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Strategies for hydrologic ensemble generation and calibration: on the merits of using model-based predictors

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Abstract

This paper investigates the hydrometeorological chain with an ensemble approach. The objective is the generation of Hydrologic Ensemble Forecasts (HEF) on the Odet catchment (France, Brittany), using the Quantile Regression Forest (QRF) method usually applied for the ensemble calibration of meteorological forecasts. First, a Global Sensitivity Analysis (GSA) in the distributed MORDOR-TS model is carried out taking into account uncertainty in forecasted rain with AromeEPS-RR1 and in model parameters. GSA highlights the role and importance of the different hydrologic model parameters during rain events and allows to only take into account the most influent parameters for the generation of an Hydrologic Ensemble Forecast (HEF).

Three strategies for the generation of HEF are then compared. First (i), a raw ensemble is built with a model-based only approach using the deterministic forecast rainfall Expert-RR3 and perturbed model parameters, without further statistical calibration. Then, the QRF calibration method is used to generate two ensembles of quantiles: (ii) the observation-based approach uses only predic-

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tors that are independent from hydrology, whereas (iii) the combined model and observation approach combines these predictors with statistics of the raw hydrologic ensemble (mean, standard deviation). This latter approach was shown to outperform the previous ones, enhancing the importance of the choice of the predictors in the QRF method. In the prospect of using the hydrologic ensemble as input for hydraulic simulation, the Ensemble Copula Coupling method (ECC) and a trajectory smoothing procedure is then applied on (iii). This step slightly deteriorates the reliability of hourly streamflows, yet Continuous Ranked Probability Score (CRPS) and forecast skills on the cumulated or maximum streamflows are improved.

Keywords: Ensemble Prediction System, Global Sensitivity Analysis, Hydrologic Ensemble Forecast, Quantile Regression Forest, MORDOR-TS, Odet catchment

2010 MSC: 00-01, 99-00

1. Introduction

In spite of the great efforts that have been put into land surface models coupled to hydrologic models, deterministic simulation and forecast of streamflow remains limited mostly due to the stochastic nature of precipitation and the complexity of meteorological and hydrologic processes. Thus an ensemble approach is favored; it provides a probabilistic hydrologic forecast needed by decision support systems dealing with risk-based stakes in real-time (low and high flow) as well as by water resources management actors (hydropower production, irrigation, navigation, tourism). Forcing hydraulic models with forecasted hydrologic inflow allows to extend forecast lead time at stations where security and production are at stake. Before use for application, the performance of the ensemble forecast should be assessed (Jolliffe and Stephenson, 2003) in terms of reliability and resolution, with respect to observations. The reliability refers to the statistical consistency between the ensemble and the observations. The resolution describes the ability of the ensemble to discriminate situations leading or not to an event.

1.1. Hydrometeorological uncertainties

The objective of ensemble forecasts is to cover and represent the uncertainties existing in the prediction chain. Numerous and various sources of uncertainties along the hydrometeorological simulation chain lead to uncertainty in discharge simulation and forecast. Three main sources of hydrometeorological uncertainties are acknowledged in the literature (Bourgin, 2014; Zappa et al., 2011; Thibault et al., 2016; Demargne et al., 2014): atmospheric forcing observation and prediction, hydrologic model initial condition, hydrologic model structure and parameters. According to the classification proposed by Krzysztofowicz (1999), atmospheric forcing is referred to as input uncertainty, whereas the other sources are referred to as hydrologic uncertainties.

On the one hand, input uncertainty, i.e meteorological uncertainty, can be accounted for by an Ensemble Prediction System (EPS), which accounts for

30 uncertainties in initial conditions and model physics in Numerical Weather Pre-
31 diction (NWP) models. The most straightforward technique to issue Hydrologic
32 Ensemble Forecasts (HEF) is to use EPS as input for a hydrologic model, thus
33 producing an ensemble of discharges. Numerous studies and operational applica-
34 tions have been conducted on this topic (Cloke and Pappenberger (2009), Papp-
35 enberger et al. (2016)). On the other hand, hydrologic uncertainty is also
36 taken into account to issue HEF considering model parameters uncertainties
37 Dietrich et al. (2009) or using a multi-model approach (Hopson and Webster,
38 2010; Velázquez et al., 2011; Thiboult et al., 2016; Bellier, 2018). Since 2004,
39 research, operational and user communities gathered around the HEPEx ini-
40 tiative (Hydrologic Ensemble Prediction EXperiment, www.hepex.org), which
41 aims at advancing the science and practice of hydrological ensemble prediction
42 and demonstrating their utility in decision making (Thielen et al., 2008; Schaake
43 et al., 2010).

44 *1.2. Uncertainty quantification for Hydrologic Ensemble Forecasts (HEF) gen-* 45 *eration*

46 The performance of the raw hydrologic ensemble is linked to how the different
47 sources of uncertainties are accounted for in the ensemble generation. The HEF
48 system should be built taking into account major sources of uncertainties (both
49 atmospheric and hydrologic) with associated ranges of uncertainty. To that end,
50 identifying and ranking sources of uncertainty is necessary. Given assumptions
51 on uncertain parameters, this can be achieved with a sensitivity analysis (SA).
52 A review of SA methods is available in Iooss and Lemaître (2015).

53 Global Sensitivity Analysis (GSA) (Saltelli, 2008) allows to quantify the
54 contribution of model inputs to its outputs. It implies the integration of an en-
55 semble of simulations from which sensitivity indices are computed; for instance
56 Sobol indices based on variance-based methods (Efron and Stein, 1981). GSA is
57 widely applied in hydrology. In Emery et al. (2016), a GSA is achieved in order
58 to highlight the key parameters impacting the river-routing scheme Total Runoff
59 Integrating Pathways (TRIP) that simulates river water height and discharge on

60 the Amazon catchment. Garambois et al. (2013) analyzed MARINE hydrologic
61 model sensitivity during flash-floods. In Michon and Castaings (2017), a GSA
62 on the Kling-Gupta Efficiency (KGE, Gupta et al. (2009)) of the MORDOR-TS
63 hydrologic model was carried out on several French catchments.

64 *1.3. Statistical calibration of ensembles*

65 Ensemble approaches aim at representing the uncertainty along a simulation
66 chain. However, the total uncertainty is rarely fully covered and raw EPS are
67 known to be underdispersive and biased (Hamill and Colucci, 1997; Schaake
68 et al., 2010). A post-processing step on the ensemble precipitation forecast
69 (post-processing with respect to meteorology, pre-processing with respect to
70 hydrology) should thus be achieved before using them as input for rainfall-
71 runoff models and issuing HEF. Similarly, HEF should be post-processed to
72 account for uncertainty in EPS as well as in hydrologic model parameters. The
73 improvement of EPSs' and HEFs' reliability and resolution relies on a statistical
74 post-processing, named ensemble calibration.

75 Statistical ensemble calibration is an active field of research in meteorology
76 and hydrology. It exploits the relation between the past previsions and their
77 corresponding observations (Wilks, 2018) to correct the forecast. Parametric
78 and non-parametric calibration methods are reported in the literature. Para-
79 metric methods rely on an a priori assumption for the output data distribution
80 which parameters are identified by the calibration algorithm. In contrast, non-
81 parametric methods are data-based only. Wilks (2018) describes the state of
82 the art of statistical postprocessing of meteorological ensemble forecasts. A re-
83 view of statistical ensemble calibration methods used in the field of hydrology
84 is available in Li et al. (2017).

85 Two widely used parametric methods are Ensemble Model Output Statistics
86 (EMOS that is a regression method) (Gneiting et al., 2005) and the Bayesian
87 Model Averaging method (BMA that is an ensemble dressing method) (Raftery
88 et al., 2005). Both EMOS and BMA provide the entire predictive distribution for
89 the output variable. In the field of EPS calibration, EMOS technique was used

90 in Taillardat et al. (2016, 2019); Bellier (2018) for calibration of temperature and
91 precipitation ensemble forecast. In the field of ensemble streamflow calibration,
92 EMOS was used in Bellier (2018); Hemri et al. (2015), and BMA was used in
93 Duan et al. (2007).

94 Popular non-parametric methods are: rank histogram recalibration (Hamill
95 and Colucci, 1997), quantile regression (Bremnes, 2004), individual ensemble-
96 member adjustments (Van Schaeybroeck and Vannitsem, 2015) or statistical
97 learning methods, also called machine learning methods (Hastie et al., 2009).
98 While non-parametric methods require very large training data sets, they are
99 flexible, data-adaptive, and adapted to non-linearities in the input-output re-
100 lation (Wilks, 2018). The non-parametric Quantile Regression Forest (QRF)
101 method proposed by Meinshausen (2006) is a statistical learning approach. QRF
102 provides an estimation of desired quantiles for the output data, but not the en-
103 tire distribution, as opposed to EMOS or BMA.

104 *1.4. Scope of the paper*

105 The objective of this paper is the implementation and assessment of an
106 HEF system for small to medium size catchments taking into account hydro-
107 logic model parameters' uncertainty. The first part of the study is dedicated to
108 the analysis and classification of uncertainties in the distributed MORDOR-TS
109 model (Garçon, 1996; Garavaglia et al., 2017; Rouhier et al., 2017) with GSA
110 in order to identify the most significant sources of uncertainties to take into
111 account into the ensemble generation. The GSA is carried out with respect to
112 uncertainty in hydrologic model parameters and EPS using forecasted precip-
113 itation provided by Arome Ensemble Prediction System ¹ (Seity et al., 2011;
114 Bouttier et al., 2012; Raynaud and Bouttier, 2016; Bouttier et al., 2016), when
115 available.

116 The second part of the study is dedicated to the HEF generation and en-

¹This product, denoted by AromeEPS-RR1 in the following, provides a forecast of 1-hour
rainfall cumul, with a maximum lead-time of 45 hours, updated every day.

117 semble calibration. Different strategies are compared : a model-based approach
 118 where the raw ensemble comes from ensemble hydrologic simulation is imple-
 119 mented, then two approaches are implemented with QRF ensemble calibration
 120 method, with different predictors.

121 Figure 1 summarizes the general process flow of the study. The two main
 122 objectives of the study correspond to the grey boxes.

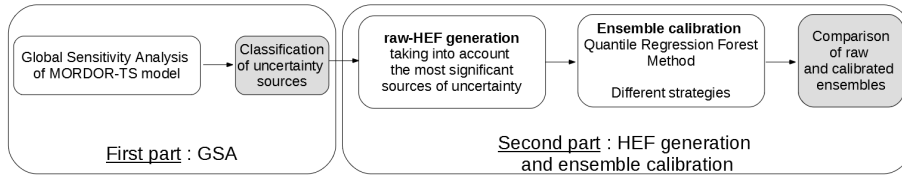


Figure 1: General process flow of the study.

123 The paper is organized as follows. Section 2 presents the Odet catchment on
 124 which the study is carried out, the hydrologic model as well as the atmospheric
 125 and hydrologic data sets. Methods for GSA and QRF are detailed in section
 126 3. Section 4 presents the experimental settings for the GSA and the framework
 127 for the generation and ensemble calibration of the HEF. Section 5.1 discusses
 128 the results of the GSA for the MORDOR-TS hydrologic model and section 5.2
 129 presents the comparative skills of the raw and calibrated hydrologic ensembles.
 130 Conclusion and perspectives are given in Section 6.

131 **2. Material: models and data**

132 *2.1. Modeling the hydrology of the Odet catchment with MORDOR-TS*

133 *2.1.1. The Odet catchment*

134 The Odet river shown in Fig. 2 is a French coastal river located in Western
135 Brittany. It flows through the city of Quimper, then South to the sea. Its mouth
136 is located at Plaisance where astronomical tide ranges between 1.40 m and 5.55
137 m. The Jet and Steir rivers are two tributaries of the Odet river. The Odet
138 catchment area is 720 km² and the Odet river is of about 60 km long. Quimper
139 is often subject to flooding in urban areas, resulting from the combination of
140 two phenomena: excessive rainfall that contribute to the rivers, and high tides
141 increased by storm surges impacting the flow up to Quimper. The distributed
142 MORDOR-TS rainfall-runoff model is built on three upstream sub-catchments
143 (Fig. 2, Tab. 1), with outlets at respectively Tréodet (Odet river), Kerjean (Jet
144 river) and Ty-Planche (Steir river).

