Using weather radar measurements for real-time river flow forecasting

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1 Introduction

This paper deals with the HYDROMAX real-time riverflow prediction system which has been developped by CESAME (Belgium) and is in permanent operation from 1995. HYDROMAX is based on a lumped grey-box rainfall-runoff model that requires only on-line rainfall and flow measurements in order to compute the riverflow predictions (Dalcin et al. 2003).

The goal of the paper is to give a systematic comparison of the HYDROMAX performance when alternative estimations of the average rainfall over a river basin are used as model inputs : estimations from pointwise rain-gauge measurements, estimations from raw weather radar measurements and estimations obtained by combining both measurement systems using geostatistical methods.

The analysis relies on application results on two river basins, tributaries of the Meuse river, in the Walloon part of Belgium (see Fig. 1) : the Ourthe catchment at Tabreux (1608 square kilometers) and the Semois catchment at Membre (1229 square kilometers). The rain-gauge measurements are given by an automatic network operated in real-time by MET/DVGH. The radar measurements are provided by the Royal Meteorological Institute (RMI) of Belgium, which operates a C-band radar, located in Wideumont in the south of Belgium.

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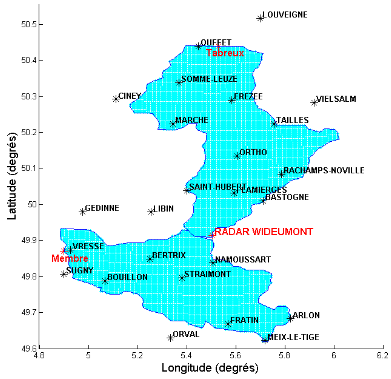

Fig. 1. Ourthe (top area) and Semois (bottom area) watersheds. Rain gauge covering the basins are represented by stars. The Wideumont radar is also represented.

2 Rainfall-runoff model

As mentionned before, the rainfall-runoff model is a lumped grey-box model. The input of the model is the hourly mean areal rainfall over the considered river basin $\Omega \subset \mathbb{R}^2$.

$$PB(k) = \frac{1}{|\Omega|} \int_{\Omega} P(\mathbf{u}, k) d\mathbf{u} \tag{1}$$

where $P(\mathbf{u}, k)$ is the hourly rainfall depth at location $\mathbf{u} \in \mathbb{R}^2$ during hour indexed by k. The model is then decomposed in two parts.

The first one is a deterministic non-linear function which computes the effective rainfall $PN(k)$, defined as the fraction of $PB(k)$ which runs off directly towards the river and contri-

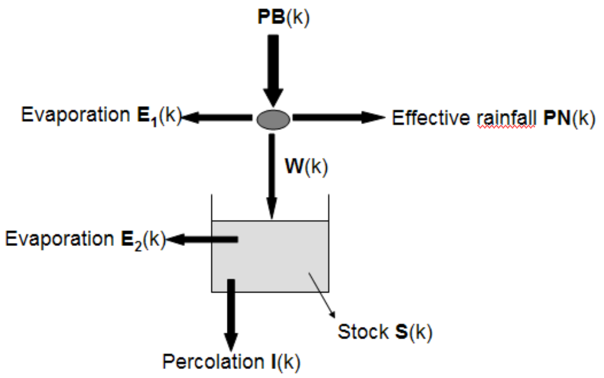

Fig. 2. Conceptual scheme of the effective rainfall production function

butes thus to the increase of the river flow.

$$PN(k) = PB(k) - E_1(k) - W(k) \quad (2)$$

where $E_1(k)$ denotes the part of $PB(k)$ which directly evaporates during the hour k and $W(k)$ represents the amount of water which is stored in the basin under various forms : vegetation interception, superficial depressions, soil moisture.

