



A scenario-incorporating analysis of the propagation of uncertainty to flash flood simulations

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SUMMARY

This study proposes a methodology to analyze the propagation of uncertainty arising from radar rainfall and model parameter estimation to the flow simulations obtained from flash flood modeling. For this purpose an ensemble approach that describes the error from radar rainfall estimation and a novel approach that considers the seasonality and variability of catchment conditions in the estimation of model parameters have been implemented. The methodology analyzes the separate effect of each source of uncertainty and their interaction on runoff simulations. The methodology has been applied in the Besòs river basin, Catalonia (Spain) with a drainage area of 1020 km². The results show that the effect of parameter estimation uncertainty produces a smaller spread in the model realizations than the effect caused by the uncertainty in rainfall estimation.

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1. Introduction

Nowadays early warning systems are the most advanced tools used for flash flood forecasting. These systems are necessary for the important task of detecting with adequate anticipation the dangerous consequences of flash flood events. In urbanized Mediterranean catchments, the effects of flash floods can be devastating 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). Thus, flash floods are considered one of the most difficult problems facing the hydrological and meteorological forecasters (Meon, 2006).

Early warning systems combine advanced methods of precipitation estimation and forecasting, with hydrological modeling systems. Each component of these systems is affected by uncertainty in the estimation of precipitation (Collier, 2009; Germann et al., 2009; Berenguer et al., 2011), model structure (Georgakakos et al., 2004; Arnold et al., 2009; Breuer et al., 2009), model parameter estimation (Beven, 2006; Vrugt et al., 2009), and errors in discharge measurements (Harmel and Smith, 2007; Liu et al., 2009). The uncertainty from these processes propagates through the

components of the modeling system to the final results of the simulation.

However, it is difficult to quantify and reduce such uncertainty in a consistent manner without an adequate understanding of what is the effect of the different sources of uncertainty in the results (Liu and Gupta, 2007). This is due to the fact that each source of uncertainty propagates errors into the modeling system whose analysis requires specific techniques.

In this work the effect of the uncertainty associated with rainfall and model parameter estimation on flow simulations has been explored. The main aim is to study the uncertainty resulting from each source of error individually and from their interaction. This study has been carried out in the Besòs river basin (1020 km²), located in Catalonia, Spain.

Rainfall intensity estimated from weather radar measurements is affected by many factors that introduce errors (Zawadzki, 1984). Many authors have developed algorithms for correcting the errors in radar rainfall estimates including the problems caused by ground clutter (see, e.g., Sánchez-Diezma et al., 2001a; Berenguer et al., 2006; Hubbert et al., 2009), signal attenuation (Vignal et al., 2003), extrapolation of reflectivity measurements to the ground (Andrieu et al., 1995; Vignal et al., 1999; Bellon et al., 2005; Franco et al., 2006) and the variability of the drop size distribution (Sempere-Torres et al., 1994, 1998; Lee and Zawadzki, 2005; Uijlenhoet et al., 2003) among others. Recently, ensemble techniques have been proposed to describe the uncertainties in

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radar rainfall estimates (Lee et al., 2007; Lloret et al., 2008; Germann et al., 2009; Villarini et al., 2009; Pegram et al., 2011) and their propagation to hydrological modeling systems (Mimikou and Baltas, 1996; Borga et al., 2006; Schröter, 2008; Germann et al., 2009; Zappa et al., 2010; Fundel and Zappa, 2011; Schröter et al., 2011).

On the other hand, the effective values assigned to model parameters are subject to the hypotheses of the model structure, the existing conditions in the catchment and quality and quantity of hydrometeorological data used during the calibration and validation of the model (Beven, 2005).

Different approaches have been proposed to quantify the uncertainty in the estimation of model parameters (Matott et al., 2009; Cullmann et al., 2011), including formal Bayesian methods (Kuczera et al., 2006) and optimization-based approaches (Vrugt et al., 2003). A common principle of these methods is the equifinality thesis, which accepts the idea that there exist multiple sets of model parameters that produce acceptable simulations of the observed discharges, based on an objective function. Equifinality is the basis of the Generalized Likelihood Uncertainty Estimation method (GLUE), a Monte Carlo based method (Beven and Binley, 1992). This method allows to perform the uncertainty analysis of model parameter and is widely accepted among hydrologists because it is simple to understand and implement. There have been many discussions concerning using formal or informal Bayesian statistical procedures within GLUE (Mantovan and Todini, 2006; Vrugt et al., 2009), although similar results have been found in the results obtained from each approach (Jin et al., 2010).

So far, the problem of the estimation of model parameters has been usually addressed as if they were constants to be optimized. However, the efforts made in understanding how the effective values of the parameters are affected by the natural changes in the hydrological regime of the catchment have been limited to the research on the variation of the distribution of parameter values along the historical time series of the hydrological data using the Dynia extension of the GLUE methodology (Wagener et al., 2001, 2003), or the study of the seasonal variability of model parameters of Freer et al. (2003), who also used a GLUE-based procedure using Dynamic Topmodel. The results from these studies give evidence that the dynamics of the hydrological processes are variable between different seasons or time periods. In this sense, additional studies are necessary for a comprehensive understanding and representation of the variation of model parameters. This work presents a GLUE-based methodology with the aim to understand how the distribution of model parameters is affected by the variability of the hydrological behavior due to seasonality and changes in antecedent moisture conditions.

Finally, the interaction between the errors in rainfall and model parameter estimation (Yatheendradas et al., 2008; Zappa et al., 2010) has also been analyzed.

2. Framework of study

2.1. Study area

The study area is the Besòs river basin (with a drainage area of 1020 km²) in the region of Catalonia (northeast of Spain), shown in Fig. 1. The basin outlet is located nearby the metropolitan area of Barcelona. The basin is highly populated with approximately two million inhabitants, includes part of the city of Barcelona, and is strongly affected by human activities, mainly industrial development. These factors have increased the vulnerability in the catchment, prone to the occurrence of flash floods.

The elevation ranges between 0 and 1500 m above the sea level. The accumulated channel length is approximately 530 km. Land

use is changing rapidly: the forest is increasing in the mountainous zones, while in the plain zones the agricultural uses are decreasing due to the expansion of urbanization. The hydrological regime of the basin is affected by the effect of the orography and by the Mediterranean climate. The mean annual precipitation is 660 mm, while the potential evapotranspiration is higher than the mean annual precipitation and it is estimated to be 776 mm. Flood peaks at the basin outlet due to short but intense rainfall events may reach 2000 m³ s⁻¹ (about 200 year return period) and the minimal base flow is about 2 m³ s⁻¹ (ACA, 2002).

In this study, the main hydrological properties of the catchment have been obtained from gridded maps of elevation, soil properties and land cover, which are available at 45 m × 45 m cell size. Additionally, vector maps of the drainage network have been used in the definition of the flow direction map. For the modeling application, a 1 × 1 km² grid map has been created to define the catchment cells, using the Digital Elevation Model (DEM) produced by the Cartographic Institute of Catalonia (Camps and Ticó, 2009).

Streamgauge information is available at six locations along the drainage network, maintained by the Catalan Water Agency (ACA), and providing river level data every 5 min. Additionally, a raingauge network (~1 raingauge per 120 km²) is available, providing precipitation data with a temporal resolution of five minutes. Meteorological information also includes the precipitation maps derived from C-band weather radar measurements with a time resolution of 10 min and over a 1 × 1 km² grid, provided by the Spanish Meteorological Agency (AEMET) and covering the entire catchment.

2.2. Data used

A dataset of twenty-six rainfall-runoff events has been used for this research, as shown in Table 1. The peak flows range from 38 to 532 m³ s⁻¹ measured in the MOCA stream gauge (see Fig. 1). The events cover a wide range of antecedent moisture conditions (such as 15 January, 2001 with 4 mm accumulated rainfall in the previous four weeks) to events with wet conditions (09 November, 2005 event with 159 mm of accumulated rainfall in the previous four weeks). Twenty-two out of the twenty-six events have been selected for performing the calibration of the model parameters. The other four events have been used for validation.

