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Reduction of the uncertainties in the water level-discharge relation of a 1D hydraulic model in the context of operational flood forecasting

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Abstract

1 This paper presents a data-driven hydrodynamic simulator based on the 1-D hydraulic
2 solver dedicated to flood forecasting with lead time of an hour up to 24 hours. The goal of
3 the study is to reduce uncertainties in the hydraulic model and thus provide more reliable
4 simulation and forecast in real time for operational use by the national hydrometeorological
5 flood forecasting center in France. Previous studies have shown that sequential assimilation
6 of water level or discharge data allows to adjust the inflows to the hydraulic network resulting
7 in a significant improvement of the discharge while leaving the water level state imperfect.
8 Two strategies are proposed here to improve the water level-discharge relation in the model.
9 At first, a modeling strategy consists in improving the description of the river bed geometry
10 using topographic and bathymetric measurements. Secondly, an inverse modeling strategy
11 proposes to locally correct friction coefficients in the river bed and the flood plain through
12 the assimilation of in-situ water level measurements. This approach is based on an Extended
13 Kalman filter algorithm that sequentially assimilates data to infer the upstream and lateral
14 inflows at first and then the friction coefficients. It provides a time varying correction of the
15 hydrological boundary conditions and hydraulic parameters.

16 The merits of both strategies are demonstrated on the Marne catchment in France for
17 eight validation flood events and the January 2004 flood event is used as an illustrative
18 example throughout the paper. The Nash-Sutcliffe criterion for water level is improved from

19 0.135 to 0.832 for a 12-hour forecast lead time with the data assimilation strategy. These
20 developments have been implemented at the SAMA SPC (local flood forecasting service in
21 the Haute-Marne French department) and used for operational forecast since 2013. They
22 were shown to provide an efficient tool for evaluating flood risk and to improve the flood
23 early warning system. Complementary with the deterministic forecast of the hydraulic state,
24 an estimation of an uncertainty range is given relying on off-line and on-line diagnosis. The
25 possibilities to further extend the control vector while limiting the computational cost and
26 equifinality problem are finally discussed.

Keywords:

Hydraulic modeling, Flood forecasting, Data assimilation, Uncertainty reduction

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27 1. Introduction

28 Flooding causes important social, environmental and economic losses and is likely to be
29 aggravated by climate change over the next decades. For example, flooding of the Var river
30 in the South-East of France in 2010 resulted in a 700 million euros loss and 25 victims (22).
31 Worldwide, national or international operational flood forecasting centers are in charge of
32 providing water level predictions and flood risks at short- to medium-range lead time (from
33 several hours to a few days) that are of great importance for civil protection. To this end, op-
34 erational centers aim at providing an accurate forecast of the hydraulic variables (i.e., water
35 level and discharge) along the monitored network. This forecast relies on the complemen-
36 tary use of numerical models and observations (18). For instance, the UK Environment
37 Agency in collaboration with the Met Office has developed the National Flood Forecast-
38 ing System (NFFS) in order to access to real-time forecasts from a large set of hydrologic
39 modeling tools (38; 37). In the Philippines, the Metro Manila model is used operationally
40 to issue 24-hour lead time forecasts using precipitation and water level measurements that
41 are collected and transmitted in real time (20). In France, since 2006, the national and hy-
42 drometeorological flood forecasting center (SCHAPI – Service Central d’Hydrométéorologie
43 et d’Appui à la Prévision des Inondations), in collaboration with the 22 local flood forecast-
44 ing services (SPC – Service de Prévision des Crues), produces a twice-daily vigilance map
45 available for governmental authorities and general public (<http://www.vigicrues.gouv.fr>).
46 Meteorological, hydrologic and geographic data (bathymetry, topography), are used as in-
47 puts to hydraulic models that are integrated in forecast mode to describe water level and
48 discharge at a limited number of observing stations over 22,000 km of rivers in France. These
49 hydraulic variables are then translated into a colored flood risk map available online. On
50 a larger scale, the European Flood Awareness System (EFAS) as part of the Copernicus
51 Emergency Management System provides probabilistic flood alert information more than 48
52 hours in advance to national authorities. This alert system covers the main European rivers
53 on a 5-km grid using a distributed hydrologic rainfall-runoff-routing model (LISFLOOD) as
54 well as ensemble weather forecasts and real-time weather observations (8; 34).

55 The capacity for real-time anticipation of extreme flood events remains limited due to
56 several sources of uncertainty in hydraulic models. On the one hand, forcing data that
57 represent boundary conditions for hydraulic models usually result from the transformation
58 of uncertain observed water levels into discharges with an uncertain rating curve (7; 3), or
59 from discharges forecasted by uncertain hydrologic models. Another source of uncertainty is
60 the description of the river channel and flood plain geometry. This requires on-site measure-
61 ments of topographic and bathymetric profiles to provide a spatially-distributed geometry.
62 On the other hand, the equations that are solved by models are based on simplification and
63 parametrization of the physics. The parametrization schemes are calibrated to adjust the
64 model behavior to observed water levels, typically, through the calibration of friction coeffi-
65 cients. The calibration of the river bed and flood plain friction coefficients is usually achieved
66 once for all using a batch of observations such as water level from a limited number of flood
67 events, thus providing time-invariant values for the model parameters. It is important to
68 mention that errors in the model inputs and in the model equations are sometimes diffi-
69 cult to discriminate (35; 30). These uncertainties usually translate into errors in the model
70 representation of the water level-discharge ($H - Q$) relation that is not coherent with that
71 from the reality. In practice, this inconsistency can be reduced when complementary data
72 become available to improve the model, for instance LIDAR data for bathymetry (horizontal
73 resolution of one point per square meter; 10 to 30 cm of vertical accuracy). When no ad-
74 ditional data are available to improve the model geometry, the error between the simulated
75 and the observed hydraulic states must be accounted for by adjusting the model parameters
76 and/or the model state itself. Many studies have attempted to account for uncertainties
77 at varying levels (36; 19), for instance by analyzing the uncertainty in hydrologic predic-
78 tion based on the Generalized Likelihood Uncertainty Estimation (GLUE) (5; 2; 25; 33),
79 Markov chain Monte Carlo (MCMC) (16), Bayesian inference (27) and Data Assimilation
80 (DA) (19; 24; 10; 9).

81 DA offers a convenient and cost-effective framework, compared to MCMC and Bayesian
82 inference, to overcome some limits of the classical calibration process for model param-
83 eters: observations and simulation outputs are combined along with their respective errors to

84 estimate an optimal set of model parameters and thereby reduce simulation uncertainties.
85 Furthermore, as the DA algorithm is sequentially applied, the analysis allows for a temporal
86 variation of model parameters errors. The classical approach in DA for meteorology and
87 oceanography is to directly correct the model output variables (also called state estimation).
88 In the hydrology and hydraulic literature, the estimation of uncertainty in model parame-
89 ters has been extensively investigated in addition to the more traditional state estimation
90 approach. Sequential state estimation for hydraulic applications was indeed found to have
91 a limited impact on the forecast performance due to the limited persistence of the model
92 initial condition. In contrast, the forecast lead time can be significantly improved via the
93 correction of the hydrologic forcing (14; 1; 31) or of the model parameters (11). Through
94 the inclusion of parameters in the DA process, it is assumed that the forecast uncertainty
95 can be efficiently reduced over a time window for which the errors statistics in the model
96 parameters are stationary. State and parameter correction can be performed independently,
97 or simultaneously (24; 23) with an augmented state as illustrated in (15). For example, (26)
98 focused on state estimation and assimilated water level observation derived from spaceborne
99 imaging and digital terrain model to estimate discharge in an un-gauged basin simulated
100 by a coupled hydrologic and hydrodynamic model. (14) and (21) used ensemble-based ap-
101 proaches (the Ensemble Kalman Filter – EnKF – and particle filters, respectively) to update
102 the state but also to infer the upstream boundary conditions. (4) explored the assimilation
103 of hydrologic data into operational hydrologic forecast to correct several input parameters
104 including river bed friction coefficients.

105 The present study illustrates how errors in the water level-discharge relation of a 1D hy-
106 draulic model can be accounted for in the context of operational flood forecasting following
107 two different approaches. The first method is based on the assumption that additional data
108 on the river bed geometry are available to directly improve the model $H - Q$ relation. In
109 the following, this approach is referred to as experiment BATHY. For the second method,
110 it is assumed that the only additional data available are in-situ water level measurements,
111 which are used in real time to adjust the river bed and flood plain friction coefficients in the
112 model using a DA algorithm. In the following, this approach is referred to as experiment

113 ASSIM. A time-dependent correction of the friction coefficients is provided by DA in order
114 to account for errors in the friction and bathymetry description that vary along with the
115 flow as water level reaches different portions of the described geometry. It should be noted
116 that the errors in the model $H - Q$ relation are potentially larger at high flow since the
117 flood plain topography is not well known and since the model is not well calibrated. Thus,
118 this study aims at demonstrating that both approaches BATHY and ASSIM can signifi-
119 cantly improve the model $H - Q$ relation and subsequently the simulated hydraulic state.
120 This work is carried out in the context of operational flood forecasting at the SAMA (Seine
121 Amont Marne Amont) SPC for the Marne catchment in France. SAMA uses the 1D hy-
122 draulic model MASCARET (12) developed by LNHE (Laboratoire National d’Hydraulique
123 et d’Environnement) from EDF-R&D (Electricité De France – Recherche et Développement)
124 to simulate real-time discharge or water level forecasts at six observing stations on the up-
125 stream part of the Marne river. Maximum forecast lead time for each site is between 5 and
126 21 hours according to the transfer time along the hydraulic network. The reference model
127 for this work, referred to as experiment REF in the following, results from a classical batch
128 calibration procedure of the un-gauged upstream and lateral inflows to the model as well
129 as of the river bed and flood plain friction coefficients. In this context, (31) demonstrated
130 that the assimilation, based on an Extended Kalman Filter (EKF) algorithm, of water level
131 observations to correct hydrologic boundary conditions and hydraulic model parameters on
132 the Adour catchment with MASCARET improves flood forecasting by 60 % for 1-hour lead
133 time and by 25 % for 12-hour lead time. A similar approach using discharge data was then
134 applied to the Marne catchment to specify upstream and lateral inflows (13), resulting in
135 the significant improvement of the simulated discharge state, while the simulated water level
136 state remained imperfect. The correction of un-gauged lateral and upstream inflows with
137 DA offers an alternative solution to the classical batch calibration procedure by considering
138 a time-varying estimation of the boundary conditions. In the present work, this corresponds
139 to the first step of the DA method referred to as experiment ASSIM1 in the following. Fur-
140 ther improvement on the river bed and flood plain friction coefficients in the neighborhood of
141 the observing stations is obtained with water level assimilation. This represents the second

142 step of the DA method referred to as experiment ASSIM2 in the following. The method
143 ASSIM is therefore a two-step DA procedure: ASSIM1 allows for the correction of upstream
144 and lateral inflows and ASSIM2 allows for the correction of river bed and flood plain friction
145 coefficients. The sequential application of both steps in ASSIM is referred to as experiment
146 ASSIM1+ASSIM2.

