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How crucial is it to account for the Antecedent Moisture Conditions in flood forecasting? Comparison of event-based and continuous approaches on 178 catchments

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Abstract

This paper compares event-based and continuous hydrological modelling approaches for real-time forecasting of river flows. Both approaches are compared using a lumped hydrologic model (whose structure includes a soil moisture accounting (SMA) store and a routing store) on a data set of 178 French catchments. The main focus of this study was to investigate the actual impact of soil moisture initial conditions on the performance of flood forecasting models and the possible compensations with updating techniques. The rainfall runoff model assimilation technique we used does not impact the SMA component of the model but only its routing part. Tests were made by running the SMA store continuously or on event basis, everything else being equal. The results show that the continuous approach remains the reference to ensure good forecasting performances. We show, however, that the possibility to assimilate the last observed flow considerably reduces the differences in performance. Last, we present a robust alternative to initialize the SMA store where continuous approaches are impossible because of data availability problems.

1 Introduction

1.1 Continuous vs. event-based approaches to modelling

From the catchment point of view, the hydrological cycle is a sequence of wetting and drying periods. On a given date, the moisture state of a catchment is the consequence of the past sequence of meteorological conditions. The initial moisture conditions at the beginning of a rainfall event have a major influence on a catchment's hydrological response. Therefore the set-up (as defined by Refsgaard and Henriksen, 2004) of a hydrological model requires choosing the initial conditions. Depending how this is done, hydrological models will be categorized as continuous or event-based.

The initialization through a continuous approach consists in running the model during a warm-up period in order to let the model states reach values that no longer depend on arbitrarily chosen initial values. The duration of this warm-up depends on the catchment (its memory of past conditions) and on the model and may last a few months (Kitanidis and Bras, 1980b). A climatic cycle (i.e. one year) is often used, although it has been shown that some catchments (especially those where large aquifers feed streamflow) need up to several years (Le Moine, 2008). In an operational forecasting perspective, the major drawback of the continuous approach lies in its data requirements: long continuous precipitation time series up to the day of interest are difficult to provide (data gaps occur frequently because of real-time data repatriation difficulties).

In contrast, event-based models require a separate method to derive the initial values of model states. Numerous methods exist. If the model states reliably represented measurable physical quantities, recent measurements or values based on climatology would be solutions. For example, Brocca et al. (2009) showed that assimilating soil moisture measurements into the event-based SCS-CN model can be useful for flow simulation on a small catchment. However, these results should be generalized, as mentioned by the authors.

Continuous approaches have been recommended to modellers for many years (e.g. Kitanidis and Bras, 1980a; Linsley, 1982) as a rigorous solution to the estimation of initial conditions. However, we must acknowledge that event-based approaches are still most often preferred in real-time operational applications (Lamb and Kay, 2004). Event-based models may be simpler because they often do not need to include all the processes necessary in a continuous model. This means more limited data requirements which may ease model implementation and use. Another reason lies in the difficulty maintaining and validating automatic measurements networks over a long period in many countries. This is a frequent situation when looking for high time resolution series. To bypass this obstacle, Nalbantis (1995) suggests relying on coarser data series (e.g. daily) to estimate fine (hourly) initial conditions. The problem may also be cultural. Some end-users, who traditionnally use hydraulic propagation methods, are culturally in favor of an event-based approach. Despite all the good resons advanced by hydrologists for using continuous approaches, pratictioners often continue using event-based models and see them as the only solution.

1.2 Sensitivity of hydrological models to the initialization procedure

The report of the National Research Council (NRC) (2002) identified as crucial the question of initial conditions. There is a wide consensus among hydrologists that hydrological models' outputs are very sensitive to initial conditions, especially soil moisture or catchment wetness (e.g. Refsgaard et al., 1999; Moore et al., 2006; Vivoni et al., 2007). Event-based models can lead to very different outputs when run with different initial conditions (Da Ros and Borga, 1997). As hydrological processes are essentially non linear, even a slight uncertainty on initial conditions can lead to dramatic uncertainty on streamflow (Zehe and Blöschl, 2004).

Many authors have studied the effects of initialization on the response of models that seek to reproduce physical processes. Already at the inception of the Soil Conservation Service (SCS) Curve Number (CN) formula, modulating the CN value according to the antecedent moisture conditions has been found to be necessary (Ogrosky and Mockus, 1964). Note, however, that for the SCS-CN formula this resulted in confusion between intrinsic parameters and initial conditions (Michel et al., 2005). More recently, Noto et al. (2008) showed that the degree of sensitivity to the initialization procedure depends on other factors, such as the intensity of precipitation or the catchment's physical properties. Vieux et al. (2004) demonstrated that the sensitivity of the model is lower when the catchment is already very wet.

1.3 The real-time forecasting specificities

The sensitivity of hydrological models to initial conditions is of prime importance for operational forecasting. For example, Norbiato et al. (2008) showed that initial conditions (antecedent soil moisture) are essential for efficient flash flood alerts.