2.3. The distributed hydrological model DiChiTop

In this research the distributed hydrological model DiChiTop (Corral, 2004) has been used. The model was developed aiming to describe the hydrological processes occurring in the catchment, differentiating the processes that govern the runoff production in rural and urban areas. The runoff generation for the rural areas is based on the loss function of Topmodel (Beven and Kirkby, 1979), while for the urban area is based on the loss function of the SCS model (Mockus, 1957). The runoff propagation is modeled using a simplified Muskingum scheme (Szymkiewicz, 2002) that differentiates the parameterization of flow velocity in hillslope and river cells. The details of the model can be found in Corral (2004), and Corral et al. (2004, 2009).

The model requires the calibration of five parameters that are supposed uniform within the catchment: the exponential variation of vertical transmissivity m , the horizontal transmissivity T_0 , a correction factor for the curve number FS , and the velocities of the flow in the hillslope V_v and in the river V_r .

The implementation of the model also requires a previous estimation of the hydrological variables and parameters involved in Topmodel and SCS loss functions. To this end, gridded maps for the topographic index and SCS Curve Number have been calculated

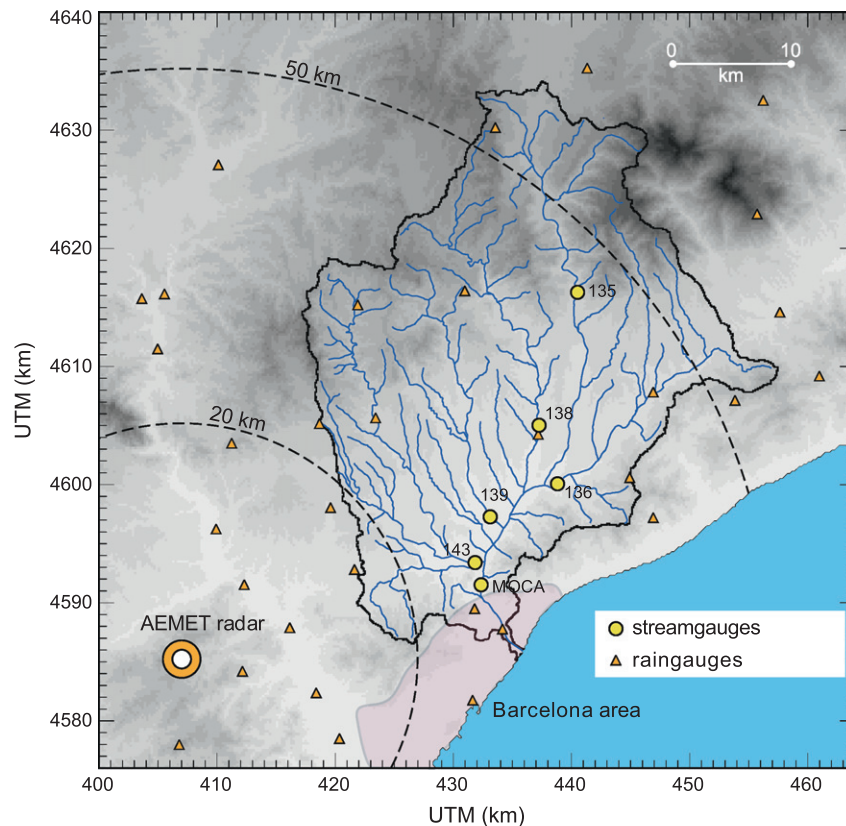


Fig. 1. The Besòs river basin in the neighborhood of Barcelona metropolitan area (in pink). The location of streamgauges and raingauges is indicated with yellow circles and orange triangles, respectively. The AEMET weather radar (in white/orange circle) covers the whole domain of the catchment (the dashed lines correspond to ranges of 20 and 50 km).

Table 1
Characteristics of the flow events used in this study. P28d is the accumulated precipitation in the previous 28 days to each event. The events marked with * are used for validation of the proposed methodology.

Event	Peak flow @ MOCA ($\text{m}^3 \text{s}^{-1}$)	Mean areal rainfall (mm)	P _{28d} (mm)	Scenarios to which they belong
22/12/2000	45	85	25	Winter, UZS(1), Runoff(1)
*15/01/2001	79	42	4	Winter, UZS(2), Runoff(1)
*19/07/2001	38	31	26	Summer, UZS(2), Runoff(1)
15/11/2001	128	72	45	Fall, UZS(1), Runoff(2)
*13/04/2002	75	47	74	Spring, UZS(2), Runoff(3)
*08/10/2002	77	82	27	Fall, UZS(1), Runoff(2)
09/12/2002	215	81	58	Winter, UZS(2), Runoff(3)
19/02/2003	62	49	10	Winter, UZS(2), Runoff(2)
25/03/2004	42	82	51	Spring, UZS(2), Runoff(3)
07/04/2004	43	93	81	Spring, UZS(2), Runoff(3)
08/07/2005	42	15	20	Summer, UZS(1), Runoff(1)
01/08/2005	96	43	14	Summer, UZS(1), Runoff(1)
27/08/2005	45	9	66	Summer, UZS(1), Runoff(1)
05/09/2005	111	75	31	Fall, UZS(1), Runoff(1)
12/09/2005	47	31	88	Fall, UZS(2), Runoff(2)
25/09/2005	219	22	100	Fall, UZS(1), Runoff(3)
11/10/2005	234	171	51	Fall, UZS(1), Runoff(3)
09/11/2005	102	72	159	Fall, UZS(2), Runoff(3)
26/01/2006	150	85	48	Winter, UZS(2), Runoff(3)
14/08/2006	70	24	22	Summer, UZS(1), Runoff(2)
11/09/2006	532	133	30	Fall, UZS(1), Runoff(3)
17/02/2007	28	16	23	Winter, UZS(1), Runoff(1)
01/04/2007	125	96	25	Spring, UZS(1), Runoff(2)
30/04/2007	90	40	119	Spring, UZS(1), Runoff(3)
05/08/2007	262	70	16	Summer, UZS(1), Runoff(3)
08/10/2007	200	50	19	Fall, UZS(1), Runoff(2)

using a GIS-based platform oriented to the retrieval of these hydrological variables.

The rainfall-runoff model DiCHitop model has been used in the past to study the hydrological behavior of Mediterranean catch-

ments (Corral et al., 2004, 2009). Recently the model has been adapted into an operational context as the basis for the EHIMI platform, a flash flood forecasting system implemented for the Catalonia region that uses a radar rainfall nowcasting technique as

meteorological input of the hydrological model (Berenguer et al., 2005; Corral et al., 2009). So far, all these implementations of the model have been developed in a deterministic framework, while in this research an attempt is made to consider the propagation of the uncertainty affecting the chain of processes of hydrological simulations in a probabilistic context.

3. Methodology

3.1. Consideration of rainfall estimation uncertainty

Due to the considerable amount of errors affecting radar-based rainfall estimates, it is necessary to characterize them in order to analyze their impact in the simulated hydrographs. There are different approaches to characterize the errors of rainfall estimation. Germann et al. (2009) classified these methods in two categories: (i) those methods that analyze separately the different sources of error (Bellon et al., 2005; Lee and Zawadzki, 2005) and their interaction (Berenguer and Zawadzki, 2008, 2009), and (ii) the methods based on comparing rainfall estimates against a 'reference' to infer the characteristics of rainfall errors (e.g. Ciach et al., 2007; Lloret et al., 2008; Germann et al., 2009; Kirstetter et al., 2010; AghaKouchak et al., 2010). The first approach provides more information about the errors themselves, but requires the study of the covariance between the sources of error in order to obtain the estimation of the total error. The second approach is simpler and provides a direct estimation of the errors, but is also affected by the errors in the reference.

