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► **To cite this version:**

J. Carreau, P. Naveau, Eric Sauquet. A Statistical Rainfall-Runoff Mixture Model with Heavy-Tailed Components. *Water Resources Research*, 2009, 45, W10437 p. 10.1029/2009WR007880 . hal-00455644

HAL Id: hal-00455644

<https://hal.science/hal-00455644v1>

Submitted on 10 Feb 2010

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A Statistical Rainfall-Runoff Mixture Model with Heavy-Tailed Components

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Abstract1
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We present a conditional density model of river runoff given covariate information which includes precipitation at four surrounding stations. The proposed model is non-parametric in the central part of the distribution and relies on Extreme-Value Theory parametric assumptions for the upper tail of the distribution. From the trained conditional density model, we can compute quantiles of various levels. The median can serve to simulate river runoff, quantiles of level 5% and 95% can be used to form a 90% confidence interval, finally, extreme quantiles can estimate the probability of large runoff. The conditional density model is based on a mixture of hybrid Paretos. The hybrid Pareto is built by stitching a truncated Gaussian with a Generalized Pareto distribution. The mixture is made conditional by considering its parameters as functions of covariates. A neural network is used to implement those functions. A penalty term on the tail indexes is added to the conditional log-likelihood to guide the maximum likelihood estimator towards solutions that are preferred. This alleviates the difficulties encounter with the maximum likelihood estimator of the tail index on small training sets. We evaluate the proposed model on rainfall-runoff data from the Orgeval basin in France. The effect of the tail penalty is further illustrated on synthetic data.

18 1 Introduction

19 River runoff modelling is relevant for hydroelectricity planning, irrigation and flood preven-
20 tion. It is a well-known fact among hydrologists that the river runoff is fat-tailed, meaning
21 that sudden large values of runoff can occur which are three or four standard deviations away
22 from the sample mean [BSS⁺08]. Taking into account those large values is essential since
23 they understandably have a very large impact. Another well-known fact is that precipita-
24 tion in the hydrographic basin influences the river runoff. However, there are many other
25 mechanisms at work such as underground water tables and soil permeability that are specific
26 to a given hydrographic basin. Most hydrological models try to reproduce the dynamics of
27 the basin by modelling the mechanisms in terms of reservoirs. An alternative approach is to
28 use a stochastic model which provides a full distribution of the river runoff. For example,
29 such a model has been proposed in Lu and Berliner [LB99]. They assume three states or
30 regimes of the runoff process: rising, falling and normal. Transitions probabilities between
31 the states are modelled depending on past runoff values and on rainfall data. Given the
32 current state, the distribution of the river runoff is assumed to follow an autoregressive pro-
33 cess which depends on the past runoff values and the observed precipitation. We propose to
34 model the distribution of the runoff at a future time step $t + 1$ given covariate information
35 available at time t with another stochastic model, the conditional mixture of hybrid Paretos
36 presented in [CB08a]. This model bears some similarities to the model of Lu and Berliner
37 [LB99]. In the conditional mixture, we can see the number of components as the number
38 of states, which is determined by model selection instead of being set a priori. The state

39 selection which is controlled by the mixture weights depends on all the covariates but not on
40 the previous state. The distribution of the river runoff given the current state is given by the
41 corresponding component density, that is a hybrid Pareto density. The parameters of this
42 density are modelled as function of covariates which include past runoff and precipitation.
43 The conditional mixture can adapt to a more general shape of the underlying distribution,
44 including asymmetry and multi-modality. Also, the hybrid Pareto enables the stochastic
45 model to take explicitly extreme values into account. Moreover, a neural network computes,
46 given the covariates, the mixture weights (or state probabilities) and the component density
47 parameters. In contrast to Lu and Berliner [LB99], we don't need to assume a specific form
48 for the relationship between the covariates and the model parameters since such a neural
49 network can in principle approximate any continuous mapping. The model will be further
50 detailed in section 2.

51 Neural networks have been popular models for a good while in hydrology, see [MD00]
52 for a survey. They were used to predict river runoff but, to our knowledge, not within a
53 conditional mixture framework. Such traditional neural networks are generally not apt at
54 capturing extreme observations. On the other hand, standard models to tackle extremes
55 are drawn from Extreme Value Theory (EVT) [EKM97]. These models consider either
56 maxima over a given period, in which case the generalized extreme-value (GEV) distribution
57 is used, or observations that exceed a selected threshold and a generalized Pareto distribution
58 (GPD) models the distribution of the exceedances. The EVT models thereby mean to
59 estimate the upper tail of the underlying distribution. The choice of the GEV and the
60 GPD is motivated by the fact that these are the limiting distributions of the maxima and

61 the exceedances respectively under some fairly general conditions. Although extreme runoff
62 behavior is utterly important, hydrologists need to model the whole runoff distribution. One
63 way to extend the GPD model to the whole distribution has been proposed by Frigessi et al.
64 [FHR02]. Their model is a two-component mixture with one light-tailed component and one
65 GPD component. The hybrid Pareto mixture can be seen as a different way to include the
66 GPD into a mixture model. The hybrid is built by stitching together a Gaussian and a GPD
67 while ensuring continuity at the junction point. In the hybrid Pareto mixture, the number of
68 components is chosen according to the data at hand. The central part of the hybrid Pareto
69 mixture consists of a Gaussian mixture which is a flexible non-parametric estimator. The
70 upper tail of the hybrid Pareto mixture is made of a linear combination of GPDs. Through
71 experiments, this approach has shown to perform well on heavy-tailed data [CB08b].

72 Vrac and Naveau [VN07] have incorporated covariates in the Frigessi mixture [FHR02] in
73 order to predict the distribution of rainfall. The covariates help discriminating between dif-
74 ferent sorts of rainfall regimes: no rainfall, regular rainfall and extreme rainfall. A particular
75 distribution is used according to which regime prevails. Another way to include covariates
76 into an EVT model has been developed by Chavez-Demoulin and Davison [CDD04]. Covari-
77 ates are assumed to influence the value taken by the GPD parameters. This relationship is
78 modelled by spline smoothers. In the conditional hybrid Pareto model, the mapping between
79 the hybrid Pareto mixture and the covariates is modelled by a neural network. In this case,
80 the whole conditional distribution is estimated, not just the conditional upper tail, as in the
81 model of Chavez-Demoulin and Davison [CDD04].

82 The tail index parameter is the most difficult parameter to estimate, whatever model is

83 used, be it the GPD, the GEV distribution or some other method which one could think of
84 for tail index estimation. This is because the tail index parameter, also termed the shape
85 parameter, gives a sense of the overall shape of the distribution and in particular, of the tail
86 behavior. Typically, few observations will occur in the tail which makes the estimation of
87 the tail index very sensitive. Despite the good asymptotic properties of maximum likelihood
88 estimators (MLEs), they are not very reliable in small samples given their high variance.
89 Estimators of moments show a better behavior in small samples, however they assume that
90 the expectation of the underlying distribution is finite (equivalently, that the tail index is
91 smaller than one). Coles and Dixon [CD99] introduced a penalty term in the MLEs of
92 the GEV parameters. The intuition behind the penalty term is to include a similar range
93 restriction on the tail index estimator as for the moment estimator. Coles and Dixon [CD99]
94 show that the penalized MLE of the tail index performs better in small samples than the
95 classical MLE.

