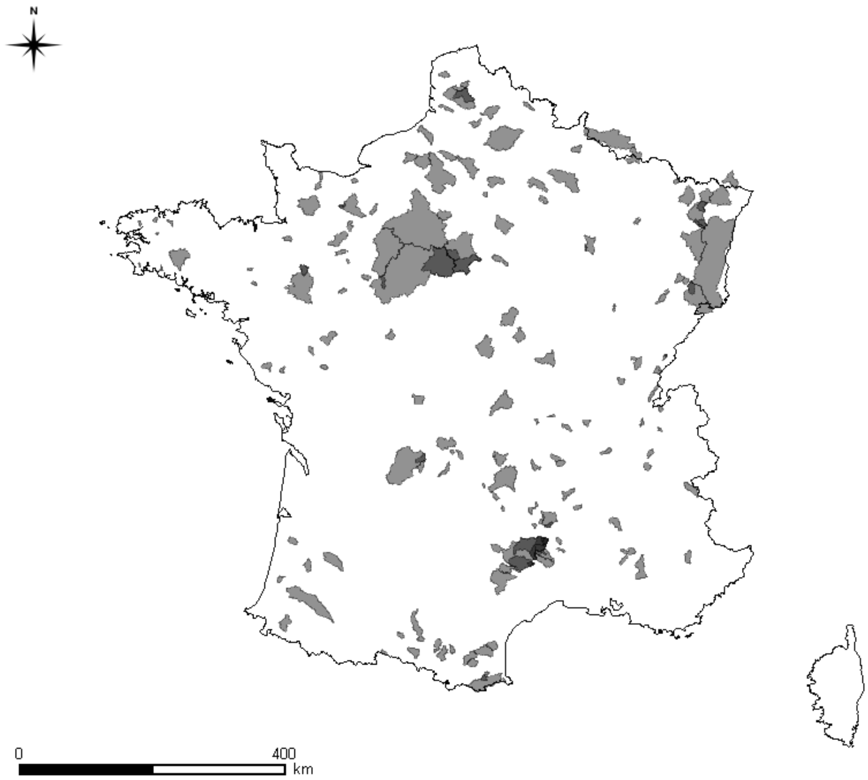

Fig. 2 Location of the 178 catchments used in this study.

Detailing the structure of the GRP model is beyond the scope of this paper; only a brief description follows.

The GRP structure was derived from that of the GR4J model (Perrin *et al.*, 2003). It can classically be described as the combination of a production function followed by a routing function. The former consists of a nonlinear soil moisture accounting (SMA) store and a volume-adjustment coefficient that determines the runoff ratio. The routing function is composed of a unit hydrograph and a nonlinear routing store.

A preliminary analysis (not shown here) indicated that the most efficient updating strategy for the GRP model is a combination of a direct updating of the routing store (using the last observed discharge measurement) and an output updating based on the last observed forecast error. For the latter, simple multiplicative regressions, as well as ARIMA corrections and artificial neural networks (ANN) output updating, lead to valuable performance gains. Only these most efficient updating techniques for the GRP model are studied and compared hereafter.

METHODOLOGY

A two-step approach was chosen. First, we studied each updating technique separately, to assess typical magnitudes of their life times by theoretical or empirical means. Then, we evaluated the losses in the performance of the GRP model when the delay N between the last available discharge observation and the moment at which the forecast is issued increases. The methodology applied is described below.

Assessment of the life times of the state updates

The life times of the routing store updates are closely linked to the dynamic of this store. The routing store of the GRP model is a quadratic one: the output discharge is controlled by its level and its total capacity.

At every time step, we can represent the behaviour of the store level by equation (1):

$$S_t = f(S_{t-1} + I_t) = S_{t-1} + I_t - O_t \tag{1}$$

where S_t is the level of the store at time step t, I_t is its input and O_t its output.

After a given number (m) of time steps following an update δS_T (at time step T), the updated store reaches the level it would have without any updating (equation (2)). The life time of the update δS_T can be defined as the minimum number of time steps, m necessary for this level to be reached without updating.

$$\underbrace{f\left(I_{T+m} + f\left(I_{T+m-1} + f\left(\ldots + f\left(I_T + S_T + \delta S\right)\right)\right)\right)}_{\text{Evolution of the store level, } m \text{ time steps after the update}} \approx \underbrace{f\left(I_{T+m} + f\left(I_{T+m-1} + f\left(\ldots + f\left(I_T + S_T\right)\right)\right)\right)}_{\text{Corresponding evolution of the store level without any update}} \tag{2}$$

For each catchment, we located the time steps corresponding to the 50 largest updates δS performed by the forecasting system during the simulation period (1995–2005). From these time steps, the model was run with and without the updates until the difference between both, updated and non-updated, simulated routing store levels was negligible. Life times were thus evaluated and statistics were calculated over the 50 available values.