In this research, the method proposed by Lloret et al. (2008) has been applied to describe the uncertainty in radar-based rainfall estimates. The method is based on comparing the observed rainfall field R_{obs} against a reference rainfall field R_{ref} . Observed rainfall is obtained through the advanced processing platform EHIMI (see Corral et al., 2009 for further details), which includes algorithms to mitigate the effects of ground clutter (Sánchez-Diezma et al., 2001b; Berenguer et al., 2006), beam blocking (Delrieu et al., 1995), signal stability (Sempere-Torres et al., 2003), extrapolation of radar measurements to the surface with a vertical profile of reflectivity (Franco et al., 2006; Franco, 2008), and Z-R conversion depending on the rainfall type (Sempere-Torres et al., 1998). The reference field R_{ref} is obtained after combining the radar rainfall map R_{obs} with the observations of raingauges using a radar-raingauge blending technique based on Kriging with external drift (Velasco-Forero et al., 2009; Sempere-Torres et al., 2012).

Considering that the errors affecting rainfall estimates are mainly multiplicative (Germann et al., 2009), the error field at time t , $E(t)$, is defined as the ratio between the reference rainfall, $R_{ref}(t)$, and radar observed rain $R_{obs}(t)$ in logarithmic units:

$$E(t) = 10 \times \log_{10} \left[\frac{R_{ref}(t)}{R_{obs}(t)} \right] \quad (1)$$

The error distribution at each time step t is described through the mean $\mu(t)$ and the standard deviation of $E(t)$, $\sigma(t)$. The technique assumes that a power-law can be fitted to the averaged spatial Fourier Power Spectrum of the error fields (Pegram and Clothier, 2001), and then the spatial autocorrelation is characterized using the exponent β of the power-law (the exponent of the best fit to the Fourier Power Spectrum). Parameters $\mu(t)$, $\sigma(t)$ and $\beta(t)$ are calculated at each time step t of the event, and then average parameters ($\bar{\mu}$, $\bar{\sigma}$ and $\bar{\beta}$) are derived for the entire event.

The characterization of the error structure is used to generate an ensemble of rainfall estimates. For this purpose, Eq. (1) can be transformed in:

$$R_{ref}(t) = R_{obs}(t) \times 10^{\frac{E(t)}{10}} \quad (2)$$

Since the error field is unknown, $E(t)$ is replaced in Eq. (2) by a stochastic perturbation field $\delta^i(t)$, giving through Eq. (3) an ensemble member $\varepsilon^i(t)$.

$$\varepsilon^i(t) = R_{obs}(t) \times 10^{\frac{\delta^i(t)}{10}} \quad (3)$$

The perturbation field $\delta^i(t)$ is produced using a simulation process, where white noise fields that are Gaussian distributed with mean $\bar{\mu}$ and standard deviation $\bar{\sigma}$ are generated and then autocorrelation is imposed in the Fourier domain using a power-law filter with exponent $\bar{\beta}$. With this process, one can generate as many perturbation fields $\delta^i(t)$ as needed with identical statistical properties, producing an ensemble that is representative of the uncertainty affecting radar rainfall estimates.

This methodology to describe the uncertainty in radar rainfall estimates has been applied in two different ways:

- (1) Event-scale description of rainfall errors: The errors in radar rainfall estimates have been studied separately for each event, obtaining a different set of ($\bar{\mu}$, $\bar{\sigma}$, $\bar{\beta}$) (presented in Table 2). Also, the bias $\bar{\mu}$ is compensated from each member of the rainfall ensemble by adding a multiplying factor in equation 3, as it is assumed that this simulation is done off-line and that the bias is known (in this way, the experiment will study the propagation of the fluctuation component of the errors in rainfall estimates through the runoff modeling system).
- (2) Global description of rainfall errors: With this analysis, we attempt to reproduce the on-line framework, in which the values of the parameters ($\bar{\mu}$, $\bar{\sigma}$, $\bar{\beta}$) needed to generate the ensemble are unknown a priori. Consequently, the values of ($\bar{\sigma}$, $\bar{\beta}$) are average values estimated from the global analysis of all the analyzed rainfall events (last line of Table 2). However, the mean value of the bias $\bar{\mu}$ (on average, close to 0) has not been used. Instead, a bias μ_k has been randomly added to each member k of the ensembles to reproduce the effect of unknown event-scale radar rainfall biases: μ_k has been randomly sampled from a 0-mean Gaussian distribution with a standard deviation of 1.25 dB(R), which is a value close to what can be expected in well-maintained radar systems (Austin, 1987; Germann et al., 2006). By doing this we include in the rainfall ensemble the effect of the event-scale rainfall biases that can affect the runoff simulation.

For each rainfall event, two ensembles of 50 time series of rainfall fields have been generated (one ensemble for each of the two approaches described above).

3.2. Consideration of the uncertainty in the estimation of model parameters

Due to the errors in the estimation of model parameters and their variability with changes in moisture conditions and seasonality, it is necessary to analyze their impact in runoff simulations. The dynamics of the hydrological processes imply that model parameters cannot be considered as constant variables. Therefore, one

Table 2

The values from mean $\bar{\mu}$, standard deviation $\bar{\sigma}$ and spatial autocorrelation $\bar{\beta}$ obtained from the characterization of error in rainfall estimation for the validation events.

Event	Duration (h)	$\bar{\mu}$ (dB)	$\bar{\sigma}$ (dB)	$\bar{\beta}$
15/01/2001	48	−0.60	2.44	−2.81
19/07/2001	24	−1.89	1.38	−3.40
13/04/2002	48	−0.61	2.15	−2.55
08/10/2002	80	−1.34	2.04	−2.88
Average	–	–	2.00	−2.91

can find effective values of the parameter sets that are acceptable for representing the hydrological processes of a particular season. Existing work on this topic suggests the use of GLUE based methods, as it is a flexible approach to obtain the most suitable parameter distribution representing particular conditions of the basin (Freer et al., 2003; Wagener et al., 2003; Choi and Beven, 2007).

For the purpose of applying the GLUE methodology, in this work we have pre-classified the events used in the calibration in terms of (1) antecedent moisture conditions, (2) seasonality and (3) a runoff generation index. The characterization of the antecedent moisture conditions has been made based on the results of the Hydrological Simulation Program – Fortran (HSPF) continuous simulation model (Donigan et al., 1984), specifically with the upper zone storage (UZS) variable. The UZS value of the day before the start of the flow event has been obtained for each calibration event. The estimated values of UZS consider explicitly the precipitation and evapotranspiration for an antecedent period and have been considered representative of the soil moisture conditions. Alternatively, a runoff generation index has been calculated as the ratio between the measured runoff and the observed rainfall during the entire event to assess the potential runoff production of the catchment. This is an indicator of the amount of precipitation that is converted into direct runoff and is also implicitly related to the moisture conditions of the catchment. Finally, taking into account that seasonality is implicitly related with the yearly variation of the soil moisture conditions and with the yearly variability of precipitation in Mediterranean regions (convective storms occurs usually during summer and fall, and stratiform rainfall occurs more frequently during winter and spring), the calibration events have also been classified in terms of the season of the year they occur.

The calibration events have been classified into ten families, hereafter referred to as scenarios, according to the soil moisture conditions and seasonality as follows: four scenarios corresponding to the four seasons of the year, three scenarios according to the values of the runoff generation index, two scenarios according to the UZS values obtained for the antecedent conditions of the flow events, and one additional scenario, referred to as global scenario, that includes all the previous scenarios. The definition of these scenarios is performed in a subjective way based on the distributions of the three variables used in the classification (presented in Fig. 2).