96 The hybrid Pareto is one such model with a tail index parameter, which is inherited from
97 the GPD. When density estimation is performed with a hybrid Pareto mixture, the tail index
98 of the underlying distribution can be estimated from the tail index of the dominant com-
99 ponent in the mixture, that is the component with the largest tail index (and consequently,
100 the heaviest tail). In this case, the MLEs sensitivity in small samples appears in the follow-
101 ing way: large tail indexes are assigned to components with negligible mixture weights. To
102 prevent this, we add a penalty term to the log-likelihood based on a prior distribution of the
103 mixture tail indexes. This is similar in spirits to the penalty proposed by Coles and Dixon
104 [CD99]. We devised a prior distribution of the mixture tail indexes based on the following

105 intuitive idea. We would expect that most components would take care of modelling the
106 central part of the distribution and therefore, have a tail index close to zero. If the tail of the
107 underlying distribution is heavy, we would then expect that some components would have a
108 tail index close to the tail index of the underlying distribution.

109 We evaluate the conditional hybrid Pareto mixture on rainfall-runoff data from the
110 Orgeval basin in France. The conditional median of the learned conditional hybrid Pareto
111 mixture serves to generate river runoff at a future time step $t + 1$. A 90% confidence interval
112 is also computed as the quantiles of level 5% and 95%. This is in contrast with the work
113 of Frigessi et al. [FHR02] and of Vrac and Naveau [VN07] who did not use their model for
114 prediction at a future time step. We also look at the distribution of the conditional tail in-
115 dexes on the test set; the effect of the tail penalty term in the maximum likelihood estimator
116 can be seen. We gain then more insight into the effect of the new penalty by looking at
117 experiments on synthetic data.

118 **2 Statistical Model of the Rainfall-Runoff Process**

119 We propose to model the rainfall-runoff process with the conditional hybrid Pareto mixture,
120 see [CB08a]. This model combines the flexibility of non-parametric modelling and the ex-
121 trapolation capability of the GPD methodology. Given a vector of covariates which describe
122 meteorological and hydrological conditions, the conditional distribution of the river runoff
123 is modelled by a mixture of hybrid Paretos whose parameters depend on covariates. Such
124 a mixture is able to adapt to asymmetry, multi-modality and tail heaviness that might be

125 present in the conditional distribution of the runoff. The neural network which learns the
 126 relationship between the covariates and the mixture parameters is able to approximate prop-
 127 erly the highly non-linear relationship between rainfall and runoff. The conditional hybrid
 128 Pareto mixture provides a conditional density model that has proven to perform well on
 129 many kind of data sets (see [CB08a]). The model is explained in details in the following
 130 subsections.

131 2.1 Hybrid Pareto Mixture

132 Suppose we want to model the distribution of Y , a variable representing the river runoff,
 133 with no additional predictive information. We could estimate the distribution of Y with a
 134 mixture of Gaussians, which is a popular non-parametric estimator [Bis95]. This type of
 135 approach circumvents the need to choose a specific parametric form for the distribution of
 136 the runoff and can take into account multi-modality and asymmetry. Mixtures of Gaussians
 137 approximate a density by adding up weighted Gaussians or "bumps", see Figure 1. The
 138 density estimator is formally given by $\sum_{j=1}^m \pi_j \phi_{\mu_j, \sigma_j}(y)$, where the π_j are the mixture weights
 139 and $\phi_{\mu_j, \sigma_j}(\cdot)$ is the Gaussian density with parameters μ_j and σ_j . The weights must sum to
 140 one, that is $\sum_{j=1}^m \pi_j = 1$, to ensure that the estimator is a proper density. A Gaussian
 141 mixture approximates the distribution of heavy-tailed data, such as runoff data, by locating
 142 one component with a large standard deviation around the largest observations. However,
 143 its capacity to extrapolate beyond the sample range might be poor.

The hybrid Pareto distribution was put forward as a way to transfer the extrapolation
 properties of the GPD [EKM97] to mixture models. The hybrid Pareto distribution is a

smooth extension of the GPD to the whole real axis. This new distribution is built by stitching a GPD tail to a Gaussian, while enforcing continuity of the resulting density and of its derivative. In this work, we focus on runoff data which is heavy-tailed so we let $\xi > 0$ in the GPD density:

$$g_{\xi;\beta}(y - \alpha) = \frac{1}{\beta} \left(1 + \frac{\xi}{\beta}(y - \alpha)\right)^{-1/\xi-1} \quad \xi > 0, \quad y > \alpha.$$

Let α be the junction point and $\phi_{\mu;\sigma}(y) = 1/(\sqrt{2\pi}\sigma) \exp(-(y - \mu)^2/(2\sigma^2))$ be the Gaussian density function with parameters μ and σ . The two constraint equations (equality of the density and of its derivative at α) are solved so that α and β , the GPD scale parameter, become functions of ξ , the GPD tail index and of μ and σ , the Gaussian parameters. Let $\theta = (\xi, \mu, \sigma)$ be the parameter vector of the hybrid Pareto. The hybrid Pareto density is given by:

$$h_{\theta}(y) = \begin{cases} \frac{1}{\gamma} \phi_{\mu;\sigma}(y) & \text{if } y \leq \alpha, \\ \frac{1}{\gamma} g_{\xi;\beta}(y - \alpha) & \text{if } y > \alpha, \end{cases}$$

where the dependent parameters are $\alpha(\xi, \mu, \sigma) = \mu + \sigma \sqrt{W((1 + \xi)^2/2\pi)}$, $\beta(\xi, \sigma) = (\sigma(1 + \xi))/(\sqrt{W((1 + \xi)^2/2\pi)})$ and W is the Lambert W function defined by $w = W(we^w)$ (see [CGH⁺96]). The re-weighting factor γ ensures that the density integrates to one and is given by:

$$\gamma(\xi) = 1 + \frac{1}{2} \left(1 + \text{Erf} \left(\sqrt{W((1 + \xi)^2/2\pi)} / 2 \right)\right),$$

144 where $\text{Erf}(\cdot)$ is the error function $\text{Erf}(z) = \frac{2}{\sqrt{\pi}} \int_0^z e^{-t^2} dt = 2\Phi(z\sqrt{2}) - 1$ and Φ is the stan-
 145 dard Gaussian distribution function, (see [PFTV92]). The hybrid Pareto, while inheriting
 146 the approximation properties of the GPD, bypasses the need for threshold selection inherent

147 in the classical GPD methodology [EKM97] since α , the junction point of the Gaussian and
148 the GPD is computed implicitly as a function of the hybrid parameters.

149 With a hybrid Pareto mixture $\sum_{j=1}^m \pi_j h_{\theta_j}(y)$ to model the distribution of the river runoff,
150 we get the best of both worlds: the central part is a mixture of Gaussians which benefits
151 from flexible approximation properties and the upper tail is a linear combination of GPD
152 densities that are capable of extrapolating in areas of unseen data under sound parametric
153 assumptions.

