

P154 A RADAR – BASED FLASH FLOOD MODELING SYSTEM FOR THE LLOBREGAT RIVER BASIN IN THE CATALONIA REGION (SPAIN)

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1. INTRODUCTION

Flash flood forecasting is one of the most important challenges in hydrological sciences nowadays. Providing alerts with an adequate anticipation time on the occurrence of flash flood events mitigates its impact and brings enormous social and economical benefits. Mediterranean catchments are especially vulnerable to the occurrence of flash flood events, due to the steep slopes and the considerable volume of runoff draining along the impermeable surface of the catchment (Drobot and Parker, 2007; Sempere-Torres, 2007).

In this research paper, a flash flood modeling system implemented in a Mediterranean river basin is presented. Radar precipitation estimation along with hydrological modeling techniques are implemented within the system for simulating the runoff generation and routing processes occurring in the catchment.

However, there exists an uncertainty related with the estimation of radar precipitation (Zawadzki, 1984) and from model calibration (Beven, 2006). Such uncertainty is propagated to the resulting discharge simulations.

The aim of this research paper is to propose a methodology to analyze the propagation of uncertainty occurring at the different processes of the modeling system. For this purpose, a Monte Carlo simulation approach is used to consider the uncertainty arising from rainfall and model parameter estimation.

2. STUDY AREA AND DATA SETS

The study area is the Llobregat basin, with an area of 4948 km² located in the region of Catalunya, in the North-East of Spain. The river has its source in the Pyrenees Mountains at 1295 m.a.s.l, draining in south direction up to the Mediterranean sea at the town of Prat de Llobregat.

A network of weather radars operated by the Catalan meteorological service covers the whole domain of the catchment. It is equipped with a dense raingauge and streamgauge network, providing real-time information of hydrometeorological data.

The average annual rainfall over the catchment is about 670 mm, measured runoff is about 140 mm, potential evapotranspiration is about 750 mm and actual evapotranspiration is about 530 mm (ACA,

2002). The discharge regime is affected by the effect of three reservoirs located inside the catchment.

For the purpose of this study, a smaller subbasin, the Anoia river catchment (with a surface of 730 km²) has been selected.

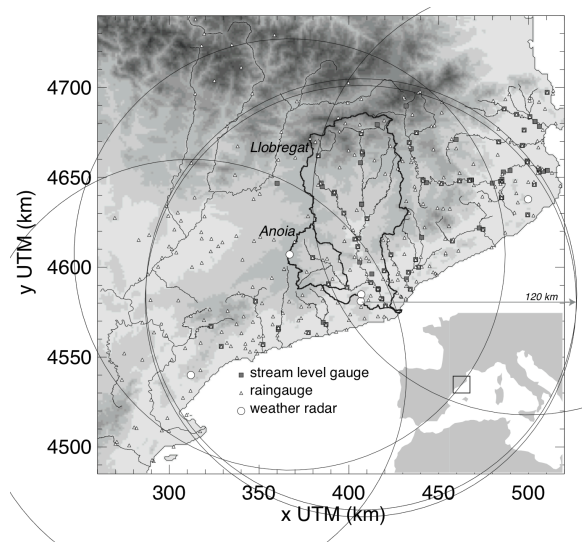


Figure 1: The study area including the weather radar, raingauges and streamgauges location.

Five rainfall-runoff events have been selected to perform this study. Table 1 shows the characteristics of these events. A window of 120 hours is considered for all the events. Four of them have been selected for the calibration process (10 June 2000, 8 October 2002, 11 September 2006, 9 October 2010) and one has been considered for validation (2 April 2007).

Table 1: Characteristics of the flow events used in this study. Validation event is marked with *

Date	Peak flow [m ³ s ⁻¹]	Mean areal rainfall [mm]
10/06/2000	95	122
08/10/2002	62	64
11/09/2006	65	55
02/04/2007*	38	79
09/10/2010	140	65

3. IMPLEMENTATION

3.1. The distributed hydrological model DiChiTop

The distributed hydrological model DiChiTop (Corral, 2004) is applied in this work. This model differentiates the runoff production processes in rural and urban areas. For the rural areas, an adaptation of the loss function of Topmodel (Beven, 1979) is

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considered. The runoff generation in urban areas is analyzed using the loss function of SCS model (Mockus, 1959). The runoff propagation is modeled using a simplified Muskingum scheme (Szymkiewicz, 2002) that differentiates the parameterization of flow velocity in hillslope and river cells.