Real-time forecasting systems most often use a data assimilation method to improve short-range prediction accuracy (Shamseldin, 2006). Among the different assimilation techniques, state updating is quite popular (Refsgaard, 1997; Moore, 2007). This method estimates state variables depending on the very last observed discharges. Consequently, the question of initial conditions appears to be less important if some (or even all) states are re-estimated by this updating technique (Nalbantis, 2000; Aubert et al., 2003; Moore et al., 2005).

State updating, when performed by assimilation of a small number of measured inputs (e.g. only discharge or discharge and soil moisture) compared to the number of internal states, leads to uncertainties which combine with the uncertainty on the initial values. Indeed, trying to update several model states simultaneously may endanger model robustness and it leaves the modeller in the uncomfortable situation where there are more unkowns than equations to solve.

The uncertainties due to the initial conditions may also be taken into account by using an ensemble forecast whose members differ in their initial conditions (e.g. Dietrich et al., 2008). However, this issue is not within the scope of this paper and we will focus on deterministic forecasting methods for the sake of simplicity.

1.4 Scope of the paper

This paper has both a theoretical and an applied objectives. The theoretical one is to contribute to a more general answer to the relative merits of continuous and event-based approaches for flood forecasting, through the comparison of different initialization approaches for the very same flood forecasting model. Indeed, although this issue has long been in the forefront, the literature does not provide a clear answer to this question. In addition, we investigate the possible interplay between the updating techniques and the initialization impact: the applied objective is to determine whether we can define simple initialization schemes which allow issuing forecasts without running the model over a long pre-forecast period. Initialization strategies are tested on a set of 178 French catchments.

Several authors compared different models with different initialization strategies. For example, Amengual et al. (2008) compared the performances of two different models – one was continuous, the other event-based – to hindcast a flash flood event and found little difference between them. Instead, we chooose to use the very same model in order to focus exclusively on the initialization strategies.

The remainder of the article is organized as follows: first the data and the model are described as well as the assessment criteria we employed. Then Sect. 3 details the methodology. The results are shown and discussed in Sect. 4. Finally a number of conclusions are drawn.

2 Catchments set, model and assessment criteria

2.1 Test set of 178 French catchments

The comparison is based on 178 French unregulated catchments (Fig. 1), chosen to represent the hydroclimatic variability encountered in the country (note, however, that we excluded higher elevation zones since we did not use a snowmelt module). Catchment areas range from 10 to 5 940 km^2 (average of 354 km^2). By working on various catchments, we aim to ensure more general conclusions to our study (Andréassian et al., 2006). We used continuous hourly precipitation, discharge and potential evapotranspiration (PE) data series from 1995 to 2005. PE values were computed using the formula proposed by Oudin et al. (2005), based on temperature and extraterrestrial radiation.

Our data set covers a varied range of hydrological behaviours: some Mediterranean catchments experience flash floods, whereas others typically have slow floods. To check whether different initialization solutions could fit different types of catchments, we divided the complete set into four subsets (of equal sizes) depending on streamflow autocorrelation. This index provides information on the way catchments behave: catchments with flash floods have a low streamflow autocorrelation, while catchments with slow variations of streamflow present a much higher autocorrelation. For the same reason, forecasts are issued for different lead times, from 1 up to 48 h.

2.2 Forecasting model

Our objective was to compare different initialization modes using the very same model structure. We deliberately used a simple model (GRP) in order to be able to analyse the effects of different initializations more easily. It is nonetheless an efficient operational model, one of those used to forecast river flows in real time on the Seine basin upstream from Paris (Cemagref, 2005). Detailing the structure of the forecasting model is not within the scope of this paper; therefore, only a brief description follows.

GRP is a hybrid metric-conceptual lumped parsimonious model, designed specifically for flood forecasting (Tangara, 2005). Its structure was derived from the structure of the GR4J model (Perrin et al., 2003). GRP can classically be described as a production function followed by a routing function (Fig. 2). The production function consists in a non-linear "soil moisture accounting" (SMA) reservoir and a volume adjustment coefficient which determine the runoff ratio. The SMA store requires either a specific initialization or a continuous running mode. The routing function is composed of a unit hydrograph (UH) and a non-linear routing store.

The forecasting model GRP uses a combinaion of two assimilation (updating) functions for flood forecasting. The first exploits the last observed discharge information to update the state of the model routing store, while the second draws information from the last model error to update the model's output through a multiplicative ARIMA model (Box and Jenkins, 1976). We do not use the Kalman filter (or one of its heirs) because we found it could lead to performance losses during flood events when it assimilates streamflow alone (Aubert et al., 2003). The important thing to note here is that the level of the SMA store is not updated in the model and its initialization will be the main focus of the tests presented hereafter.

The model includes two main state variables: the levels of the production store and of the routing store. We do not consider the internal states of the unit hydrograph since they are very transient states: their values no longer depend on their initial values after a finite number of time steps because the model UH has a finite number of ordinates.