154 2.2 Conditional Density Model

155 Our goal is to provide a model of the river runoff at a future time step. We have at our
156 disposal rainfall data in the hydrographic basin of interest which influences river runoff.
157 We therefore look into modelling the distribution of the runoff at time $t + 1$ given covariate
158 information at time t , which includes rainfall observations and past runoff. The hybrid Pareto
159 mixture can be turned into a conditional density model by thinking of the parameters of the
160 mixture as function of covariates [Bis95]. These functions can be implemented in many ways.
161 The simplest model would be a linear model. However, the relationship between rainfall and
162 runoff is highly non-linear. A one-layer feedforward neural network of which the linear model
163 is a special case (no hidden units) is able, if the number of hidden units is well chosen, to
164 approximate any continuous relationship between covariates and mixture parameters. Data-
165 driven selection of the number of hidden units provides a proper level of complexity (or
166 non-linearity). A representation of the conditional mixture model with a neural network is
167 given in Figure 2. The covariates, or inputs, are combined linearly and either fed to the

168 hidden units or directly connected to the neural network outputs. We took the hyperbolic
 169 tangent as the activation function of the hidden layer. The neural network outputs are then
 170 transformed into the mixture parameters. Different transformation functions constrain the
 171 range of each mixture parameter. The $a_j^{(0)}$ in Figure 2 are dedicated to the mixture weights.
 172 The transformation function, the *softmax*, ensures that these weights are positive and sum
 173 to one. The $a_j^{(1)}$ and $a_j^{(3)}$ control the tail index and the spread parameter respectively of the
 174 j^{th} component. They are guaranteed to be positive by using a *softplus* [DBB⁺01], a slow-
 175 growing version of the exponential. Finally, the $a_j^{(2)}$'s are assigned to the location parameters
 176 and need no range constraint.

177 There are two hyper-parameters to adjust the level of complexity in the conditional
 178 hybrid Pareto mixture: the number of hidden units in the neural network and the number of
 179 components in the mixture. The former controls the degree of non-linearity of the mapping
 180 between the covariates and the mixture parameters and the latter accounts for the complexity
 181 of the conditional density (in particular, the multi-modality and asymmetry). Given the
 182 approximation capabilities of the neural network and of the mixture model, if the complexity
 183 level is well chosen, the conditional mixture should be able to approximate any type of
 184 conditional density. The hyper-parameters are chosen so as to maximize the conditional log-
 185 likelihood on a validation set, distinct from the training set and thus, should be reasonably
 186 close to the ones that give the best generalization performance (the capacity to perform well
 187 on unseen data). Because there are many sources of variability (training data, optimization
 188 process), the hyper-parameter selection can be variable as well. Overall, the conditional
 189 hybrid Pareto mixture gave a better performance than other conditional density estimator

190 in the presence of heavy-tailed data [CB08a].

191 2.3 Learning and Regularization

The conditional mixture parameters are the neural network parameters ω . These are learned by minimizing the negative conditional log-likelihood on the training data:

$$\mathcal{L}(\omega) = - \sum_{i=1}^n \log(\psi_{\omega}(y_i|x_i)),$$

192 where the sum is over the training set $\mathcal{D}_n = \{(x_1, y_1), \dots, (x_n, y_n)\}$ and $\psi_{\omega}(y_i|x_i)$ is the
193 hybrid Pareto conditional mixture model evaluated at the data point i .

194 In [CB08a], the authors have observed empirically that maximum likelihood estimation of
195 the hybrid Pareto mixture, conditional or not, can lead to over-estimation of the tail indexes.
196 This is especially striking for small training sets. The over-estimation of the tail index, even
197 by a small amount, leads to gross over-estimation of the extreme quantiles. In order to guide
198 maximum-likelihood estimation and avoid the over-estimation of the tail indexes, we use a
199 penalty term based on the prior density of Equation (1):

$$f(x; \tau, \eta, \rho) = \tau \eta \exp\{-\eta x\} + (1 - \tau) \frac{\exp\{-(x - 0.5)^2/(2\rho^2)\}}{\sqrt{2\pi\rho}}. \quad (1)$$

200 Figure 3 illustrates two typical shapes of the prior density. In the case of runoff data, we
201 can safely assume that the distribution has a tail index around 0.5 ([BSS+08]). This implies
202 that a variant of the full line density in Figure 3 will hold. Most components will be light-
203 tailed, with tail indexes close to zero. These components will take care of modelling the
204 central part of the distribution. Some components will be heavy-tailed, with a tail index
205 value close to the one of the underlying density and these will estimate the upper tail of the

206 distribution. Hence, the full line density is bimodal, with one mode at zero and the other
 207 one, smaller, around 0.5. On the other hand, if the data is light-tailed, then we assume that
 208 all the components will have tail indexes close to zero. The prior density in this case would
 209 look like the dashed line density in Figure 3.

210 The two-component mixture of Equation (1) can generate densities such as those il-
 211 lustrated in Figure 3. The exponential component with parameter η controls the density
 212 assigned to the small tail indexes and the Gaussian component centered at 0.5 with stan-
 213 dard deviation ρ determines how wide the range of the larger tail indexes can be. The
 214 mixture weight τ establishes the trade-off between the two components. When τ is equal to
 215 zero, we are in the light-tail case.

The conditional mixture parameters ω are now learned by minimizing a new cost function,
 the negative conditional log-likelihood minus the penalty term:

$$\mathcal{L}(\omega) = - \sum_{i=1}^n \log(\psi_{\omega}(y_i|x_i)) - \frac{\lambda}{n} \sum_{i=1}^n \sum_{j=1}^m \log f(\xi_{i,j}; \tau, \eta, \rho)$$

216 where the first sum is over the training set \mathcal{D}_n , the second sum in the penalty term is over
 217 the number of components m , $\psi_{\omega}(y_i|x_i)$ is the hybrid Pareto conditional mixture model
 218 evaluated at point i and $f(\xi_{i,j}; \tau, \eta, \rho)$ is the prior density evaluated at the tail index of the
 219 j^{th} component of the conditional mixture at point i . The penalty term introduces four other
 220 hyper-parameters: λ which controls the weight of the penalty with respect to the conditional
 221 log-likelihood and τ , η and ρ from the prior density (see Equation (1)). A restricted set of
 222 values for the prior density parameters was selected so as to ensure that the prior density
 223 follows our prior information about the shape of the distributions of the tail indexes. The

224 model is trained for several combinations of hyper-parameters (which include the number of
225 hidden units and the number of components of the conditional hybrid Pareto mixture and
226 the hyper-parameters attached to the penalty term). The set of hyper-parameters which
227 gives the smallest cost in terms of negative conditional log-likelihood on data unseen during
228 training (the validation set) is selected.

229 **3 Experiments**

230 We evaluate the conditional hybrid Pareto mixture on the rainfall-runoff data from the
231 Orgeval basin in France. Synthetic data experiments help to gain more insight into the role
232 of the new penalty term in the cost function. Since the generative model is known, the
233 predicted tail indexes can be compared with the tail indexes of the generative model. We
234 also compare the conditional quantiles of the generative versus learned model.