The watershed is seen as a water reservoir (see figure 2). The state model describing the evolution of the storage of the water $S(k)$ in the basin is :

$$S(k) = S(k-1) + W(k) - I(k) - E_2(k) \quad (3)$$

where $I(k)$ is the amount of water drained by percolation and $E_2(k)$ is the part of water which evapotranspirates during hour k. Percolation $I(k)$ is represented by a linear function of the available stock :

$$I(k) = \alpha\,(S(k-1) + W(k)) \quad (4)$$

where α is a specific percolation parameter. The evapotranspiration terms are :

$$E_1(k) = \min(PB(k), ETP(k)) \quad (5)$$

$$E_2(k) = \max(0, \min(ETP(k) - PB(k), S(k-1) + W(k) - I(k))) \quad (6)$$

where $ETP(k)$ is an estimate of the seasonal potential evapotranspiration for the considered basin. We further assume that the basin stock has an upper limit, denoted S_{max}. The last term, $W(k)$, is represented by :

$$W(k) = (S_{max} - S(k-1))\left(1 - \exp\left(-\beta\frac{PB(k) - E_1(k)}{S_{max} - S(k-1)}\right)\right) \quad (7)$$

This ensures that the stock $S(k)$ is comprised between 0 and S_{max} and that the effective rainfall $PN(k)$ increases when $PB(k)$ and/or $S(k)$ increase. The three considered parameters (α, β and S_{max}) are positive parameters. In addition, β needs to be lower or equal to 1 in order to ensure that $PN(k)$ is positive. It is clear that these three parameters are different for each river basin. They must thus be calibrated with experimental data for each watershed.

The second part of the model is a stochastic linear model (ARX type). At time step k, it computes a flow prediction $\widehat{Q}(k+h)$, with h the prediction horizon, as a linear combination of present and past river flow measurements and effective rainfall values available at time k.

$$\widehat{Q}(k+h) = \sum_{i=1}^{n_a} a_i Q(k-(i-1)h) + \sum_{j=1}^{n_b} b_j PN_h(k-(j-1)h) \quad (8)$$

where $Q(k-(i-1)h)$ is the flow measure at time $k-(i-1)h$ and $PN_h(k-(j-1)h)$ represents the effective rain cumulated over h time steps from $k - jh + 1$ to $k - (j-1)h$. The dimensions n_a, n_b and the parameters a_i and b_j are determined by using standard identification methods. It should be noted that the prediction horizon must be smaller than the natural response time of the river basin.

3 Rainfall measurements systems

To run the model described above, we need to have the input $PB(k)$ at each time step. But this signal is not directly available. We need to estimate it from rainfall measurements provided by a rain gauge network or by a weather radar.

Rain gauges provide accurate pointwise measures of the precipitation field. Unfortunately rain gauges are usually quite scattered in an area of the size of a watershed. For the two basins we studied, we had one rain gauge for 176 km^2 and for 179 km^2. This low density may prevent from detecting correctly the spatial variability of the precipitation field (see figure 3). In this study, rain gauge measurements are provided by an automatic network operated in real-time by MET/DVGH which gives cumulated hourly precipitation data.

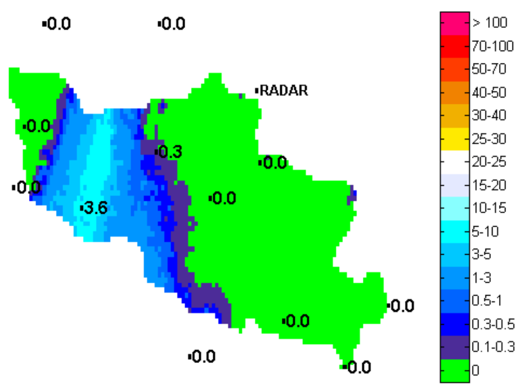

Fig. 3. Semois watershed at Membre : hourly radar rainfall (in [mm/h]) in grey and values at several rain gauge (1/5/2002 at 21 pm).

Weather radars are able to detect precipitation and to provide rainfall estimates. The main asset of this device is the spatial and temporal resolution it allows. Indeed, the Wideumont weather radar, operated by RMI, gives measurements every five minutes with a spatial resolution of less than one square kilometer. We can thus obtain a good measure of the precipitation field spatial variabilty. However, quantitative measures provided by the radar may be rather bad since they are affected by a lot of error sources whose the main one is the non-uniformity of the vertical profile of reflectivity.

Both measurement systems seem to have complementary advantages. Combining them should produce better precipitation estimates. A comparison between different merging methods to estimate 24h pointwise precipitation accumulation is presented in Delobbe et al. 2008.

4 Results

Two river basins are used to compare our methods : the Ourthe catchment at Tabreux (1608 square kilometers) and the Semois catchment at Membre (1229 square kilometers). The considered identification period is twenty months long, from 1st May 2002 to 31st December 2003. The same period is used for the comparison of methods. To generate hourly radar data accumulations, we simply sum all five-minutes radar data images over one hour.