2.3 Assessment criteria

For a given lead time L, the overall evaluation of the forecasts is based on the persistence index PI (Kitanidis and Bras, 1980a).

$$\mathrm{PI}(L) = 1 - \frac{\sum_t \left(\widehat{Q}_{t+L|t} - Q_{t+L}\right)^2}{\sum_t \left(Q_t - Q_{t+L}\right)^2}$$

where Q_t and Q_{t+L} are the observed discharge at time step t and $t+L$, respectively, while $\widehat{Q}_{t+L|t}$ is the forecast issued at time step t for time step $t+L$. A PI value of 1 indicates a perfect fit between forecasted and observed discharges. A positive value means that the root mean square error (RMSE) of the assessed model is lower than the RMSE of the persistence model. A negative value implies that the model is less efficient than a model giving the last observed discharge as a prediction for the future time steps. The criterion value for the most part reflects performances during floods since it is a quadratic criterion. The PI is a well-suited quadratic criterion to assess forecasting models, since it compares the tested model to a naive one that uses the same information of observed discharge.

In addition, we use a time criterion to assess the time difference between the observed and forecasted flood events. We are interested in the time-to-peak delay (or the time to a fraction – say 90% – of the peak). Then we considered the mean time-to-peak delay for the floods we identified.

Last, the visual comparison of observed and forecasted hydrographs for significant events will complete our analysis.

3 Methodology

3.1 Modus operandi

Since only the effects of the initialization procedure are to be assessed, we used the same model and the same sets of parameters for the various initialization methods we tested. For each catchment, the model was calibrated by an automatic algorithm in a continuous mode (over a continuous series of 5 years). The PI was used as the objective function for parameter calibration. Even if the effects of the calibration approach (continuous or event-based) are not insignificant for the overall performance of the model (see e.g. Tan et al., 2008), we do not discuss this aspect here for the sake of brevity.

Flood forecasting requires future precipitation scenarios. In real-time conditions, some quantitative precipitation forecasts (QPF) may be available. In our study, we adopted a perfect foreknowledge scenario: this scenario corresponds to observed precipitations for the future time steps. While this is clearly not a realistic scenario in real-time conditions (it is overly optimistic), we selected this approach because we wish to focus the analysis on the effect of the initial conditions without adding other sources of uncertainty.

We used a classical split-sample test scheme (Klemeš, 1986) to assess the model's versions. The complete 10-year record available on every catchment was split into two 5-year sub-periods that alternatively served for calibration and validation. Only the results obtained on validation periods are shown.

Given that different catchments may have very different responses, we assessed our results for 1-, 3-, 6-, 12-, 18-, 24-, 36- and 48-h lead times.

3.2 Tested continuous approach

We first tested the continuous approach: the model runs continuously for 1 year of warm-up (to obtain model states that are independent of the initial conditions) then continuously for the 4-year validation period. A previous analysis of our catchments (not shown here) demonstrated that a year of warming up is sufficient to reach states that no longer depend on the initial values.

3.3 Tested event-based approaches

As the routing store of the selected model is updated using observed flow, the difference between the continuous and event-based approaches lies in the need to initialize the SMA store when working on an event basis. Different simple event-based initializations are tested. For all of them, the performance criteria are computed over the same 4-year validation period so that they can be directly compared to the values obtained by the continuous approach.

3.3.1 Poor-man's initialization

The simplest initialization of the production store level is to choose an arbitrary value and then to run the model on a very short pre-forecast period (5 days) before issuing the forecast. Different values of the SMA store level (zero, one, two and three thirds of its capacity) are tested. This option makes it possible to check that the forecasts are indeed sensitive to the initialization of this store level.

3.3.2 Climatic initialization

The second approach consists in initializing the level of the production store at its pluriannual average value (as calculated on the calibration period, i.e. over 5 years) at the beginning of a very short simulation period preceding the date of the forecast issue. Different simulation period lengths (from 5 to 15 days) are considered.

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3.3.3 Antecedent moisture conditions initialization

The third initialization procedure is more elaborate. It looks in the calibration period archive for the time step that has the most similar antecedent precipitation index value to the API value of the time step t at which we issue the forecast. The API (see e.g. Kohler and Linsley, 1951) is computed as follows:

$$\mathrm{API}(t) = \sum_{i=0}^{N_\alpha} \alpha^i P_{t-i}$$

where α is a decay rate, N_α is the number of antecedent time steps taken into account and P_{t-i} is the precipitation at time step $t-i$. N_α is chosen to ensure that $\alpha^i P_{t-i}$ would be negligible compared to any precipitation P_t. Different values of α from $1\text{–}10^{-1}$ to $1\text{–}10^{-5}$ were tested but not shown here for the sake of simplicity.

4 Results and discussion

4.1 Results on the whole catchment set

First the Poor-man's initialization showed wide performance differences depending on the initial conditions for the tested model and our catchments (Fig. 3). Thus, at the 1-h lead time, the persistence differences for different (arbitrary) initial values are greater than 0.03 (which is a significant difference) on more than 75% of the catchments; for the 48-h lead time, this difference is greater than 0.14 for more than 90% of the catchments.

The results clearly show that the continuous approach gives the best results (see Table 1 and Figs. 4 and 5), and that the longer the lead time, the greater the difference in performance. Our interpretation is the following: model states do not reflect reality directly but are distorted images of the real world as seen by the model. It is a better choice to initialize the model states as if they were seen from a given reality (continuous approaches) by the model rather than to impose measurements that do not correspond to the model internal's logic. These results can be compared to those presented by Merz and Blöschl (2009) and Anctil et al. (2004a): antecedent soil moisture is a better control on the runoff coefficient ratio than antecedent precipitation depth and the state of a conceptual rainfall-runoff model can give valuable information on catchment moisture state.