235 **3.1 Orgeval Basin Data**

236 The Orgeval Basin is located in France, East of Paris. There is no snow accumulation
237 in the area that could affect the river runoff. Therefore, we focus on rainfall as a pre-
238 dictor of the river runoff. In order to capture the mechanisms of the basin, moving av-
239 erages and moving standard deviations of various window lengths of the river runoff are
240 included in the covariates. The river runoff Q_t from the Avenelles sub-basin and the pre-
241 cipitations at four surrounding stations, P_t^j , $j = 1, \dots, 4$, are available at a hourly time
242 step for over thirty years but we use approximately ten years of data, from 1986 to 1996 (see

243 <http://www.antony.cemagref.fr/qhan/Site%20orgeval/Page%20accueil%20français.htm> for more
 244 details on the data and the basin.). We also have daily average temperatures at this site for
 245 the same time period. Date variables serve to capture the cycles and trends in the data. Pre-
 246 cisely, there are 16 covariates to predict the river runoff distribution: rainfall from the four
 247 precipitation stations at the previous time step, the runoff at the two previous time steps,
 248 moving averages and standard deviations with daily, weekly and monthly window widths,
 249 three date variables concerning the year, the month and the week and the daily average
 250 temperature at the previous day. Three time periods where there is no missing data are split
 251 into training and test sets. The data sets are summarized in Table 1. For this experiment,
 252 we set $Y_t = Q_{t+1}$ and $X_t = [Q_t, Q_{t-1}, P_t^1, \dots,]$ which means that given information available
 253 at time t , we model the distribution of the runoff at time $t + 1$. With the hourly data, we
 254 thus model the conditional distribution of the runoff at the next hour. In order to increase
 255 the prediction horizon to 6 and 12 hours, the hourly data are aggregated to form 6h and 12h
 256 time steps. To this end, we take the average of the runoff and the sum of the rainfall over
 257 the appropriate time period. This means that the lengths of our initial data sets in Table
 258 1 are divided by the length of the time steps. We thus have three different models, one for
 259 each time step.

260 We assume that given the covariate vector X_t , the Y_t are independent and identically
 261 distributed. It is thus possible to perform model selection via five-fold cross-validation (as
 262 opposed to sequential cross-validation which is more computationally intensive, see Bishop
 263 for details [Bis95]). Model selection works as follows. The training set is divided into five
 264 subsets or folds. The conditional hybrid Pareto mixture is first trained on four of those folds

265 for each set of hyper-parameters considered and the performance of each trained model is
 266 evaluated on the left out fold. This process is repeated five times, so that each fold in turn
 267 was left out and that the model performance was evaluated on all the data of the training
 268 set. The hyper-parameters that gave the best performance in validation are selected. The
 269 model with the selected hyper-parameters are trained again this time on the whole training
 270 set. The generalization ability, that is the performance on unseen data, is then estimated
 271 on the test set, which is distinct from the training set. Results from the experiments on
 272 the Orgeval basin data are summarized in Table 2 for each time step (1h, 6h, 12h). The
 273 selected hyper-parameters for the penalty term, $(\lambda, \tau, \eta, \sigma)$, correspond to the prior belief that
 274 the distribution is heavy-tailed. The confidence interval is computed from the conditional
 275 quantiles of level 0.05 and 0.95, therefore, the observed runoff should fall into that interval
 276 nine times out of ten. The percentage given on the row *Confidence Interval* is the actual
 277 percentage of observed runoff on the test set which fall into the confidence interval. We can
 278 see that it is pretty close to the expected one. A measure of goodness-of-fit is the so-called
 279 R-square given as $R^2 = 1 - \sum_i (y_i - \hat{y}_i)^2 / \sum_i (y_i - \bar{y})^2$, where y_i is the observed runoff, \hat{y}_i is the
 280 prediction and \bar{y} is the sample average. The closer R^2 is to one, the better the prediction is.
 281 The R-square is computed on the test set and the conditional median of the trained model
 282 is used to predict the runoff. We can see from the last row of Table 2 that the R-square
 283 for all time steps are very good, although the accuracy of the prediction decreases with the
 284 length of the time step. Prediction at longer time steps are understandably more difficult. A
 285 different test set is used for the 12h time step data (the data set number 2 in Table 1) in
 286 order to leave more data for the training set. The prediction is possibly more challenging on

287 that time period and at least, not directly comparable with the other two models, 1h and
288 6h, which uses a similar test set.

289 The river runoff for the test period is illustrated in the left column of Figure 4, each row
290 corresponding to one time step. The model prediction, which is the conditional median of
291 the trained model, is plotted for each test set in the right panel of Figure 4. For all time
292 steps, we can see that the model captured very well the dynamics of the river runoff. In the
293 left panel of Figure 5, we have plotted the confidence intervals in light grey with quantiles
294 of level 0.05 and 0.95 for the first 100 points of the test set. The black line is the observed
295 runoff. Sometimes, the confidence interval is very narrow while it grows larger where the
296 model perceives more uncertainty. We can check the effect of the tail penalty by looking at
297 the distribution of the tail indexes of the conditional hybrid Pareto mixture on the test set.
298 This is illustrated in the right panel of Figure 5 by an histogram. Except for a few cases in
299 which the tail index exceeds one (which is allowed by the prior), the largest tail index values
300 vary between 0.2 and 0.6 while most tail indexes take on values near zero. The distribution
301 of the tail indexes is thus consistent with our prior belief.

302 **3.2 Synthetic Data**

We generate synthetic data which resemble the runoff data in the sense that there are cycles
and that the tail indexes are in the same range. Let Y be a random variable distributed
according to a Fréchet distribution whose parameters are functions of an input variable X .

Then the distribution function of $Y|X = x$ is given by:

$$P(Y \leq y|X = x) = \begin{cases} 0 & \text{si } y \leq \mu(x), \\ \exp \left\{ - \left(\frac{y - \mu(x)}{\sigma(x)} \right)^{-1/\xi(x)} \right\} & \text{si } y > \mu(x). \end{cases}$$

The Fréchet distribution is a canonical heavy-tail distribution: the tail of most heavy-tailed distribution eventually behaves like the Fréchet tail. The input variable X is distributed according to a standard Normal distribution. We chose the following sine-shaped functional form for the dependence function $\xi(\cdot)$:

$$\xi(x) = \beta_1 + \beta_2 \sin(\gamma_1 + \gamma_2 x).$$

303 Since $X \sim \mathcal{N}(0, 1)$, we select the parameters of $\xi(\cdot)$ so that $\xi(X) \in [0.25, 0.5]$ with probability
 304 0.99. The dependence function $\mu(\cdot)$ and $\sigma(\cdot)$ have a similar sine-shaped form but their
 305 parameters are chosen so that $\mu(X) \in [2, 6]$ and $\sigma(X) \in [0.5, 1]$ with probability 0.99. We
 306 generated pairs of observations (X_i, Y_i) according to this generative model. The left panel of
 307 Figure 6 illustrates the training set which is made of 2 000 such pairs of observations. The
 308 right panel shows the corresponding tail indexes. Model selection (the choice of the proper set
 309 of hyper-parameters) is performed via five-fold cross-validation on the training set. Results
 310 are presented on a test set, distinct from the training set, which consists of 10 000 pairs of
 311 observations generated according to the conditional Fréchet distribution described above.

