

# Extreme sea level estimation combining systematic observed skew surges and historical record sea levels

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## Key Points:

- The exhaustiveness of historical sea record information is demonstrated based on French Atlantic coast data
- A comparative analysis of approaches to integrate historical information is carried out
- The efficiency of a new method for the combination of systematic skew surges and historical records is verified

## Nomenclature

$X_{sys}$	POT sample of systematic skew surges
$u$	threshold value for $X_{sys}$ , $u \geq \min(X_{sys})$ (m)
$n$	length of $X_{sys}$
$w_S$	systematic duration (years)
$Z_{hist}$	historical record sea levels
$\eta_H$	threshold value for $Z_{hist}$ , $\eta_H \geq \min(Z_{hist})$ (m)
$h_z$	length of $Z_{hist}$
$X_{hist}$	corresponding skew surges of $Z_{hist}$ and exceeding $u_H$
$u_H$	threshold value for $X_{sys}$ , $u_H \geq \min(X_{hist})$ and $u_H \geq u$ (m)
$h_x$	length of $X_{hist}$ , $h_x \leq h_z$
$w_H$	historical duration (years)
$\lambda$	intensity of Poisson process, $\lambda > 0$
$\sigma$	scale parameter of the GP distribution, $\sigma > 0$
$\xi$	shape parameter of the GP distribution, $\xi \in \mathbb{R}$
$\theta$	parameters to estimate, $\theta = (\sigma, \xi, \lambda)$

## List of abbreviations

GP	General Pareto
POT	Peaks Over Threshold
ML	Maximum Likelihood
MCMC	Monte Carlo Markov Chain
RSD	Relative Standard Deviation
RRMSE	Relative Root Mean Square Error

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## Abstract

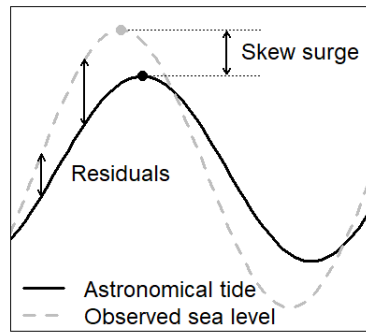
The estimation of sea levels corresponding to high return periods is crucial for coastal planning and for the design of coastal defenses. This paper deals with the use of historical observations, i.e. events that occurred before the beginning of the systematic tide gauge recordings, to improve the estimation of design sea levels. Most of the recent publications dealing with statistical analyses applied to sea levels suggest that astronomical high tide levels and skew surges should be analyzed and modelled separately. Historical samples generally consist of observed record sea levels. Some extreme historical skew surges can easily remain unnoticed if they occur at low or moderate astronomical high tides and do not generate extreme sea levels. The exhaustiveness of historical skew surge series, which is an essential criterion for an unbiased statistical inference, can therefore not be guaranteed. This study proposes a model combining, in a single Bayesian inference procedure, information of two different nature for the calibration of the statistical distribution of skew surges: measured skew surges for the systematic period and extreme sea levels for the historical period. A data-based comparison of the proposed model with previously published approaches is presented based on a large number of Monte Carlo simulations. The proposed model is applied to four locations on the French Atlantic and Channel coasts. Results indicate that the proposed model is more reliable and accurate than previously proposed methods that aim at the integration of historical records in coastal sea level or surge statistical analyses.

## 1 Introduction

Coastal defenses must be designed for very low probabilities of failure. Their design values, generally resulting from the statistical analyses of relatively short series of tide gauges, are particularly sensitive to inherent statistical estimation uncertainties. During the last decade, a number of coastal floods due to exceptional surges, resulted in significant damages, pointing to the importance of an appropriate design of coastal defense structures (Aelbrecht et al., 2004; Gerritsen, 2005; De Zolt et al., 2006; Kolen et al., 2013). It is now widely accepted that historical information even if partial and inaccurate, may significantly reduce statistical inference uncertainties, if properly processed (Ouarda et al., 1998; Benito et al., 2004; Reis & Stedinger, 2005; Gaal et al., 2010; Payraastre et al., 2011; Hamdi et al., 2015). This paper proposes some methodological improvements for the incorporation of historical information in coastal risk assessment studies.

The measured sea levels can be interpreted as the combination of two temporal signals: astronomical tides which can be predicted and residuals due to atmospheric and meteorological processes (see Figure 1). On average, 706 tidal cycles occur during a year. The maximum tidal sea level during a cycle can also be seen as the sum of the astronomical high tide and the skew surge - i.e. the difference between the observed maximum sea level and the predicted astronomical high tide (see Figure 1).