Assessment of the life times of the error correction updates

Output corrections are based on the use of the information contained in the model error (i.e. the error between forecast and observed discharges). They most often use a statistical relationship linking observed and forecast flows: $\varepsilon_{t+L|\mathrm{t}} = g(Q_{t1}, Q_{t2}, \ldots, \hat{Q}_{t1}, \hat{Q}_{t2}, \ldots)$, where $\varepsilon_{t+L|\mathrm{t}}$ is the error made on the forecast issued at time step t for a lead time L; $Q_{t1}, Q_{t2}, \ldots$ are observed discharges at time steps $t1$, $t2$ prior to t; and $\hat{Q}_{t1}, \hat{Q}_{t2}, \ldots$ are the corresponding forecast discharges. The analysis of the calibrated parameters of the different output updating techniques allowed us to estimate their life times for every catchment. For example, we assessed ARIMA updating life times as the minimum value of l such that $\rho^l \cdot \bar{\varepsilon}_1$ is negligible compared to $\bar{\varepsilon}_l$ where ρ is the calibrated autocorrelation parameter; $\bar{\varepsilon}_1$ and $\bar{\varepsilon}_l$ are the average forecast errors for lead times 1 and l hours.

Assessment of the loss in model performance when discharge data availability for updating decreases

The GRP model (using the routing store updating and an ARIMA output updating) was run on our set of 178 catchments with updating performed only with the discharge values observed at N time steps prior to the time at which the forecast is issued (Fig. 1). Forecasts for different lead times L and for different availabilities of past discharge observations, characterized by the delay N, were assessed. In our study, lead times ranged from 1 to 48 h, while N values ranged from 0 (ideal case: current discharge data are available at the time step the forecast is issued) to a maximum lag of 72 h.

We used *a posteriori* observed precipitations for the future precipitation scenarios rather than quantitative precipitation forecasts (which usually drive operational RR forecasting models), as we wanted to focus on the impact of low availability of discharge observations. In this way, no bias was introduced due to the typical decrease of skill in precipitation forecasts when increasing lead times.

The performance of the model was assessed by the root mean square error (RMSE) between observed and forecasted discharges, normalized by the RMSE computed when $N = 0$ and $L = 1$. This ratio represents the error multiplicative factor when discharge observation availability decreases and when the lead time increases. Following classical procedures advocated by Klemeš (1986), data were divided in two periods for model calibration and validation and only performances on validation data are shown.

RESULTS AND DISCUSSION

Assessments of the life times of the GRP model updates

Table 1 shows the median values (computed over the 178 catchments) of the life times obtained when considering three classes of the routing store updates among the 50 largest updates detected on the validation period: a series with the smallest updates over all catchments, a series with their median values and a series with the largest updates. On events that have long-lasting impacts, the life times of the updating procedure are typically much larger than the considered forecast lead times: for a lead time of 24 h, for instance, the median life time of the updating procedure is of 197 h (Table 1), i.e. approximately eight times greater than the forecast lead time. When considering the smallest updates, their life times are still significant. These results indicate that the updating technique considered (routing store updating) can still be useful even if the availability of the discharge observations is low (i.e. if the last assimilation of a discharge observation takes place on average long before the forecast time).

In contrast, the results from the assessment of life times of error correction updates show that the impacts of simple regression and ARIMA corrections become very limited after a small number of time steps due to the auto-regressive nature of these updating techniques: typically, after 12 time steps (hours), the correction is nil on most of the 178 catchments. The limited impact of these techniques make them not very useful for forecasting systems where data retrieval can only be done once a day.

Table 1 Median life times m (in hours) for the smallest, the median and the largest updates among the 50 largest updates on every catchment.

Lead times (h)	Smallest update	Median update	Largest update
1	44	85	166
6	44	90	175
24	51	103	197
48	57	110	224

Losses in model performance

Since we used *a posteriori* observed precipitations as future precipitation scenarios, the performances of the model do not depend directly on N and L, but only on the operational forecast length $\Delta t = N + L$. Figure 3 shows the evolution of the error multiplicative factor with Δt. This criterion first increases very rapidly with Δt. Then, the performance losses increase more slowly and become much more stable after approximately $\Delta t = 3$ days.

These results are in accordance with the previous results: the initial fast performance loss corresponds to the fast extinction of the output updating. Once the output updating is totally ineffective, the performance losses increase slowly because the extinction of the routing store updating is much slower (as shown in Table 1).

Regarding the plateau observed after $\Delta t = 3$ days, the associated performances do not correspond to the performances obtained by the model with no updating at all (shown as $N = +\infty$ on Fig. 3). In fact, even for the maximum operational forecast length ($\Delta t = 120$ h), the performance of the updated model is significantly better than those obtained with no updating on more than 75% of the studied catchments (Fig. 4). This indicates that the life time of the routing store updating is greater than five days on most of the cases: this data assimilation scheme improves the forecasts significantly, even when performed only every five days.