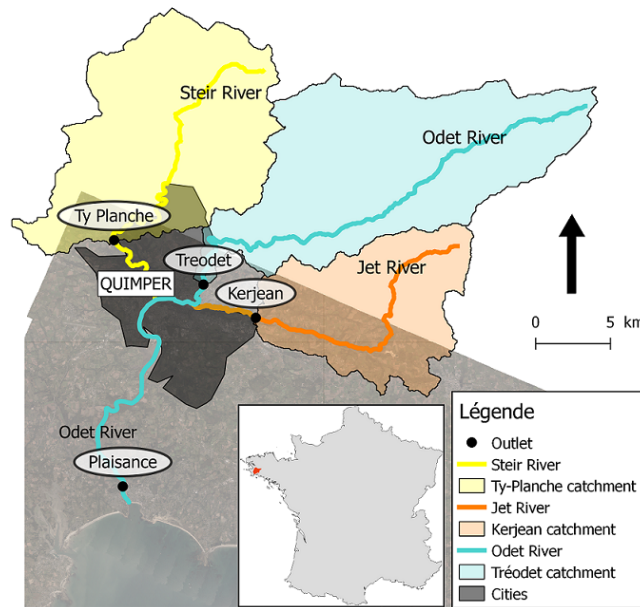


Figure 2: Odet catchment

Table 1: Characteristics of the Tréodet, Kerjean, Ty-Planche sub-catchments

Sub-catchment	Tréodet	Kerjean	Ty-Planche
Elevation of the source	175 m	200 m	100 m
Total river length (km)	37	21	23
Catchment area (km ²)	205	107	179
Mean flow (m ³ /s)	4.8	2.27	3.79
10-year flow (m ³ /s)	55	19	39
50-year flow (m ³ /s)	75	25	53
Highest flow recorded 12-2000 (m ³ /s)	110	46.6	81
Second highest flow recorded 12-2013 (m ³ /s)	91.5	17.6	42.7
Mean rainfall (mm/yr)	743	672	671

145 *2.1.2. The MORDOR-TS distributed conceptual rainfall-runoff model*

146 The MORDOR-TS model (Garçon, 1996; Garavaglia et al., 2017; Rouhier
147 et al., 2017) dedicated to water resource management is implemented on each
148 sub-catchment of the Odet catchment. MORDOR-TS is a spatialized and con-
149 tinuous conceptual rainfall-runoff hydrologic model that connects the mesh cells
150 according to the hydrographic network. At each time step, the production is
151 calculated for each cell and then routed to simulation points on the mesh. The
152 structure of the production module is presented in Fig. 3 and MORDOR-TS’s
153 hydrologic parameters are described in Tab. 2. The production module takes
154 spatially distributed precipitation (P) and temperature (T) as input data and
155 adjusts the water balance through two coefficients c_p and k_{min} . This latter pa-
156 rameter is involved in the calculation of the actual evapotranspiration AET .
157 The production module is then composed of six conceptual reservoirs; two for
158 ice and snow (not active here), and four others: a superficial reservoir U of ca-
159 pacity U_{max} , an intermediate reservoir L of capacity L_{max} of which filling level
160 is driven by the parameter ev_L , an evaporating reservoir Z of capacity Z_{max} and
161 a deep reservoir N of which filling level is driven by the parameter lk_N . Three
162 fluxes components are transferred from the production module to the routing
163 module: area runoff Q_s , subarea runoff Q_v and base runoff Q_b . The parameter

164 k_r determines the ratio of the water feeding reservoir N and the subarea runoff.
 165 The routing module propagates the water production of each cell into the hy-
 166 drographic network. The transfer function is based on the 1D diffusive wave
 167 model, with celerity Cel and diffusion $Diff$ coefficients independent from the
 168 runoff (Hayami, 1951).

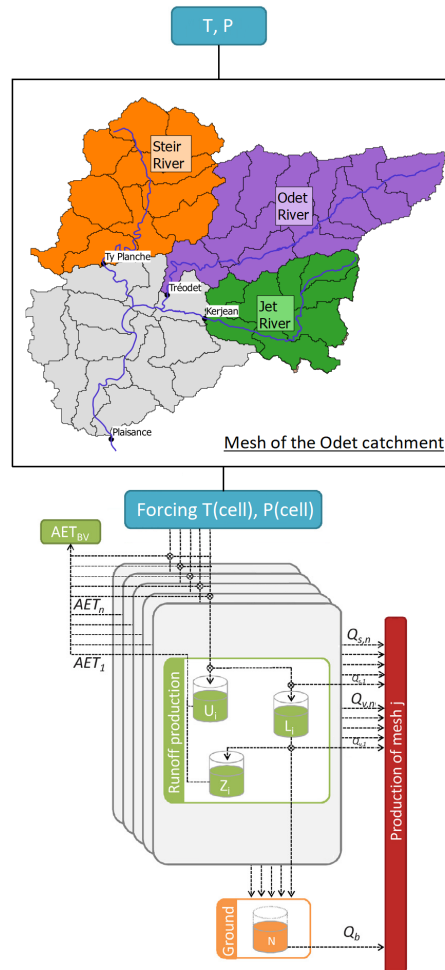


Figure 3: Structure of the MORDOR-TS model over the Odet catchment. Adapted from Rouhier et al. (2017)

Table 2: Description of the parameters of MORDOR-TS hydrologic model

Parameter	Unit	Description	Module
c_p	-	Precipitation multiplicative correction factor	Water balance
k_{min}	-	Maximum seasonal crop coefficient	
U_{max}	mm	Maximum capacity of the root zone U	Runoff production
L_{max}	mm	Maximum capacity of the hillslope zone L	
ev_L	-	Outflow exponent of storage L	
Z_{max}	mm	Maximum capacity of the capillarity storage Z	
k_r	-	Runoff coefficient	
lk_N	mm.h ⁻¹	Outflow coefficient of storage N	
Cel	m.s ⁻¹	Wave celerity	Routing module
$Diff$	m ² .s ⁻¹	Wave diffusion	

169 The hydrologic calibration ² of the 10 previously described parameters of
170 MORDOR-TS (Tab. 2) is achieved after a one-year spinup, using Banque Hy-
171 dro streamflow observations, ANTILOPE rainfall and SAFRAN surface tem-
172 perature forcing described in Sect. 2.2. The hydrologic calibration is carried out
173 with respect to a multi-objective function using the caRamel genetic algorithm
174 (Le Moine et al., 2015; Monteil et al., 2019). The multi-objective function gath-
175 ers three scores : (i) Nash-Sutcliffe Efficiency (NSE, Nash and Sutcliffe (1970))
176 over the entire time serie, (ii) NSE over the inter-annual daily regime and (iii)
177 NSE over the empirical cumulative distribution.

178 The hydrologic calibration is first achieved over a 6-year period (01/01/2007-
179 12/31/2013) and validated over the period 01/01/2014-05/31/2017. Over the
180 validation period, scores values are of the same order of magnitude as over the
181 calibration period, which validates the hydrologic calibration. In the following,
182 the deterministic simulation with calibrated hydrologic parameters is referred to

²In this paper, the term *calibration* refers either to the calibration of the parameters of the hydrologic model MORDOR-TS or to the statistical ensemble calibration with the Quantile Regression Forest (QRf) method. To avoid confusion, the calibration of the hydrologic parameters is always denoted as *hydrologic calibration*. The statistical calibration with QRF is denoted as *ensemble calibration* when necessary.

183 as the *reference simulation*. In a second time, a set of hydrologic calibrations is
184 achieved over 2-year periods from 01/01/2007 to 05/31/2017 in order to estimate
185 the uncertainty in each parameter, required to perform the GSA and to generate
186 the raw HEF (methodology fully described in Sect. 4.2.1).

187 2.2. Data sets

188 Depending on their availability, different data sets are used in the study.

189 2.2.1. Observed data

190 Spatially distributed observed rainfall, temperature data and flow discharge
191 are available at hourly time step from January 2006 to May 2017 on the Odet
192 catchment.

- 193 • Rain data: The ANTILOPE rainfall product is a combination of radar and
194 gauge rainfall data from Météo-France (Champeaux et al., 2009). The grid
195 resolution is 1 km.
- 196 • Temperature data: Surface temperature is extracted from SAFRAN re-
197 analysis (Vidal et al., 2010). The grid resolution is 8 km.
- 198 • Discharge data: River flow discharge time series at Tréodet, Kerjean and
199 Ty-Planche are extracted from the French national archive (Banque hydro,
200 <http://www.hydro.eaufrance.fr>, Leleu, Isabelle et al. (2014)).

201 2.2.2. Forecasted data

202 AromeEPS-RR1 ensemble rain forecast product is used to describe uncer-
203 tainty in rainfall for the GSA. As this product is available over a limited period
204 only, the deterministic Expert-RR3 rain forecast product is used by default, in
205 particular for the generation and the ensemble-calibration of the HEF.

206 *AromeEPS-RR1*. AromeEPS-RR1 uses the regional atmospheric model AROME
207 described in Seity et al. (2011) with ensemble perturbations documented in
208 Bouttier et al. (2012); Raynaud and Bouttier (2016); Bouttier et al. (2016),
209 accounting for uncertainties in initial conditions, boundary conditions, surface

210 conditions and the model physics. Its large scale boundary conditions are pro-
211 vided by the global PEARP ensemble (Descamps et al., 2015). AromeEPS-RR1
212 ensemble is composed of 12 equiprobable members and covers a 1800x1700km
213 ² Western European domain that encompasses the Odet catchment with a hor-
214 izontal grid at 2.5 km resolution. AromeEPS-RR1 is operational since the end
215 of 2016. A limited period of 112 days in early 2016 was made available *a poste-*
216 *riori* for this study in order to cover former rain events on the Odet catchment.
217 It provides a daily forecast at 21:00 UTC, with hourly output over a 45-hour
218 forecast range.

219 *Expert-RR3*. Expert-RR3³ is a 3-hours deterministic rainfall accumulation fore-
220 cast specified by human experts on the basis of numerical forecasts from atmo-
221 spheric models, with a 72 hours forecast range. These data are used opera-
222 tionally for flood forecasting in the French governmental services and available
223 over 2011-2014 for this study.

³RR3 provide a forecast of 3-hour rainfall cumul, with a maximum lead-time of 72 hours,
updated every 15 minutes

224 **3. Methods**

225 *3.1. Global Sensitivity Analysis (GSA)*

In the present study, the GSA stands in the computation of Sobol' indices (Sobol, 2001), with the assumption that the input aleatory variables are independent. Sobol' indices apportion the variance of the output $Y = f(X)$ with $X = (X_1, X_2, \dots, X_k)$, to the variation of different inputs X_1, \dots, X_k on their uncertainty domain. With the assumption that the variance of Y is finite and the input variables are independent, the Hoeffding decomposition (Hoeffding, 1948) leads to the definition of the Sobol' indices :

$$1 = \sum_i S_i + \sum_i \sum_{j>i} S_{i,j} + \dots + S_{1,2,3,\dots,k} \quad (1)$$

226 where

227 • $S_i = \frac{V_i}{V(Y)}$ is the first order Sobol index of X_i and represents the normal-
 228 ized elementary contribution of X_i to $V(Y)$,

229 • $S_{i,j} = \frac{V_{i,j}}{V(Y)}$ is the second order Sobol index of X_i and X_j and represent
 230 the normalized contribution due to interactions between X_i et X_j to $V(Y)$,

231 and so on.

The total Sobol' index S_{T_i} , gathering all contributions related to X_i is then defined as

$$S_{T_i} = S_i + \sum_{j \neq i} S_{i,j} + \sum_{j \neq i, k \neq i, j < k} S_{i,j,k} + \dots + S_{1,2,3,\dots,k} = \sum_{l \in \#i} S_l \quad (2)$$

232 where $\#i$ are all the subsets of $\{1, \dots, k\}$ including i .