In order to implement the GLUE methodology, a total of 5000 parameter sets have been produced with a uniform distribution defined for each parameter (shown in Table 3). To implement GLUE it is necessary to define a likelihood function and a threshold value for the selection of the acceptable parameter sets. The Nash efficiency (Nash and Sutcliffe, 1970) is selected as the likelihood function for the evaluation of the simulation results, and a threshold value of 0.5 has been applied. In consequence, those parameter sets producing values lower than 0.5 in the Nash efficiency have been rejected from the acceptable parameter sets.

One can obtain the parameter distribution representative of each of the 10 scenarios mentioned above by updating the obtained likelihood values using the Bayes equation. The distribution of the model parameters that better describes the hydrological behavior for the seasonal scenarios is presented in Fig. 3. From this figure it can be seen that there are variations in the distribution of

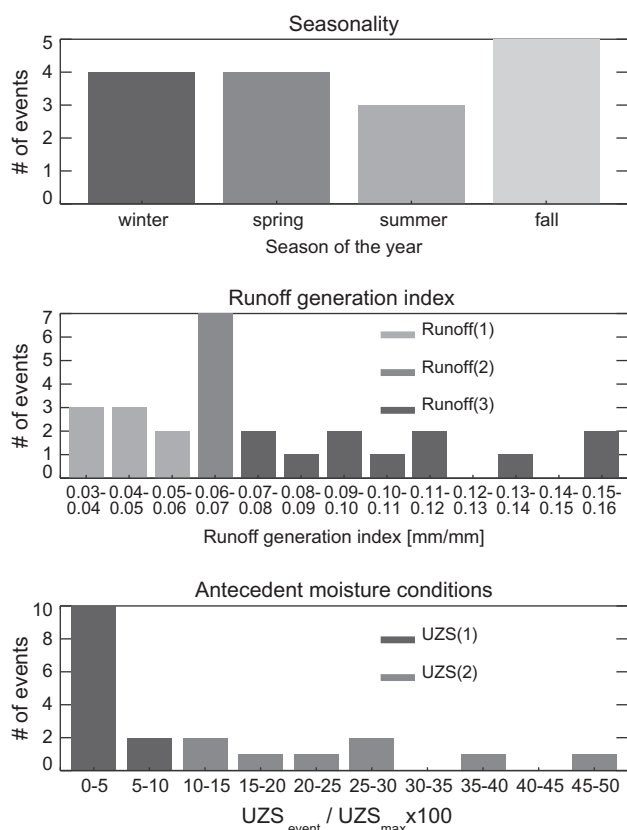


Fig. 2. Distribution of the variables used for the definition of scenarios based on the seasonality, the runoff generation index and the antecedent moisture conditions from the calibration flow events. The colors in each variable represent the different scenarios: 4 for seasonality, 3 for runoff generation index, and 2 for antecedent moisture conditions.

model parameters among different seasons. For example, for winter conditions higher likelihood values have been obtained with low values of the V_r , while in other seasons high values of V_r seem to be more adequate (as they produce higher likelihood values). This might be related with the less torrential behavior of stream-flow during winter (dominated by long-lasting widespread precipitation events) compared to the warm season (in which convective events dominate the hydrological response of the basin). Similar differences have been obtained for the UZS and runoff generation index scenarios. The parameter set showing the highest likelihood value has been considered in this paper as the representative parameter set for each scenario.

4. Implementation

4.1. Framework for studying the effect of different sources of uncertainty

For the cases where multiple sources of uncertainty are considered, a simulation approach is a direct strategy to assess total

Table 3
Range of values of the parameters of DiChiTop used for the use of the GLUE methodology. A number of 5000 parameter sets have been obtained by sampling these ranges with a uniform distribution.

Symbol	Parameter name	Units	Min	Max
V_v	Flow velocity in hillslope cells	(m min^{-1})	5.0	40.0
V_r	River velocity in river cells	(m min^{-1})	80.0	240.0
m	Exponential variation of transmissivity	(m)	0.00	0.10
T_0	Horizontal transmissivity	($\ln(\text{m}^2 \text{h}^{-1})$)	−1.0	4.0
FS	Correction factor for curve number	(−)	0.00	0.85

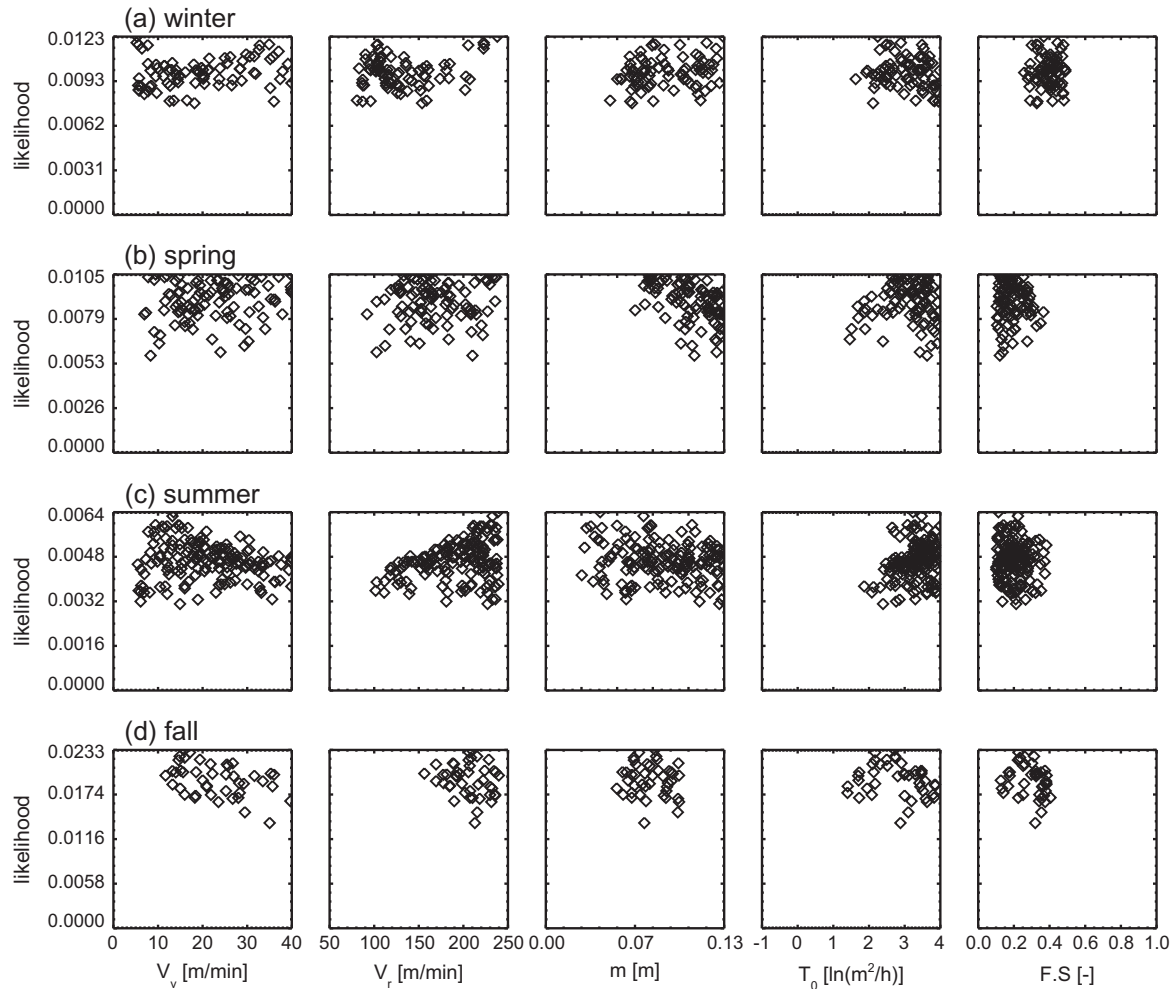


Fig. 3. Model parameter distributions obtained from the classification of events by scenarios, depending on the season of the year (from top to bottom: winter, spring, summer and fall). The panels show the likelihood as a function of the values of the five model parameters [from left to right: hillslope and river velocities (V_v and V_r), exponential variation of vertical transmissivity, m , horizontal transmissivity, T_0 , and correction factor of the curve number, FS].

uncertainty. Our approach gives the possibility to produce an ensemble of flow simulations, resulting from the combination of the different realizations representative of each source of uncertainty in a Monte Carlo simulation experiment. The main advantage of this approach is the explicit consideration of the non-linearities existing in the propagation of the different sources of uncertainty involved into the system.