The common practice in extreme value statistics for coastal studies consists in fitting a theoretical statistical distribution to a sub-sample of the observed series. The sub-sample is generally a peaks over threshold (POT) sample of either maximum tidal sea levels (direct method) or skew surges or even maximum tidal residuals (indirect methods). The direct method, based directly on the analysis of maximum tidal water levels (Arns et al., 2013; Bulteau et al., 2015) does not exploit the available knowledge on the astronomical tidal component of the sea level (Tawn et al., 1989; Mazas et al., 2014). Moreover it seems to provide biased estimates of sea level quantiles corresponding to high return periods for locations with large tidal amplitudes (Haigh et al., 2010; Andreewsky et al., 2014). Indirect methods are therefore nowadays privileged. Indirect methods were first introduced based on the separate analysis of residuals and astronomical tides (Pugh & Vassie, 1978, 1980; Tawn et al., 1989; Tawn, 1992). They are nevertheless uneasy to implement, since the reconstruction of the maximum sea level statistical distribution im-



**Figure 1.** Definition of residuals and skew surges

89 plies a complex convolution between the astronomical tidal signal and the common and  
 90 and extreme residuals (Dixon & Tawn, 1994, 1999; Tomasin & Pirazzoli, 2008; Liu et al., 2010).  
 91 Moreover, residuals and astronomical high tides may be dependent at some locations.  
 92 Accounting for this dependence makes the approach even more challenging (Mazas et  
 93 al., 2014). The indirect method, based on skew surges was introduced more recently in  
 94 order to reduce the implementation complexity (Batstone et al., 2013; Kergadallan et  
 95 al., 2014; Mazas et al., 2014; Hamdi et al., 2015). Note that the latter approach is used  
 96 herein on a POT sample of skew surges  $X_{sys}$  larger than a threshold  $u$ .

97 Historical information, when available, is composed of a series of record sea levels  
 98  $Z_{hist}$  exceeding a threshold  $\eta_H$ . The corresponding historical skew surge series  $X_{hist}$  and  
 99 the associated threshold  $u_H$  may be estimated for statistical inference combining sys-  
 100 tematic  $X_{sys}$  and historical  $X_{hist}$  skew surges. However, the exhaustiveness of the series  
 101 of skew surges exceeding  $u_H$  during the historical period cannot be guaranteed. In-  
 102 deed, some extreme historical skew surges may in fact remain unnoticed if they occur  
 103 at low or moderate astronomical high tides and do not generate extreme sea levels (Outten  
 104 et al., 2020). The exhaustiveness of the historical POT series is an essential criterion for  
 105 an unbiased statistical inference (Gaume, 2018). Some authors have proposed to pro-  
 106 ceed with the statistical inference including historical skew surges without considering  
 107 their non-exhaustiveness (Hamdi et al., 2015). We suspect that the under-sampling of  
 108 historical skew surges due to their non exhaustiveness could leads to some bias. Some  
 109 others have proposed to adjust (i.e. reduce) the length of the historical period to account  
 110 for the non-exhaustiveness (Frau et al., 2018). Reducing the historical duration leads to  
 111 a possible over-representation of extreme skew surges in a very short duration and the  
 112 introduction of some bias is suspected. None of these two approaches appears to be to-  
 113 tally satisfactory. It is therefore proposed hereafter to keep the historical information  
 114 in its original form and to combine, in the same inference procedure, two different types  
 115 of information: systematic skew surges  $X_{sys}$  and historical record sea levels  $Z_{hist}$ . A like-  
 116 likelihood based inference procedure is implemented. The main idea consists in replacing  
 117 the analytical form of the sea level cumulative distribution function, which is unknown,  
 118 by a numerical estimate in the likelihood formulation.

119 This paper presents the background of the proposed approach and its performances:  
 120 accuracy of the estimated skew surge quantiles and of the corresponding Bayesian credi-  
 121 bility intervals. These performances are evaluated through Monte Carlo experiments in-  
 122 spired by four real-life implementation case studies. The results are compared to those  
 123 of several other inference methods: without the use of any historical information, when

124 historical skew surges are exhaustively known, the method proposed by Hamdi et al. (2015),  
 125 the method proposed by Frau et al. (2018) and a modification of this last method (sec-  
 126 tion 2.1). The proposed approach is then applied to the four observed data sets in or-  
 127 der to evaluate its relevance and efficiency when implemented on real-life case studies.