We are mainly interested in comparing the flow prediction accuracy obtained with two different mean areal rainfall estimators. The first one is the ordinary kriging estimator, PB_{OK}, which is based on rain gauge measurements only. Ordinary kriging is a geostatistical method which gives an optimal unbiased estimator. It is assumed that the rainfall (random) field is homogeneous (spatially stationnary). The HYDROMAX real-time riverflow prediction system has used this estimator from 1995. The second estimator, PB_{RR}, is simply obtained by averaging the raw radar data over the whole watershed.

Figure 4 gives an example showing that both mean areal rainfall estimators may give very different results. The two estimations are clearly quantitatively different with an obvious underestimation of the mean areal rainfall from the radar data.

The criterion we use to identify the flow prediction model parameters and compare the precision of flow predictions is the mean square error, $MSE = \frac{1}{K}\sum_{k=1}^{K}(Q(k) - \widehat{Q}(k))^2$ where K is the number of time steps we use for the comparison (14638 hours in our analysis).

The identification has been carried out for each of these two methods and for each river basin. Figure 5 shows the criterion MSE in function of the number of parameters in the ARX model for both methods and for both watersheds. Although the estimates may be rather different (Fig. 4), we see that rain gauge estimators (OK) and raw radar estimators (RR) give a similar prediction accuracy, whatever the number N of parameters. For the Semois river basin, raw radar predictions are a bit less precise than rain gauge predictions while for the Ourthe catchment, they are slightly better (the MSE values can be found in table 1).

The fact that the bias which affects the raw radar measurements has a negligible impact on the accuracy of the river flow predictions can be explained as follows. During flood periods, the rainfall-runoff system can be considered as being almost linear and the flow prediction model approximately reduces

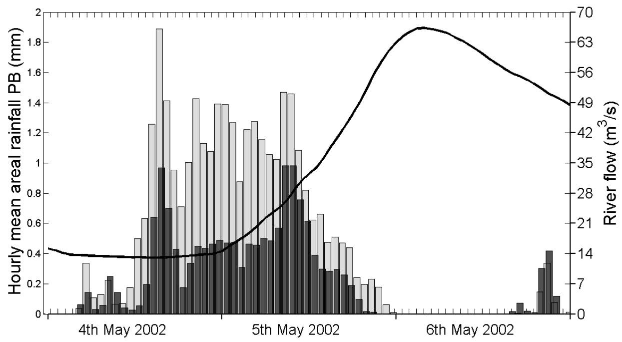

Fig. 4. Mean areal rainfall (in mm) estimated by the radar (dark gray bars) and by 14 rain gauges (light gray bars), for the Ourthe watershed at tabreux, from 4^{th} May 2002 to 6^{th} May 2002. The continous black line represents the measured river flow (in m^3/s).

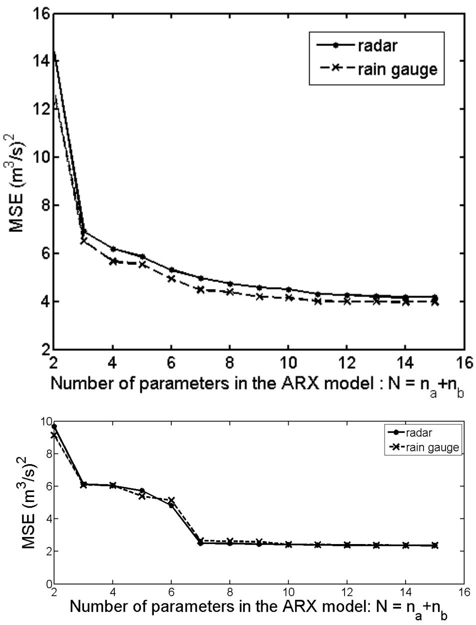

Fig. 5. Semois (top) and Ourthe (bottom) watersheds : mean square error (MSE) of flow prediction in function of the number N of model ARX parameters, for the raw radar (RR) input and the rain gauge estimator (OK).

Table 1. Mean square error (MSE) of the flow prediction for different model input estimators.