A framework to study the effects of different sources of uncertainty on the simulated flows is proposed here. The aim is to study, first, the separate effects of each source of uncertainty in the model outputs and, then, study the effect of their interaction. For this purpose, it is necessary to define the meteorological input and model parameter sets required for the comparison of the effects of each source of uncertainty. With this aim, the following three experiments have been carried out.

- The first experiment analyzes the effect of the uncertainty in radar rainfall. In this case, 50 members of the rainfall ensemble have been forced as meteorological input for the model. The model is set to the best parameter set for the season of the event (i.e. for the event of 08 October, 2002, the Fall parameters have been used). The model output is 50 runoff simulations, which describe the effect of the uncertainty in radar rainfall estimates. In the scheme of Fig. 4, this experiment results from setting $m = 50$ rainfall inputs and $n = 1$ parameter set. As men-

tioned in Section 3.1, this experiment has been carried out with two different sets of rainfall ensembles have been used (one based on an event-based description of rainfall errors, and another based on a global-description of errors).

- The second experiment focuses in the effect of the uncertainty due to the estimation of model parameters. In this case the observed rainfall is used as meteorological input for the model. The 10 parameter sets representative of each scenario obtained in the proposed calibration approach (see Section 3.2) have been used as the 10 selected configurations of the hydrological model. This results in 10 flow simulations that assess the effect of parameter estimation uncertainty (i.e. $m = 1$ rainfall input and $n = 10$ parameter sets in the diagram of Fig. 4).
- The third experiment studies the interaction between both sources of uncertainty. In this case, the fifty members of the two sets of rainfall ensembles described in Section 3.1 have been combined with the ten parameter sets representative of the hydrological scenarios (Section 3.2), producing a total of 500 flow simulations representative of the total considered uncertainty ($m = 50$ rainfall inputs and $n = 10$ parameter sets in Fig. 4).

4.2. Quantification of the uncertainty in flow simulations

The metric used to quantify the propagation of the uncertainty through the perturbed modeling system assumes that the average

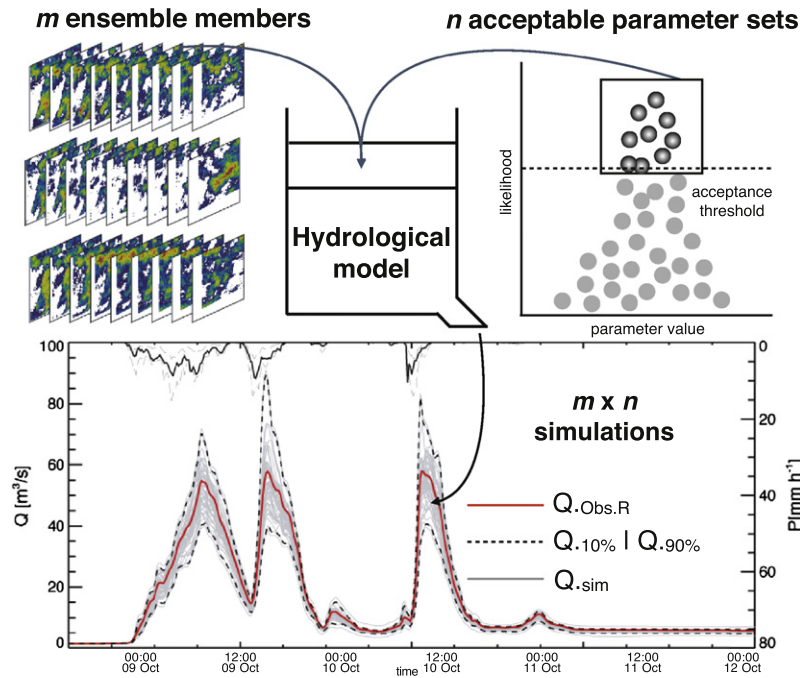


Fig. 4. Scheme of the framework used for study the propagation of uncertainty from rainfall estimation, model parameter estimation and their interaction. The m members of the rainfall ensemble are combined with n acceptable parameter sets used in the hydrological model, resulting in $m \times n$ flow simulations (gray lines) representative of the propagation of uncertainty. The red line is the flow simulation obtained when using observed rainfall and the optimal global parameter set.

spread of the flow simulations ensemble is a measure of the uncertainty. The average spread is computed using the equation:

$$\bar{D}_Q = \frac{\bar{Q}_{p_1} - \bar{Q}_{p_2}}{\bar{Q}_{Obs.R}} \times 100 \quad (4)$$

where $\bar{Q}_{p_1}$ and $\bar{Q}_{p_2}$ are the time-averaged flows of the upper and lower confidence intervals of the flow ensemble for $p_1 = 10\%$ and $p_2 = 90\%$. $\bar{Q}_{Obs.R}$ is the time-average flow simulated using observed radar rainfall and the parameter set of the best scenario for each event. Thus, $\bar{D}_Q$ can be interpreted as the area of the envelope of flow simulations. This metric summarizes the spread of the ensemble of simulated runoff for a given event and enables comparing the results obtained for the proposed experiments (Zappa et al., 2010).

5. Results

5.1. Propagation of rainfall estimation uncertainty

The mean areal precipitation obtained with the observed rainfall and the percentiles 10% and 90% of the fifty members of the rainfall ensembles (see Section 3.1) are shown in Fig. 5 for the event of 08 October, 2002. For this experiment, the members of the two rainfall ensembles are forced as meteorological input to DiChiTop, which uses the best scenario parameter set.

Fig. 6 shows the hydrographs resulting from the propagation of these ensemble rainfall inputs through the rainfall-runoff model (results for the rest of the analyzed events are presented and discussed in Section 5.3). The uncertainty in rainfall estimates affects mainly the estimation of peak flow during the event. Other components of the simulated flow curve like the timing of the rise and the recession limbs are less affected by the uncertainty in rainfall inputs. Table 4 presents the relative average spread obtained for this experiment. It is shown that the hydrological ensembles resulted in a relative average spread D_Q ranging between 18% and 50% (with a mean value of 37.7%) for the ensemble using the event-scale description of the errors, and between 50% and 173% (with a mean value of 135.2%) for the global description of rainfall errors.

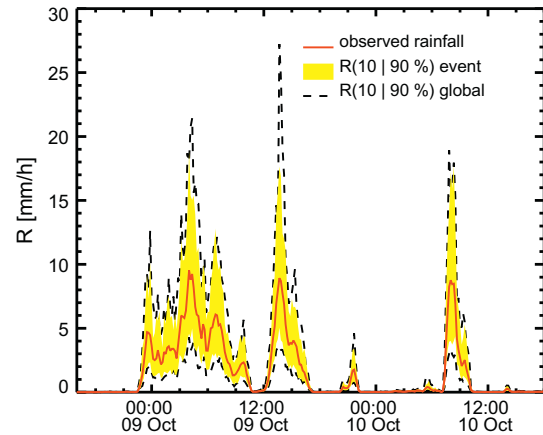


Fig. 5. Mean areal precipitation obtained with the observed rainfall (red line), and with the rainfall ensembles described in Section 3.1. The yellow-shaded area shows the 10% and 90% percentiles of the ensemble resulting from the event-scale description of rainfall errors. Similarly, the black dashed lines show the 10% and 90% percentiles from the global description of rainfall errors.