233 Sobol' indices thus measure the influence of the different independent im-
 234 puts X_1, X_2, \dots, X_k and their interactions on the output $Y = f(X)$. The more
 235 sensitive the model response is to an input parameter, the larger its associated
 236 Sobol index. Usually only first and total Sobol indices are computed. The first
 237 order indices are useful for factor prioritization (FP) and provides the parame-
 238 ter(s) that most significantly control(s) the most the output variance, whereas

239 the total order indices are helpful in factor fixing (FF), to determine which pa-
240 rameters can be fixed without consequences on the output (Saltelli, 2008). In
241 practice, the estimation of Sobol' indices is generally achieved with a stochastic
242 estimation using an ensemble of model output realizations (Saltelli and Annoni,
243 2010). The computation of Sobol' indices is here achieved using the python
244 modules OpenTURNS (<http://openturns.org/>) and OT-Batman (T.Roy et al.,
245 2018).

246 3.2. Quantile Regression Forest (QRF)

247 *Non parametric regression with QRF method.* The Quantile Regression For-
248 est (QRF) method (Meinshausen (2006)) technique is detailed in Zamo et al.
249 (2014); Taillardat et al. (2019). The principle of the method is the aggregation
250 of meteorological or hydrological situations according to their forecasts, with the
251 assumption that close forecasts predictors lead to close observations. In that
252 way, this method can be linked to the analog method (Hamill and Whitaker,
253 2006; Zalachori et al., 2012; Delle Monache et al., 2013). QRF is a non-parametric
254 and non-linear regression, which consists in building random forests from binary
255 decision trees given a set of predictors (Breiman, 2001). Contrary to random
256 forests that approximate the conditional mean, QRF estimates the full condi-
257 tional distribution of the response variable.

258 *Choosing the predictors.* A wide range of predictors are available for the QRF
259 method. They can obviously stem from the ensemble forecast : statistics (en-
260 semble mean, variance or percentiles) of the variable to calibrate or other vari-
261 ables within the ensemble, as well as other characteristics of the forecast, such
262 as the time or day (providing a modality instead of a value). Predictors can
263 also be described from real observation of the forecasted variable. The choice
264 of the predictors represents a key element in the implementation of the QRF
265 calibration method. In the following, a learning sample is formed by choosing a
266 set of predictors and picking the associated observations.

267 *Building a binary decision tree.* A binary decision tree is built by iteratively
 268 splitting the learning sample into two groups. For a quantitative predictor, the
 269 split is done according to a threshold, while for a qualitative predictor, the split
 270 is done according to the modality. The predictor and the splitting criteria are
 271 chosen to minimize the variability of the associated observations in the resulting
 272 two groups. Each resulting group is then itself split in two following the same
 273 algorithm, until a stopping criterion is reached (for example a minimum number
 274 of data in the sub-groups, or an insufficient decrease of variance). Each final
 275 group is called leaf and contains a set of observations, also called predictand.
 276 The splitting algorithm is illustrated in Fig. 4 with two predictors p1 and p2
 277 ranging between 0 to 1. In this example, the tree has three leaves with associated
 278 observations (rain or discharge for our purpose).

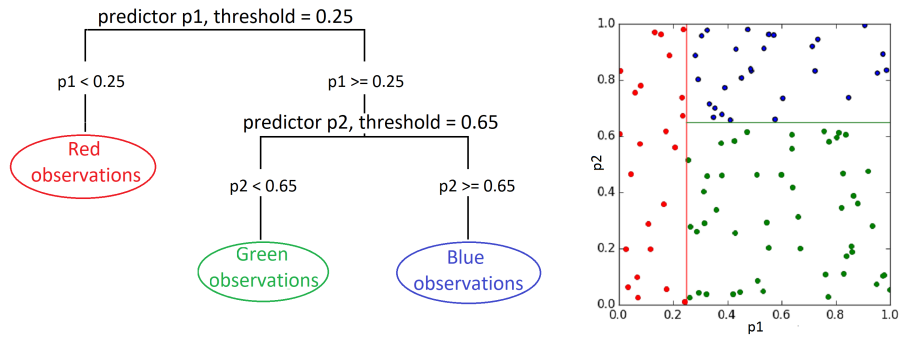


Figure 4: Illustration of binary decision tree with 2 predictors p1 and p2.

279 *Building a forest.* Breiman (1996) proposes to improve the robustness of the
 280 prediction issued from a decision tree by selecting different learning samples
 281 to build several trees and form a forest. Since this approach would require a
 282 large amount of data, usually not available in practice, bootstrap sampling is
 283 often used. Randomly choosing a subset of predictors for each split of each tree,
 284 as suggested by Breiman (2001), enhances the independence of the trees and
 285 consequently forms a *random* forest.

286 *How to use QRF to calibrate a new ensemble forecast ?*. In operational mode,
287 when a new ensemble forecast is available for calibration, its associated pre-
288 dictors are computed and run through each tree of the previously constructed
289 forest. The terminal leaf predictand values are used to estimate the predictive
290 CDF and quantiles of the calibrated forecast.

291 *Merits and limitation of the QRF method*. It should be noted that no a priori
292 assumption is made on the distribution of the variable to calibrate neither before
293 nor after calibration. Also, since the terminal leaves are composed of observa-
294 tions, the ensemble calibration is bound to output physically consistent values
295 (for example, no negative amount of precipitation). The associated drawback is
296 that by construction, the predicted CDF is unable to predict values outside of
297 the observation range within the learning sample. This may be limiting when
298 dealing with extreme values but may be overcome when working with anomalies
299 or fitting a parametric function to the CDF (Taillardat et al., 2019). It should
300 finally be noted that one of the main drawback of QRF method stands in the
301 need of a large data set.

302 *Reconstruction of the calibrated members*. In the following, the Ensemble Cop-
303 ula Coupling (ECC, Schefzik et al. (2013)) method is used to reorder the post-
304 processed quantiles to recreate time-series, but this method yields unrealistic
305 jumps when applied to HEF streamflows. The Trajectory Smoothing (TS) pro-
306 cedure proposed by Bellier (2018) was thus applied to preserve temporal cor-
307 relation consistency, in the perspective of using the ensemble of reconstructed
308 streamflow time series as forcing to hydraulic ensemble simulations. It should be
309 noted that, as opposed to Ensemble Copula Coupling, the Trajectory Smoothing
310 procedure modifies the post-processed ensemble.

Ensemble evaluation metrics. Various tools are available to evaluate proba-
bilistic forecasts and are well described in the literature. In this study, two
widely used verification measures for ensemble forecast are used. The Contin-
uous Ranked Probability Score (Matheson and Winkler (1976), Hersbach (2000),

Gneiting and Raftery (2007)) assesses reliability and resolution simultaneously. It is negatively oriented: the lower the better. The Rank Histogram (Talagrand et al. (1997), Hamill and Colucci (1997), Anderson (1996)) is useful to assess reliability only. A reliable ensemble implies that each rank is filled with the same probability, so the rank histogram is flat. Candille and Talagrand (2005), then Delle Monache et al. (2006) and Taillardat et al. (2016) introduced the notion of norms of a rank histogram with $K+1$ ranks. In particular, $\|\cdot\|_2$ can be defined as :

$$\|\cdot\|_2 = \sqrt{\sum_{i=1}^{K+1} (f_i - \frac{1}{K+1})^2} \quad (3)$$

311 where f_i represents the frequency of observations in the i th rank. For a perfectly
 312 reliable ensemble system, $\|\cdot\|_2$ is equal to zero.

313 **4. Experimental settings**

314 *4.1. General ensemble workflow*

315 The first part of the study consists in a Global Sensitivity Analysis (GSA)
 316 applied to the distributed MORDOR-TS model, taking into account (i) un-
 317 certainties in rainfall and hydrologic model parameters (GSA-Arome), or (ii)
 318 only uncertainty in hydrologic model parameters (GSA-hydro). This last GSA
 319 without uncertainty in rainfall aims at assessing the consistency of the results
 320 when a deterministic rainfall (ANTILOPE) is taken into account in place of an
 321 EPS (AromeEPS-RR1). The implementations of the two GSAs are described in
 322 Sect. 4.2. It should be noted that the use of AromeEPS-RR1 for GSA-Arome is
 323 preceded by a QRF ensemble-calibration step. These two GSAs studies validate
 324 the methodology used for HEF generation in the second part of the study: hy-
 325 pothesis on the choice of uncertain variables, associated statistical distributions
 326 and related hyper parameters.

327 The second part of the study is dedicated to the HEF generation and cal-
 328 ibration over a three-year (2011-2014) period over which there was significant
 329 hydrological events. Only uncertainty in hydrologic parameters is considered
 330 since the AromeEPS-RR1 product is not available over this period. The raw
 331 HEF ensemble is then calibrated with the QRF method.

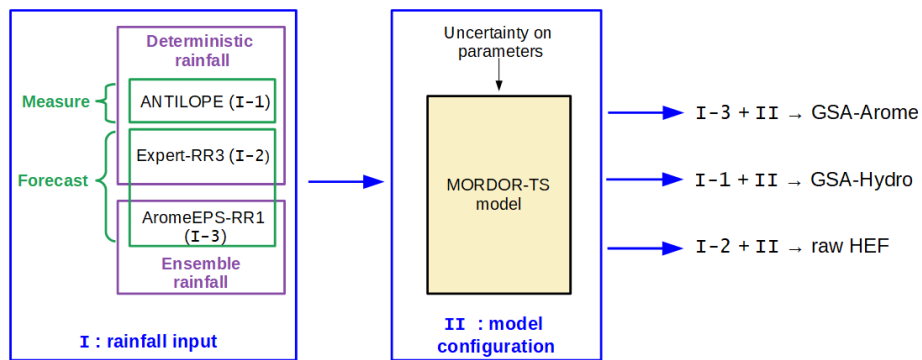


Figure 5: Configurations for GSA-Arome, GSA-hydro and raw HEF

332 Fig. 5 presents the different model settings for the three hydrologic raw
333 ensembles built in the study: GSA-Arome, GSA-hydro and raw HEF. Tab 3
334 presents the required data needed for each step of the study :

- 335 • The GSA-Arome requires the integration of an ensemble of hydrology
336 simulations over $P_{GSA-Arome}$ from 12/24/2015 to 03/15/2016. The atmo-
337 spheric forcing is provided by AromeEPS-RR1 ensemble calibrated with
338 QRF against ANTILOPE rainfall observed data.
- 339 • The GSA-hydro is carried out over two periods. It requires the integration
340 of an ensemble of hydrology simulations over the period $P_{GSA-hydro}$ that
341 is either $P_{GSA-Arome}$ or a sub period of P_{HEF} (12/23/2013-12/26/2013).
342 The deterministic atmospheric forcing is provided by ANTILOPE for both
343 periods.
- 344 • The raw HEF generation is achieved using atmospheric forcing from the
345 Météo-France Expert-RR3 deterministic forecast (as AromeEPS-RR1 is
346 not available) over P_{HEF} (09/01/2011-06/01/2014). HEF ensemble stream-
347 flows are calibrated with QRF against Banque Hydro streamflow obser-
348 vations, using ANTILOPE observations, Expert-RR3 rain forecast and
349 Banque Hydro streamflow observations as predictors.

350 In both GSAs and HEF, hydrology simulations start from a spin-up forced by
351 ANTILOPE and SAFRAN observed data.

352 4.2. GSAs for MORDOR-TS model

353 The GSA-Arome and GSA-hydro for streamflow on the Odet catchment
354 are carried out with respect to the forecasted runoff at the outlet of each of
355 the subcatchments Tréodet, Kerjean and Ty-Planche. Both GSA take into
356 account uncertainties that relate to a set of 10 parameters for MORDOR-TS
357 (Sect. 4.2.1). GSA-Arome (Sect. 4.2.2) is performed for each lead-time with a
358 cycled procedure and takes also into account uncertainties that relate to rain
359 forcing, considering an integer that represents the index within the 12-member

Table 3: Data for the GSA and QRF calibration of rainfall and streamflow

Type	Name	QRF			QRF HEF
		AromeEPS-RR1	GSA-Arome	GSA-hydro	
	Period	$P_{GSA-Arome}$	$P_{GSA-Arome}$	$P_{GSA-hydro}$	P_{HEF}
Observed data	rainfall	ANTILOPE	X	X	X
	temperature	SAFRAN		X	X
	streamflow	BanqueHydro			X
Forecasted data	rainfall	AromeEPS-RR1	X	X	
	rainfall	Expert-RR3			X

360 calibrated AromeEPS-RR1 ensemble, drawn from a uniform distribution $U_{[1,12]}$.
361 In GSA-hydro (Sect. 4.2.3), ANTILOPE deterministic rain is used to force all
362 model runs within the ensemble while hydrologic parameters vary.