The model has small time-to-peak errors: even for a 48-h lead time, the time-to-peak errors of the model on more than 90% of the catchments are smaller than 5 h. No significant difference in time-to-peak errors can be noted, whatever initialization method is considered. Event-based initialization can even lead to very slightly smaller time-to-peak error than the continuous approach. Using an example (Tarn River at Millau, spring 2004 floods, Fig. 6c), we can see that the different initializations lead to very different discharge magnitudes, but they all have the same temporal behaviour.

As expected, the event-based initialization strategies lead to poorer forecasting performances. However the good news (from an operational point of view) is that the performance loss due to the use of a simple event-based initialization strategy is not large for most catchments (see Figs. 4 and 5).

The event-based initialization strategies we tested ranked in a quite logical manner: the best one is not surprisingly the API method, which is the most informative approach (concerning the catchment initial moisture conditions). Then comes the climatic solution, which provides little information and the strategy which leads to the lowest performances is the Poor-man's approach.

4.2 Use of a pre-forecast period: a compromise approach?

Actually, many so called event-based approaches are not purely event-based since they use a short pre-forecast period on which the model is run before issuing the forecast. Many event-based approaches consider initial conditions to be parameters; this requires pre-forecast period data to calibrate the initial conditions: these models can not really be considered purely event-based. Thus, some modellers, e.g. Merz and Bárdossy (1998) and Sheikh et al. (2009), chose to use an inter-event model to initialize the most sensitive states. Another example is given by Anctil et al. (2004a), who used artificial neural networks (ANN) for flow forecasting on two catchments: they showed that a long-term soil moisture index derived from a continuous model is a valuable input which improves forecasts. Here again the resulting models are not purely event-based: they belong to a continuum between event-based and continuous models.

In this paper, our initialization strategies also use a short pre-forecast period to come closer to a continuous approach: the initial conditions obtained are a mix of assumptions implied by the initial choice and of the model's internal representation of the catchment behaviour.

In the strategies tested, this pre-forecast period lasts at least the length of the UH (to obtain proper values in the UH) and was tested up to 15 days. It is clear for all event-based initializations that the longer the pre-forecast period, the better the performance was (Fig. 7). For the climatic initialization, a pre-forecast period of 5 days leads to performance that is significantly lower than the performance obtained with a continuous initialization. However, a 15-day pre-forecast period allows performances close to what is given by the continuous approach (see Table 2).

4.3 Do results depend on catchment size?

Figure 8 shows the difference in performances obtained by the same model running in continuous mode and in event-based mode (with climatic initialization) depending on the catchment area. No clear trend can be detected from these analyses. It is interesting to note that the model's performance does not decrease as the catchment size increases: the catchment behaves as a low-pass filter (Oudin et al., 2005) and as the catchment size increases, forecasting in fact becomes an easier task.

4.4 Do results depend on catchment reactivity?

We found no relationship between catchment response time and the impact of choosing a continuous or an event-based strategy. Figure 9 shows the difference in performances obtained by the same model running in continuous mode and in event-based mode (with climatic initialization) depending on the catchments discharge autocorrelation. No trend was detected from these analyses.

4.5 Impacts of the updating procedure

When used to issue discharge forecasts, hydrological models are most often updated (Refsgaard, 1997). In practice, this means that the discharge forecast no longer depends on forcing variables only (e.g. precipitation, evapotranspiration, etc.) but also on the information contributed by the data assimilation process. The discharge forecast is constrained by data assimilation and consequently it may depend (much) less on the internal states and so on their initialization.

We used the GRP model with and without updating techniques to compare the influence of initialization of the model's SMA store (which is never updated) on forecasts in both cases. Figure 6 shows an example of spring floods for the Tarn River at Millau (2170 km^2). We chose different initial production store levels from 0 (empty store) to its maximum capacity A (full store). From those initial values, the production store levels converge slowly; convergence is mostly achieved during showers (Fig. 6a, b). The differences in production store levels lead to dramatic differences in discharge forecasts when no updating technique is applied (Fig. 6c), whereas the 6-h forecasts are much more constrained with data assimilation (Fig. 6d).

Thus, the updating procedure used in forecasting models does limit the impact of crude initialization procedures, in comparison with simulation models: this explains why a rather simple procedure with a short pre-forecast period gives results close to those obtained when using a continuous initialization.

5 Synthesis and conclusions

Initial conditions are known to be of crucial importance for hydrological models. In this paper, we compared different initialization strategies of the soil moisture component of a rainfall-runoff forecasting model. The continuous mode was compared to several event-based approaches for the same model. As expected, the best results were obtained when the model was run in a continuous mode. This corroborates the results of previous studies (e.g., Anctil et al., 2004b). However, we showed that one of our tested initialization strategies could lead to performances close to what is obtained with the continuous approach.