The spread of the runoff ensembles is sensitive to the method used for the description of the radar rainfall uncertainty. The results show that the larger variability in rainfall volumes in the members of the global-scale description of rainfall errors (see Section 3.1), and consequently in the mean areal precipitation in the catchment (as shown in Fig. 5), produces a much larger spread in the simulated hydrographs than with the event-scale description of rainfall errors.

5.2. Propagation of parameter estimation uncertainty

5.2.1. Calibration of DiChiTop

In the second experiment (for the estimation of the uncertainty due to the parameter estimation – see Section 4.1) the 10 resulting

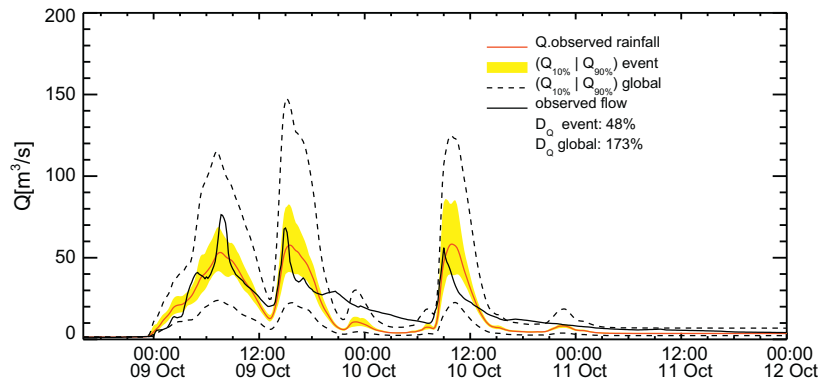


Fig. 6. Flow event occurred on 08 October 2002. The solid red line is the simulation obtained using the observed radar rainfall and using the best parameter set from the different scenarios. The solid black line is the observed flow of the event. The yellow-shaded area shows the 10% and 90% percentiles of the flows simulated with the rainfall ensemble based on the event-scale description of rainfall errors. Similarly, the black dashed lines show the 10% and 90% percentiles of flows obtained with the rainfall ensemble based on the global description of rainfall errors. The value of the spread $\bar{D}_Q$ obtained for both approaches is also indicated.

Table 4

Comparison of the relative average spread $\bar{D}_Q$ (in%) obtained on each event from the effect of the different sources of uncertainty in the results of the hydrological modeling and from their interaction. $\bar{Q}_{Obs,R}$ is the average flow obtained from the simulation using the observed rainfall and using the parameter set of the best scenario.

Event	$\bar{Q}_{Obs,R}$ ($\text{m}^3 \text{s}^{-1}$)	$\bar{D}_Q$ (%) – Experiments of flow simulation uncertainty (Section 3.1)				
		Rainfall estimation		Parameter estimation	Interaction	
		Event-scale uncertainty	Global uncertainty	Observed rainfall	Event-scale uncertainty	Global uncertainty
15/01/2001	13.56	50	169	54	112	244
19/07/2001	7.33	35	149	56	101	206
13/04/2002	6.40	18	50	23	49	88
08/10/2002	13.89	48	173	87	131	399
Average	10.29	37.7	135.2	55	98.2	234.2

parameter sets representative from the selected soil moisture and season scenarios are used as configuration of DiChiTop model (see Section 3.2), using the observed radar rainfall.

The results obtained for each scenario are shown in Table 5. In this table it can be seen that the number of acceptable parameter sets in the global scenario is very small compared to the number of parameter sets for the other scenarios. This can be explained because during the calibration process, a large number of parameter sets are rejected when they fail to reproduce the behavior of one among all the considered events. Only 6 out of a total of 5000 parameter sets are acceptable for the 12 events used in the global scenario.

Fig. 7 shows the simulations obtained for a calibration event with the 10 parameter sets representative for the 10 scenarios presented in Section 3.2 to describe the different behaviors that could be expected in the hydrological response of the catchment. The uncertainty bounds are derived from the percentiles 10% and 90%

of the resulting flow simulations and the resulting uncertainty is quantified in terms of the average spread, $\bar{D}_Q$.

5.2.2. Validation

The purpose of the presented approach is to produce an ensemble of flow simulations representing the possible situations occurring in the catchment, to associate uncertainty bounds to the deterministic flow simulations. The performance of the model for the four selected validation events is summarized in Table 6. It can be seen that the Nash efficiency values obtained with the parameter set of the global scenario are poor compared to the values obtained with the best parameter sets of the specific scenarios. Furthermore, there seems to be a remarkable correspondence between the best Nash efficiency values are obtained, in general, for the scenarios that match the conditions of the basin for each event, marked in gray in Table 6. Thus, an interesting result from the proposed approach of calibration by scenarios is that it produces better results than the traditional global calibration approach. On the other hand, one of the limitations that can be found when comparing the streamflow simulations with actual observations is that the model has a poor performance in some scenarios during the low flow periods, as shown in Fig. 8. These errors can be due to the model structure of DiChiTop.

The results show that the effect of parameter uncertainty affects the estimation of peak flow as well as other parts of the hydrograph such as the recession curves and the low flows, as shown in Fig. 8. The hydrological ensemble resulted in a relatively constant spread along the event ranging between 23% and 87% of $\bar{Q}_{Obs,R}$ for the different events (with a mean value of 55%), as shown in Table 4. If these results are compared with the outcome of the experiment of global description of rainfall errors, a larger spread is obtained due to the effect of rainfall estimation by a factor of about 2.5. This result is coherent with the findings of Zappa et al.

Table 5

Number of events used in the calibration of the DiChiTop model (Section 3), and number of valid parameter sets (with values of the Nash efficiency greater than 0.5).

Scenario	Number of events	Number of acceptable parameter sets
Global	12	6
Winter	4	81
Spring	4	95
Summer	3	156
Fall	6	43
Runoff(1)	4	57
Runoff(2)	5	185
Runoff(3)	8	25
UZS(1)	10	10
UZS(2)	5	283

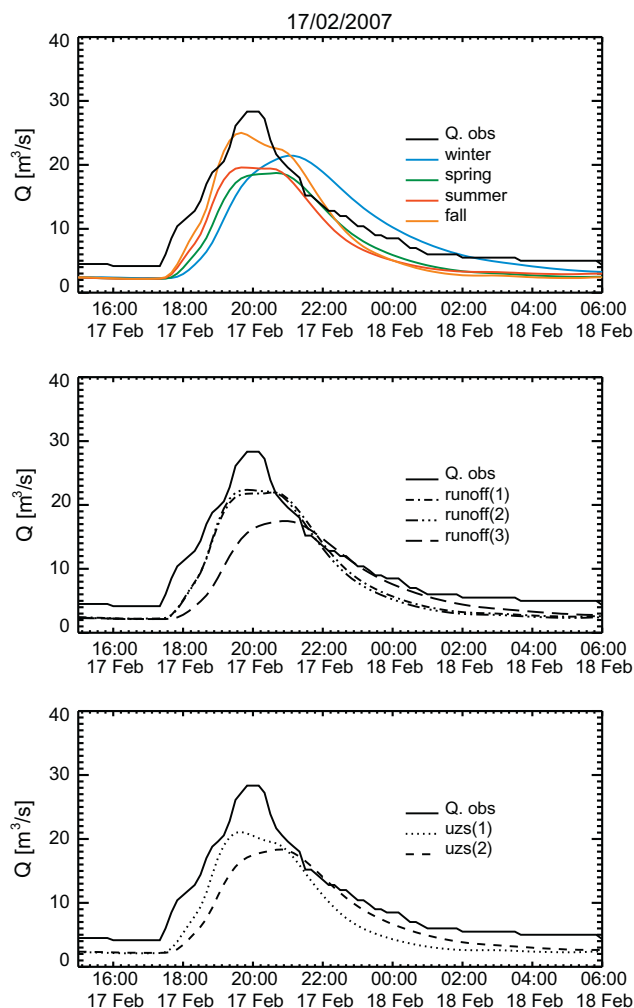


Fig. 7. Runoff observed and simulated for the event of 17 February, 2007. Flow simulations derived from the optimal parameter sets for the different scenarios depending on the season of the year (top panel), the runoff generation index (middle panel), and the antecedent moisture conditions scenarios (bottom panel).

