

Pseudocode

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Algorithm 0.1: MCMC Algorithm

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1 input: observations  $(x_i(s_0), \dots, x_i(s_M))_{i=1, \dots, n_{\text{obs}}}$ , risk functional  $r$ , threshold  $u$ , parametric model,
2 prior  $\pi$ , proposal  $q(\cdot, \cdot)$ , chain length  $n_{\text{MCMC}}$ , fine grid points  $t_0, \dots, t_N$ 
3 output: Markov chain of parameters of length  $n_{\text{MCMC}}$ 
4 begin
5   initialize parameter  $(\theta_0, \alpha_0)$  from prior  $\pi$ 
6   for  $n \in \{1, \dots, n_{\text{MCMC}}\}$ 
7     sample  $r(X_i) \mid X_i(s_0) = x_i(s_0), \dots, X_i(s_M) = x_i(s_M)$  under parameter  $(\theta_{n-1}, \alpha_{n-1})$ 
8     using Algorithm 2
9     set  $I = \{i \mid r(X_i) > u\}$ 
10    sample  $(\theta_{\text{prop}}, \alpha_{\text{prop}}) \sim q((\theta_{n-1}, \alpha_{n-1}), \cdot)$ 
11    sample  $v \sim \text{Unif}[0, 1]$ 
12    if  $v < a((\theta_{n-1}, \alpha_{n-1}), (\theta_{\text{prop}}, \alpha_{\text{prop}}))$ 
13      set  $(\theta_n, \alpha_n) = (\theta_{\text{prop}}, \alpha_{\text{prop}})$ 
14    else
15      set  $(\theta_n, \alpha_n) = (\theta_{n-1}, \alpha_{n-1})$ 
16    end if
17  end for
18  return  $(\theta_0, \alpha_0) \dots, (\theta_{n_{\text{MCMC}}}, \alpha_{n_{\text{MCMC}}})$ 
19 end

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Algorithm 0.2: Cond-X Algorithm

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1 input: observations  $(x_i(s_0), \dots, x_i(s_M))_{i=1, \dots, n_{\text{obs}}}$ , risk functional  $r$ , fine grid points  $t_0, \dots, t_N$ ,
2 parametric model with parameter  $(\theta, \alpha)$ , chain length  $n_{\text{condX}}$ 
3 output: sample  $r(X_i) \mid X_i(s_0) = x_i(s_0), \dots, X_i(s_M) = x_i(s_M)$  under parameter  $(\theta, \alpha)$ 
4 begin
5   for  $i \in \{1, \dots, n_{\text{obs}}\}$ 
6     initialize  $w \sim W \mid W(s_1) = \frac{x_i(s_1)}{x_i(s_0)}, \dots, W(s_M) = \frac{x_i(s_M)}{x_i(s_0)}$  under parameter  $(\theta, \alpha)$ 
7     for  $n \in \{1, \dots, n_{\text{condX}}\}$ 
8       sample  $w_{\text{prop}} \sim W \mid W(s_1) = \frac{x_i(s_1)}{x_i(s_0)}, \dots, W(s_M) = \frac{x_i(s_M)}{x_i(s_0)}$  under parameter  $(\theta, \alpha)$ 
9       sample  $v \sim \text{Unif}[0, 1]$ 
10      if  $v < a(w, w_{\text{prop}}) = \min \left\{ \frac{r^\alpha(w_{\text{prop}})}{r^\alpha(w)}, 1 \right\}$ 
11        set  $w = w_{\text{prop}}$ 
12      end if
13    end for
14    set  $w_i = w$ 
15  end for
16  return  $r(X_i) = x_i(s_0) \cdot r(w_i)$ 
17 end

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Algorithm 0.3: CondGaussian Simulation Algorithm

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1 input: observations  $(x_i(s_0), \dots, x_i(s_M))_{i=1, \dots, n_{\text{obs}}}$ , fine grid points  $t_0, \dots, t_N$ ,
2 parametric model with parameter  $(\theta, \alpha)$ 
3 output: sample  $W \mid W(s_1) = \frac{x_i(s_1)}{x_i(s_0)}, \dots, W(s_M) = \frac{x_i(s_M)}{x_i(s_0)}$  under parameter  $(\theta, \alpha)$ 
4 begin
5   sample  $w_{\text{uncond}}(t_1), \dots, w_{\text{uncond}}(t_N)$  unconditional on fine grid with parameter  $(\theta, \alpha)$  via alg. 4
6   set  $\Sigma_{ts} = (\gamma_\theta(t_i - s_0) + \gamma_\theta(s_j - s_0) - \gamma_\theta(t_i - s_j))_{i \in \{1, \dots, N\}, j \in \{1, \dots, M\}}$ 