Indeed, the sensitivity of the model outputs in forecasting mode is much lower than the sensitivity of the model in simulation mode (i.e. with no updating through the assimilation of measured streamflow): the output is considerably constrained by the information contributed during the assimilation process, which partly compensates for the errors in initial values.

Given the large and varied data set used here, we believe that these results are not catchment-dependent (in particular we found no relation to catchment size or reactivity). The results may remain to some extent model-dependent. However, we expect that the behaviours observed can also be found for many forecasting models, since they all have to use efficient data assimilation.

The loss in performance when running the model using event-based strategies is not substantial: indeed, in most cases, the difference is not really significant. This means that if an efficient assimilation of last observed streamflow is possible, event-based strategies can be efficiently used for operational purposes when and where it is impossible to run a model continuously.

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Table 1. Medians of persistence index values obtained using the GRP model on the 178 catchment set with different initialization approaches for 1-, 6-, 24- and 48-h lead times.

Initialization	1-h lead time	6-h lead time	24-h lead time	48-h lead time
Continuous	*0.58*	*0.45*	*0.63*	*0.70*
Best Poor man's	0.56	0.40	0.50	0.64
Best climatic	0.57	0.44	0.61	0.67
Best API-based	0.58	0.45	0.62	0.68

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Table 2. Medians of persistence index values obtained by the selected model with the climatic initialization approach using pre-forecast period of different lengths for 1-, 6-, 24- and 48-h lead times. HU length ranges from 1 to 64 h depending on the catchment.

Pre-forecast length	1-h lead time	6-h lead time	24-h lead time	48-h lead time
HU length	0.57	0.42	0.57	0.64
5 days	0.57	0.44	0.59	0.65
10 days	0.57	0.44	0.61	0.66
15 days	0.57	0.43	0.60	0.67
Continuous	*0.58*	*0.45*	*0.63*	*0.70*

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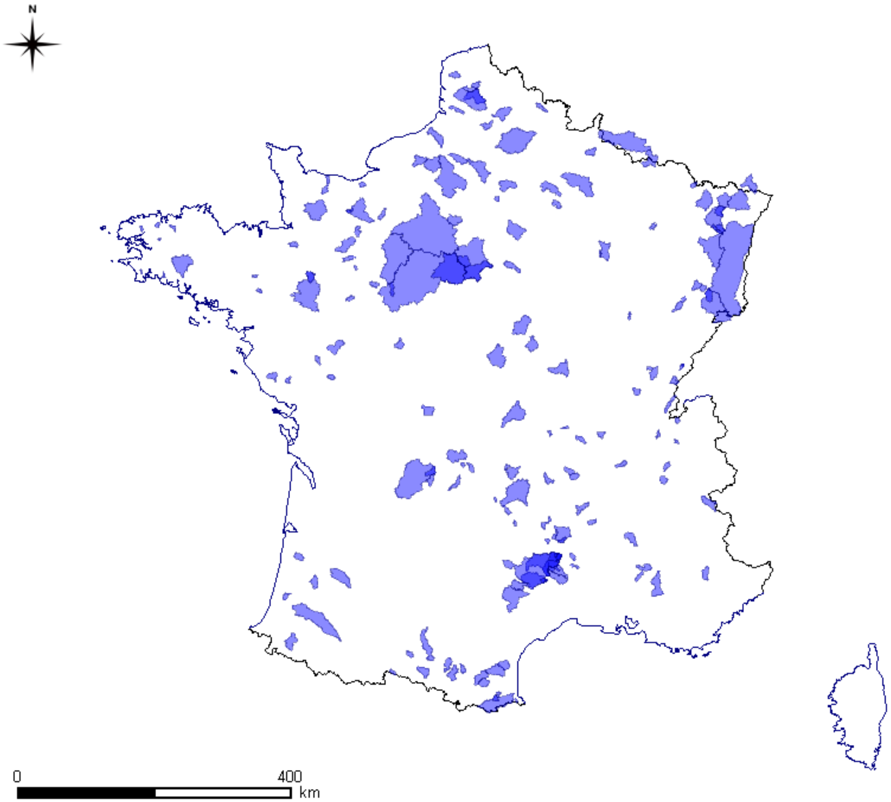

Fig. 1. Locations of the 178 French catchments used in this study.

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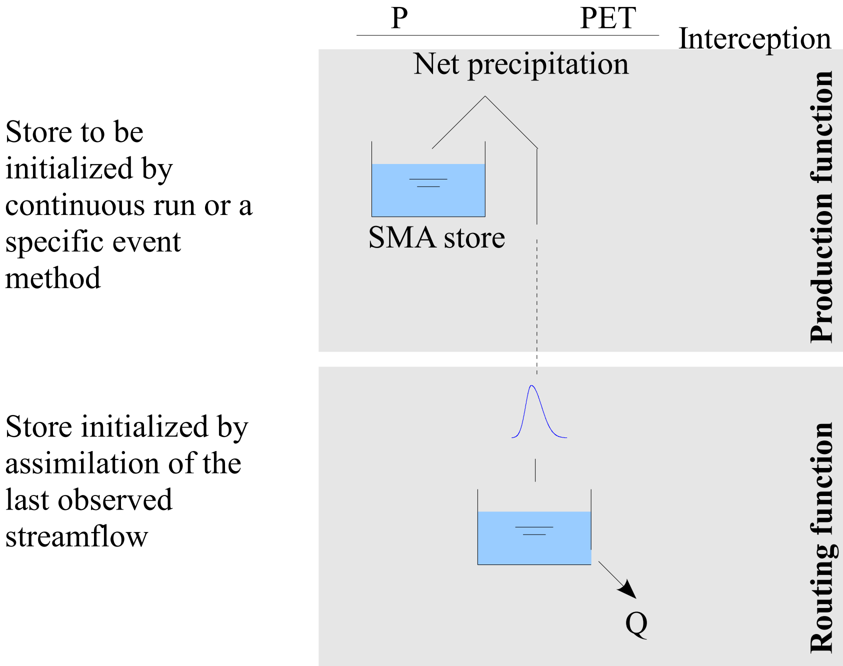