DiCHitop model has been used in the past to study the hydrological behavior of Mediterranean catchments. Recently, the model has been adapted into an operational context as the basis for the GenHi platform, an operational flash flood forecasting system implemented in the Catalan Water Agency (Corral et al., 2009).

So far, all these implementations of the model have been developed in a deterministic framework. In this research, an attempt to consider the propagation of the uncertainty affecting the chain of processes of hydrological simulations is presented.

3.2. Consideration of rainfall estimation uncertainty

The propagation of errors affecting radar rainfall estimates to runoff simulations is considered through the ensemble approach proposed by Llorc et al. (2008).

In this method, the error field of rainfall estimates $E(t)$ is characterized as the ratio between a reference rainfall field $R_{ref}(t)$, which is the best rainfall estimation available, and the observed rainfall $R_{obs}(t)$ in logarithmic units as:

$$E(t) = 10 \cdot \text{Log}_{10} \frac{R_{ref}(t)}{R_{obs}(t)} \quad (1)$$

The mean of the error field $\mu(t)$, the standard deviation $\sigma(t)$ and a parameter related with the spatial autocorrelation of the field $\beta(t)$, are calculated at each time step t of the event, and then mean parameters ($\bar{\mu}$, $\bar{\sigma}$ and $\bar{\beta}$) are derived for the entire event.

An ensemble of rainfall estimates $\varepsilon^i(t)$ is generated with:

$$\varepsilon^i(t) = R_{obs}(t) \cdot 10^{\frac{\delta^i(t)}{10}} \quad (2)$$

where using a stochastic process, one can generate as many perturbation fields $\delta^i(t)$ as needed with identical statistical properties (i.e. imposing the values of $\bar{\mu}$, $\bar{\sigma}$ and $\bar{\beta}$), producing an ensemble that is representative of uncertainty in quantitative radar rainfall estimation.

3.3. Consideration of parameter estimation uncertainty

The uncertainty derived from parameter estimation is considered using the Generalized Likelihood Uncertainty Estimation method GLUE,

(Beven and Binley, 1992). This method is widely accepted because it is easy to be understood and implemented using formal Bayesian statistical procedures (Romanowicz and Beven, 1998; Beven and Freer, 2001) or using non-formal likelihood measures (Beven and Binley, 1992).

In order to implement the GLUE methodology, a total of 5000 parameter sets are produced from uniform distributions defined in ranges for each parameter shown in Table 2. It is necessary to define a likelihood function and a threshold value for the selection of the acceptable parameter sets. The Nash efficiency coefficient (Nash and Sutcliffe, 1970) is selected as the likelihood function for the evaluation of the simulation results, and a threshold value of 0.5 is applied. In consequence, those parameter sets producing values lower than 0.5 in the Nash efficiency are rejected from the acceptable parameter sets.

Table 2: Feasible range values of the parameters from DiCHitop model.

Symbol	Parameter name	Units	Min	Max
V_v	Velocity of flow in hillslope	[m min ⁻¹]	5	40
V_r	Velocity of flow in river	[m min ⁻¹]	80	240
m	Exponential variation of transmissivity	[m]	0	0.1
T_0	Horizontal transmissivity	[ln(m ² h ⁻¹)]	-1	4
$F.S$	Correction factor for curve number	[-]	0	0.85

4. RESULTS

4.1. Calibration process

A calibration procedure based in GLUE has been applied on the events from Table 1. The resulting distribution of model parameters has been obtained and the results are shown in Figure 2.