147 The structure of the paper is as follows: Section 2 provides a description of the Marne
148 catchment and of the materials (hydraulic model, DA method) used to perform flood fore-
149 casting. The evaluation of the linearity of the water level with respect to the friction coeffi-
150 cients is investigated. The limitations of the reference model REF are highlighted and the
151 two-step DA strategy ASSIM is presented in detail. In Sect. 3, the results of both BATHY
152 and ASSIM approaches are presented using the January 2004 flood event as an illustrative
153 example. The operational implementation of the ASSIM approach at the SAMA SPC is
154 described in Sect. 4. Conclusions and perspectives for this work are given in Sect. 5.

155 **2. Materials and methods**

156 *2.1. The 1D hydraulic model MASCARET*

157 The Marne river is an important tributary of the Seine river in France. Its source is
158 located on the Langres plateau in the Haute-Marne department. A mono-dimensional hy-
159 draulic model is used to simulate the hydrodynamics of the 180-km Marne river as presented
160 in Figure 1. This study is carried out in the upstream part of the Marne river where flash
161 floods frequently occur; for instance, in December 2011, the discharge at Condes raised
162 from 25 to 125 m³/s in 24 hours. Upstream boundary conditions (black dots in Figure 1)
163 for the hydraulic network are described with observed water levels that are translated into
164 discharges with a local rating curve; the downstream boundary condition at Chamouilley
165 is also described with a local rating curve. There are six observing stations located on
166 the main stream of the river (black triangles in Figure 1) where water level is measured
167 hourly. These data are provided by the DREAL (Direction Régionale de l'Environnement,
168 de l'Aménagement et du Logement) hydrometeorological service in the Champagne-Ardenne
169 region.

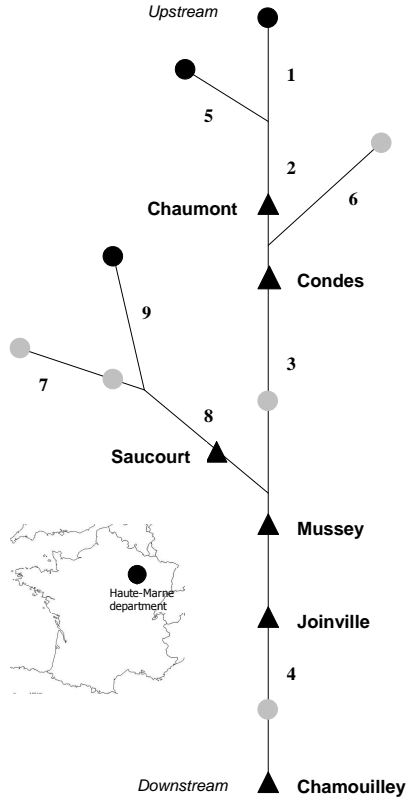


Figure 1: Schematic of the Marne model hydraulic network (Haute-Marne, France).

Observed upstream flows are represented with black dots; additional inflows are represented with grey dots; and observing stations over the hydraulic network are represented with triangles.

170 Along this hydraulic network, the 1D form of the Saint-Venant equations is solved with
 171 the MASCARET (12) software developed by EDF-R&D and CEREMA (Centre d'Etudes et
 172 d'Expertise sur les Risques, l'Environnement, la Mobilité et l'Aménagement), widely used
 173 for modeling flood events, submersion waves resulting from the failure of hydraulic infras-
 174 tructures, river control, and channel waves propagation. The 1D Saint-Venant equations
 175 read (non-conservative form):

$$\frac{\partial S}{\partial t} + \frac{\partial Q}{\partial x} = q_a \quad , \quad \frac{\partial Q}{\partial t} + \frac{\partial QV}{\partial x} + gS\left(\frac{\partial Z}{\partial x} + J + J_s\right) = 0 \quad \text{with } J = \frac{Q^2}{S^2 K_s^2 R_H^{4/3}}. \quad (1)$$

176 where S [m²] is the river section, Q [m³/s] is the discharge, $q_a(x,t)$ is the lateral lineic

177 discharge, K_s [$\text{m}^{1/3} \cdot \text{s}^{-1}$] is the friction coefficient, R_H is the hydraulic radius, g is the gravity,
178 J and J_s represents regular and singular head losses respectively. The river section S is, for
179 each location x , a function of the water level $H = Z(x, t) - Z_{bottom}(x, t)$, where $Z(x, t)$ [m] is
180 the free surface height and where Z_{bottom} [m] corresponds to the river bed bathymetry. The
181 unsteady kernel of MASCARET was used in this study.

182 The Marne terrain model was built with 110 topographic and bathymetric cross sections;
183 it was calibrated in 2011 using a batch of water level and discharge measurements from ten
184 flood events at Chaumont, Condes, Saucourt, Mussey, Joinville and Chamouilley. The
185 model was then validated over eight independent flood events that occurred between 2004
186 and 2013; these events can be classified in three types: two events with a maximum discharge
187 of $100 \text{ m}^3/\text{s}$ at Mussey, two events with a maximum discharge at Mussey ranging between
188 115 and $240 \text{ m}^3/\text{s}$, and three stronger events with a maximum discharge at Mussey above
189 $260 \text{ m}^3/\text{s}$ (among which the January 2004 flood event used in this paper for illustrative
190 purposes). Five upstream and lateral inflows (grey dots in Figure 1) were added to the
191 model to represent additional water input to the network. At these five locations, despite
192 the lack of hydrologic rainfall-runoff model, the hydrograph is described as proportional to
193 a mean upstream area hydrograph; the multiplicative coefficients used for the model in the
194 present work were optimized by a batch calibration procedure. Additionally, the river bed
195 and flood plain friction coefficients (denoted respectively by m and n) were calibrated by
196 minimizing simulated and observed discharge differences; the resulting calibrated friction
197 coefficients that have a straightforward influence on the $H - Q$ relation in the model are
198 given in Table 1. In the following, the model with batch calibration corresponds to the
199 reference model denoted by REF.

200 The Nash-Sutcliffe criteria for water level N_H and discharge N_Q were calculated for the
201 eight validation flood events for each observing station using the following formulation given

202 for Q :

$$N = 1 - \frac{\sum_{i=1}^n (Q_i^{obs} - Q_i^{sim})^2}{\sum_{i=1}^n (Q_i^{obs} - \overline{Q}^{obs})^2}, \quad (2)$$

203 where Q_i^{obs} and Q_i^{sim} correspond to the observed and simulated discharges at time indexed
204 by i , and where \overline{Q}^{obs} denotes the time-averaged value of the observed discharges. The
205 Nash-Sutcliffe criteria results are presented in Table 1. In general, the quality of the results
206 decreases from upstream to downstream as the use of mean multiplicative coefficients gener-
207 ates errors in the lateral and upstream inflows estimation. Additionally, the Nash-Sutcliffe
208 criteria computed with respect to discharge Q are generally better than when computed
209 with respect to water level H , especially at Mussey (Reach 4, Portion 1 in Table 1). It
210 should be noted that there is no rating curve available at Joinville, thus no discharge data
211 at this observing station. For the January 2004 flood event used in this work for illustra-
212 tive purposes, the Nash-Sutcliffe criteria associated with the REF model and presented in
213 Table 2 are respectively 0.773 and 0.894 for water level and discharge. The criteria are here
214 computed in re-analysis mode that corresponds to a 0-h forecast lead time (details are given
215 in Sect. 2.2). REF (dashed lines) and observed (dotted lines) hydraulic states at Mussey
216 are compared in Figure 2 over the January 2004 flood event (thin lines correspond to water
217 level, thick lines correspond to discharges). The difference between REF and observations
218 varies over time for both water level and discharge, thus arguing for a time-dependent cor-
219 rection as enabled by DA in Sect. 2.2. It is important to notice that the sign of the error
220 in discharge and in water level are different for high flow conditions (flood peak from day 4
221 to day 5), while similar away from the flood peak. For high water levels, the discharge is
222 slightly overestimated (by 25 m³/s at day 5), whereas the water level is significantly un-
223 derestimated (by 0.4 m at day 5). During this period, the $H - Q$ relation in the model is
224 incorrect, a negative correction in the discharge would further deteriorate the water level
225 state. Thus, for this event, the batch calibration process is to fail at providing parameters
226 (friction coefficients and upstream/lateral inflows) that would improve both discharge and

227 water level at the flood peak (the same assumption seems legitimate at Joinville). It is then
 228 obvious that the reference model (REF) should be improved as explained in the following.