363 4.2.1. Hydrologic parameters' distributions

364 The 10 MORDOR-TS parameters are drawn from uniform distributions with
365 V_{min} and V_{max} extreme values, shown in Tab 4 and determined from a set of
366 2-year of hydrologic calibrations. The lower bound (respectively upper bound)
367 of the uniform distribution is chosen as the minimum (respectively maximum)
368 of the values reached in the different hydrologic calibrations (Sect. 2.1.2).

Table 4: Extreme values for MORDOR-TS model parameters' uniform PDFs

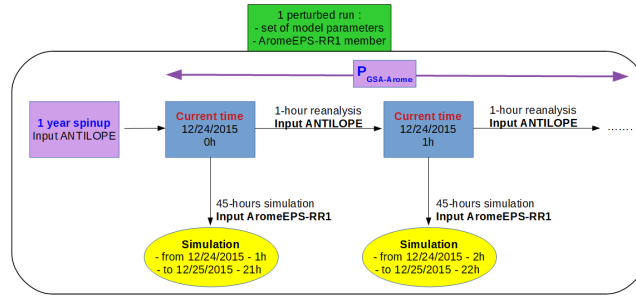
Paramètre	Tréodet	Tréodet	Kerjean	Kerjean	Ty-Planche	Ty-Planche
	min	max	min	max	min	max
c_p (-)	0.98	1.21	0.97	1.13	0.99	1.18
k_{min} (-)	0.18	1.11	0.14	1.03	0.32	0.79
U_{max} (mm)	75	196	30	111	39	116
L_{max} (mm)	64	153	30	493	74	298
ev_L (-)	3.95	4.00	1.50	3.98	3.38	4.00
Z_{max} (mm)	47	138	77	256	72	482
k_r (-)	0.10	0.28	0.10	0.41	0.10	0.30
lk_N (mm.h ⁻¹)	-5.8	-5.2	-6.2	-5.5	-5.7	-5.4
Cel (km.h ⁻¹)	0.44	0.56	0.45	1.10	0.50	0.55
$Diff$ (km ² .h ⁻¹)	1	659	1	5000	329	731

369 *4.2.2. GSA-Arome implementation*

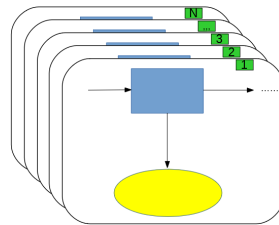
370 *Ensemble calibration of AromeEPS-RR1.* AromeEPS-RR1 ensemble is calibrated
371 with the QRF method before its use in GSA-Arome. In order to increase the vol-
372 ume of data available for AromeEPS-RR1 ensemble calibration over the limited
373 period $P_{GSA-Arome}$ in 2016, the calibration is carried out without discrimi-
374 nating the lead-times. The ensemble gathers all AROME cells within a sub-
375 catchment (63, 36 and 51 for Tréodet, Kerjean and Ty-Planche respectively);
376 thus forming a new ensemble with (12*number of cells) members. The size of
377 the learning sample is 45 (lead-times) \times 112 (days). The ensemble is calibrated
378 against the ANTILOPE observations, averaged over the whole subcatchment.
379 For each subcatchment, the predictors are the percentiles 10, 50 and 90 of the
380 raw AromeEPS-RR1 hourly rainfall, surface humidity, surface temperature and
381 the moment of the day of the lead-time (morning, afternoon, evening, night).
382 The evaluation of the calibration is achieved with a leave-one out method: each
383 element of the training sample is alternatively used for validation, while the
384 other are used for learning. This AromeEPS-RR1 calibration strategy relies
385 on the fact that the error in rainfall intensity is homogeneous over a small
386 catchment, and that it only depends on the moment of the day. The loss of
387 predictability as the lead time increases is assumed to be negligible. It is also
388 assumed that the rainfall intensity data are non correlated over time. This
389 assumption would not be valid for temperature or streamflow. For rainfall,
390 a 6h correlation is suspected and could be taken into account to improve the
391 robustness of the calibration, especially if used to calibrate new data.

392 *GSA-Arome.* The GSA-Arome study is carried out in an operational framework
393 with hourly updated AromeEPS-RR1 forecast. For that purpose, the ensemble
394 is built as shown in Fig. 6(a) over a spin-up, a re-analysis and a forecast period.
395 Each ensemble member is associated to a realisation of the set of hydrologic
396 parameters and of AromeEPS-RR1. Each hydrologic simulation is run over a
397 1-year spin-up and a 1-hour re-analysis with ANTILOPE rainfall, then run over
398 a 45-hour forecast AromeEPS-RR1 rainfall. This is cycled hourly as the rain

399 product is updated hourly. The GSA-Arome indices are computed hourly for
 400 the 45 lead times over the N cycled simulations (Fig. 6(b)). Here, to ensure the
 401 convergence of the Sobol' indices estimation, the GSA-Arome study is achieved
 402 with an ensemble of 192000 MORDOR-TS simulations.



(a) 1 cycled run



(b) N cycled runs

Figure 6: Cycled runs for GSA-Arome

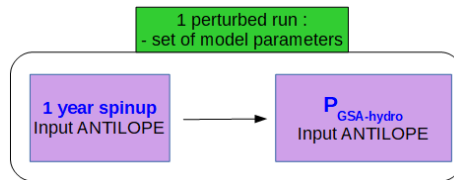


Figure 7: Continuous runs for GSA-hydro

403 *4.2.3. GSA-hydro implementation*

404 The GSA-hydro study uses the observed rainfall ANTILOPE as input for
405 every member, thus the notion of lead-time is no longer relevant. Each member
406 is initiated with a 1-year spin-up, then integrated over $P_{GSA-hydro}$ using its
407 associated set of hydrologic parameters as illustrated in Fig. 7. To ensure the
408 convergence of the Sobol' indices estimation, the GSA-hydro Sobol indices are
409 computed hourly over 154000 MORDOR-TS simulations.

410 *4.3. Generation and ensemble-calibration of the HEF*

411 It was not possible to apply the QRF calibration on the ensemble of stream-
412 flows from the MORDOR-TS simulations that were used for the GSA-Arome
413 over $P_{GSA-Arome}$. Indeed, this period is too short, the learning sample for the
414 QRF method is thus too small, especially given that it should be further re-
415 duced to account for temporal correlation of streamflow. Another ensemble was
416 thus generated, over a longer period P_{HEF} (2011-2014) over which significant
417 hydrological events occurred, but without considering uncertainty related to the
418 rainfall since the AromeEPS-RR1 product was not available over this period.
419 Expert-RR3 deterministic forecast rain was used to generate the raw HEF. The
420 HEF generation and calibration is achieved with a hydrologic ensemble of 99
421 members. The raw HEF is generated in an operational framework with hourly
422 updated RR3 forecast. For that purpose, the ensemble is built as shown in
423 Fig. 8(a), similarly to that for GSA-Arome over a spin-up, a re-analysis and a
424 forecast period, except that the deterministic forecast Expert-RR3 is used in
425 place of AromeEPS-RR1. This is cycled hourly as the RR3 forecast rain prod-
426 uct is updated several times per hour. Only the predominant parameters that
427 were previously identified by the GSA are taken into account for the ensemble
428 generation of raw HEF. The forecasts are calibrated and evaluated against ob-
429 servations over 27 months, from October 2011 to June 2014, excluding summer
430 months (July, August and September). A cross-validation method is used: each
431 month of the calibration period is alternatively used for validation, while the 26
432 other months are used for learning. It should be noted that data over a 10-day

433 period before and after the validation month was removed from the learning
 434 sample to avoid auto-correlation between learning and validation data.

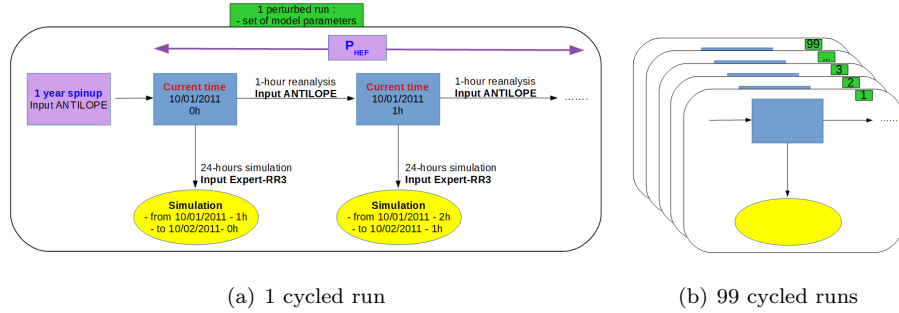


Figure 8: Cycled runs for HEF

435 *Ensemble calibration strategies.* Different strategies to generate hydrologic en-
 436 sembles are implemented as shown in Fig. 9. The model-based-only approach
 437 relies on the integration of MORDOR-TS forced by observed ANTILOPE and
 438 forecast RR3 rain product with perturbed hydrologic parameters; this leads to
 439 the raw ensemble denoted as raw HEF. Then, two approaches are implemented
 440 with QRF calibration method. QRF aims at constructing a relation between
 441 chosen predictors and corresponding observations, which further allows to es-
 442 timate desired quantiles of the observed quantity. All available predictors for
 443 QRF are presented in Tab 5. In the observation-based approach, predictors for
 444 the QRF method use no information from the hydrologic simulations. Strictly
 445 speaking, this is not a calibration strategy as the raw ensemble is not used;
 446 QRF is used to generate calibrated quantiles of an observed variable. This
 447 leads to the ensemble denoted as QRF-nohydro quantiles. In the combined
 448 model-observation approach, predictors for QRF calibration uses the mean and
 449 standard deviation of the raw ensemble. The resulting ensemble is denoted as
 450 QRF-hydro quantiles. After applying the Ensemble Copula Coupling (ECC)
 451 method to reorder the calibrated QRF-hydro quantiles, the Trajectory Smooth-
 452 ing (TS) procedure was finally applied, leading to QRF-hydro-TS ensemble.

453 The impact of smoothing the reconstructed hydrologic time-series from QRF
 454 quantiles is here investigated in the prospect of using the hydrologic ensemble
 455 as input for hydraulic simulation. It should be noted that the ECC method can
 456 not be applied on QRF-nohydro quantiles, since it requires the availability of
 457 the raw ensemble as dependence template.

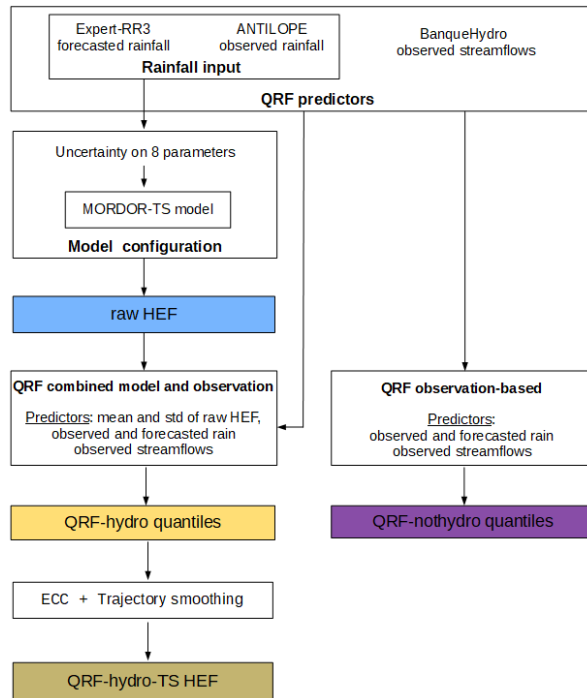


Figure 9: Strategies for Hydrologic Ensemble Forecast generation. Data used for hydrologic model integration as well as QRF predictors are shown. The resulting four HEFs or ensemble of quantiles are indicated in colored boxes.

458 *Computation of CRPS and RH for HEF assessment.* HEF assessment is first
 459 achieved with univariate criteria with CRPS and RH computed for streamflow
 460 over each catchment and for each lead-time. As suggested by Bellier (2018),
 461 cumulated and maximum quantities are also considered, and such quantities
 462 are denoted as global variables in the following. CRPS and RH are thus com-
 463 puted for the cumulated and maximum streamflow that respectively relate to

Table 5: Choice of predictors for QRF-hydro and QRF-nohydro HEF calibration strategies.