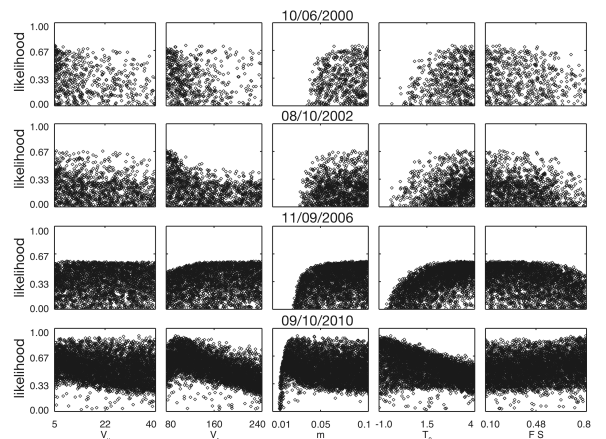


Figure 2: Nash efficiency values obtained for the evaluated parameter sets on each calibration event.

From this figure, one can see that for independent events, multiple parameter sets produce simulations with Nash values larger than the acceptance threshold values. The shape of the distribution of the parameters is uniform during all the

cases. Thus, it can be seen that there is not a clear identifiability of the model parameters.

The likelihood values obtained for each model parameter are updated using the GLUE method, and only ten parameter sets have been found to produce acceptable simulations for all the calibration events. The acceptable parameters for all the events are shown in Figure 3. These parameter sets are used to produce the confidence limits for the simulations.

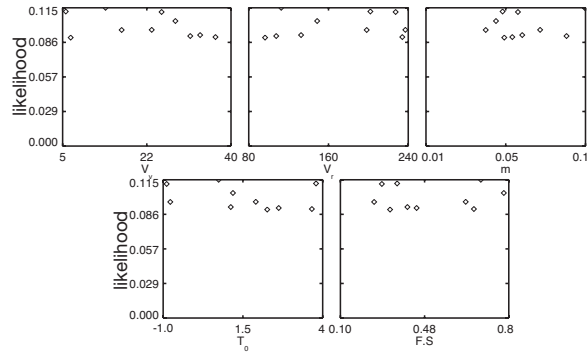


Figure 3: Acceptable parameter sets for all the calibration events obtained after updating the likelihood values using the GLUE method.

In Figure 4, one can see the results obtained in the four calibration events. During the 10 June 2000 event the model has a good performance. Lower performance is obtained during the simulations of the 08 October 2002 event. For the other events the results are acceptable. In all the events the model estimates accurately the observed time peak. However, it is not able to reproduce the magnitude of the peak value, except in the 10 June 2000 event.

4.2. Validation process

4.2.1. Propagation of parameter estimation uncertainty

The ten acceptable model parameters found during the calibration procedure have been used to configure the model for the validation event. In order to evaluate the effect of the model parameters, the ten acceptable sets are evaluated using the observed radar rainfall as meteorological input to the model. With the aim of comparing the results obtained in the simulations, a reference simulation is produced using the observed radar rainfall precipitation as input to the model and the optimal model parameter set as configuration of the model. The spread of the obtained simulations is representative of the uncertainty derived from parameter estimation. The results of these simulations are shown in Figure 5. Different model parameters produce different results in the behavior of the peak flow, time peak and recession curve. None of the simulations has been able to reproduce accurately the behavior of the observed flow. However the spread of the simulations contains almost every time step to the observed flow. The deviation between the observed and simulated discharges can be explained by errors in the model structure or errors in the time series of the observed discharge.