Table 6

Nash efficiency values obtained in the validation events, using the parameter set representative of the corresponding scenario. In gray it is shown the events that belong to the corresponding scenario, and the bold numbers correspond to the best efficiency values for each event and for each family of scenarios.

Scenario	15/01/2001	19/07/2001	13/04/2002	08/10/2002
Global	0.54	0.42	0.42	0.73
Winter	0.63	0.49	0.29	0.65
Spring	0.72	0.89	0.33	0.68
Summer	0.80	0.92	0.39	0.62
Fall	0.58	0.67	0.44	0.74
UZS(1)	0.58	0.77	0.42	0.69
UZS(2)	0.74	0.88	0.30	0.68
Runoff(1)	0.73	0.87	0.39	0.73
Runoff(2)	0.54	0.71	0.43	0.67
Runoff(3)	0.62	0.68	0.28	0.61

(2010) who found that the uncertainty from radar-based rainfall estimation produces a larger spread in flow simulations (by a factor larger than four) compared to the effect of the uncertainty in model parameters.

The scenario approach proposed here aims to provide robust confidence limits of the flow simulations, even when not all the space of parameters is evaluated. However, this would require verifying that the spread of the simulations from one single scenario is

less than the one derived from the inter-scenario approach. Fig. 9 shows a comparison of the spread that is obtained with the optimal parameters for the 10 scenarios (the inter-scenario approach presented here) and the spread that is obtained using the acceptable parameter sets for each single scenario (intra-scenario uncertainty) for the Fall scenario. The spread of the inter-scenario ensemble is clearly larger than that of the intra-scenario ensemble (in fact, a good part of the later falls within the inter-scenario ensemble). Very similar results (not shown) have been obtained for the other scenarios. In particular, for the Fall scenario presented in Fig. 9, the spread of the intra-scenario ensemble is specially narrow in the recession of the hydrographs. This shows that only a small range of the parameters controlling the recession of the hydrographs (mainly, m and T_0) is acceptable for this scenario (as can be seen in Fig. 3).

The use of the flow simulations derived from the inter-scenario approach is relevant because it facilitates the interpretation of the outputs of the hydrological forecasts, since in this case any of the hydrographs can be interpreted by the meaning of a scenario. Another advantage of this approach is that the method can be used in the decision-making process related with the selection of the expected discharge values, by accepting or rejecting the simulations from different scenarios according to the most feasible situation during the model evaluation, and it can be done at a reasonable computational cost (given that the number of hydrological scenarios is limited to 10).

5.3. Interaction between both sources of uncertainty

The third experiment combines the effect of the uncertainty in rainfall estimation, using the rainfall ensemble as meteorological input, with the model configuration, with the ten parameter sets representative of the uncertainty in parameter estimation.

Fig. 10 shows the envelopes resulting from the combined effect of the two ensembles (note that the red¹ line shows the reference hydrograph, obtained with the observed rainfall and the best-scenario parameters, as in Fig. 6), and Fig. 11 compares the effects of each source of uncertainty and their interaction. One can see that there is an amplification of the spread of the simulations due to the interaction of both sources of uncertainty: the resulting spread of the simulations cannot only be explained by the individual effects of the analyzed sources of uncertainty, but from their interaction. From Table 4 it can be seen that the relative average spread obtained in the hydrograph ensemble ranges between 49% and 131% of $\bar{Q}_{obs,R}$ (with a mean value of 98.2%) for the event-scale description of rainfall errors, and between 88% and 399% (with a mean value of 234.2%) for the global description of rainfall errors. This means that the interaction generates, on average, a 23% larger spread than the sum of the spread obtained from the individual effects (190.2%). This amplification is attributed to the non-linear response in the generation of runoff with the DiChitop model. This effect has been observed for all the validation events (Fig. 12) and is quantified in terms of D_Q in Table 4.

5.4. Conclusions and recommendations

The aim of this research is to develop a methodology that addresses a question concerning the propagation of uncertainty to the results of hydrological modeling, due to errors arising from rainfall and model parameter estimation. The framework proposed here is a valuable tool for quantifying and ranking the sources of

¹ For interpretation of color in Figs. 1, 4–12, the reader is referred to the web version of this article.

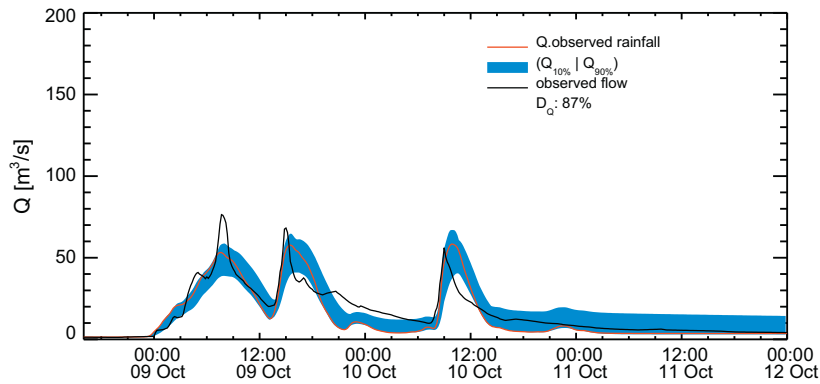


Fig. 8. As in Fig. 6, but the blue area corresponds to the envelope of the 10% and 90% percentiles of the ensemble reproducing the uncertainty in parameter estimation (experiment 2 of Section 4.1). The solid red line is the simulation obtained using the observed radar rainfall and using the corresponding Fall scenario.

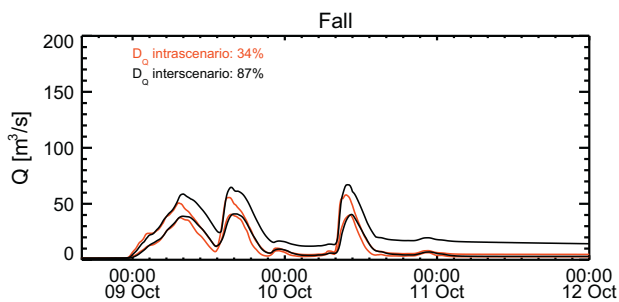


Fig. 9. Comparison of the spread resulting from the uncertainty in model parameter estimation. The red lines show the 10% and 90% simulated flow percentiles for the intra-scenario approach for the fall scenario (i.e. the parameter sets shown in Fig. 3d), and the black lines correspond to the 10% and 90% percentiles for the inter-scenario approach. The spread D_Q for both cases is indicated in the figure.

predictive uncertainty, and has been applied for 26 rainfall–runoff events recorded in the Besòs river basin.

It has been found that the relative spread of model outputs, D_Q , caused by the propagation of the uncertainty in rainfall inputs ranges between 18% and 50% of $\bar{Q}_{Obs.R}$ for the event-scale description of rainfall errors, and between 50 and 173% for the global description. This source of uncertainty affects the estimation of the hydrological response in the catchment, particularly in the peak flow estimation. The relative spread of the model outputs caused by the propagation of parameter estimation uncertainty ranges between 23% and 87% of $\bar{Q}_{Obs.R}$. This source of uncertainty affects the peak flow estimation of the event, as well as other components of the hydrograph, such as the recession curves and the

low level flows. That is, unlike what happens with rainfall ensembles, the effect of the uncertainty in model parameters also affects the representation of the slow response of the basin.