128 The paper is structured as follows. The various tested methods and the statisti-  
 129 cal inference procedure are presented in section 2. The evaluation methodology is ex-  
 130 plained in section 3. The performances of the tested methods are compared in section 4  
 131 and some reference methods as well as the proposed method are implemented on the ob-  
 132 served data sets in section 5. Section 6 is devoted to some discussion and conclusions.

## 133 2 Models and statistical inference procedure

### 134 2.1 The tested methods

135 The proposed method is compared to several methods including methods of ref-  
 136 erence (with only systematic data sets or in the case of perfect knowledge of historical  
 137 skew surge series) and previously published methods integrating historical information  
 138 (Hamdi et al., 2015; Frau et al., 2018). In total, six different methods are implemented  
 139 and tested herein for the estimation of the 100-year skew surge quantile:

- 140 • **Method 1:** The inference is only based on the series of systematic skew surges  
 141  $X_{sys}$  exceeding a threshold value  $u$  (see Section 2.2.1). This method with no his-  
 142 torical information included is considered herein as the reference one.
- 143 • **Method 2:** All historical skew surges exceeding the threshold  $u$  are known for  
 144 the systematic and historical period. This is the ideal situation.
- 145 • **Method 3:** The series of systematic skew surges  $X_{sys}$  exceeding  $u$  and histori-  
 146 cal record sea levels  $Z_{hist}$  exceeding a threshold value  $\eta_H$  are combined in a sin-  
 147 gle likelihood formulation (see Section 2.2.3). This is the proposed method.
- 148 • **Method 4:** The series of historical skew surges exceeding  $u_H$ , corresponding to  
 149 the record sea levels exceeding  $\eta_H$  is supposed to be exhaustive. This method pro-  
 150 posed by Hamdi et al. (2015) (see Section 2.2.2) will be called "naive", as the ex-  
 151 haustiveness of the historical skew surge series can never be guaranteed.
- 152 • **Method 5:** The FAB method proposed by Frau et al. (2018) adjusts the dura-  
 153 tion of the historical observation period, assuming that the mean annual frequency  
 154 of a skew surge exceeding the threshold value  $u$  is the same during the historical  
 155 and the systematic periods (see Section 2.2.2).
- 156 • **Method 6:** A modification of the FAB method accounting for the fact that the  
 157 real skew surge sampling threshold  $u_H$  for the historical period may be much larger  
 158 than  $u$  and that the mean annual frequency of exceedance should therefore be ad-  
 159 justed (see Section 2.2.2).

160 The likelihood formulations for all of these methods are provided in the next sec-  
 161 tion.

### 162 2.2 Likelihood formulations

163 Let us denote  $X_{sys} = \{x_{sys,1}, x_{sys,2}, \dots, x_{sys,n}\}$  the POT series of  $n$  skew surges  
 164 exceeding a threshold value  $u$  during the systematic observation period  $w_S$  (years).  $Z_{hist} =$   
 165  $\{z_{hist,1}, z_{hist,2}, \dots, z_{hist,h_z}\}$  are the  $h_z$  record historical sea levels. It is assumed - ideally  
 166 cross-checked with available archives - that the sample of record sea levels exceeding a  
 167 threshold  $\eta_H$  is exhaustive over the considered historical period.  $\eta_H$  is often chosen equal  
 168 to the minimum historical value:  $\min(Z_{hist})$ . Finally,  $X_{hist} = \{x_{hist,1}, x_{hist,2}, \dots, x_{hist,h_x}\}$   
 169 is the series of  $h_x$  historical skew surges, corresponding to the historical record levels and  
 170 in the same time, exceeding the threshold  $u$ . Note that  $h_x \leq h_z$ . Let us also note  $\theta$  the

171 parameters of the skew surge statistical distribution to be estimated using the available  
 172 observed data set.

173 Depending on whether the historical record sea levels or the historical skew surges  
 174 are considered, the combined likelihood of the systematic and historical data sets may  
 175 have two distinct formulations:

$$176 \quad L(X_{sys}, X_{hist}|\theta) = L(X_{sys}|\theta) \cdot L(X_{hist}|\theta) \quad (1)$$

$$177 \quad L(X_{sys}, Z_{hist}|\theta) = L(X_{sys}|\theta) \cdot L(Z_{hist}|\theta) \quad (2)$$

178 The likelihood terms  $L(X_{sys}|\theta)$ ,  $L(X_{hist}|\theta)$  and  $L(Z_{hist}|\theta)$  are described in the next  
 179 sections.