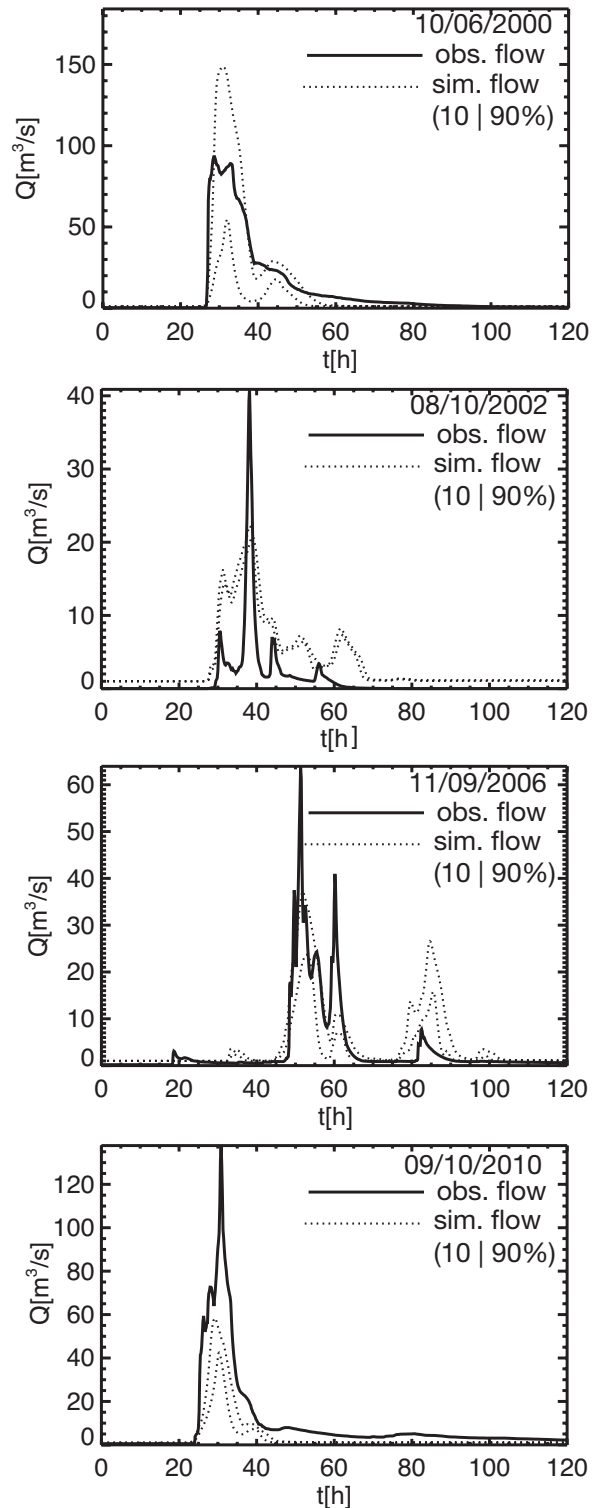


Figure 4: Results obtained during the calibration events. Solid line represents the observed flow. The dashed lines are the envelopes produced with the confidence intervals of 10% and 90% of the simulations.

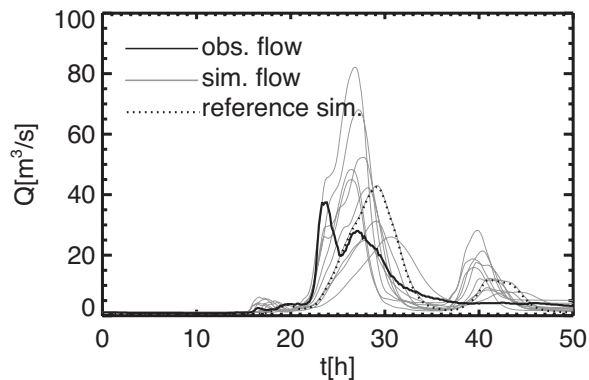


Figure 5: Results for the analysis of uncertainty due to the estimation of model parameters obtained in the 2 April 2007 validation event. The solid line represents the observed flow. Grey lines are the simulated flows. The dashed line is the reference simulation.

4.2.2. Propagation of rainfall estimation uncertainty

The effect of the uncertainty in the estimation of precipitation is also analyzed. For this purpose, an ensemble of ten members of radar precipitation estimates has been used as input to the hydrological model. Aiming to study separately the effect of each source of uncertainty at this experiment, the model parameter is set to the one with the highest likelihood value derived from calibration. Figure 6 shows the results obtained during the validation event of 2 April 2007 for rainfall estimation uncertainty. One can see that the effect of precipitation estimation uncertainty affects mainly the estimation of peak flow, where the higher spread of the simulations is obtained. The errors in time peak estimation are due to the effect of the parameter estimation, where the selected parameter case in this event can not reproduce adequately the behavior of the discharges.