Name	Unit	Description	QRF-hydro	QRF-nohydro
<i>Mean</i>	m ³ /s	mean of raw ensemble streamflows	X	
<i>Sigma</i>	m ³ /s	standard deviation of raw ensemble streamflows	X	
<i>Month</i>		month of the validation time	X	X
<i>Period</i>		period of validation time (0 am - 6 am, 6 am - 12 am, 0 pm - 6 pm, 6 pm - 12 pm)	X	X
<i>Q₀</i>	m ³ /s	measured streamflow at the current time	X	X
<i>GradQ₀</i>	m ³	gradient of the measured streamflow at the current time	X	X
<i>M_{rain}</i>	mm	measured rain over the catchment during the N_b past hours of re-analysis ($N_b = 24$ hours - lead-time)	X	X
<i>F_{rain}</i>	mm	forecasted rain over the catchment between the current time and the lead-time	X	X

464 volume and peak flow (Hemri et al., 2015). Following conclusions from Bel-
465 lier et al. (2017) and Gneiting and Ranjan (2011), the HEF is assessed with
466 a forecast-based stratification for CRPS and RH computation, focusing on the
467 (*forecast, observation*) pairs for which the maximum of the ensemble is be-
468 yond the 90th percentile of the associated observation (hourly, cumulated or
469 maximum measured streamflow), computed for heavy rainfall.

470 **5. Results**

471 *5.1. GSAs for MORDOR-TS model*

472 *5.1.1. Calibration of AromeEPS-RR1*

473 As shown in Fig. 10, ensemble calibration improves AromeEPS-RR1 with
 474 smaller mean CRPS value and flatter rank histograms than that of the raw
 475 ensemble (0.119 and 0.1351 respectively for the CRPS). The $\|\cdot\|_2$ norm for the
 476 QRF rank histogram (1.11×10^{-2}) is smaller than that of the raw ensemble
 477 (3.58×10^{-2}). The calibrated AromeEPS-RR1 data are thus more consistent
 478 with observations than before calibration, and thus can be used as input of
 479 GSA-Arome.

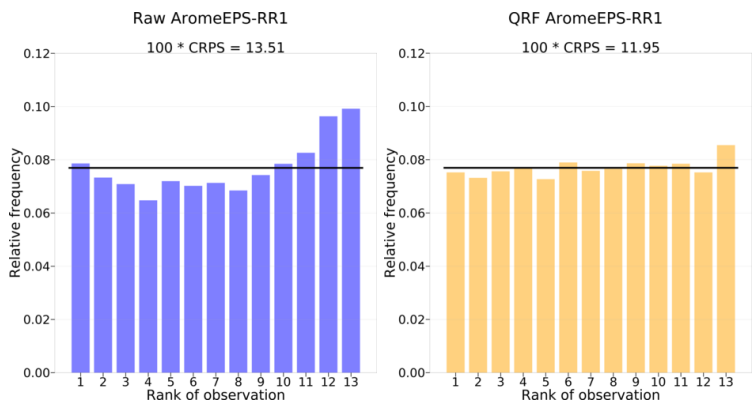
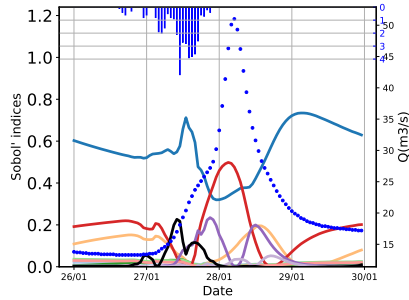


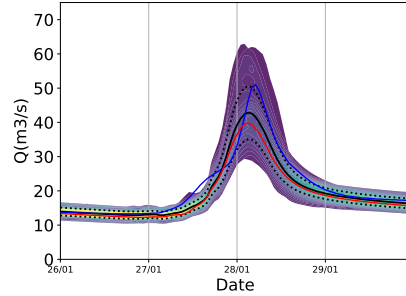
Figure 10: Rank histogram and CRPS for the raw and calibrated AromeEPS-RR1 ensemble.

480 *5.1.2. GSA-Arome Results*

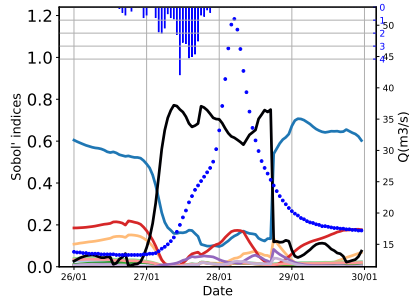
481 Results for the hydrologic GSA-Arome on forecasted streamflow are shown
 482 here over the subperiod 01/26/2016-01/30/2016 of $P_{GSA-Arome}$ for 6-hour and
 483 21-hour lead-times. Time-varying Sobol' indices and streamflow hydrographs
 484 at Tréodet are shown in Fig. 11. A vertical section of Fig. 11(b) and Fig. 11(d)
 485 displays the probability density function at the given date. Similar results for
 486 Kerjean and Ty-Planche can be found as supplementary material in Section 7
 487 (Fig. 17 and 18).



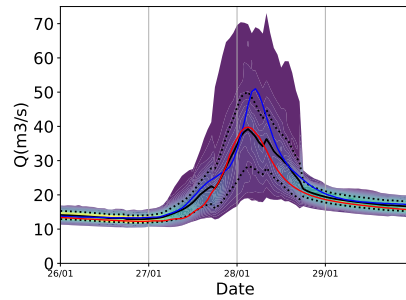
(a) Sobol' indices - 6h lead-time



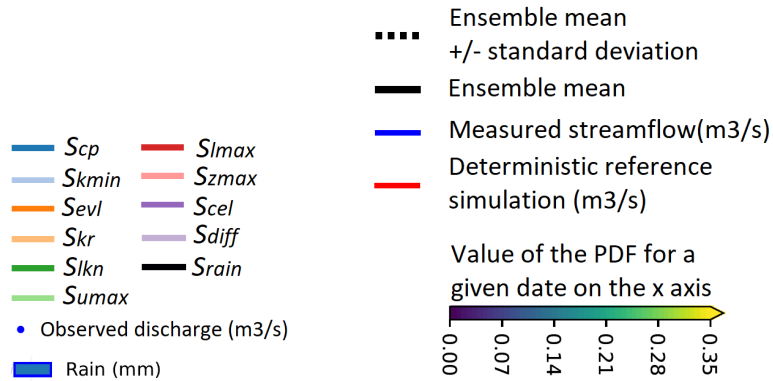
(b) Streamflow hydrographs - 6h lead-time



(c) Sobol' indices - 21h lead-time



(d) Streamflow hydrographs - 21h lead-time



(e) Legend for MORDOR-TS Sobol' indices

(f) Legend for streamflow graphs

Figure 11: First order Sobol' indices and associated hydrographs for the event between 01/26/2016 and 01/30/2016 at Tréodet catchment for GSA-Arome. A vertical section of Fig(b) and Fig(d) displays the probability density function at the given date, according to the legend shown in (f). The results are shown for 6-hour ((a) and (b)) and 21-hour ((c) and (d)) lead-times.

488 *Sobol' indices.* The Sobol' indices time-series for GSA-Arome are presented in
 489 Fig. 11(a) and 11(c) for 6-hour and 21-hour lead times with time on the x-
 490 axis. The observed discharge is represented by the blue dotted curve (right
 491 y-axis) and the observed rainfall histogram is represented at the top of the
 492 panel. It shows that, for both lead times, the simulated streamflow is dominated
 493 by the precipitation correcting factor c_p (dark blue curve). This predominance
 494 decreases in favor of the choice of the AromeEPS-RR1 rain scenario when heavy
 495 precipitations occur, especially for longer lead-times, since this choice strongly
 496 influences the total amount of water in the MORDOR-TS reservoirs. Streamflow
 497 is thus mostly dominated by c_p and rain that both control the water balance
 498 of the model. Rainfall mostly matters for lead-times that are greater than the
 499 concentration time of the catchment. This implies that the construction of
 500 HEF for short lead times can be achieved only taking into account uncertainties
 501 that relate to hydrology. To a lesser extent, at the beginning of the event, the
 502 streamflow is influenced by the capacity of the reservoir L_{max} (red curve) that
 503 directly feeds the runoff. The importance of L_{max} decreases before the end of
 504 the event; indeed, when the reservoir is full, the overflow directly feeds the runoff
 505 and its capacity no longer has impact on the simulated streamflow. For 6-hour
 506 lead-time, the wave celerity Cel (dark purple curve) has noticeable importance
 507 when the streamflow gradient is strong (both in increase and decrease phases).
 508 The runoff coefficient k_r (light orange curve) has noticeable importance at the
 509 peak of the event (and beyond). Indeed, when reservoir Z is full, part of the
 510 excess amount of water $k_r \times out_Z$ directly feeds the runoff. Finally, simulated
 511 streamflow is not sensitive to the two parameters k_{min} and $Diff$ over the three
 512 catchments.

513 *Temporal PDF.* The streamflow probability density functions represented over
 514 time for GSA-Arome are displayed in 11(b) and 11(d) for 6-hour and 21-hour
 515 lead times respectively, with time on the x-axis. The observed discharge is plot-
 516 ted in blue, the deterministic reference simulation with parameters issued from
 517 the hydrologic calibration presented in Section 2.1.2 is plotted in red and the

518 MORDOR-TS ensemble mean and mean plus or minus standard deviation are
519 plotted in black (solid and dotted lines). The reference simulation clearly un-
520 derestimates the flood peak (except for the Kerjean catchment). The ensemble
521 probability density function underestimates the flood peak since the measured
522 streamflow is closer to the upper dotted black line in Fig. 11 (ensemble mean
523 + standard deviation) than to the mean curve; neither the perturbation of the
524 hydrologic model parameters nor that of the rain scenario allows to overcome
525 this effect.

526 5.1.3. Consistency between GSA-Arome and GSA-hydro results

527 GSA-hydro was carried out over the subperiod of $P_{GSA-Arome}$ (01/26/2016-
528 01/30/2016) and over a subperiod of P_{HEF} (12/23/2013-12/26/2013) and as-
529 sociated Sobol' indices are shown in Fig. 12 at Tréodet. Results at Kerjean and
530 Ty-Planche can be found in Fig. 19 and 20 as supplementary material in section
531 7.

532 For the 2016 event, GSA-hydro (Fig. 12(a)) and GSA-Arome (Fig. 11(a))
533 at short lead time, for which uncertainty in rainfall is not significant, show
534 similar results. This allows to rely on GSA analysis when rainfall uncertainty
535 is neglected for HEF construction at short forecast lead time. Moreover, GSA-
536 hydro over $P_{GSA-Arome}$ (Fig. 12(a)) and P_{HEF} (Fig. 12(b)) show similar results
537 since these two events correspond to similar weather conditions. This allows to
538 further the study with HEF construction over P_{HEF} . Finally, as previously
539 stated over the three catchments, the two parameters k_{min} and $Diff$ have very
540 low Sobol' indices meaning that these two parameters have thus no impact
541 on the simulated runoff. These parameters were thus fixed to their hydrologic
542 calibration value for HEF generation in the following while the other parameters
543 are drawn from uniform distribution described in Tab. 4.