### 180 **2.2.1 Likelihood of the systematic skew surge sample: $L(X_{sys}|\theta)$**

181 The General Pareto (GP) distribution is usually selected as the statistical distri-  
 182 bution of skew surges exceeding  $u$ . Indeed, according to the extreme value theory, it has  
 183 been proven that a POT independent random sample converges to a GP distribution (Coles,  
 184 2001). The GP cumulative distribution function  $F_\theta$  is given by:

$$185 \quad \forall x > u, F_\theta(x) = \begin{cases} 1 - [1 + \xi (\frac{x-u}{\sigma})]^{-\frac{1}{\xi}} & \text{if } \xi \neq 0, \\ 1 - \exp(-\frac{x-u}{\sigma}) & \text{if } \xi = 0. \end{cases} \quad (3)$$

186 with  $\sigma > 0$  the scale parameter and  $\xi \in \mathbb{R}$  the shape parameter.

187 The number of skew surges exceeding the threshold  $u$  per year is generally assumed  
 188 to follow a Poisson process (Coles, 2001) with parameter  $\lambda$  (average number of skew surges  
 189 exceeding the threshold  $u$  per year). The probability of observing  $n$  skew surges exceed-  
 190 ing  $u$  during a systematic observation period of duration  $w_S$  years is then equal to:

$$191 \quad \mathbb{P}_\theta(N = n) = \frac{(\lambda w_S)^n}{n!} \exp(-\lambda w_S) \quad (4)$$

192 If the observed systematic skew surges  $x_{sys,j}=\{1,\dots,n\}$  are considered independent  
 193 and identically distributed, the likelihood of the systematic sample is given by equation (5)  
 194 where  $f_\theta$  is the GP probability density function.

$$195 \quad L(X_{sys}|\theta) = \mathbb{P}_\theta(N = n) \cdot \prod_{j=1}^n f_\theta(x_{sys,j}) \quad (5)$$

196 The parameters to be estimated through the inference procedure are the scale and  
 197 shape parameters of the GP distribution and the intensity of the Poisson process:  $\theta =$   
 198  $(\sigma, \xi, \lambda)$ .

### 199 **2.2.2 Likelihood of the historical skew surge sample: $L(X_{hist}|\theta)$**

200 Considering the  $h_x$  historical skew surges exceeding a threshold value  $u_H \geq u$  over  
 201 a historical period of  $w_h$  years as independant and identically distributed, the likelihood  
 202 of the historical skew surge sample is:

**Table 1.** Likelihoods of the historical skew surge samples for methods 4, 5 and 6.  $\hat{\theta}$  and  $\hat{\lambda}$  represent the parameter set and the Poisson process intensity estimated with the maximum likelihood based on the systematic skew surges only and  $R_\lambda(u_H) = h_x \frac{\lambda [1 - F_\theta(u_H)]}{\hat{\lambda} [1 - F_{\hat{\theta}}(u_H)]}$ .

Method	$u_H$	$w'_H$	$L(X_{hist} \theta)$
4	$\min(X_{hist})$	$w_H$	$\frac{[\lambda w_H]^{h_x}}{h_x!} \exp(-\lambda w_H [1 - F_\theta(u_H)]) \prod_{j=1}^{h_x} f_\theta(x_{hist,j})$
5	$u$	$\frac{h_x}{\hat{\lambda}}$	$\frac{(h_x \lambda / \hat{\lambda})^{h_x}}{h_x!} \exp\left(-h_x \frac{\lambda}{\hat{\lambda}}\right) \prod_{j=1}^{h_x} f_\theta(x_{hist,j})$
6	$\min(X_{hist})$	$\frac{h_x}{\hat{\lambda} [1 - F_{\hat{\theta}}(u_H)]}$	$\frac{R_\lambda(u_H)^{h_x}}{h_x!} \exp(-R_\lambda(u_H)) \prod_{j=1}^{h_x} \frac{f_\theta(x_{hist,j})}{1 - F_\theta(u_H)}$

$$L(X_{hist}|\theta) = \mathbb{P}_\theta(H_X = h_x) \cdot \prod_{j=1}^{h_x} \frac{f_\theta(x_{hist,j})}{1 - F_\theta(u_H)} \quad (6)$$

where  $\mathbb{P}_\theta(H_x = h_x)$  is given by the following equation:

$$\mathbb{P}_\theta(H_x = h_x) = \frac{[\lambda w_H (1 - F_\theta(u_H))]^{h_x}}{h_x!} \exp(-\lambda w_H [1 - F_\theta(u_H)]) \quad (7)$$

Methods 4, 5 and 6 differ by the estimation of the threshold value  $u_H$  and the considered effective duration of the historical period  $w'_H$ . The various proposed estimates and the final formulation of the likelihood  $L(X_{hist}|\theta)$  are provided in Table 1.