Reaches	Portions	Length	m	n	Observing stations	N_H	N_Q
1	1	5,172	24	14			
2	1	21,753	24	14	Chaumont	0.922	
3	1	660	36	22	Condes	0.821	0.835
	2	44,842	24	14			
4	1	578	20	13	Mussey	0.544	0.743
	2	8,200	24	18			
	3	300	14	8	Joinville	0.531	
	4	26,383	24	14	Chamouilley	0.614	0.621
5	1	4,150	24	14			
6	1	27,101	24	14			
7	1	7,600	9	7			
8	1	16,266	9	7			
	2	500	13	8	Saucourt	0.797	0.821
	3	5,680	9	7			
9	1	10,819	9	7			

Table 1: Mean friction coefficients obtained after calibration for the river bed (m) and the flood plain (n) in $[m^{1/3}.s^{-1}]$, as well as Nash criteria for water level (N_H) and discharge (N_Q) calculated for eight validation flood events and for reaches 1 to 9 over the Marne model hydraulic network. Reaches lengths are in meters.

229 *2.2. Sequential DA method*

230 *2.2.1. DA algorithm*

231 The DA method (ASSIM) is a two-step procedure using an EKF algorithm.

232 The first step ASSIM1 consists in correcting the upstream and lateral inflows to the
 233 model using discharge data, with the objective to improve the simulated discharge. The

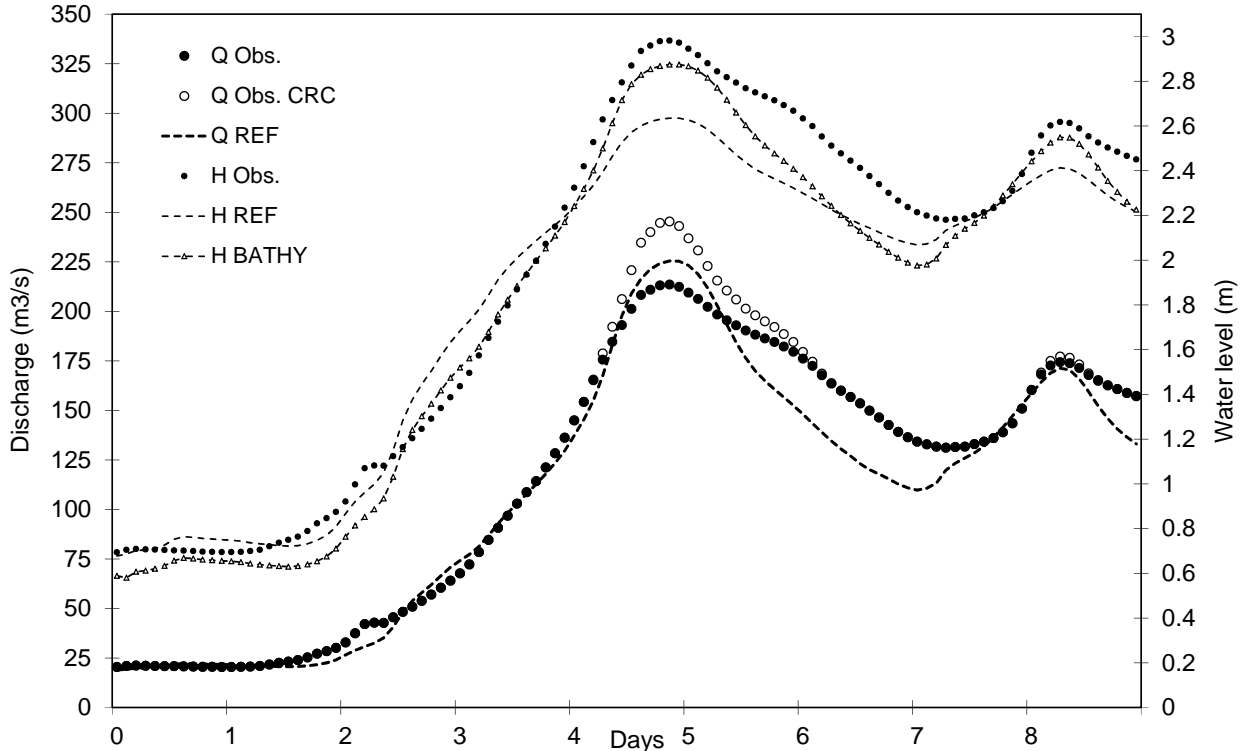


Figure 2: Simulated water levels (thin lines) and discharges (thick lines) at Mussey for REF (dashed line) and BATHY (dashed line with triangle – discharges are unchanged) for the January 2004 flood event. Observations are represented with small and large black dots for water level and discharge, respectively. Circles represent the discharge observations obtained with the Corrected Rating Curve (CRC).

234 ASSIM1 method is presented in details in (31) and (13). For the Marne applicative test
 235 case, discharge observations (Condes, Mussey, Chamouilley and Saucourt) are assimilated
 236 to correct the five upstream and lateral inflows along the hydraulic network (represented by
 237 grey dots in Figure 1) in order to correctly represent discharge.

238 In spite of the discharge improvement, when the model $H - Q$ relation is incorrect (at
 239 high flow), the simulated water level remains imperfect. These errors are here accounted
 240 for in the second step ASSIM2, which uses water level data to locally correct river bed and
 241 flood plain friction coefficients in the neighborhood of the observing stations. The batch
 242 calibration process leads to an estimate that allows, on average, the model to correctly

	N_H	N_Q
REF	0.773	0.894
BATHY	0.923	0.897
ASSIM1	0.784	0.976
BATHY+ASSIM1	0.986	0.987
ASSIM1+ASSIM2	0.97	0.978

Table 2: Nash-Sutcliffe criteria for REF, BATHY, ASSIM1 and ASSIM1+ASSIM2 experiments for water level (N_H) and discharge (N_Q) in re-analysis mode for the January 2004 flood event at Mussey.

243 simulate a set of flood events. Depending on the choice of this set of events, the calibrated
 244 friction coefficients might be better fitted for low, medium or high flow. Usually, high flow
 245 are not well represented. It thus makes sense to look for a time-varying correction of the
 246 friction coefficients during a flood event. Additionnaly, the bathymetry is described from a
 247 limited number of measured cross sections. The correction of the friction coefficients offers
 248 a way to also account for the uncertainty related to bathymetry. In the present study, the
 249 friction coefficients are corrected over a 600-m section in the vicinity of the observing station
 250 at Mussey (Portion 1 of reach 4) and over a 300-m section in the vicinity of Joinville (Portion
 251 3 of reach 4). These coefficients were chosen as their uncertainty has a significant influence
 252 on the simulated water level at the observing stations; still the following method could be
 253 applied to any friction coefficient for the hydraulic network. The friction coefficients in the
 254 river bed and in the flood plains, respectively denoted by m and n , are gathered in the
 255 control vector \mathbf{x} of size $s = 4$ in the present case study. The background values in \mathbf{x}^b are
 256 those specified from the calibration procedure ($m^b = 20$ and $n^b = 13$ for Mussey; $m^b = 14$
 257 and $n^b = 8$ for Joinville). The errors in m and n are supposed to be uncorrelated, and the
 258 respective standard deviation (STD) are set according to the variability in the calibration
 259 procedure ($\sigma_m^b = 3$ and $\sigma_n^b = 4$ at Mussey; $\sigma_m^b = 3$ and $\sigma_n^b = 2$ at Joinville). Hourly water
 260 level observations are assimilated over a time window at Mussey and Joinville and gathered
 261 in the observation vector \mathbf{y}^o of size p . The errors in the water level observations are supposed

262 to be uncorrelated; the observation error STD σ_o is set to 0.025 m to account for errors in
 263 the adjustment of the measurement pressure tube.

264 Following the classical equations of the Kalman filter (17), the analysis vector \mathbf{x}_k^a for
 265 cycle k can be formulated as a correction to the background vector \mathbf{x}_k^b as follows:

$$\mathbf{x}_k^a = \mathbf{x}_k^b + \mathbf{K}_k \left(\mathbf{y}_k^o - H_k(\mathbf{x}_k^b) \right), \quad (3)$$

266 where $\mathbf{K}_k = \mathbf{B}_k \mathbf{H}_k^T (\mathbf{H}_k \mathbf{B}_k \mathbf{H}_k^T + \mathbf{R}_k)^{-1}$ is the gain matrix, \mathbf{B}_k and \mathbf{R}_k are respectively the
 267 background and observation errors covariance matrices, and \mathbf{H}_k is the Jacobian of H_k at \mathbf{x}_k^b .
 268 The analysis error covariance matrix is:

$$\mathbf{A}_k = (\mathbf{I} - \mathbf{K}_k \mathbf{H}_k) \mathbf{B}_k. \quad (4)$$

269 The generalized observation operator H_k is used to describe the model counterpart of the
 270 observations $\mathbf{y}_k^o = H_k(\mathbf{x}_k)$ associated with the control vector \mathbf{x}_k . It consists in, first integrat-
 271 ing the hydraulic model using the friction coefficients in \mathbf{x}^b , then selecting the corresponding
 272 simulated water level at the observed point and time. This operator is non-linear with re-
 273 spect to \mathbf{x} as it implies the integration of the hydraulic model; this issue will be further
 274 investigated in Sect. 2.2.2 as it is a limiting point for the EKF algorithm optimality. The
 275 Jacobian \mathbf{H}_k of the observation operator H_k is a $s \times p$ matrix: each column represents the
 276 variation in the hydraulic variables at the observing locations and times that are due to the
 277 perturbation of an element of the control vector (corresponding to one friction coefficient
 278 over a given location). In the present work, it is conveniently computed in the vicinity of
 279 the background vector at the analysis time k with a finite difference scheme that requires
 280 additional hydraulic model integrations; these independent integrations are run in parallel
 281 using the Parasol functionality of the OpenPALM dynamic coupler (6), a framework that
 282 is convenient to develop DA methods in a modular way. The Jacobian matrix is computed
 283 for each analysis cycle as the impact of a perturbation in the friction coefficients on the
 284 hydraulic variables depends on the hydraulic state itself.