312 The model selected via five-fold cross-validation for the training set of Figure 6 has eight
 313 hidden units and two mixture components. The hyper-parameters for the tail penalty are
 314 the following: $\lambda = 0.1$, $\tau = 0.45$, $\eta = 50$ and $\sigma = 0.05$. This corresponds to the shape
 315 of a prior density for heavy tails in Figure 3. The effect of the tail penalty can be seen in

316 the left panel of Figure 7: the histogram of the conditional tail indexes of the conditional
317 hybrid Pareto mixture on the test set reflects the shape of the prior density. Note that less
318 than 1% of the tail indexes are larger than 1 and are thus not shown in the Figure, this is
319 due to the upper tail of the prior which still has some significant density in that area. For
320 the generative model, the conditional tail indexes $\xi(X)$ vary between 0.25 and 0.5 (see the
321 right panel of Figure 6). According to our prior belief, there should be a small subset of tail
322 indexes from the conditional hybrid Pareto mixture which take care of modelling the upper
323 tail and thus should take values in the same interval $[0.25, 0.5]$. The histogram of Figure 7 is
324 consistent with this prior belief. In the right panel of Figure 7 we have plotted the test set
325 together with the quantiles of level 0.05% and 0.95% which form a 90% confidence interval
326 as predicted from the trained conditional hybrid Pareto mixture. Among the test set, 89%
327 of the data points fall into the confidence interval.

328 In order to check how well the conditional density is learned in the upper tail, we compare
329 three conditional quantiles of levels 0.9, 0.95 and 0.99 as computed from the generative model
330 and the learned model. These are plotted in Figure 8: the black line is the quantile as
331 computed from the trained conditional hybrid Pareto mixture and the light grey line is the
332 quantile from the generative model. For the levels 0.9 and 0.95 (the top row), the two lines
333 are almost indistinguishable from one another except for the lower and upper ends. The data
334 density is much lower in these areas (see Figure 6) because the X variable follows a standard
335 Normal distribution and this makes learning more difficult. The conditional quantile of level
336 0.99 is less well approximated. This is also due to data scarcity and shows that the model is
337 less reliable in that case. Table 3 compares the percentage of the data in the test set which

338 fall below the conditional quantiles of the generative model and the trained model for the
339 three quantile levels. The picture is pretty similar for both models. Overall, the performance
340 of the conditional hybrid Pareto mixture with the new tail penalty proves to be satisfying.

341 4 Conclusion

342 We have propose a new stochastic model based on the conditional hybrid Pareto mixture
343 [CB08a], in order to model the distribution of the river runoff at a future time step given
344 rainfall observations in the hydrographic basin. This model relies on non-parametric algo-
345 rithms, namely a feed-forward neural network and a mixture of distributions, from which it
346 gains flexibility. Moreover, the component of the mixture, the hybrid Pareto, inherits the tail
347 approximation properties of the generalized Pareto distribution which are thus transmitted
348 to the conditional hybrid Pareto mixture. Therefore, the conditional hybrid Pareto mixture
349 has good approximation properties, as much in the central part of the distribution as in the
350 upper tail area.

351 We have introduce a penalty term in the maximum likelihood estimator in order to yield
352 more realistic conditional tail index estimation. The penalty is based on a bimodal density
353 which captures our prior knowledge of the distribution of the tail index. A hybrid Pareto
354 mixture has as many tail indexes as there are components in the mixture. In the conditional
355 case, the number of tail indexes is further multiplied by the number of data points. Our
356 intuition is that the distribution of the tail indexes should have two modes, one around zero
357 and one around the value of the tail index of the underlying distribution, if the latter is

358 heavy-tailed. Most components would be light-tailed and take care of modelling the central
359 part of the distribution whereas few components would have a heavier tail, near the value
360 of the tail index of the generative model, and would thus approximate the upper tail of the
361 underlying distribution.

362 The conditional hybrid Pareto mixture has been trained on data from the Orgeval basin in
363 France. Rainfall at four surrounding stations and the river runoff are available at hourly time
364 step. These data were aggregated to obtain 6 hour and 12 hour time steps. The stochastic
365 model was trained on three data sets, the hourly, six and 12 hour time steps. Each model
366 can then be used to forecast the river runoff at the next hour, six or 12 hours later. Our
367 experiments have shown that the conditional hybrid Pareto mixture is able to capture the
368 dynamics of the basin for the three predictive time horizons. In addition, the model provides
369 reliable confidence intervals. The tail index penalty introduces the expected distribution of
370 the conditional tail indexes, with one mode at zero and the second mode around 0.5, more
371 or less sharp depending on the data set.

372 Finally, the conditional hybrid Pareto mixture was trained on synthetic conditional data
373 based on the Fréchet distribution. The distribution of the tail indexes is consistent with the
374 values of the conditional tail indexes of the generative model. On the test set, 89% of the
375 data points falls into the 90% confidence interval predicted by the model. Moreover, the
376 trained model compares favorably with the generative model in terms of extreme quantiles.

377 The conditional hybrid Pareto mixture with the new penalty term has proven to be
378 effective at modelling the rainfall-runoff process for various time steps on the Orgeval basin
379 and more insight into the model was gain by looking at an experiment on synthetic data.

380 This model is very flexible and could be useful to model the rainfall-runoff process in other
381 hydrographic basins, by using appropriate covariates.

382 **Acknowledgments**

383 The authors thank the following funding organizations: FQRNT, CNRS, CEA and the

384 AssimileX and ACQWA projects.

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416 **List of Tables**

417 1 Three periods with no missing value in the Orgeval basin data in order of
 418 decreasing lengths. 29

419 2 Experiments for the Orgeval basin data, for each time step (1h, 6h, 12h) we
 420 have: the sizes of the training and test sets (data set number from Table 1),
 421 the selected number of hidden units and components (h, m) followed by the
 422 selected penalty hyper-parameters ($\lambda, \tau, \eta, \sigma$), the percentage of the runoff in
 423 the test set which falls in the predicted 90% confidence interval and the R^2 of
 424 the predicted median on the test set. 30

425 3 Experiments with the conditional Fréchet data: percentage of the data in the
 426 test set which fall below the conditional quantiles of levels 0.9, 0.95 and 0.99
 427 for the generative and the trained models. 31

428 **List of Figures**

429 1 Gaussian mixture density (full line) with seven components trained on heavy-
 430 tailed data. The dashed lines represent the contribution of each component
 431 to the density. Five components model the central part and the other two
 432 components contribute to the density in the upper tail. 32

433 2 Representation of a conditional mixture model with hybrid Pareto compo-
 434 nents $\psi_{\omega}(y|x)$. Inputs are fed to a one-layer feedforward neural network with
 435 an extra linear connection directly to the outputs. The outputs are then
 436 transformed into the mixture parameters so as to fullfil range constraints. . . 33

437 3 The distribution in full line has one mode at zero and one mode at 0.5 while
 438 the distribution in dashed line has only significant density around zero. The
 439 former distribution reflects our prior information about how the tail indexes of
 440 a hybrid Pareto mixture should be distributed when the data is heavy-tailed
 441 and the latter distribution when the data is light-tailed. 34

442 4 Left column: observed runoff of the Avenelles sub-basin for the test period,
 443 each row corresponding to a given time step (1h, 6h and 12h). Right column:
 444 predicted median on the test set from the learned hybrid Pareto conditional
 445 mixture for the three time steps. 35