544 5.2. Calibration of the HEF

545 Ensemble reliability and resolution are assessed with univariate and global
546 RH and CRPS metrics computed over streamflow. Fig. 13 shows rank his-

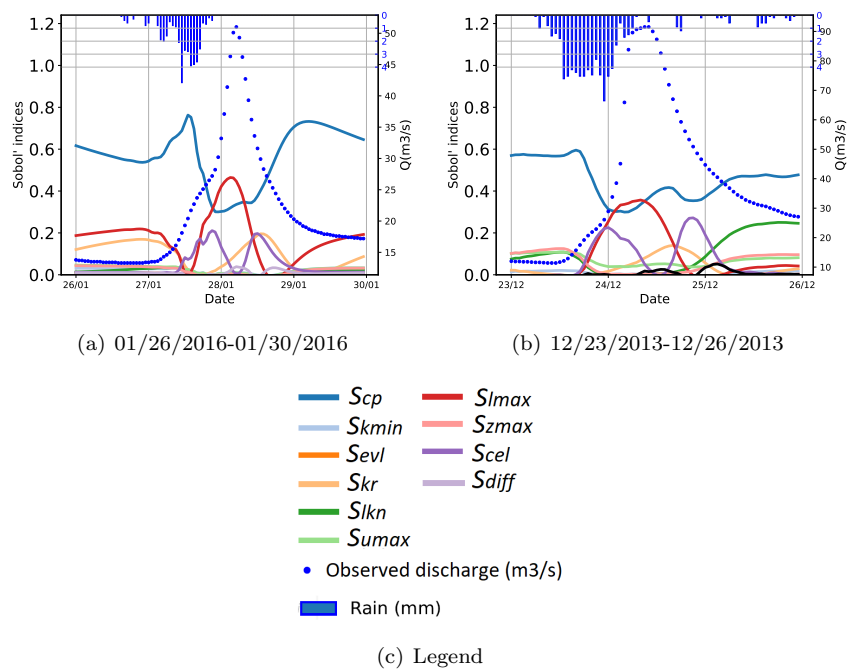


Figure 12: First order Sobol' indices without uncertainty on rain input for the events 01/26/2016-01/30/2016 (12(a)) and 12/23/2013-12/26/2013 (12(b)) at Tréodet catchment

547 tograms for raw HEF, QRF-hydro quantiles, QRF-nohydro quantiles and QRF-
 548 hydro-TS HEF for 6-hour and 21-hour lead-times with associated CRPS, for
 549 Tréodet catchment. Similar results for Kerjean (respectively Ty-Planche) are
 550 given in Fig. 21 (respectively Fig. 22) as supplementary material in Section 7.
 551 Tab. 6 presents the time-averaged $\|\cdot\|_2$ norm for RHs and Fig. 14 shows the
 552 time-varying CRPS for the four ensembles on all catchments.

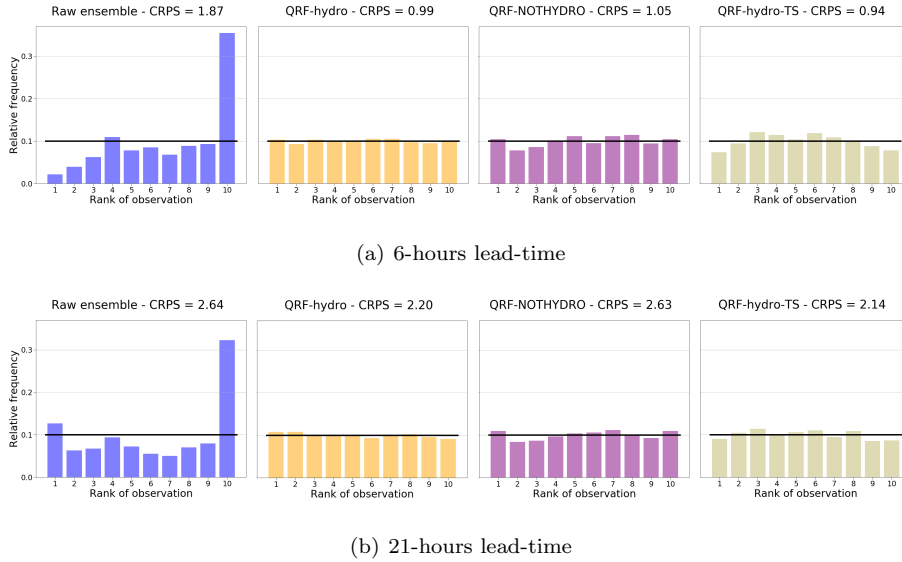


Figure 13: Rank histograms for raw HEF, QRF-hydro quantiles, QRF-nohydro quantiles and QRF-hydro-TS HEF for 6-hours and 21-hours lead-times for Treodet. The associated CRPS is given at the top of the panel.

Table 6: Time-averaged $\|\cdot\|_2$ RHs norm over lead-times ranging from 1 to 24 hours for raw HEF, QRF-hydro quantiles, QRF-nohydro quantiles and QRF-hydro-TS HEF, for Tréodet, Kerjean and Ty-Planche.

Catchment	$10^{-2}\ \cdot\ _2$	$10^{-2}\ \cdot\ _2$	$10^{-2}\ \cdot\ _2$	$10^{-2}\ \cdot\ _2$
	raw	QRF-hydro	QRF-nohydro	QRF-hydro-TS
Tréodet	25.8	1.8	3.3	4.5
Kerjean	15.8	1.8	2.8	4.0
Ty-Planche	9.3	1.9	3.6	3.1

553 The raw ensemble is biased and underdispersive over all three catchments,

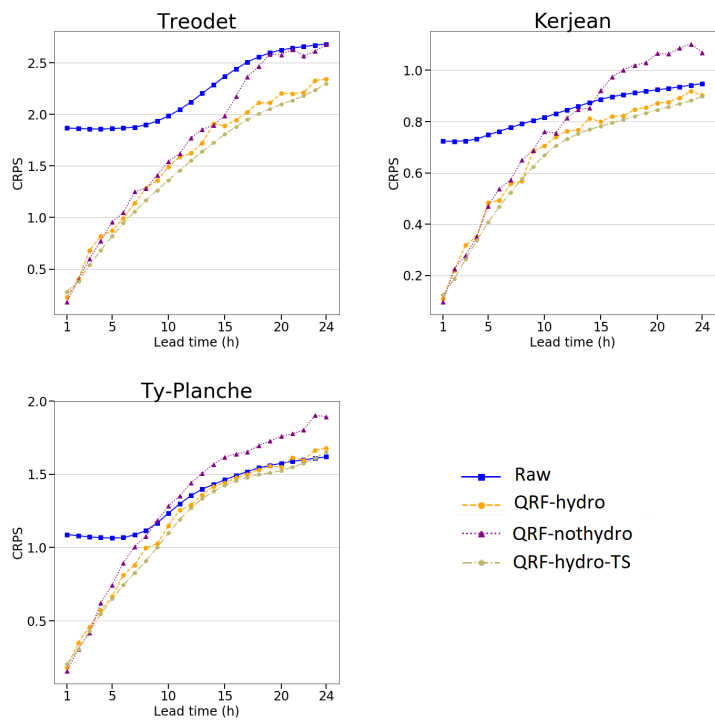


Figure 14: Time-varying CRPS for raw HEF, QRF-hydro quantiles, QRF-nohydro quantiles and QRF-hydro-TS HEF over lead-time for Tréodet, Kerjean and Ty-Planche.

554 and tends to underestimate the flood peak values. QRF-hydro and QRF-
555 nohydro calibrated ensembles display flatter RH with significantly smaller $\|\cdot\|_2$
556 values. The use of hydrology-related predictors for calibration leads to the most
557 satisfying results in terms of reliability. The TS smoothing procedure slightly
558 deteriorates reliability. This is confirmed with statistical tests for the detection
559 of slope, convexity or waves in the rank histograms (Jolliffe and Primo, 2008;
560 Zamo, 2016) that lead to the rejection of the flatness hypothesis for the raw and
561 the QRF-hydro-TS ensembles. It should be noted that reliability improvement
562 remains significant as lead-time increases as shown in Fig. 13. Ensemble cali-
563 bration considerably improves CRPS values for QRF-hydro and QRF-nohydro
564 as shown in Fig. 14. Yet, the improvement decreases as the lead-time increases,
565 especially when no hydrology-related predictors are used. The TS smoothing
566 procedure further improves the CRPS values as this strategy provides less dis-
567 persive trajectories, a priori centered on observations after calibration step. In
568 conclusion, QRF-hydro calibration leads to the best reliability. It should be
569 noted that TS slightly degrades reliability, yet provides far better results than
570 the raw ensemble. The CRPS simultaneously assesses for reliability and res-
571 olution. Since the reliability of QRF-hydro-TS is degraded and the CRPS is
572 improved against QRF-hydro, that means that the TS procedure improves the
573 resolution of the ensemble.

574 The cumulated and maximum streamflow over the 24 lead-times are com-
575 puted for the four ensembles. For both quantities, the rank histogram, $\|\cdot\|_2$
576 associated norm and CRPS are computed and shown in Fig. 15 and in Tab. 7.
577 Similar results for Kerjean (respectively Ty-Planche) are given in Fig. 23 (re-
578 spectively Fig. 24) as supplementary material in Section 7.3.

579 Ensemble calibration improves the rank histogram for both cumulated and
580 maximum streamflow. The rank histogram for cumulated and maximum stream-
581 flow shows that the raw ensemble is underdispersive and biased as it tends to
582 underestimate high cumulated and maximum streamflows for all three catch-
583 ments. For Tréodet, all calibrated ensembles show overdispersive rank histogram
584 for cumulated streamflow while it is rather flat for Kerjean and Ty-Planche when

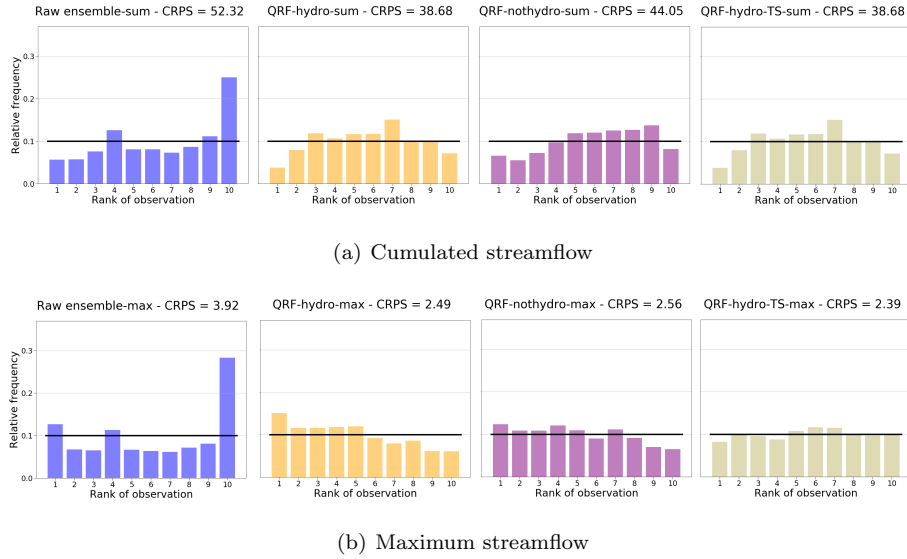


Figure 15: Rank histograms for the cumulated and the maximum streamflows over the 24 hours lead-time for the four ensembles for Tréodet catchment. The associated CRPS is given at the top of the panel.

Table 7: Time-averaged $\|\cdot\|_2$ RHs norm for cumulated and maximum streamflow cumulated over 24 lead-times for the four ensemble for Tréodet, Kerjean and Ty-Planche catchments.

		$10^{-2}\ \cdot\ _2$	$10^{-2}\ \cdot\ _2$	$10^{-2}\ \cdot\ _2$	$10^{-2}\ \cdot\ _2$
Catchment		raw	QRF-hydro	QRF-nohydro	QRF-hydro-TS
Cumulated Stramflow	Tréodet	17.1	9.4	8.8	9.4
	Kerjean	13.3	6.9	11.1	6.9
	Ty-Planche	9.1	6.8	9.5	6.8
Maximum streamflow	Tréodet	20.5	8.6	6.0	3.3
	Kerjean	16.8	6.6	4.8	3.9
	Ty-Planche	20.1	4.0	3.6	6.7

585 hydrology-related predictors are used. It should be noted that TS has no im-
 586 pact on rank histogram for cumulated streamflow, meaning that it preserves
 587 the volume of water within each simulated member. The rank histogram for
 588 maximum streamflow is further improved when trajectory smoothing is used at
 589 Tréodet and Kerjean but not at Ty-Planche. The merits of ensemble calibration
 590 on reliability is confirmed by the $\|\cdot\|_2$ norm values that are significantly reduced
 591 for cumulated and maximum streamflow ensembles. Ensemble calibration also
 592 significantly improves CRPS values, especially when hydrology-related predic-
 593 tors are used for the three catchments. For the three catchments, the CRPS
 594 computed for maximum streamflow is minimized when trajectory smoothing is
 595 applied. To conclude, ensemble calibration with hydrology related predictors
 596 globally improves reliability and CRPS values for both maximum and cumu-
 597 lated streamflow and TS procedure brings a slight additional improvement for
 598 the maximum streamflow.