285 Since there is no explicit propagation model for parameters (29; 24; 28; 32), the usual
 286 propagation steps of the KF algorithm are irrelevant here; a persistence model is often

287 assumed for the parameters between the analysis cycles. In the present implementation, the
288 background vector \mathbf{x}_k^b and the background error covariance matrix \mathbf{B}_k are kept invariant
289 between the cycles (for every cycle k). For that reason, the present EKF algorithm can
290 be considered as an invariant EKF (relatively to the background information). It is worth
291 noting that for a given cycle, the initial condition for the background simulation is derived
292 from the analysis simulation obtained during the previous cycle; consequently, each cycle
293 restarts with an improved initial condition. Thus, the background 78-hour run differs from
294 the corresponding portion (in time) of the continuous reference run (REF) since both runs
295 start from a different model state at the cycle initial time. It is also worth mentioning that
296 advanced pseudo-model for parameters could be implemented; this question will be addressed
297 in further work. The small size of the control vector (less than 10 for the Marne test case)
298 enables the use of an EKF algorithm, involving matrix operations for the computation of
299 the gain matrix along with a finite difference scheme for the computation of the generalized
300 observation operator Jacobian.

301 The cycling of the analysis is presented in Figure 3 for ASSIM1 and in Figure 4 for
302 ASSIM2 following ASSIM1. The assimilation is performed over a cycle k of 66 hours with
303 54 hours of re-analysis and 12 hours of forecast at Mussey. The forecast period is adjusted for
304 each observing station and decreases going downstream. Over the 54-hour re-analysis period,
305 the hydrologic upstream and lateral forcings are supposed to be known (either observed or
306 calibrated). Over the forecast period, the forcings are supposed to be unknown and set
307 constant to the last known value. The 54-hour re-analysis period corresponds to a 48-hour
308 period over which the model adjusts to the initial state, plus a 6-hour period over which
309 observations are assimilated using the EKF algorithm. Hence, the size of the observation
310 vector in the present study is $p = 12$. The last observation time from which the forecast
311 integration starts is the analysis time T . For cycle k , in ASSIM1 (Figure 3), over the 6-hour
312 assimilation period (hatching area), the background issued from the previous analysis cycle
313 (solid line) and observed discharges (black dots) are compared and a correction to the inflows
314 is obtained through the EKF analysis step. The correction is applied over the re-analysis
315 and the forecast periods, thus assuming that the nature of the errors in the upstream and

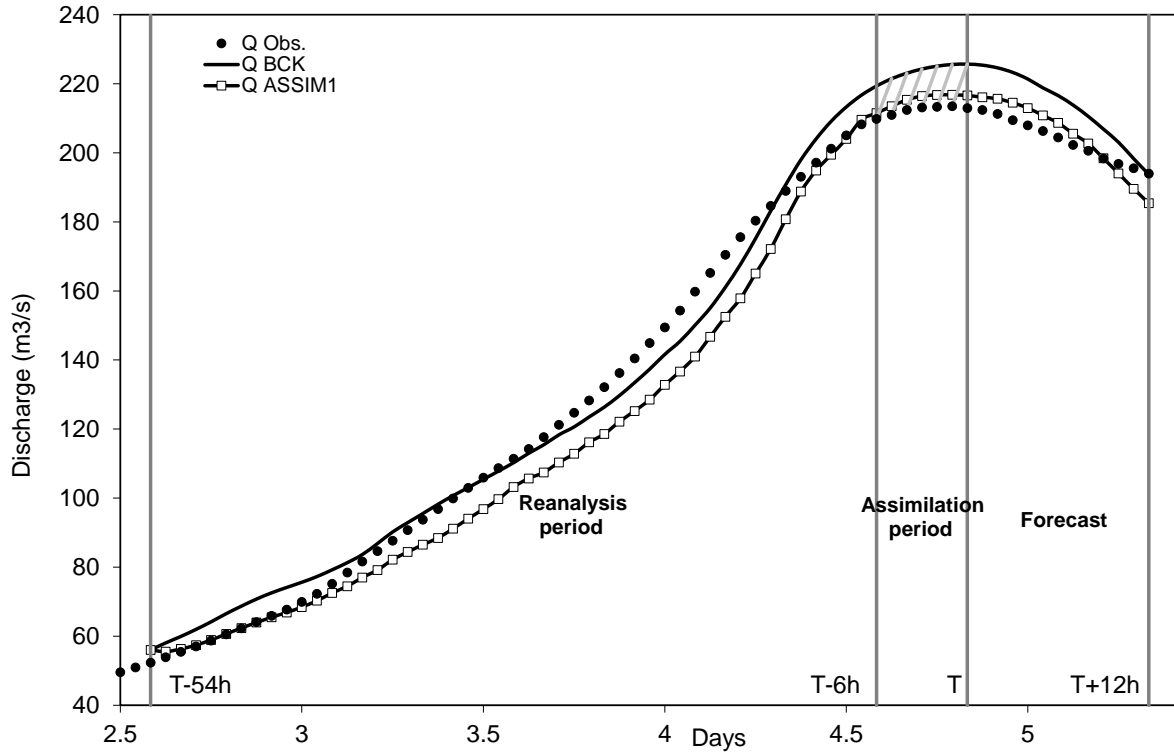


Figure 3: Observed (black dots), background from previous cycle (BCK solid line) and analyzed discharges (squared solid line) for the ASSIM1 approach at the flood peak at Mussey for the January 2004 flood event for $T = 417,600 \text{ s} = 4.83 \text{ days}$.

316 lateral inflows remains the same over the forecast period. The analyzed forcings are used
 317 to achieve a new model integration (over the 66-hour time period), which provides a better
 318 discharge state, while the water level can be either improved or degraded depending on the
 319 coherence between the model and the observation $H - Q$ relation.

320 The analyzed water level from ASSIM1 is then used as the background state for ASSIM2;
 321 it is compared to water level observations over the 6-hour assimilation period and the EKF
 322 update provides a correction to the river bed and flood plain friction coefficients m and n ,
 323 which results in the water level improvement as shown in Figure 4 (squared solid line). The
 324 oscillations at the beginning of the cycle are due to the inconsistency between the initial state
 325 (stored from a previous cycle analysis) and the friction coefficients for the current cycle. The
 326 assimilation window is shifted hourly and the sequential application of ASSIM1+ASSIM2

327 provides a corrected hydraulic state and forecast. This cycled DA procedure allows for
 328 a temporal variability of the friction coefficients over a flood event, which can be either
 329 associated to real changes in the river bed and flood plain friction or geometry properties
 330 as well as to various types of errors that are artificially accounted for here by correcting m
 and n .

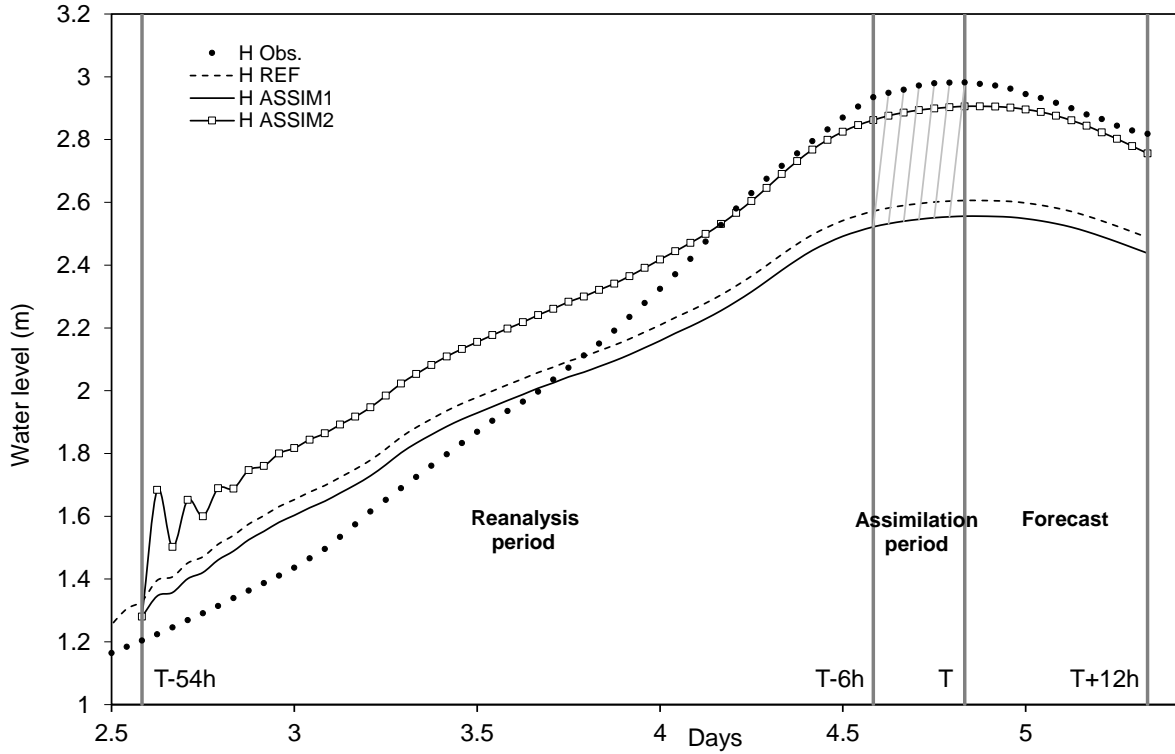


Figure 4: Observed (black dots), background from ASSIM1 (solid line) and analyzed (squared solid line) water levels for the ASSIM2 (following ASSIM1) approach at the flood peak at Mussey for the January 2004 flood event for $T = 417,600 \text{ s} = 4.83 \text{ days}$. Water level from ASSIM1 used as the background state for ASSIM2 is compared to water level observations to provide analyzed friction coefficients and subsequently, corrected water level.