Considering that a global description of rainfall errors is what is available in an operational context, our results are coherent with those of Yatheendradas et al. (2008), Zappa et al. (2010), who obtained that the propagation of rainfall estimation uncertainty produces larger spread than the uncertainty related to model parameters. Comparing the results obtained for the event-scale and global description of rainfall errors our results show that the inclusion of relatively small biases in radar rainfall estimates results in about a factor 3 in the spread of the generated runoff ensembles. However, our results are subject to the representativeness of the description of rainfall errors derived from the available data sets.

The interaction of the uncertainty in the estimation of rainfall and model parameters produces an amplification of the spread of flow simulations (on average, the overall relative spread is 23% larger than the sum of the individual effects from rainfall and model parameter uncertainty). This can be explained by the state-dependent nonlinearities in the response of DiChiTop model. Although the significance of these results is strictly valid for DiChiTop model and the studied basin, Hossain et al. (2004) and Zappa et al. (2010) presented qualitatively similar results in their analyses of the propagation of uncertainty.

On the other hand, it is worth noting the better flow simulations obtained when using the approach based on the scenario-dependence calibration of model parameters compared to the global calibration approach. This is a remarkable result that could improve the quality of the performance of existing flash flood forecasting

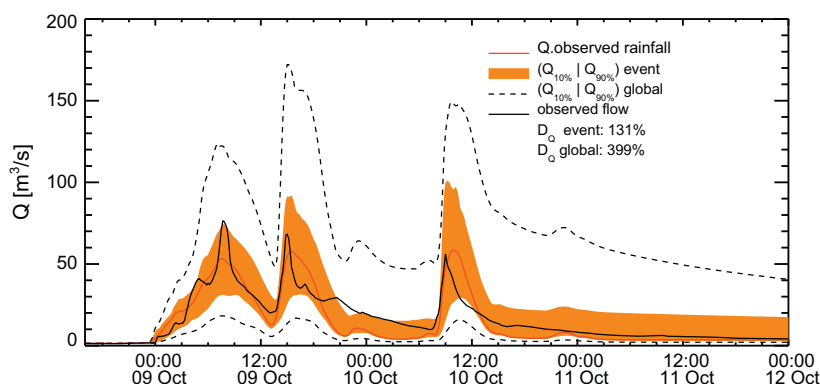


Fig. 10. As Fig. 6 but the orange area corresponds to the envelope of the 10% and 90% percentiles resulting from the combination of the ensembles representing the uncertainty in rainfall inputs and in model parameters (experiment 3 in Section 4.1).

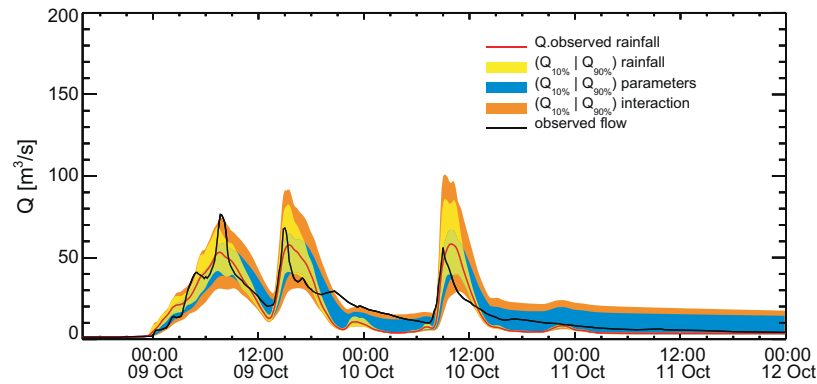


Fig. 11. As Figs. 6 and 8 but the orange area corresponds to the envelope of the percentiles 10% and 90% from the effect of the interaction of rainfall and parameter estimation uncertainty. The green area is the intersection between the effect of the uncertainty from rainfall and parameter estimation.

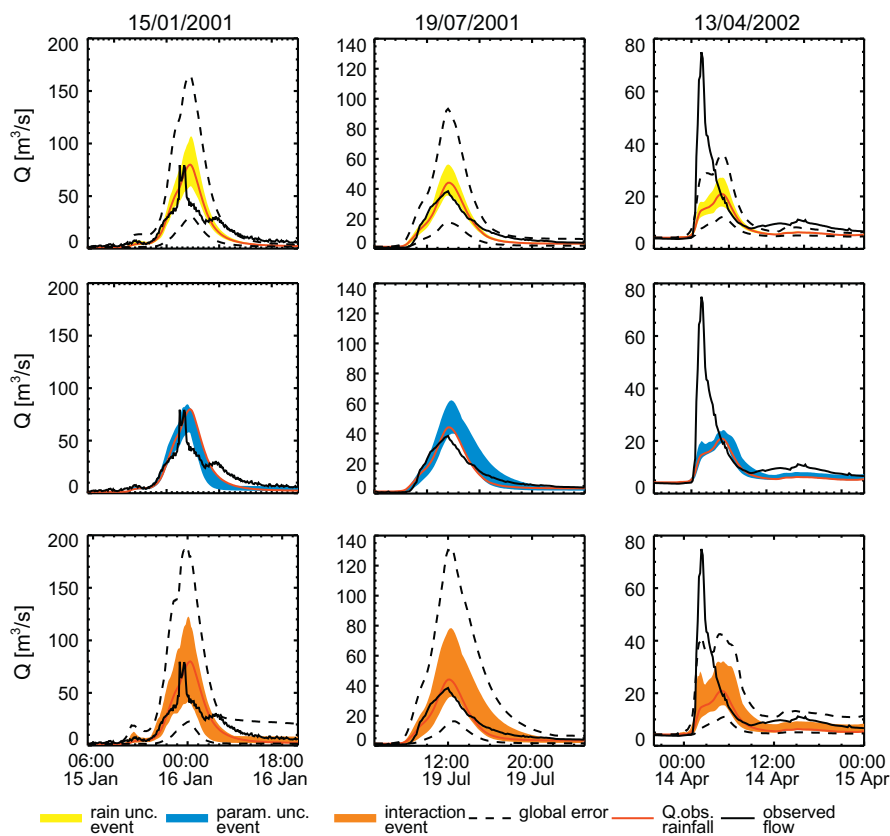


Fig. 12. Envelopes of the percentiles 10% and 90% from flow simulations derived from the propagation of uncertainty in the rest of validation events. First row: Propagation of rainfall estimation uncertainty using (i) the event-scale (yellow area), and (ii) the global description of rainfall errors (dashed lines). Second row: Spread resulting from the uncertainty in the estimation of model parameters (blue area). Third row: Interaction of both sources of uncertainty using (i) the event-scale (orange area), and (ii) the global description of rainfall errors (dashed lines). In all panels, the red line is the flow simulation obtained using observed rainfall, and the black solid line is the observed flow.

systems fitted using global calibration of parameters. Incorporating new events to the calibration procedure can be used to improve also the definition of the scenarios and in consequence the flow simulation results. Additionally, the approach provides valuable information concerning the distribution of parameters that better represent the behavior of a specific scenario, and allows a physically-based interpretation of the results from hydrological modeling.

Suggestions based on this work can include the consideration of other methods to describe the uncertainty in rainfall estimation based on ensembles, which would allow us to understand the sensitivity of the results to the method. The approach used for the esti-

mation of model parameters can be also extended with the definition of new scenarios based on other meaningful variables, such as the statistical properties of rainfall events. Taking into account that the land use in Mediterranean urban catchments changes rapidly, it could also be interesting to explore the trend of model parameters in time. However, a larger time series would be necessary for that purpose.

Also, a complete characterization of the propagation of uncertainty through the modeling system, would need to account for other sources of error such as the model structure or the consideration of the errors in the measured discharges that are used in model calibration. The framework proposed in this research can

be extended to take them into account, and gain a better understanding of the problem of propagation of uncertainty on hydrological modeling.

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