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7      set  $\Sigma_{ss} = (\gamma_\theta(s_i - s_0) + \gamma_\theta(s_j - s_0) - \gamma_\theta(s_i - s_j))_{i \in \{1, \dots, M\}, j \in \{1, \dots, M\}}$ 
8      return  $\exp($ 
9           $\log w_{\text{uncond}}(t_1, \dots, t_N) + \Sigma_{ts} \Sigma_{ss}^{-1} (\log \left( \frac{x_i(s_1)}{x_i(s_0)}, \dots, \frac{x_i(s_M)}{x_i(s_0)} \right) - \log w_{\text{uncond}}(s_1, \dots, s_M))$ 
10      $)$ 
11 end

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Algorithm 0.4: log-Gaussian Simulation Algorithm

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1 input:   fine grid points  $t_0, \dots, t_N$ , parametric model with parameter  $(\theta, \alpha)$ 
2 output:  sample from  $W$  under parameter  $(\theta, \alpha)$  on fine grid
3 begin
4   sample  $g(t_1), \dots, g(t_N) \sim$  standard FBM under parameter  $(\theta, \alpha)$ 
5   return  $w_j = \exp\left(\frac{1}{\alpha}(g(t_j) - g(s_0) - \gamma_\theta(t_j, s_0))\right)$ 
6 end

```

Algorithm 0.5: Acceptance Rate MCMC Algorithm

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1 input:   exceedance observations  $(x_i(s_0), \dots, x_i(s_M))_{i \in I_{\text{exceed}}}$ , risk functional  $r$ ,
2           prior  $\pi$ , proposal  $q(\cdot, \cdot)$ , parametric model with parameter  $(\theta_{\text{prop}}, \alpha_{\text{prop}})$  and  $(\theta_{\text{old}}, \alpha_{\text{old}})$ ,
3           sample size  $n_{\text{CondGauss}}$ , sample size  $n_{\text{Gauss}}$ , fine grid points  $t_0, \dots, t_N$ 
4 output:  acceptance rate  $a((\theta_{\text{old}}, \alpha_{\text{old}}), (\theta_{\text{prop}}, \alpha_{\text{prop}}))$ 
5 begin
6   for  $\theta \in \{(\theta_{\text{prop}}, \alpha_{\text{prop}}), (\theta_{\text{old}}, \alpha_{\text{old}})\}$ 
7     for  $i \in I_{\text{exceed}}$ 
8       set  $a = \text{GaussianDensity}((\theta, \alpha), \alpha \cdot \log\left(\frac{x_i(s_1)}{x_i(s_0)}, \dots, \frac{x_i(s_M)}{x_i(s_0)}\right)) \cdot \alpha^M$ 
9       set  $b = \alpha \left(\frac{x_i(s_0)}{u}\right)^{-\alpha-1}$ 
10      estimate  $c = \mathbb{E}(l(W)^\alpha)$  under parameter  $(\theta, \alpha)$  via  $n_{\text{Gauss}}$  times algorithm 4
11      set  $\log \text{likelihood}((\theta, \alpha), i) = \log a + \log b - \log c$ 
12    end for
13    set  $\log \text{likelihood}(\theta, \alpha) = \sum_{i \in I_{\text{exceed}}} \log \text{likelihood}((\theta, \alpha), i)$ 
14  end for
15  return  $\min \left\{ 1, \frac{\pi((\theta_{\text{prop}}, \alpha_{\text{prop}}))q((\theta_{\text{prop}}, \alpha_{\text{prop}}), (\theta_{\text{old}}, \alpha_{\text{old}})) \text{likelihood}((\theta_{\text{prop}}, \alpha_{\text{prop}}))}{\pi((\theta_{\text{old}}, \alpha_{\text{old}}))q((\theta_{\text{old}}, \alpha_{\text{old}}), (\theta_{\text{prop}}, \alpha_{\text{prop}})) \text{likelihood}((\theta_{\text{old}}, \alpha_{\text{old}}))} \right\}$ 
16 end

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