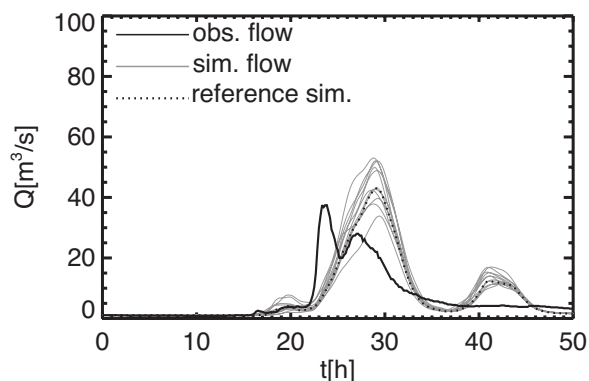


Figure 6: Results for the analysis of uncertainty due to the estimation of radar rainfall in the event of 2 April 2007. The solid line represents the observed flow. Grey lines are the simulated flows. The dashed line is the reference simulation.

Comparing the spread of the simulations due to the effects of precipitation and model parameter estimation, it can be found that model parameters produce higher spread of the flow simulations. This can be also understood as that there is a higher uncertainty in the estimation of discharges due to the

effect of parameter estimation that for the effect of rainfall estimation.

4.2.3. Interaction between both sources of uncertainty

Once the effects of each source of uncertainty have been analyzed separately, it is analyzed the effect of their interaction. For this purpose, the ten model parameter sets are combined with the input obtained from the ensemble of ten members of precipitation estimates, producing a total of 100 flow simulations, which are representative of the effect of the interaction of both sources of uncertainty. The obtained results are shown in Figure 7. The interaction of these sources produces an amplification effect of the spread of the simulations. This effect can be explained due to non-linear processes occurring in the model structure. As in the previous cases, a problem occurs in the estimation of time peak, where can be seen a delay between 5 and 10 hours approximately. When both the precipitation and parameter estimation uncertainties are taken into account within the modeling system, the ensemble of discharge simulations is able to contain to the observed hydrograph, producing more confident simulations of the discharge behavior in the catchment.

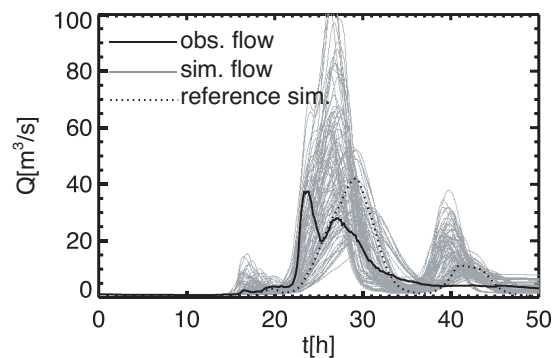


Figure 7: Results for the analysis of uncertainty due to the interaction between radar rainfall and parameter estimation in the event of 2 April 2007. The solid line represents the observed flow. Grey lines are the simulated flows. The dashed line is the reference simulation.

5. CONCLUSIONS

In this research, a radar-based flood modeling system is implemented in a Mediterranean catchment. The aim of this research is the provision of a methodology that addresses a question concerning the propagation of uncertainty to the results of hydrological modeling, due to errors arising from rainfall estimation and parameter estimation.

Five rainfall runoff events occurring in a Mediterranean catchment have been selected in order to implement the proposed methodology. However, only one out of the five events could be used during the validation process. It is found that a larger uncertainty is derived to the resulting simulations due to the effect from model parameter estimation compared with the effect produced by the estimation of radar rainfall.

Analyzing separately each source of uncertainty allows understanding how these affect the results of the simulations. The analysis of the interaction of these sources of error allows understanding also the non-linearity of the model structure.

The methodology proposed in this research can be extended to take into account other sources of uncertainty, such as model structure or the errors from discharge observations, and gain a better understanding of the problem of propagation of uncertainty on hydrological modeling. The proposed methodology can be extended also to analyze the propagation of uncertainty into flash flood forecasting systems.

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