331

332 *2.2.2. Study on the linear assumption of the generalized observation operator*

333 The EKF algorithm relies on the hypothesis that the generalized observation operator can
 334 be approximated by a linear operator on the $[\mathbf{x}^b, \mathbf{x}^a]$ interval. The linearity of the hydraulic
 335 model response to a perturbation in the river bed and flood plain friction coefficients m
 336 and n was thus investigated. Figure 5 presents the probability density function (pdf) of the
 337 simulated water level at Mussey for a permanent flow ($Q = 150 \text{ m}^3/\text{s}$) when the friction
 338 coefficient at Mussey for the minor bed is perturbed around the background mean value
 339 $m = 20$. The 10,000 perturbations are randomly chosen following a Gaussian function with
 a variance of 12.

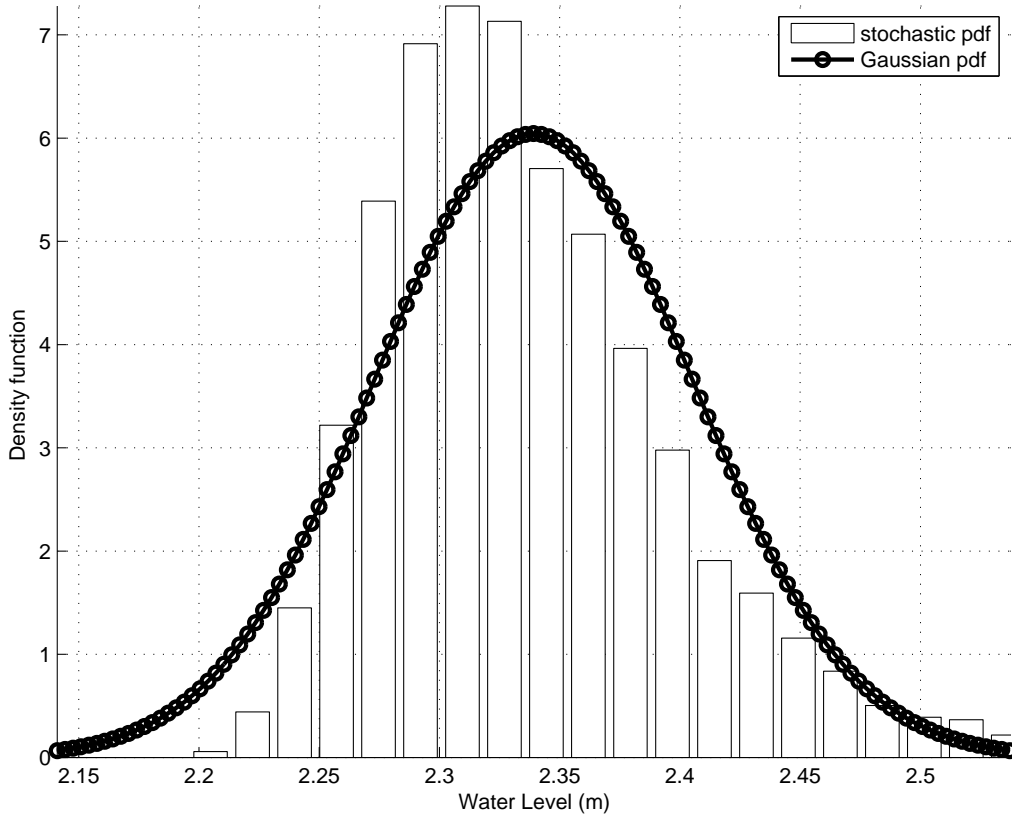


Figure 5: Water level pdf for 10,000 perturbations of the river bed friction coefficient m with a variance of 12. The solid line represents the analytical pdf corresponding to a Gaussian model response; and the histogram represents the actual MASCARET hydraulic model response reconstructed from the 10,000 model outputs.

341 In Figure 5, the pdf in solid line is a Gaussian function built from the first two moments
 342 (mean and variance) of the system response assuming a linear relation in the model. The
 343 actual response is represented by the shaded histogram that is obviously non-symmetrical.
 344 First, there is a larger amount of water-level values that are smaller than the mean of the
 345 Gaussian pdf. This means that the (negative) water level anomaly resulting from a small
 346 positive perturbation δm of the friction coefficient is bigger than the (positive) water level
 347 anomaly resulting from a negative perturbation $-\delta m$ of the friction coefficient. Secondly,
 348 the stochastic pdf is amplified for extreme water level values, meaning that a large (negative)
 349 perturbation of the friction coefficient m results into a large (positive) perturbation of the
 350 water level when a large (positive) perturbation of the friction coefficient has a smaller
 351 impact. The same test was carried out with n ; similar conclusions were drawn. It was also
 352 found that the impact of a perturbation of m and n increases when the discharge increases.
 353 Figure 6 assesses the impact of a perturbation δn (where $x^b = 13$) between -12 and 12 on the
 354 simulated water level at Mussey for different discharges. A perturbation of -6 for n leads to
 355 a variation of 0.01 m when $Q = 80$ m³/s and to a variation of 0.03 m when $Q = 225$ m³/s.

356 Based on these results, it is assumed in the following that the relation between the friction
 357 coefficients and the hydraulic state is reasonably approximated by a linear function in the
 358 vicinity of \mathbf{x}^b . The Jacobian matrix of the generalized observation operator \mathbf{H}_k is computed
 359 around the background values for m and n for a perturbation $\delta m = -2$ and $\delta n = -1$ using
 360 a finite differences scheme in consistency with the linearity study. In order to avoid non-
 361 physical values for the friction coefficients as well as to limit the nonlinear impact, minimum
 362 and maximum threshold values are applied to the friction coefficients with $[14, 24]$ for m
 363 and $[8, 20]$ for n .

364 **3. Correction of the model $H - Q$ relation**

365 *3.1. Bathymetric profiles densification (BATHY)*

366 This section presents the method for experiment BATHY; it is assumed that the $H - Q$
 367 relation in the 1D hydraulic model is improved by adding geometric data to the model.

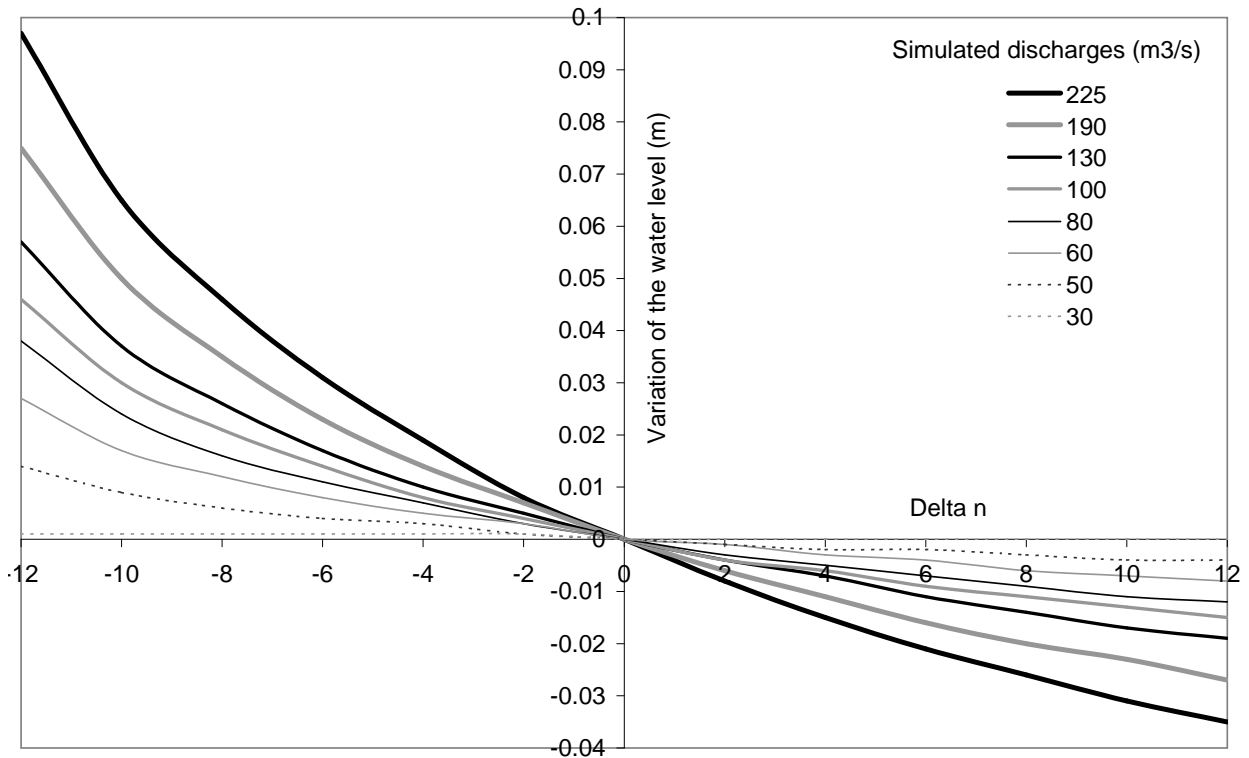


Figure 6: Impact of the flood plain friction coefficient perturbations δn on the water level [m] for different simulated discharges [m^3/s]. A -10 and +10 perturbation of n generates a non equivalent variation of the water level but for low perturbations, the relation between friction coefficients and water level can be considered as linear.