CONCLUSIONS

In this paper, we evaluated to what extent data assimilation techniques can efficiently improve flow forecasting models when few discharge data are available. Different updating techniques for

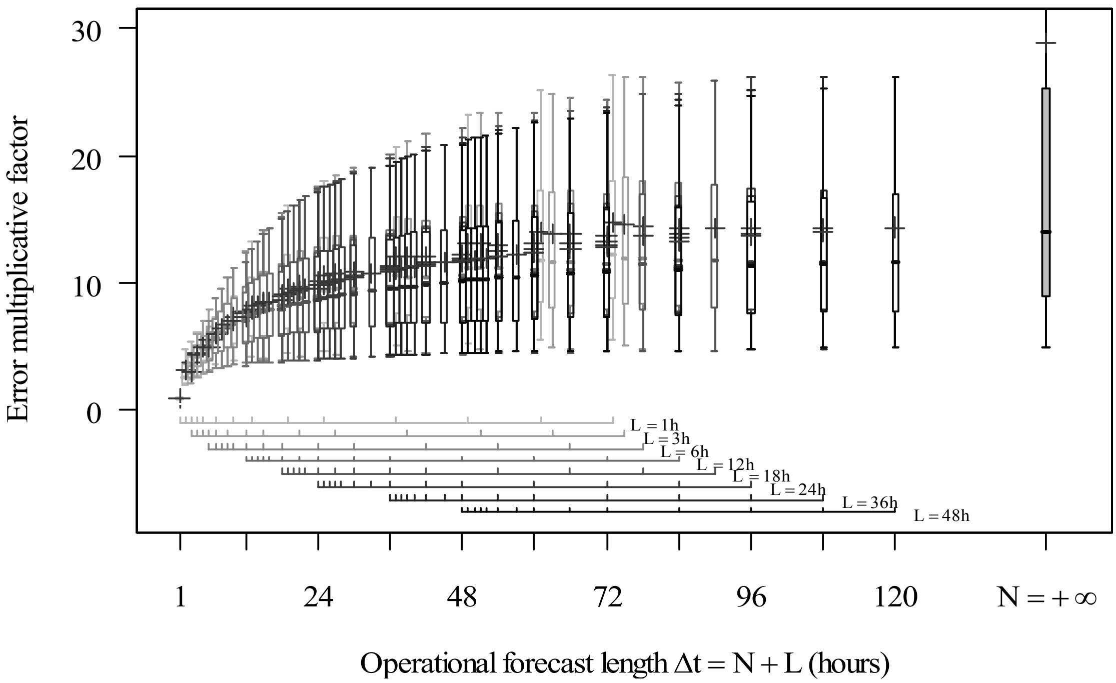

Fig. 3 Distributions (box plots) of the error multiplicative factor as a function of the operation forecast length. The box plots depict the quantiles 0.05, 0.25, 0.5 (median), 0.75 and 0.95. Crosses represent the mean of each distribution.

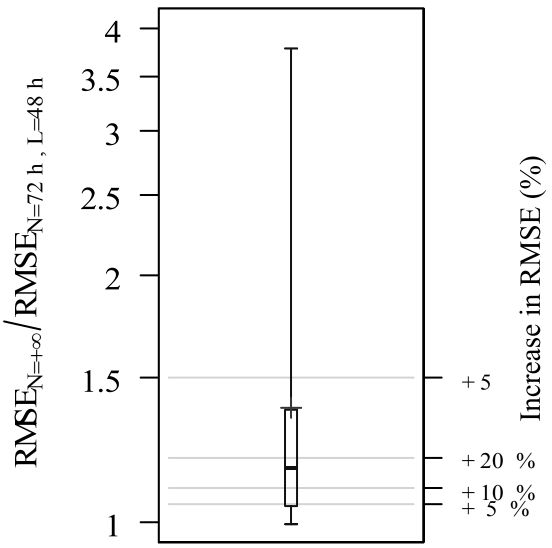

Fig. 4 Distribution (box plot) of the ratio of the RMSE obtained by the model with no updating to the RMSE obtained for Δt =120 h over the set of 178 catchments (left y-axis) and the corresponding increase of the RMSE from the case (Δt =120 h) to the situation with no assimilation at all (Δt =+∞), expressed as a fraction of the RMSE obtained for Δt =120 h (right *y*-axis). The box plot shows the quantiles 0.05, 0.25, 0.5, 0.75 and 0.95. For example, for almost 50% of the catchments, the increase of RMSE is higher than 20% of the RMSE obtained at Δt =120 h.

a simple rainfall–runoff model were compared over a set of 178 catchments: state updating proved to be effective for a longer time than output updating for the flood forecasting model studied. This updating method brings valuable improvements to the forecasts even when discharge data is available only once every five days. Further work is needed to apply this methodology on different models and on more updating techniques. In operational forecasting, the approach presented can be useful to evaluate life times of local updates and provide guidance to data monitoring strategies in real time.

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