Fig. 2. Simplified structure of GRP model showing the role of the SMA store in the production function. This model structure is updated when used in forecasting mode.

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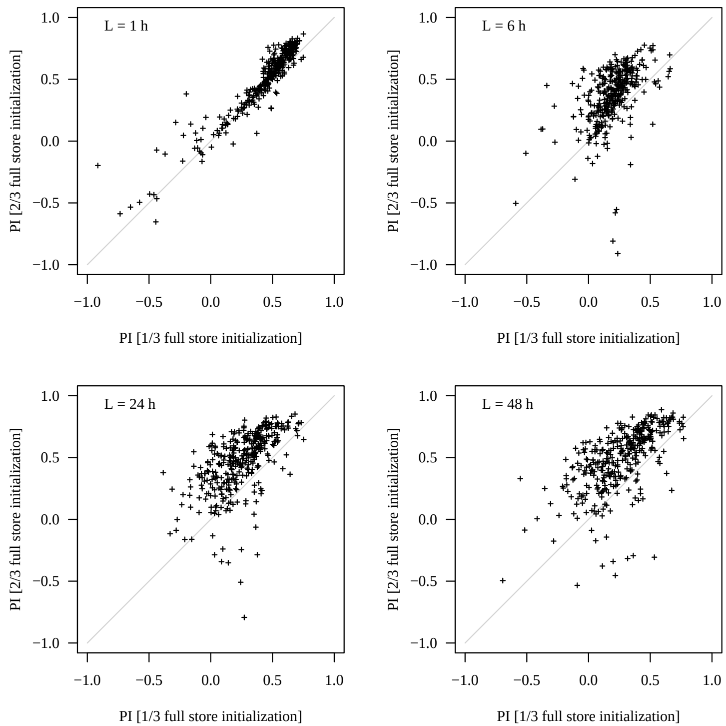

Fig. 3. Persistence indexes for two Poor-man's initializations at different initial values: the level of the SMA store is initially set at one-third or two-thirds of its capacity. Different initializations lead to very different performances.

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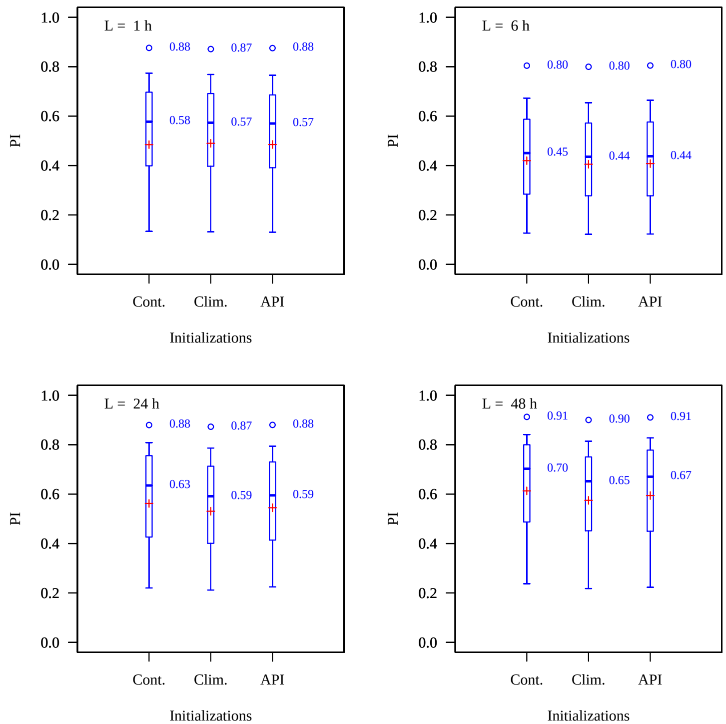

Fig. 4. Performance (persistence index) obtained by the model on 178 catchments, according to the initialization modes: the continuous strategy is depicted on the left and two event-based strategies (climatic and API strategies) are on the depicted right. The results are displayed for lead times ranging from 1 to 48 h. The pre-forecast period for event-based strategies lasts 120 h (5 days). Boxplots give minimum and maximum values (dots) as well as 0.05 and 0.95 quantiles (whiskers), 0.25, 0.50, 0.75 quantiles (boxes). Mean values are indicated by crosses.