599 5.2.1. Importance of the QRF predictors

600 The a priori choice of the predictors is a key element in the QRF calibration.
 601 The a posteriori usefulness of the predictors is assessed as the loss in the mean-
 602 squared error of the whole forest if the predictor is randomly permuted without
 603 replacement: the values of the given predictor is a random sample of the original
 604 values. The predictor is of great (little) importance if the mean-squared error
 605 does (not) significantly increase when the predictor is randomly permuted.

606 Fig. 16 displays the log-importance of the QRF-hydro predictors for 2-hour
 607 and 16-hour lead-times for Tréodet. Since the QRF calibration is achieved with
 608 a cross-validation approach, a forest is built for each of the 27 months of P_{HEF} ,
 609 and the importance of each predictor is thus computed over each of the 27
 610 forests. For short lead-times, the most important predictor is the measured
 611 streamflow Q_0 ; that is consistent with the fact that hourly streamflows are
 612 strongly correlated in time. The second most important predictor is the gradient
 613 of the measured streamflow $GradQ_0$ that accounts for the flow dynamics. When
 614 the lead-time increases, rain-related predictors become predominant. When

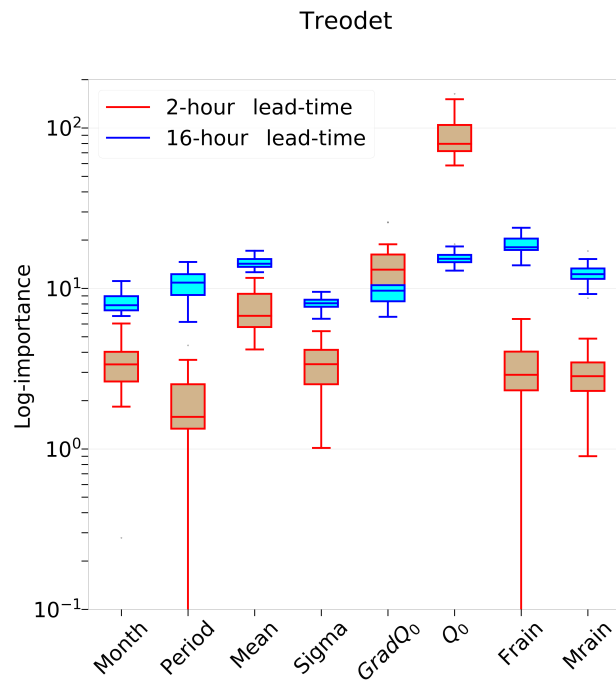


Figure 16: Log-importance of QRF-hydro predictors for the 2-hour and 16-hour lead-times at Tréodet. The box-plot is built for the measure of importance over 27 forests. The box extends from the lower to upper quartile values of the data, with a line at the median. The whiskers extend from the box to show the range of the data.

615 the lead-time exceeds the catchment concentration time (about 15 hours for
616 Tréodet), the cumulated forecasted rain since the beginning of the run F_{rain} ,
617 is the most important predictor, before Q_0 . It also predominates the impact
618 of the measured rain M_{rain} , meaning that the measured rainfall before the run
619 has less importance than forecasted rainfall between the current time and the
620 lead-time.

621 For the short and long lead-times, the raw ensemble mean and the standard
622 deviation (*Mean* and *Sigma*) have moderate influence (with a slight predom-
623 inance of *Mean* over *Sigma*). This is consistent with the fact that the QRF-
624 nohydro ensemble, which has not been built with these predictors, presents
625 comparatively less favourable performances than the QRF-hydro ensemble. It
626 should finally be noted that the importance of the different predictors tend
627 to homogenise as the lead-time increases, and the interquartile range tends to
628 decrease.

629 **6. Discussion and perspectives**

630 In this study, the hydrometeorological chain was investigated with an en-
631 semble approach at a catchment scale, with the aim of issuing a statistically
632 coherent Hydrological Ensemble Forecast (HEF) for up to 24 hours for the
633 Odet cathment in France. The predominance of uncertainty sources is as-
634 sessed with a global sensitivity analysis, first taking into account uncertainty in
635 rain using AromeEPS-RR1, then only focusing on hydrological parameters from
636 MORDOR-TS model. Predominant parameters were identified and taken into
637 account in the HEF generation.

638 Because of the lack of AromeEPS-RR1 availability, the HEF is generated
639 without taking into account uncertainty in rain forecast. However, it should
640 be pointed out that for smaller lead-times than the concentration time of the
641 catchments, the conclusions of this study are expected to be similar, as demon-
642 strated by the comparative GSA without uncertainty in rainfall: the Sobol
643 index associated to the rain is negligible at 6-hour lead-time. It was shown that
644 the raw hydrological ensemble is underdispersive and underestimates observed
645 streamflows, especially large values. The model-based-only approach is thus
646 not sufficient to generate well-calibrated ensembles. The QRF calibration strat-
647 egy is also applied for quantiles generation, with two different approaches: an
648 observation-based-only approach, where the hydrologic model is not used and a
649 combined model-observation approach where both observed and simulated infor-
650 mation from the raw ensemble are used as predictors. The merits of the QRF
651 calibration are assessed with reliability and resolution metrics computed for
652 time-varying, cumulated and maximal streamflow. This article demonstrates,
653 on the Odet catchment, that forest-based techniques, often used for the cal-
654 ibration of EPS, are also suitable for hydrologic ensemble calibration. QRF
655 calibration provides an improvement of the reliability and CRPS values over
656 the three studied sub-catchments. It was shown that better forecast skills are
657 obtained when hydrology-related predictors are used. This highlights that the
658 choice of the predictors is of great importance for the QRF calibration strategy

659 to be successful. Moreover, it also shows that statistically learning from obser-
660 vation fails to substitute for solving partial derivative equations when it comes
661 to representing and forecasting the dynamics of the catchment. It should also
662 be kept in mind that the reconstruction step following QRF-calibration requires
663 the availability of the raw HEF in the Ensemble Copula Coupling method. The
664 reconstructed HEF should finally be smoothed out before use as input for a
665 hydraulic simulation with a hydrometeorological chain. The reliability of the
666 smoothed ensemble is slightly deteriorated for hourly streamflow, but CRPS
667 and global skills are mainly improved.

668 This strategy paves the way for an operational HEF system. A straightfor-
669 ward perspective is to apply this study over a period for which AromeEPS-RR1
670 is available, hydrological events occurred, and that is long enough for QRF cali-
671 bration to be applied on streamflows. This would allow to fully consider sources
672 of uncertainty, especially those that relate to precipitation. Taking into account
673 a larger variation of the corrective rain factor in MORDOR-TS jointly to using
674 EPS could also be considered. This methodology could *a priori* be applied and
675 assessed to other catchments for consistency check. The choice of predictors
676 may be catchment dependant. For instance, the predictors M_{rain} and F_{rain}
677 are closely related to the concentration time of the catchment: the period (in
678 hours) over which the mean of measured or forecasted rain is computed may be
679 adjusted, hence reduced for catchments that are subject to flash floods. The pre-
680 dictor *Month* may also be more significant as it allows to discriminate autumn
681 flash floods from other events.

682 Finally, the hydrometeorological simulation chain could be extended to hy-
683 draulics, using forecasted calibrated streamflows as inputs to a hydraulic model
684 to provide Hydraulics Ensemble Forecast. GSA on discretized water level and
685 discharge in the river would be carried out with respect to rain-, hydrology- and
686 hydraulic- related sources of uncertainty, now also considering uncertain friction
687 and river bathymetry. Major sources uncertainties in the meteo-hydro-hydraulic
688 chain could then be corrected in real time with assimilation of observed water
689 level relying on the multi-physics ensemble simulation system.

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694 the Python API interface to MORDOR-TS and Charles Perrin and Julie Viatgé
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697 DATARMOR storage and computational resources (<http://www.ifremer.fr/pcdm>).

⁶⁹⁸ **7. Supplementary material**

⁶⁹⁹ *7.1. Sobol' indices at Kerjean and Ty-Planche*

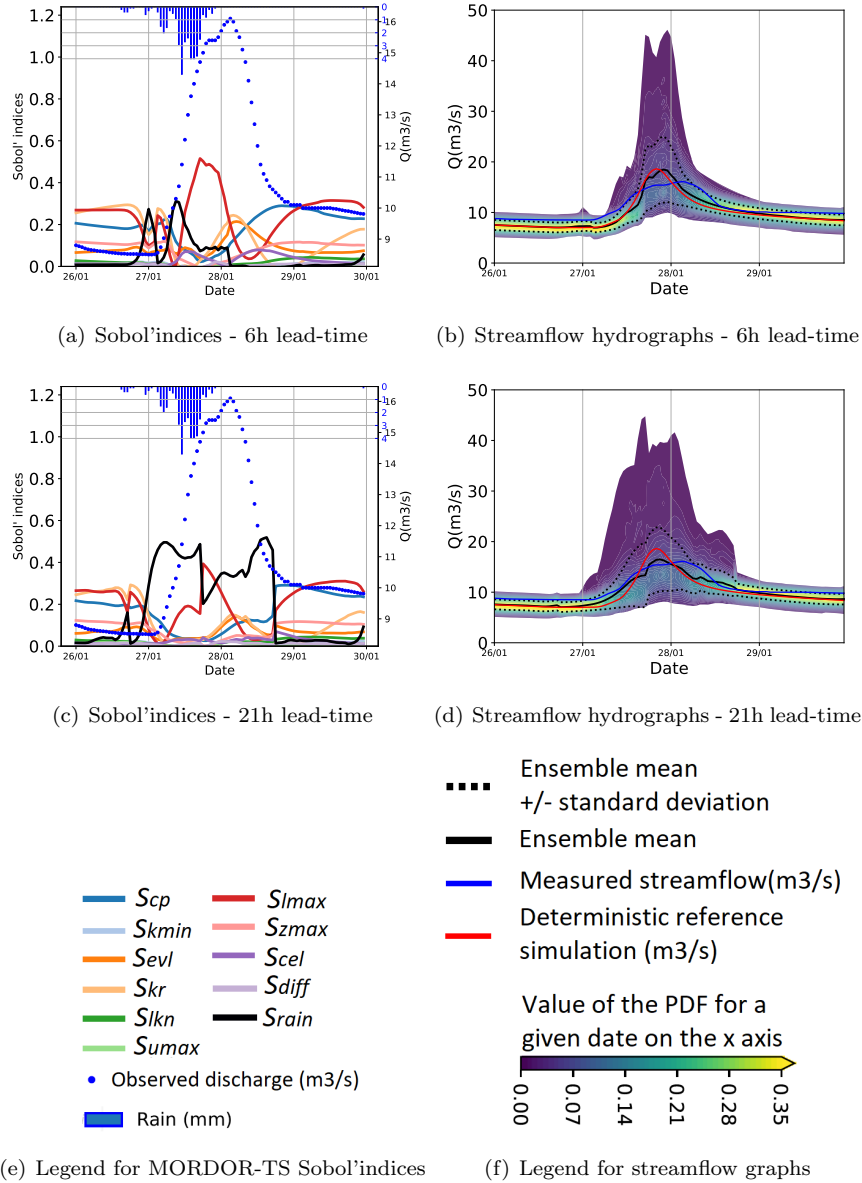


Figure 17: First order Sobol' indices and associated hydrographs for the event between 01/26/2016 and 01/30/2016 at Kerjean catchment for GSA-Arome. A vertical section of Fig(b) and Fig(d) displays the probability density function at the given date, according to the legend shown in (f). The results are shown for 6-hour ((a) and (b)) and 21-hour ((c) and (d)) lead-times.