	Mean square error MSE $(m^3/s)^2$	
Model input	Ourthe (Tabreux)	Semois (Membre)
OK	2.542	4.346
RR	2.490	4.583

to :

$$\widehat{Q}(k+1) = \sum_{i=1}^{n_a} a_i Q(k-i+1) + \sum_{j=1}^{n_b} b_j PB_t(k-j+1) \quad (9)$$

The parameters a_i and b_i are estimated by minimizing the MSE from experimental data of $Q(k)$ and the areal rainfall estimates PB_{OK} and PB_{RR} obtained from rain gauge and radar measures respectively (for each choice of the dimensions n_a and n_b).

Assuming that the raw radar mean areal rainfall is biased by a factor "b" : "$PB_R(k) = bPB_t(k)$", it is clear that a linear least square estimation will produce the same predictions "$\widehat{Q}(k+1)$" with both sets of data (obviously with the parameter b_i scaled by the bias factor "b").

Furthermore, by artificially varying the bias b between 0.2 and 8 for the twenty months identification period, we see in Fig. 6 that the prediction accuracy is nearly not affected by factor b. The same effect is observed for the Semois watershed. It is due to the adaptation of the parameters of the non linear part of the model which are identified separately for each different value of b (see Leclercq et al. 2008 for further details).

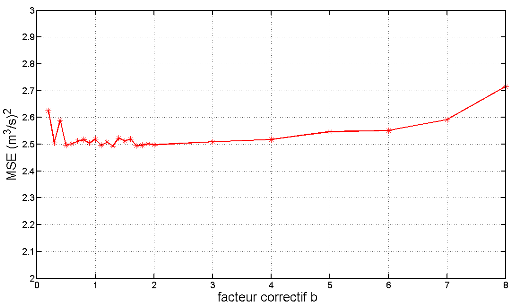

Fig. 6. Mean square error (MSE) of flow prediction for the Ourthe catchment in function of the artificial bias b.

Another interesting fact is that the correlation between both mean areal rainfall estimators (see Leclercq et al. 2008) is much higher and less noisy than the correlation between the pointwise precipitation measures (see table 2).

We also compared the flow predictions when using a few merging methods which combine radar and rain gauge measurements. For the identified period and for both basins, we did not find any significant improvement by using one merging method or another.

Table 2. First row : correlation coefficients between pointwise radar and rain gauge data (for both basins). Second row : correlation coefficients between mean areal radar (PB_{RR}) and rain gauge (PB_{GG}) estimators (for both basins)

	correlation coefficient	
Type	Ourthe (Tabreux)	Semois (Membre)
pointwise	0.70	0.73
mean areal	0.84	0.83

5 Conclusion

Two mean areal rainfall estimators (one from rain gauge measurements only, one from raw radar data) were compared in their ability to yield accurate river flow predictions. It turns out that the flow predictions are almost not affected by the measurement bias which is known to be significative for raw radar measurements. This is due to the adaptation of the model parameters which are identified separately for each estimation method. We show that the predictions obtained with both types of measurements have the same level of accuracy despite the fact that quantitative radar measurements are much less accurate than rain gauge measurements. It is also shown that the lumped grey box rainfall-runoff model we use is unable to take advantage of the better mean areal rainfall estimates given by merging radar and rain gauge measurements.

However, these results need to be confirmed on a longer time period including several flood episods and with a validation period different from the identification period. Furthermore the reader should be aware that the radar bias b is not constant in time but may vary drastically from one day to another. Maybe the good prediction results we obtain with raw radar data are due to the fact that there are only two (resp. one) major flood events occuring during the twenty months period in the Semois (resp. Ourthe) watershed.

References

Dalcin, C., L. Moens, P. Dierickx, G. Bastin and Y. Zech, 2005 : An integrated approach for realtime floodmap forecasting on the belgian Meuse river. *Natural Hazards*, **36**, 237–256

Delobbe, L., G. Bastin, P. Dierickx, E. Goudenhoofdt, G. Leclercq, L. Moens and M. Thunus, 2008 : Evaluation of several radar rain-gauge merging techniques for operational use in the Walloon regio of Belgium, *Proceedings of WraH 2008*.

Leclercq, G., G. Bastin, L. Moens, L. Delobbe, P. Dierickx and M. Thunus, 2008 : Using weather radar measurements for real-time river flow forecasting, *paper in preparation*.