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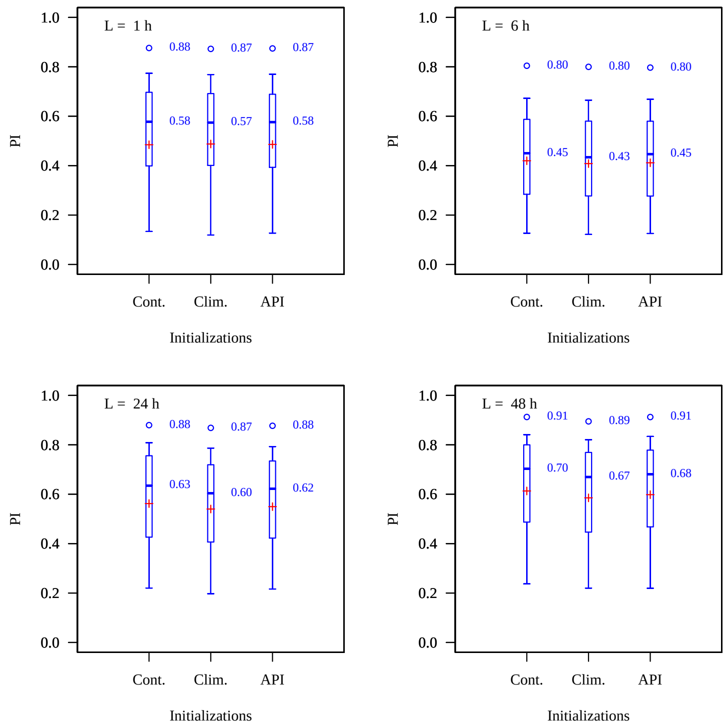

Fig. 5. Performance (persistence index) obtained by the model on 178 catchments, according to the initialization modes: continuous or event-based (climatic and API) strategies with a pre-forecast period lasting 360 h. Results are displayed for lead times ranging from 1 to 48 h.

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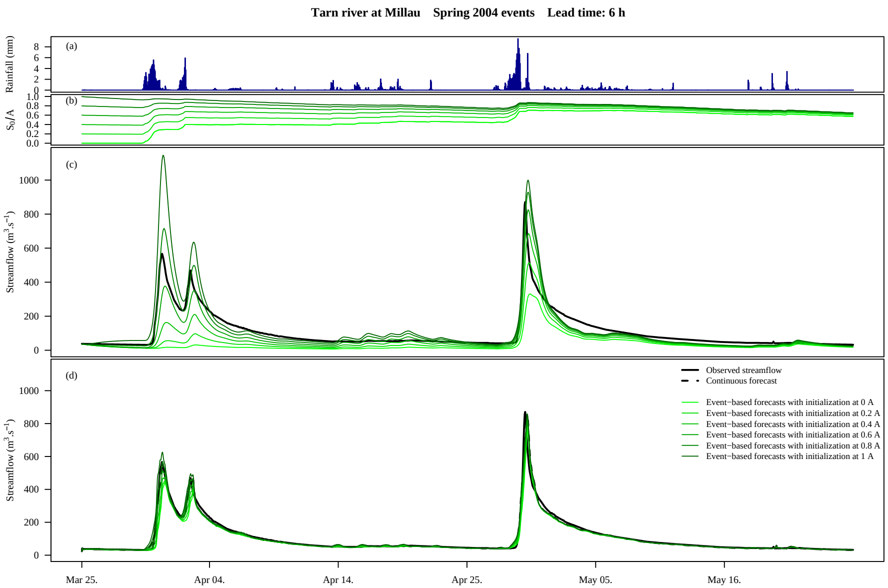

Fig. 6. **(a)** Precipitation during spring 2004 events. **(b)** Changes in the production store level after its initialization at different values on the 25 March 2004: there is convergence mainly during showers. Different initializations lead to very different forecasts when no updating technique is applied **(c)**, whereas forecasts depend much less on the initial production store content when the model is updated **(d)**.

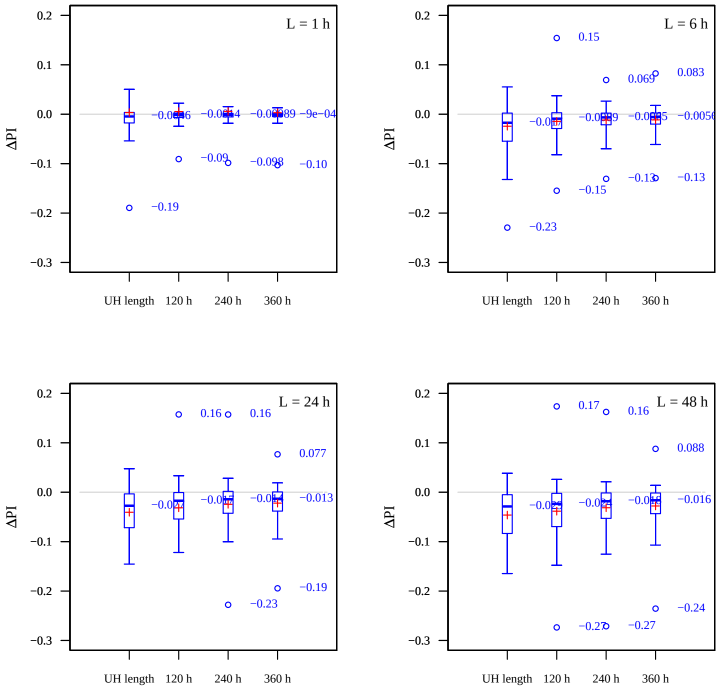

Fig. 7. Differences between the performance (persistence index) obtained by the model on 178 catchments in continuous mode and using an event-based climatic initialization, according to the pre-forecast period length: the longer the pre-forecast period, the smaller the differences.