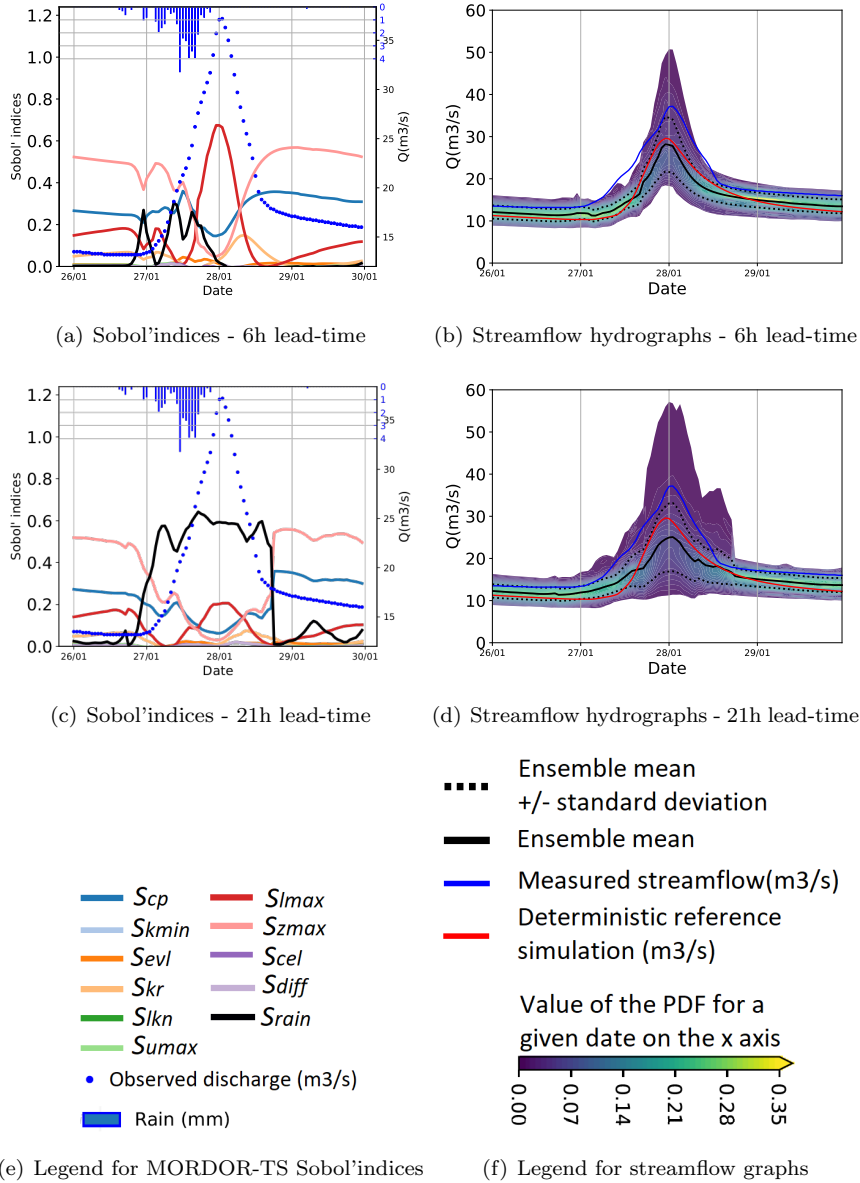


Figure 18: First order Sobol' indices and associated hydrographs for the event between 01/26/2016 and 01/30/2016 at Ty-Planche catchment for GSA-Arome. A vertical section of Fig(b) and Fig(d) displays the probability density function at the given date, according to the legend shown in (f). The results are shown for 6-hour ((a) and (b)) and 21-hour ((c) and (d)) lead-times.

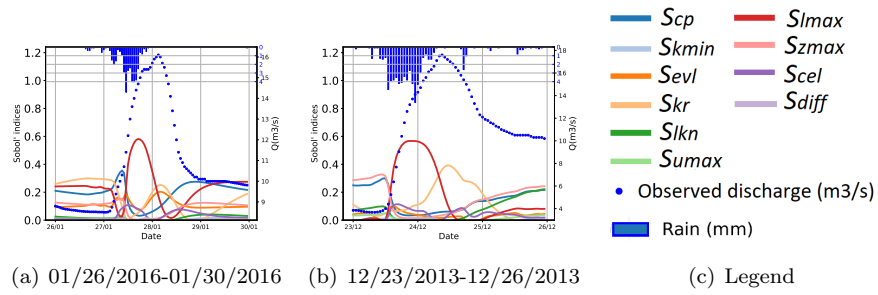


Figure 19: First order Sobol' indices without uncertainty on rain input for the events 01/26/2016-01/30/2016 (19(a)) and 12/23/2013-12/26/2013 (19(b)) at Kerjean catchment

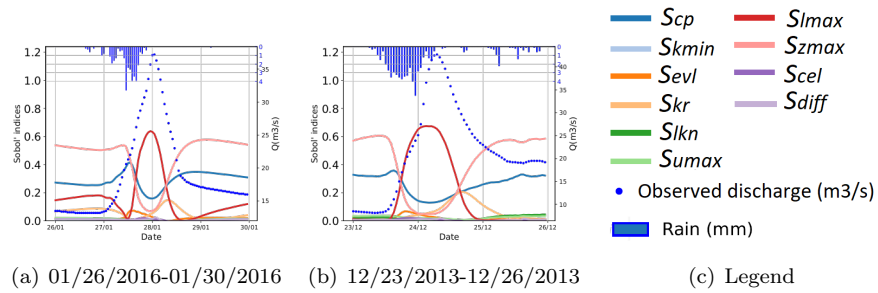


Figure 20: First order Sobol' indices without uncertainty on rain input for the events 01/26/2016-01/30/2016 (20(a)) and 12/23/2013-12/26/2013 (20(b)) at Ty-Planche catchment

700 7.2. Rank Histograms for Kerjean and Ty-Planche catchments

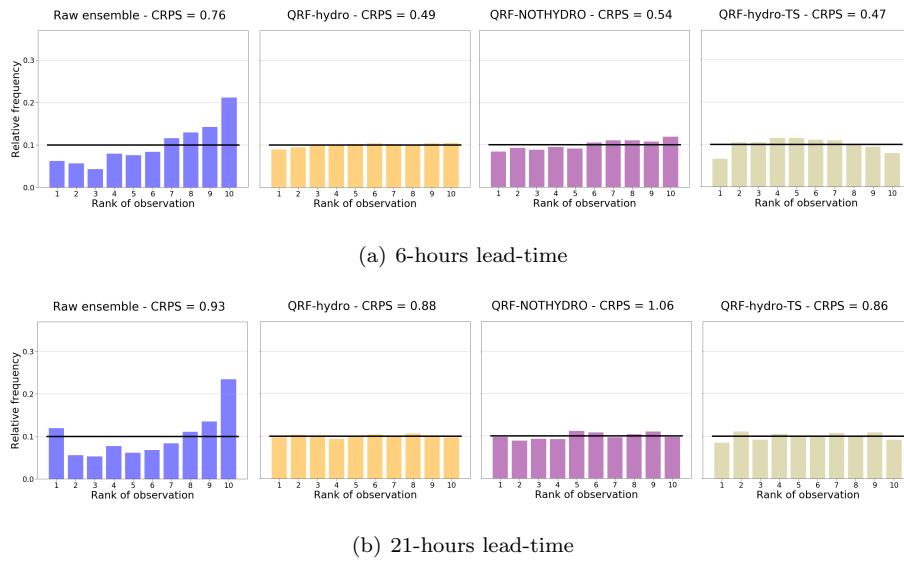
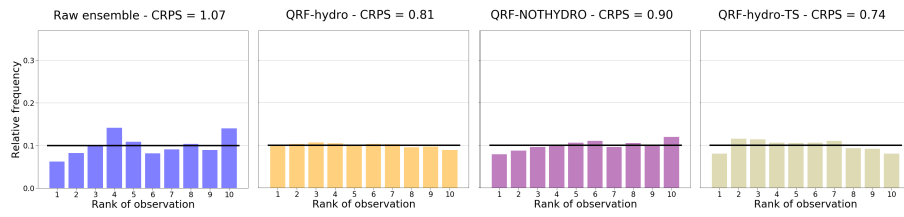
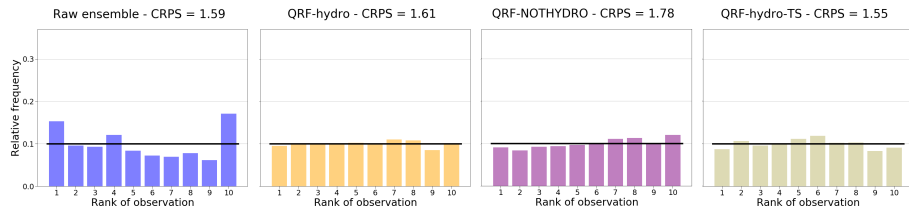


Figure 21: Rank histograms for raw HEF, QRF-hydro quantiles, QRF-nohydro quantiles and QRF-hydro-TS HEF for 6-hours and 21-hours lead-times for Kerjean. The associated CRPS is given at the top of the panel.



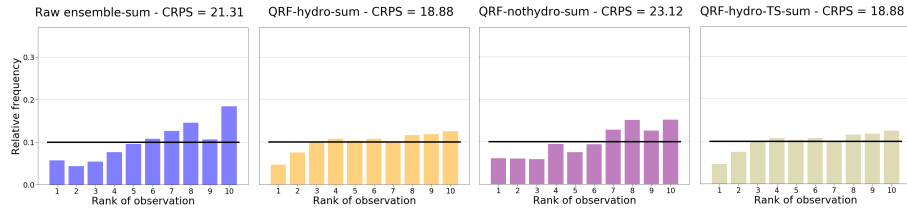
(a) 6-hours lead-time



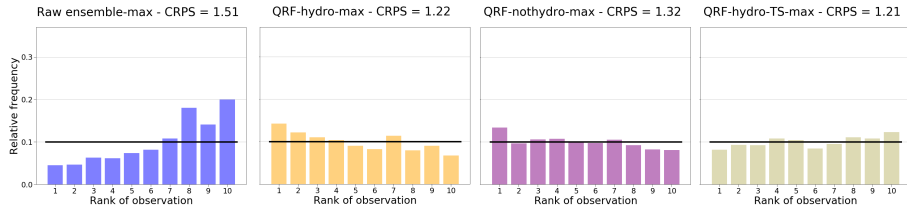
(b) 21-hours lead-time

Figure 22: Rank histograms for raw HEF, QRF-hydro quantiles, QRF-nothydro quantiles and QRF-hydro-TS HEF for 6-hours and 21-hours lead-times for Ty-Planche. The associated CRPS is given at the top of the panel.

701 7.3. Global skills for Kerjean and Ty-Planche catchments

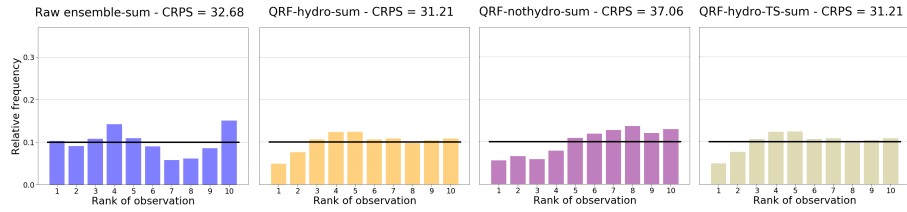


(a) Cumulated streamflow

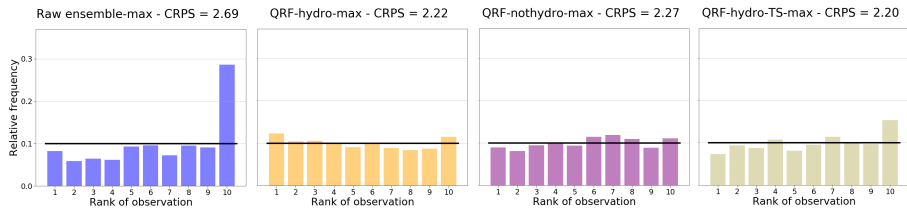


(b) Maximum streamflow

Figure 23: Rank histograms for the cumulated and the maximum streamflows over the 24 hours lead-time for the four ensembles for Kerjean catchment. The associated CRPS is given at the top of the panel.



(a) Cumulated streamflow



(b) Maximum streamflow

Figure 24: Rank histograms for the cumulated and the maximum streamflows over the 24 hours lead-time for the four ensembles for Ty-Planche catchment. The associated CRPS is given at the top of the panel.

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