446	5	Left panel: in black, the observed runoff for the first 100 points of the test set	
447		illustrated in Figure 4 together with a 90% confidence interval in light grey	
448		predicted from the conditional mixture. Right panel: histogram of the tail	
449		indexes of the conditional hybrid Pareto mixture on the test set.	36
450	6	Left panel: training set of 2 000 data points distributed according to the con-	
451		ditional Fréchet distribution with a sine-shaped functional for the dependent	
452		parameters. Right panel: the corresponding conditional tail indexes of the	
453		generative conditional Fréchet model.	37
454	7	Left panel: histogram of the conditional tail indexes of the trained conditional	
455		hybrid Pareto mixture on the test set. Right panel: 90% confidence interval	
456		from the trained model on the test set together with the data points (89% of	
457		the data fall into the confidence interval).	38
458	8	Conditional quantiles of level 90%, 95% and 99% clockwise, in black, as com-	
459		puted from the mixture model and in light grey, from the generative condi-	
460		tional Fréchet model.	39

	Time period	Hourly observations
1:	03/26/86 18:00:00 to 05/22/94 08:00:00	71 487
2:	07/22/96 15:00:00 to 08/24/01 16:00:00	44 618
3:	05/30/94 18:00:00 to 06/18/96 03:00:00	17 987

Table 1: *Three periods with no missing value in the Orgeval basin data in order of decreasing lengths.*

	Hourly	6 hours	12 hours
Training data	52 846 (1)	9 913 (1)	7 455 (1,3)
Test data	10 000 (1)	2 000 (1)	3 717 (2)
(h, m)	(4,4)	(4,8)	(4,12)
$(\lambda, \tau, \eta, \sigma)$	(0.01,0.5,50,0.1)	(0.1,0.1,50,0.2)	(1,0.1,50,0.1)
Confidence Interval	91.94%	92.1%	87.6%
R^2	0.99	0.92	0.73

Table 2: Experiments for the Orgeval basin data, for each time step (1h, 6h, 12h) we have: the sizes of the training and test sets (data set number from Table 1), the selected number of hidden units and components (h, m) followed by the selected penalty hyper-parameters $(\lambda, \tau, \eta, \sigma)$, the percentage of the runoff in the test set which falls in the predicted 90% confidence interval and the R^2 of the predicted median on the test set.

	0.9	0.95	0.99
Generative model	89.64%	94.54%	98.97%
Trained model	89.16%	94.1%	98.39%

Table 3: *Experiments with the conditional Fréchet data: percentage of the data in the test set which fall below the conditional quantiles of levels 0.9, 0.95 and 0.99 for the generative and the trained models.*

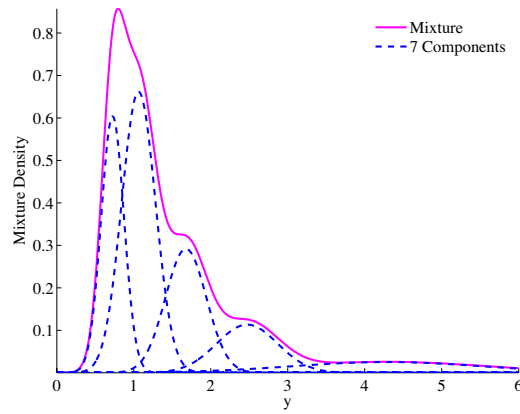


Figure 1: *Gaussian mixture density (full line) with seven components trained on heavy-tailed data. The dashed lines represent the contribution of each component to the density. Five components model the central part and the other two components contribute to the density in the upper tail.*

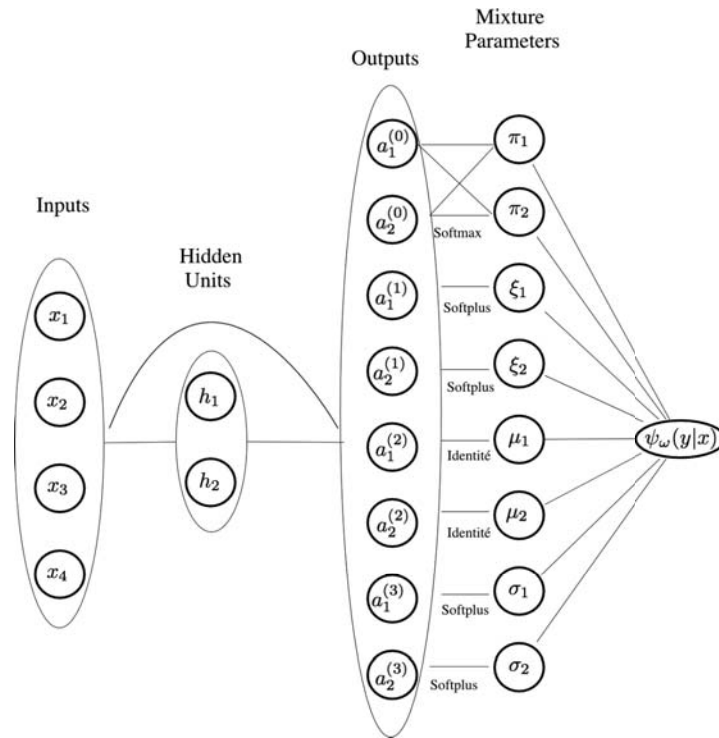


Figure 2: Representation of a conditional mixture model with hybrid Pareto components $\psi_\omega(y|x)$. Inputs are fed to a one-layer feedforward neural network with an extra linear connection directly to the outputs. The outputs are then transformed into the mixture parameters so as to fulfill range constraints.

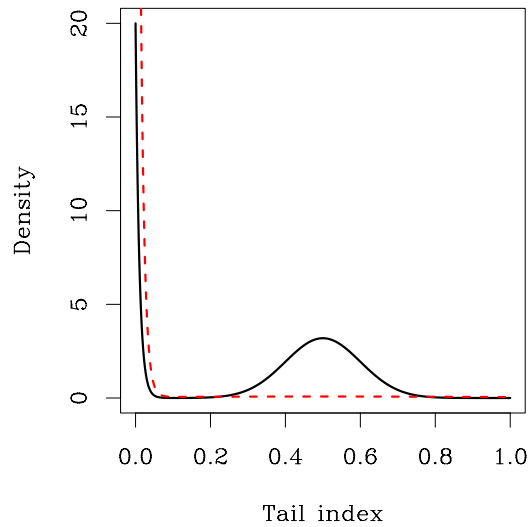


Figure 3: *The distribution in full line has one mode at zero and one mode at 0.5 while the distribution in dashed line has only significant density around zero. The former distribution reflects our prior information about how the tail indexes of a hybrid Pareto mixture should be distributed when the data is heavy-tailed and the latter distribution when the data is light-tailed.*