368 Additional measurements of the river bed and flood plain geometry were made available near
 369 Mussey: 4 topographic and bathymetric measurements were performed in the surrounding
 370 of the observing station. The batch calibration of the local friction coefficients was then
 371 re-processed on sections 1 and 2 for reach 4. The friction coefficients for these two sections
 372 were set to $m = 30$ and $n = 8$. Figure 2 illustrates the positive impact of the cross-section
 373 densification for the January 2004 flood event for water level (dashed line with triangles). As
 374 presented in Table 2, for experiment BATHY, the Nash-Sutcliffe criterion for H is improved
 375 from 0.773 to 0.923, even though a 10-cm underestimation remains. The discharge results
 376 are left unchanged by this local bathymetry correction with a 0.897-Nash-Sutcliffe coefficient
 377 for BATHY (compared to 0.894 for REF); a small overestimation at the flood peak remains

378 (10 m³/s) for this event. As shown in Table 3, the Nash-Sutcliffe criteria values computed
 379 for water level over the eight validation flood events in re-analysis mode for BATHY are
 380 better than those computed for REF, especially at Mussey where the additional geometry
 measurements were made; in contrast, the impact at Joinville is small.

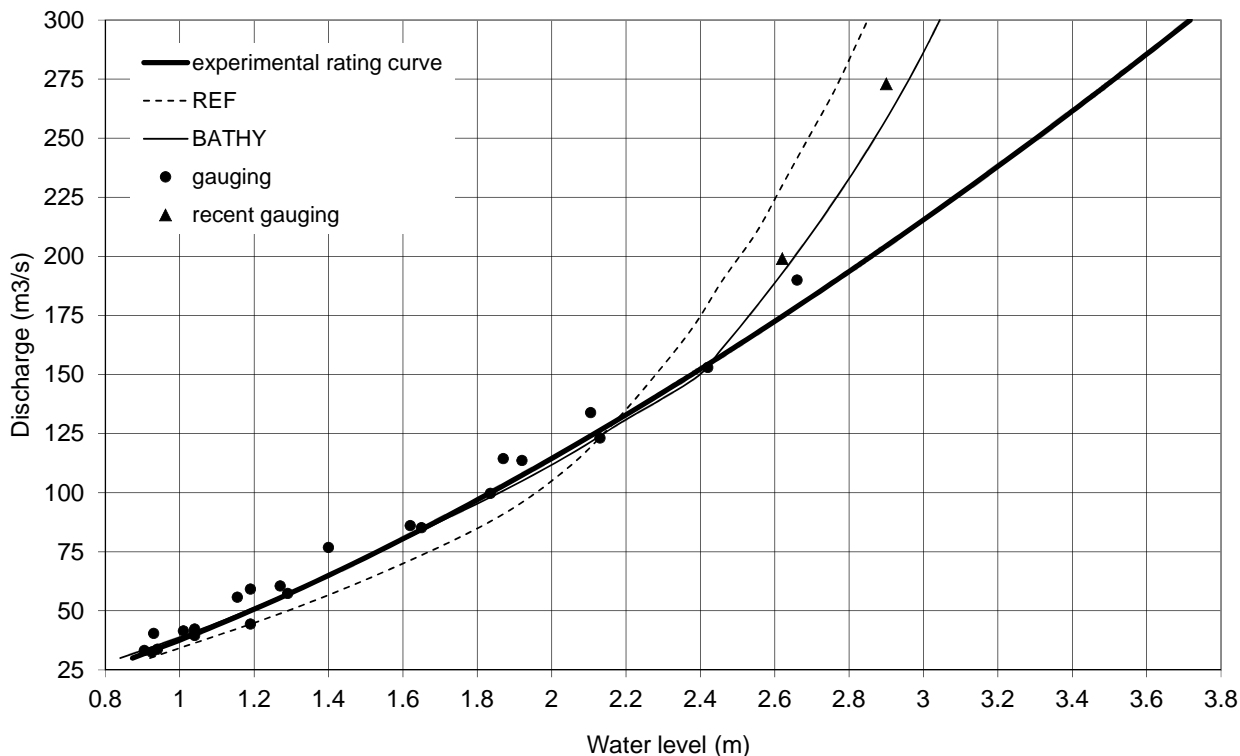


Figure 7: Comparison of the $H - Q$ relation at Mussey, derived experimentally (thick solid line) from gauging (black dots/triangles), involved in the reference model REF (thin dashed line) and obtained through the BATHY approach (thin solid line). Recent gaugings are represented with black triangles.

381
 382 In Figure 7 the $H - Q$ relation for REF is represented by the thin dashed line, and
 383 the $H - Q$ relation for BATHY is represented by a thin solid line. It is shown that the
 384 BATHY $H - Q$ relation is in better agreement with all available gauging (black dots and
 385 triangles) than the REF $H - Q$ relation. As a consequence, the new model $H - Q$ relation
 386 should be used to produce discharge data from water level measurements at Mussey, in
 387 place of the experimental rating curve (thick solid line) that is in good agreement with low

Observing stations	Mussey		Joinville
	N_H	N_Q	N_H
Forecast lead time	0h	0h	0h
REF	0.601	0.722	0.653
BATHY	0.681	0.721	0.661
ASSIM1	0.754	0.854	0.779
BATHY+ASSIM1	0.858	0.853	0.784
ASSIM1+ASSIM2	0.859	0.842	0.992
Forecast lead time	12h	12h	12h
REF	0.135	0.238	0.154
BATHY	0.272	0.241	0.158
ASSIM1	0.689	0.807	0.695
BATHY+ASSIM1	0.781	0.802	0.698
ASSIM1+ASSIM2	0.832	0.807	0.907

Table 3: Nash-Sutcliffe criteria for REF, BATHY, ASSIM1, ASSIM1+ASSIM2 and BATHY+ASSIM1 computed over eight flood events for 2004-2013 at maximum lead time (12 hours) at Mussey and Joinville.

388 flow measurements but can lead to an underestimation of up to $60 \text{ m}^3/\text{s}$ for high flow. It
 389 should be noted that the experimental rating curve was built from numerous gaugings below
 390 $150 \text{ m}^3/\text{s}$ (black open dots) and only two gaugings above $150 \text{ m}^3/\text{s}$. Additionally, two recent
 391 gaugings for high flow (black triangles) allow to validate the BATHY model $H - Q$ relation
 392 over the entire range of discharge values at the observing station. Figure 2 presents the
 393 corrected observed discharges that are derived from water level measurements at Mussey
 394 using the BATHY densified model $H - Q$ relation (black circles). Using these corrected
 395 measurements, the model now slightly underestimates both water level (thin dashed line)
 396 and discharge (thick dashed line) at the flood peak. The sign of the errors in discharge and
 397 water level are now the same over the entire flood event, meaning that the optimization of
 398 upstream and lateral inflows as proposed in (13) is an appropriate solution for further flood

399 forecast improvement for both discharge and water level states.

400 *3.2. Data assimilation for friction coefficients correction (ASSIM)*

401 In this section, it is assumed that no additional geometric measurement is available. The
402 reference model $H - Q$ relation is improved accounting for errors in friction coefficients and
403 by artificially accounting for local bathymetry error with the sequential estimation of the
404 river bed and flood plain friction coefficients m and n in the surrounding of the observing
stations at Mussey and Joinville (experiment ASSIM).

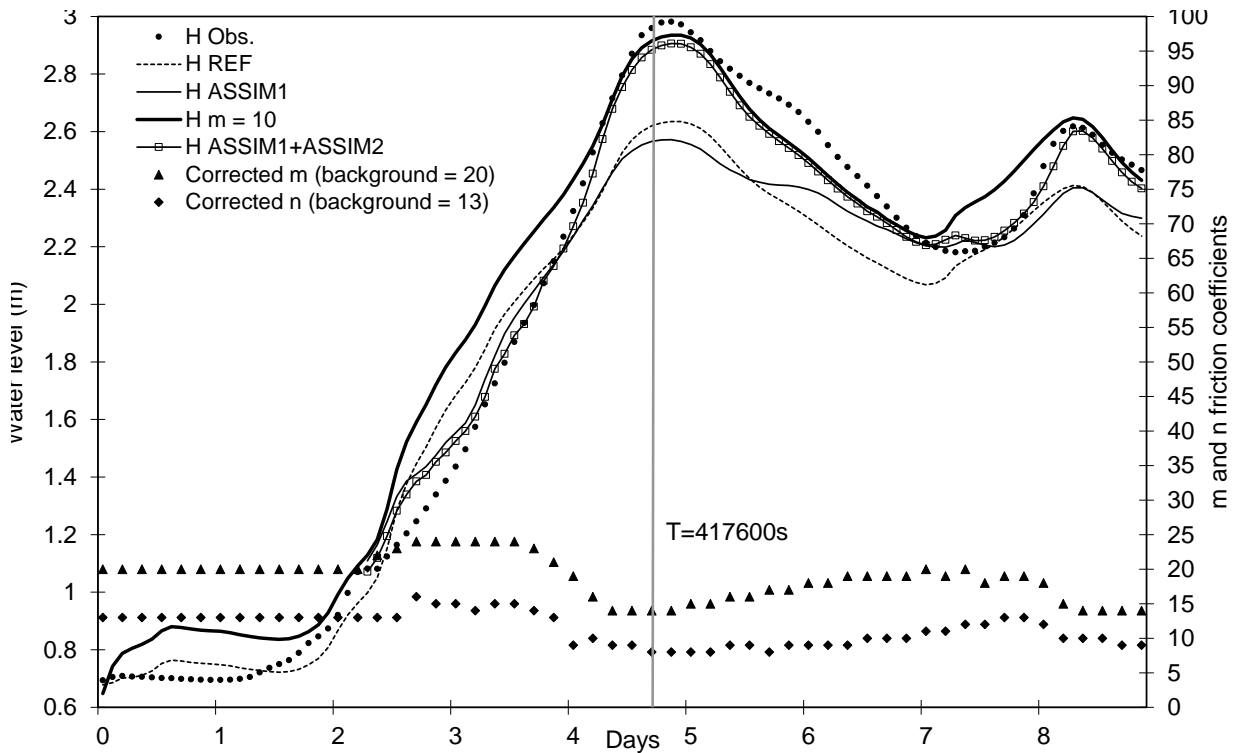


Figure 8: Observed water levels, REF (dashed line), model with $m = 10$ (thick solid line), background from ASSIM1 (thin solid line), ASSIM1+ASSIM2 (squared solid line) for the January 2004 flood event at Mussey. Corrected friction coefficients for river bed (m) and flood plain (n) from DA analysis are represented with triangles and diamonds respectively.