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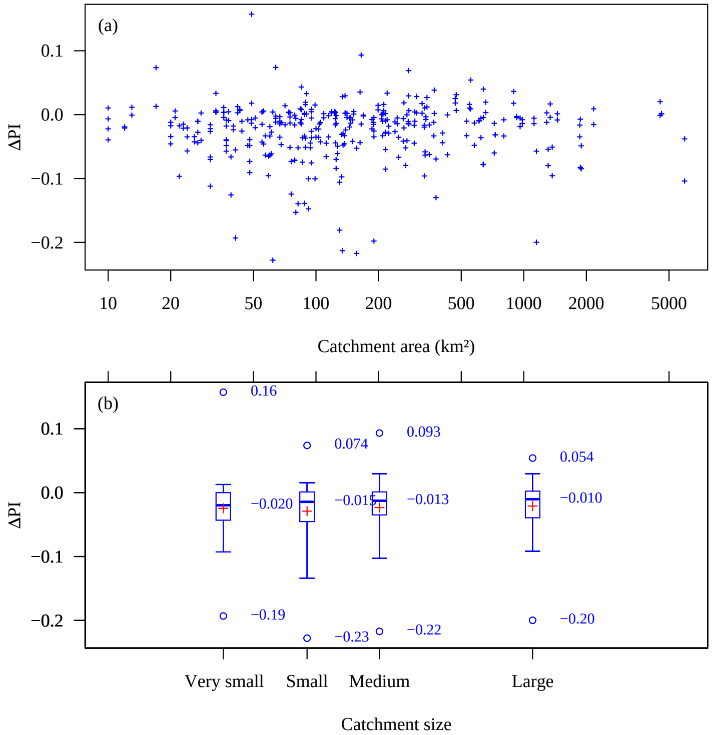

Fig. 8. Differences between the performance (persistence index) obtained by the model on 178 catchments in continuous mode and using an event-based climatic initialization approach, depending on the catchments' areas **(a)**. Here lead time is 6 h. The pre-forecast period for the event-based strategy lasts 240 h. Four classes of catchments are defined: the first class groups the 25% smallest catchments, the second class, the following 25%, etc. Distributions of the difference in performance for every class are displayed **(b)**.

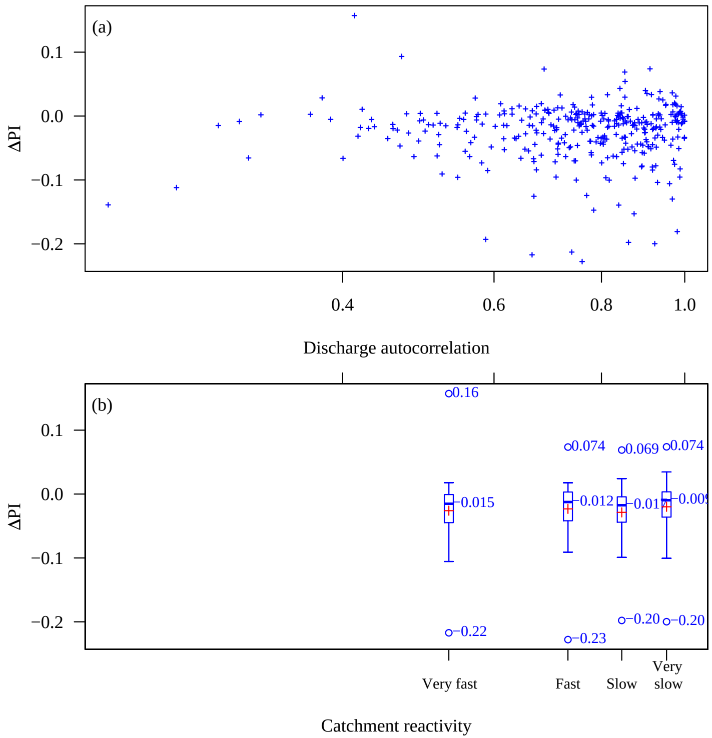

Fig. 9. Differences between the performance (persistence index) obtained by the model on 178 catchments in continuous mode and using an event-based climatic initialization approach, depending on the discharge autocorrelation **(a)**. Here the lead time is 6 h. The pre-forecast period for the event-based strategy lasts 240 h. Four classes of catchments are defined: the first class groups the 25% of catchments with the lowest discharge autocorrelation, the second class, the following 25%, etc. Distributions of the difference in performance for every class are displayed **(b)**.