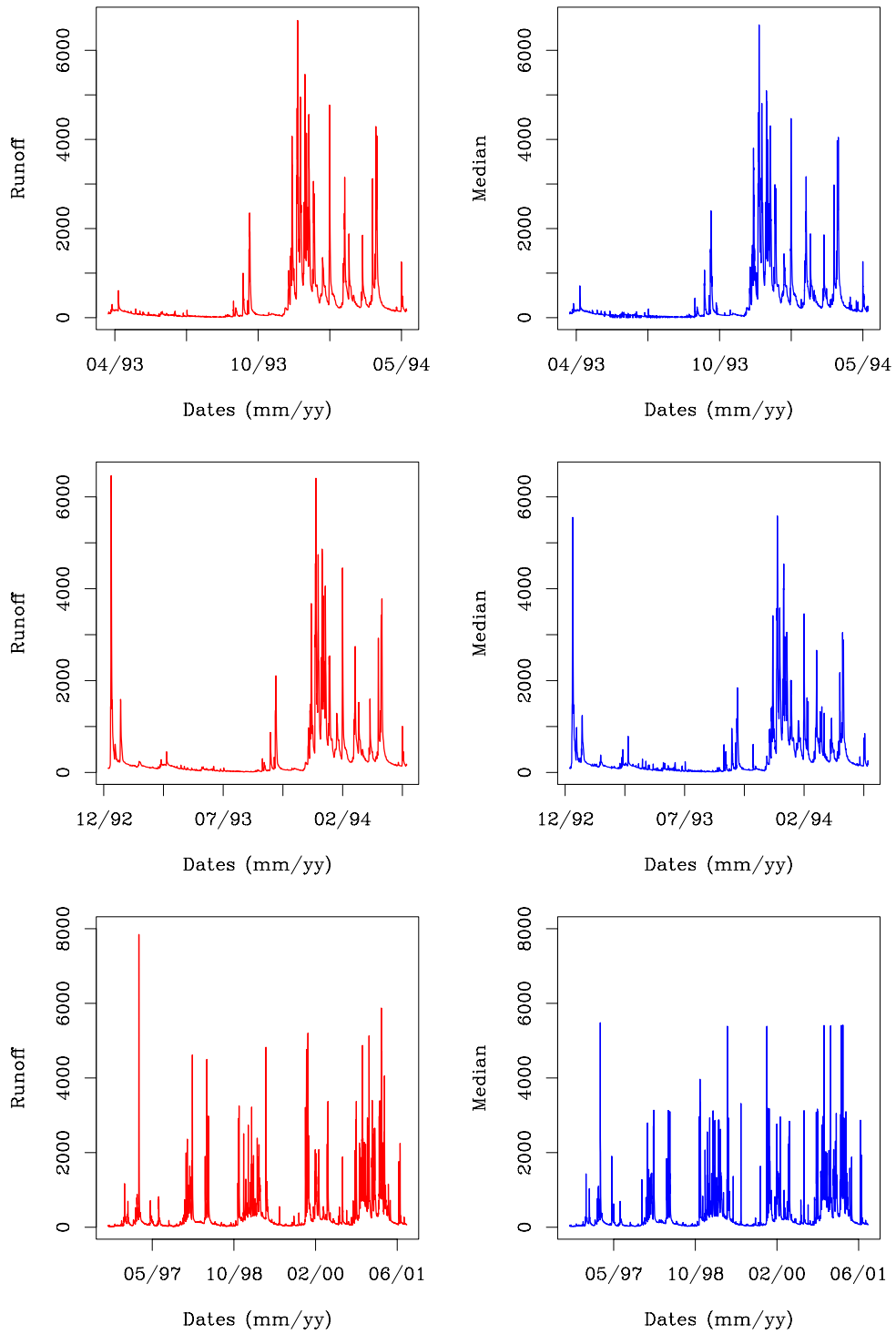


Figure 4: *Left column: observed runoff of the Avenelles sub-basin for the test period, each row corresponding to a given time step (1h, 6h and 12h). Right column: predicted median on the test set from the learned hybrid Pareto conditional mixture for the three time steps.*

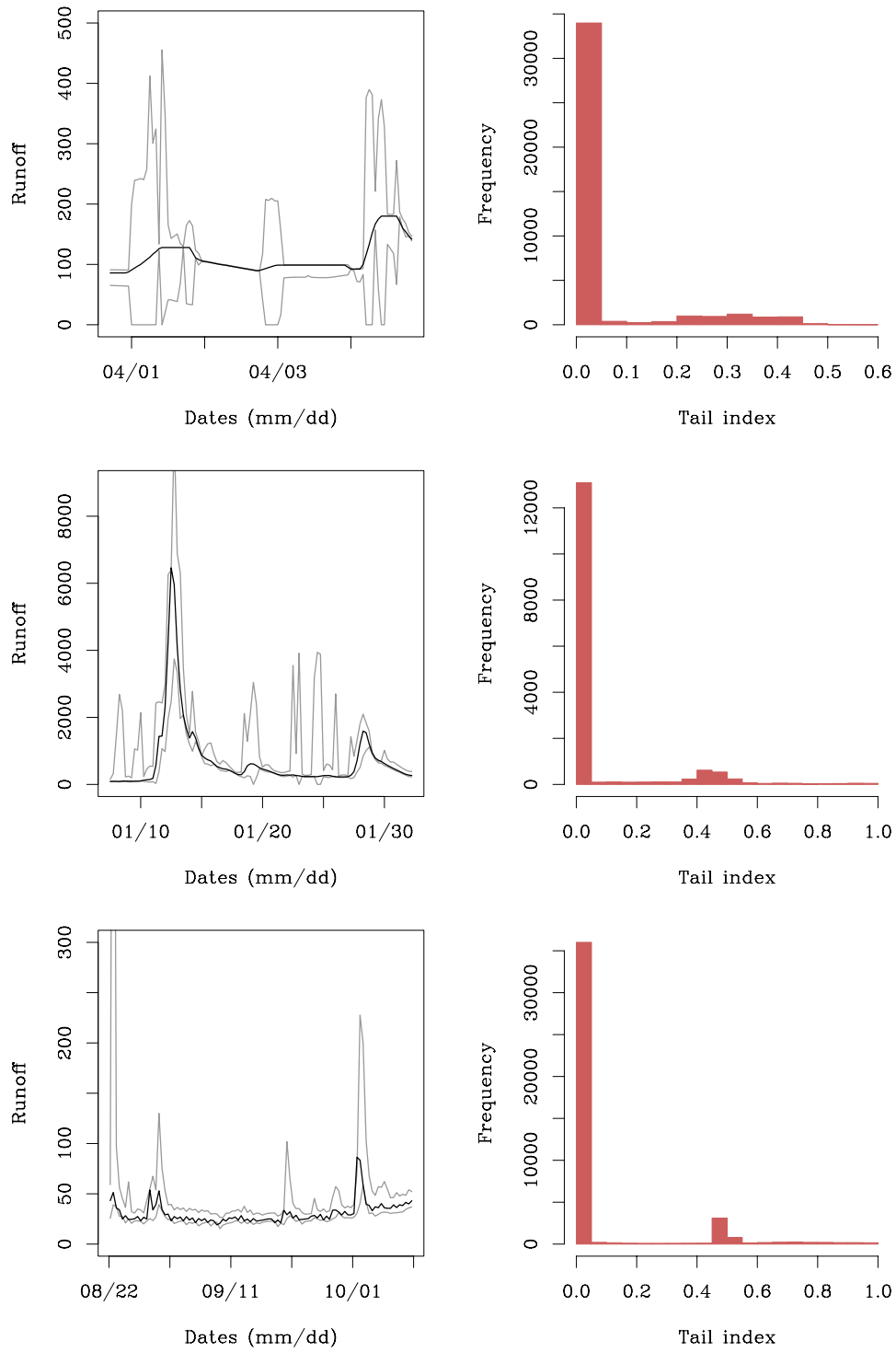


Figure 5: Left panel: in black, the observed runoff for the first 100 points of the test set illustrated in Figure 4 together with a 90% confidence interval in light grey predicted from the conditional mixture. Right panel: histogram of the tail indexes of the conditional hybrid Pareto mixture on the test set.