405
406 Figure 8 illustrates that the water level can be efficiently increased at Mussey, compared
407 to that of REF ($m = 20$ and $n = 13$ represented with a thin dashed line), when decreasing the

408 river bed friction coefficient to $m = 10$ (thick solid line), while discharges are left unchanged
409 (not shown). The value $m = 10$ is appropriate for high flow but leads to a water level
410 overestimation for low flow condition. The friction coefficient estimation should then be flow
411 dependent and provide time-dependent friction coefficients that account for varying errors in
412 the friction and bathymetry river bed as the flow occupies a varying portion of the river and
413 the flood plain. For this purpose, the DA method ASSIM detailed in Sect. 2.2 is cycled over
414 the entire flood event to estimate upstream and lateral inflows (ASSIM1), and river and flood
415 plain friction coefficients (ASSIM2) over time using hourly observed discharge and water level
416 at Mussey. Corrected lateral and upstream forcings from ASSIM1 are used to provide the
417 background state (thin solid line) for the friction coefficient estimation in ASSIM2. It should
418 be noted that while ASSIM1 leads to a significant correction of discharge, the water level in
419 ASSIM1 remains close to that of REF. The ASSIM1+ASSIM2 DA analysis for water level is
420 presented for time T from day 2.25 to the end of the flood event in Figure 8 (squared line).
421 For instance, at day 3, REF overestimates the water level, ASSIM1+ASSIM2 increases the
422 friction coefficients in order to decrease the simulated water level. On the contrary, over
423 the flood peak period (days 4-7), REF underestimates the water level, ASSIM1+ASSIM2
424 decreases the friction coefficients in order to increase the simulated water level.

425 The Nash-Sutcliffe criteria for water level and discharge computed at Mussey for January
426 2004 in re-analysis mode are presented in Table 2. ASSIM1 improves the discharge Nash
427 value from 0.894 (REF) to 0.976; it is not significantly affected by ASSIM2 (0.978). The
428 water level Nash value is not significantly modified by ASSIM1 (0.773 for REF compared to
429 0.784 for ASSIM1); it should be noted that ASSIM1 can either lead to an improvement or
430 a degradation of the water level (as it is the case at the flood peak). However, it is greatly
431 improved with ASSIM2 to 0.97. These results are also obtained over the eight validation
432 flood events: the Nash-Sutcliffe criteria computed at Mussey and Joinville in re-analysis
433 mode (0-hour forecast lead time) as well as at the maximum lead time forecast (12 hours)
434 are presented in Table 3 for REF, BATHY and ASSIM. In re-analysis mode, ASSIM1 greatly
435 improves the discharge results, while ASSIM2 provides improved water level states at Mussey
436 and Joinville since the friction coefficients are corrected in the vicinity of both observing

437 stations. In forecast mode, the upstream and lateral hydrologic forcings are supposed to
438 be unknown and set constant to the last observed value. As a consequence, the Nash-
439 Sutcliffe coefficients for REF and BATHY decrease as the forecast lead time increases. The
440 correction of upstream and lateral inflows from ASSIM1 enables a correction of the forcing
441 over the forecast period, thus allowing for a significant improvement of the results at a 12-
442 hour forecast lead time. The water level Nash criteria is further improved by ASSIM2 for
443 Mussey and Joinville. For ASSIM1 and ASSIM2, it is assumed that the correction computed
444 over the analysis period can be applied over the forecast period; as the nature of the errors
445 varies in time, this assumption is less and less valid as the forecast lead time increases and
446 the merits of ASSIM decrease.

447 It should be noted that the local densification of the geometric description (BATHY)
448 when applied sequentially with ASSIM1, leads to similar results to ASSIM1+ASSIM2 at
449 Mussey but not at Joinville, where no additional bathymetric measurements were available.
450 ASSIM thus appears as an efficient approach for improving and forecasting both discharge
451 and water level given no additional data on the river bed and flood plain geometry. Fol-
452 lowing these tests, the approach ASSIM1+ASSIM2 has become recently operational at SPC
453 SAMA: the assimilation of discharge measurements used in real-time mode to better quan-
454 tify upstream and lateral inflows (ASSIM1) has successfully run since December 2013; the
455 extension of the control vector to the river bed and flood plain friction coefficients (ASSIM2)
456 has recently been added into the operational flood forecasting chain and has shown very good
457 results. The details for the ASSIM implementation in the framework of operational flood
458 forecasting are given in Sect. 4.

459 **4. Operational implementation at SPC SAMA**

460 The SPC SAMA transfers a vigilance map to SCHAPI twice a day at 8:45 a.m and 2:45
461 p.m so that the national vigilance map can be issued at 10:00 a.m and 4:00 p.m. The real-
462 time forecast operational chain for the Marne Amont Global (MAG) hydraulic model using
463 DA from the ASSIM1+ASSIM2 previously described approach is presented in Figure 9 and

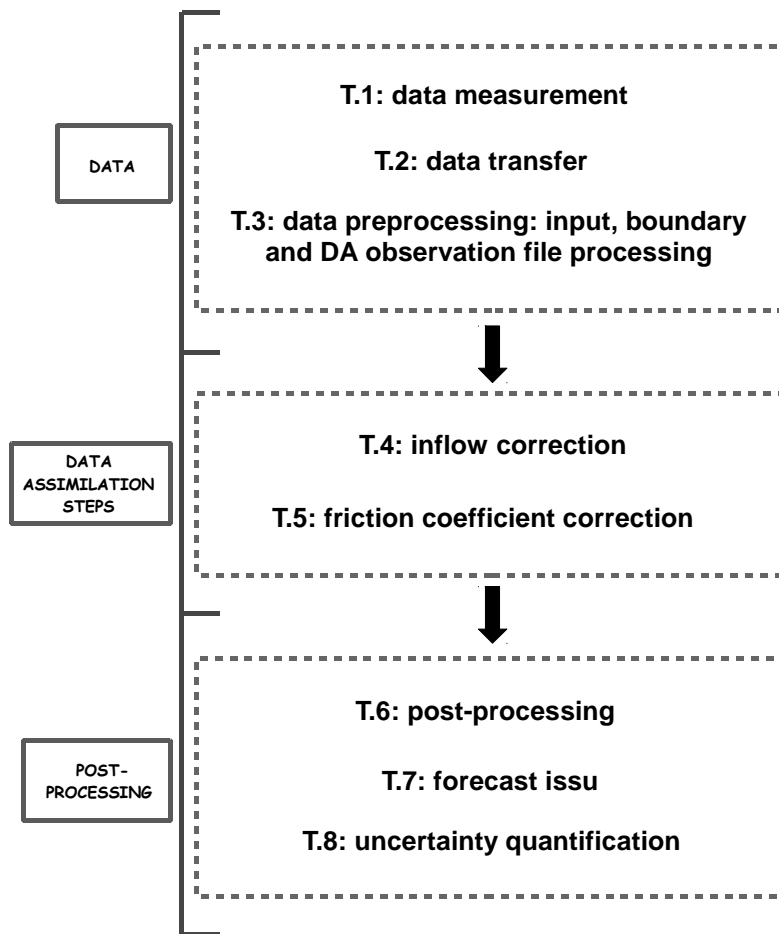


Figure 9: Operational organigram for DA applied to the Marne Amont forecast model divided in eight tasks.

464 is broken down in three modules. This chain should be computationally efficient to allow
 465 for the use of recently acquired data while providing informed forecasts.

466 The first module, named DATA, is composed of three tasks. In task 1, in-situ mea-
 467 surement of water levels are made at approximately 50 observing stations with automatic
 468 instruments over the SAMA catchment. In task 2, these data are gathered at SPC through
 469 telephone network four times a day, up to hourly during a flood event. The quality of these
 470 data is controlled and, when not observed, discharge data are computed using a local rating
 471 curve. Task 3 consists in pre-processing the observed data to provide to input files for the
 472 hydraulic model. Depending on the average flow conditions in the network, an initialisation

473 file for the MAG model is chosen amongst a pre-computed input files data base for low,
474 medium and high flow. Using data from the upstream observing stations, 9 files for the
475 boundary conditions for the hydraulic network are automatically generated for each analy-
476 sis time T over $[T-54h,T]$, with a constant extension over $[T,T+21h]$ (maximum lead time
477 at Chamouilley). Water level and discharge observations files are automatically generated
478 at the assimilation station of Condes, Mussey, Joinville, Chamouilley and Saucourt over
479 $[T-6h,T]$ for the assimilation analysis.

480 The second module, DA STEPS, gathers two tasks that launch the DA steps. Task 4
481 represents the ASSIM1 step of the DA procedure : observed discharges are assimilated at
482 Condes, Mussey, Chamouilley and Saucourt to correct upstream and lateral inflows. The
483 corrected forcing files are stored for use in task 5. Task 5 represents the ASSIM2 step of the
484 DA procedure: observed water levels at Joinville are assimilated to correct the local friction
485 coefficients. The improved bathymetry from BATHY in the neighboring of Mussey is used
486 in the operational model MAG, thus improving the model $H - Q$ relation locally. As a
487 consequence, there is no need to assimilate observed water level at Mussey.