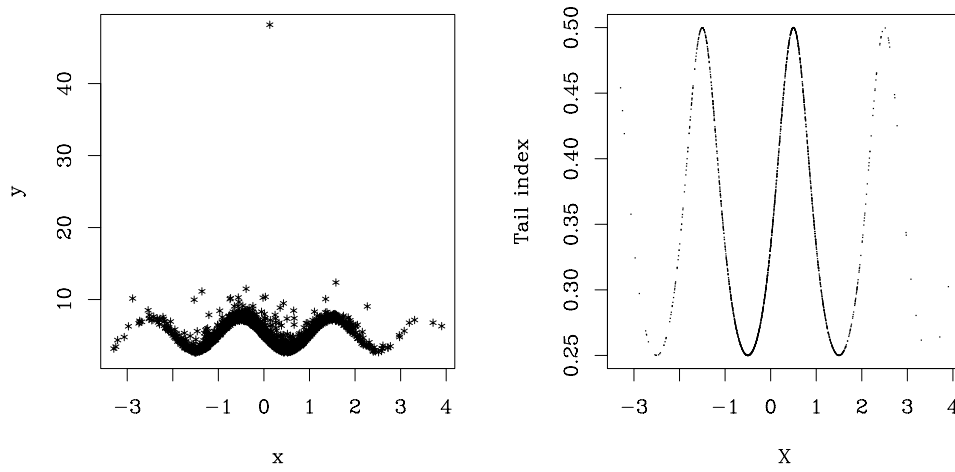


Figure 6: *Left panel: training set of 2 000 data points distributed according to the conditional Fréchet distribution with a sine-shaped functional for the dependent parameters. Right panel: the corresponding conditional tail indexes of the generative conditional Fréchet model.*

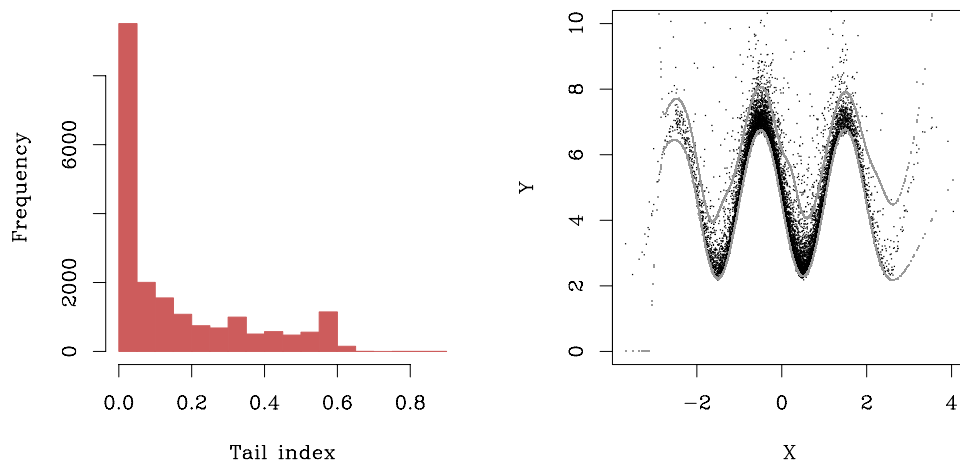


Figure 7: *Left panel: histogram of the conditional tail indexes of the trained conditional hybrid Pareto mixture on the test set. Right panel: 90% confidence interval from the trained model on the test set together with the data points (89% of the data fall into the confidence interval).*

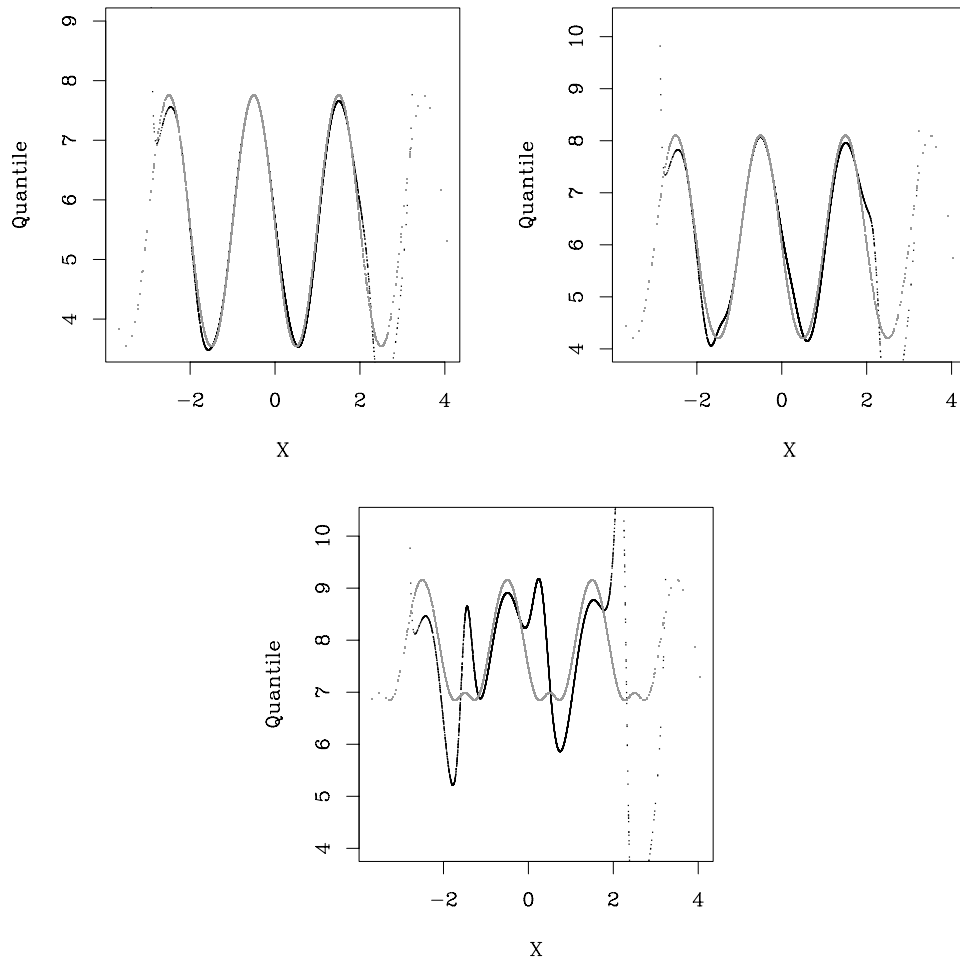


Figure 8: *Conditional quantiles of level 90%, 95% and 99% clockwise, in black, as computed from the mixture model and in light grey, from the generative conditional Fréchet model.*