488 The third module is dedicated to POST-PROCESSING of the analysis. The REF and
489 ASSM1+ASSIM2 result files are exported in task 6 to a server for post-treatment using a
490 supervision software that provides the forecaster with an integrated hydrological situation
491 of the catchment. In task 7, based on the provided forecast and his expertise, the forecaster
492 is finally able to characterize the flood risk within the risk-color panel.

493 In the third module, this information is then published by SCHAPI on the vigicrues
494 web site and communicated to the Civil Services. Task 8 is dedicated to quantifying the
495 uncertainty (UQ) related to the forecasted water level. Considering a gaussian-shaped error
496 on the controled friction coefficients and forcing corrective parameters, the analysis error
497 is used to define a so-called analysis interval between the 10th and the 90th quantiles.
498 Integrating a limited number of additional model runs for these interval limits thus provides
499 an on-line envelope for forecasted water level. An additional information on the forecasted
500 water level is given by a set of abacus that are set up off line. The difference between the
501 simulated and observed water level for the eight validation flood events are computed and

502 classified in quantiles for each forecast lead time. The median, 10th and 90th quantiles are
 503 identified and used in the operational chain to provide an uncertainty range for the analysed
 504 water level. The computational cost of the full chain is about 4 minutes on a mono processor
 505 work station. Both uncertainty ranges are represented in Figure 10 for the December 2011
 506 event at Joinville. On December 18th at 1 p.m, the REF model (dashed line) overestimates
 507 the observed water level (black dots) reaching the orange threshold. ASSIM1+ASSIM2
 508 analysis (squared solid line) provides a water level that is below the threshold with an
 509 uncertainty range that remains below (or extremely close to) the orange threshold for both
 510 off-line and on-line UQ methods (grey and hatched envelopes).

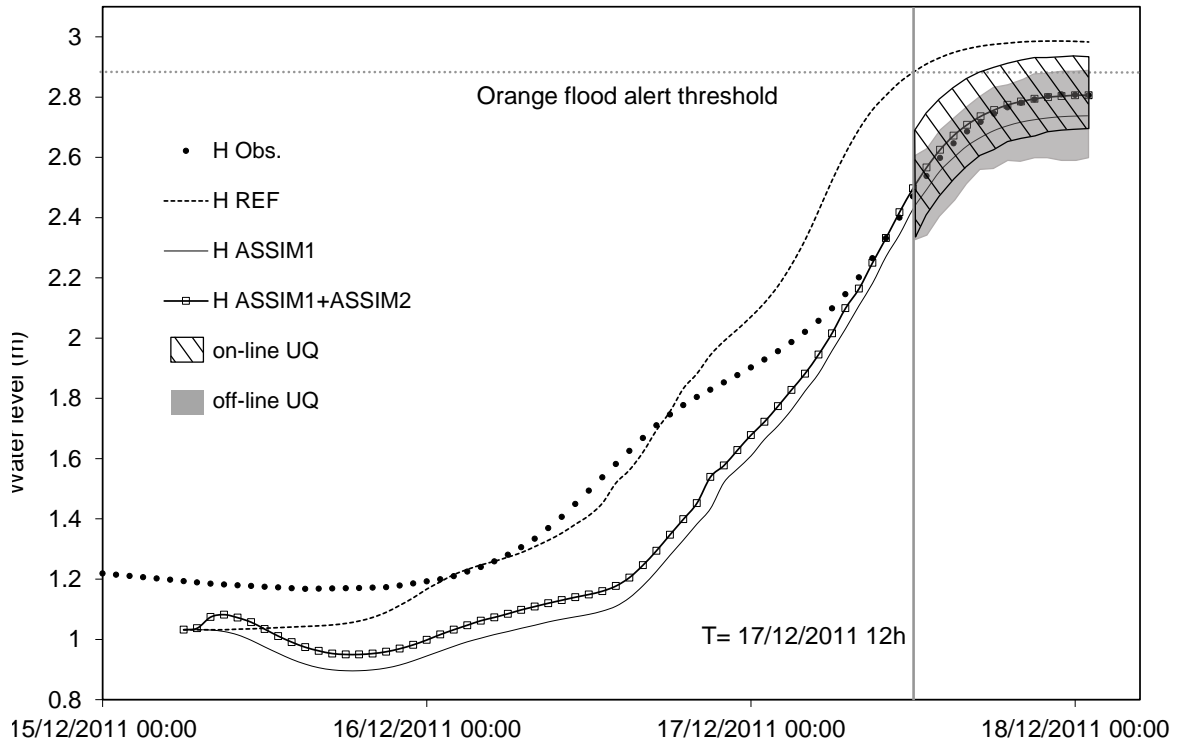


Figure 10: Observed water level (black dots) and forecasts for REF (dashed line),
 background from ASSIM1 (thin solid line) and ASSIM1+ASSIM2 (squared solid line) at
 Joinville for the December 2011 flood event. Uncertainties computed with on-line and
 off-line methods are represented with grey-colored and hatched areas.

511 5. Conclusion

512 This paper addressed the errors in the water level-discharge relation of a 1D hydraulic
513 model (MASCARET) in order to improve the forecasted water level state in the context of
514 operational flood forecasting; this water level is used to generate a colored flood risk map
515 at the French national level by SCHAPI. This improvement is obtained over the Marne
516 catchment through the integration of additional bathymetry data and water level measure-
517 ments. In this work, it was first exhibited that a local densification of the description of the
518 river bed geometry leads to an improved water level simulation compared to the reference
519 model issued from a batch calibration process. The corrected bathymetry is used in the
520 model to build a rating curve that is found to be in good agreement with recent high flow
521 gauging. In operational context, this new rating curve is used to provide discharge from
522 hourly observed water level. At high flow, both water level and discharge are slightly under-
523 estimated. The model can thus be improved by sequentially correcting the upstream and
524 lateral inputs to the models that are known to be imperfect approximation of hydrologic
525 flows for the hydraulic network. In an alternative strategy, it was assumed that no addi-
526 tional bathymetry measurement could be made and that the water level-discharge relation
527 was improved by sequentially correcting the river bed and flood plain friction coefficients.
528 An extended Kalman filter (EKF) algorithm assimilates first hourly discharge observations
529 to correct inflows, then water level observations are assimilated to locally correct the friction
530 coefficients. This sequential approach provides a time-dependent correction of the friction
531 coefficients that accounts for errors in the friction and bathymetry description that vary
532 along with the flow as water level reaches different portions of the described geometry. A
533 sensitivity study showed that the model response is weakly nonlinear with respect to the
534 friction coefficients when the perturbation in the friction coefficient values remains bounded.
535 Both methods were applied in operational context and the Nash-Sutcliffe coefficient for both
536 water level and discharge was computed over eight validation flood events and greatly im-
537 proved compared to the reference model.

538 At SPC SAMA, both approaches are currently used for operational flood forecasting. The

539 densified bathymetry description is used in the neighboring of the Mussey observing station
540 and water level data are assimilated to improve the water level-discharge relation in the
541 model in the neighboring of the Joinville observing station. An estimation of the analyzed
542 water level is also provided based on off-line abacus computed from a set of comparisons
543 between the model and the observations over past events. The two-step EKF-based data
544 assimilation approach also provides an error analysis variance for the river bed and flood
545 plain friction coefficients that are used to describe a confidence interval for the forecasted
546 water level.

547 In further work, the control vector should be extended to bathymetry profiles using
548 parametric correction, in order to limit the equifinality issue as well as the size of the control
549 vector to remain compatible with operational framework. The friction coefficients correction
550 will be extended to long-distance reaches; it should allow for a temporal adjustment over a
551 flood event and thereby for a significant improvement of the forecast lead time. A spatially
552 and time varying correction of the hydraulic parameters is the next challenge in line. For
553 that purpose, the use of spatially distributed data such as remote sensing data should be
554 investigated. High-resolution data with global coverage such as those from the upcoming
555 SWOT (Surface Water and Ocean Topography) mission will provide a new way to fully
556 describe the river hydrodynamics. Operational flood forecasting centers should thus be
557 prepared to make the most of the combination of remote sensing and in-situ data to design
558 future vigilance products.

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This paper presents a data-driven hydrodynamic simulator based on the 1-D hydraulic solver dedicated to flood forecasting with lead time of an hour up to 24 hours. The goal of the study is to reduce uncertainties in the hydraulic model and thus provide more reliable simulation and forecast in real time for operational use by the national hydrometeorological flood forecasting center in France. Previous studies have shown that sequential assimilation of water level or discharge data allows to adjust the inflows to the hydraulic network resulting in a significant improvement of the discharge while leaving the water level state imperfect. Two strategies are proposed here to improve the water level-discharge relation in the model. At first, a modeling strategy consists in improving the description of the river bed geometry using topographic and bathymetric measurements. Secondly, an inverse modeling strategy proposes to locally correct friction coefficients in the river bed and the flood plain through the assimilation of in-situ water level measurements. This approach is based on an Extended Kalman filter algorithm that sequentially assimilates data to infer the upstream and lateral inflows at first and then the friction coefficients. It provides a time varying correction of the hydrological boundary conditions and hydraulic parameters.

The merits of both strategies are demonstrated on the Marne catchment in France for eight validation flood events and the January 2004 flood event is used as an illustrative example throughout the paper. The Nash-Sutcliffe criterion for water level is improved from 0.135 to 0.832 for a 12-hour forecast lead time with the data assimilation strategy. These developments have been implemented at the SAMA SPC (local flood forecasting service in the Haute-Marne French department) and used for operational forecast since 2013. They were shown to provide an efficient tool for evaluating flood risk and to improve the flood early warning system. Complementary with the deterministic forecast of the hydraulic state, an estimation of an uncertainty range is given relying on off-line and on-line diagnosis. The possibilities to further extend the control vector while limiting the computational cost and equifinality problem are finally discussed.