In the naive method (method 4), the threshold  $u_H$  is the minimum value of the historical skew surge sample  $\min(X_{hist})$ . But, due to the sampling approach based on record sea levels, there is a risk that this sample represents a partial and not the exhaustive record of all skew surges that have exceeded the threshold  $u_H$  during the historical period. A statistical inference based on the hypothesis of exhaustiveness and conducted on a partial sample will provide biased quantile values. To avoid this problem, the FAB method (method 5), proposes to introduce a corrected duration for the historical period  $w'_H$ . This duration is chosen to be perfectly consistent with the average number  $\hat{\lambda}$  of skew surges exceeding the threshold per year and with the number of recorded historical skew surges  $h_x$ :  $w'_H = h_x / \hat{\lambda}$ . In the initial version of the FAB method (Frau et al., 2018), the historical sampling threshold was considered equal to the systematic threshold  $u$ . Since the minimum value of historical sampled skew surges appears often much larger than  $u$ , this *a priori* choice may be a source of significant biases as will be illustrated hereafter. A modified version of the FAB method is therefore tested here (method 6), where the historical threshold is adapted to the available sample and the corrected duration  $w'_H$  is adjusted accordingly (see Table 1).

### 2.2.3 Likelihood of the historical sea level sample: $L(Z_{hist}|\theta)$

The likelihood formulation of the historical sea levels comprises (a) the probability associated to the  $N - h_z$  ( $N = 706 \times w_H$ ) maximum tidal levels that did not exceed the historical threshold  $\eta_H$  and (b) the probability associated to the  $h_z$  extreme his-

229 torical maximum tidal levels that exceeded  $\eta_H$  during the historical period of duration  
 230 of  $w_H$  years (equation (8)).

$$231 \quad L(Z_{hist}|\theta) = \underbrace{\tilde{G}_\theta(\eta_H)^{N-h_z}}_{(a)} \cdot \underbrace{\left[1 - \tilde{G}_\theta(\eta_H)\right]^{h_z} \cdot \prod_{j=1}^{h_z} \frac{\tilde{g}_\theta(z_{hist,j})}{1 - \tilde{G}_\theta(\eta_H)}}_{(b)} \quad (8)$$

232  $\tilde{g}_\theta$ ,  $\tilde{G}_\theta$  are respectively the probability density and cumulative distribution func-  
 233 tions of maximum tidal levels which result from the combination of (1) the statistical  
 234 distribution of the maximum astronomical tidal levels, (2) the statistical distribution of  
 235 skew surges lower than the threshold  $u$ , and (3) the calibrated statistical distribution ( $f_\theta$ ,  
 236  $F_\theta$ ) of the skew surges exceeding  $u$ . The proposed numerical approximations of the func-  
 237 tions  $\tilde{g}_\theta$  and  $\tilde{G}_\theta$  are presented in Appendix A.

### 238 3 Test and evaluation methodology

239 The comparison of the different methods is based on samples generated through  
 240 Monte Carlo simulations inspired by four real world case studies in order to verify the  
 241 accuracy of the maximum likelihood (ML) estimates and the posterior credibility inter-  
 242 vals.

#### 243 3.1 Monte Carlo experiments

244 1000 synthetic series are randomly generated with characteristics corresponding to  
 245 each of the four observed data sets: duration of the systematic and historical observa-  
 246 tion periods  $w_S$  and  $w_H$ , systematic and historical sampling thresholds  $u$  and  $\eta_H$ , pa-  
 247 rameters of the GP distribution and Poisson intensity for the skew surges exceeding  $u$   
 248 and empirical statistical distributions of the astronomical high tides and of the ordinary  
 249 skew surges (lower than  $u$ ) as well as the astronomical high tide/skew surge relation (see  
 250 Section 3.2 and Appendix C).

251 Each synthetic sample is generated as follows:

- 252 • For the systematic period,  $n$  systematic skew surges  $X_{sys}$  are drawn from the Pois-  
 253 son process (intensity  $\lambda w_S$ ) and GP distribution.
- 254 • For the historical period,  $n_2$  skew surges  $X_{hist}$  larger than  $u$  are drawn from the  
 255 Poisson process (intensity  $\lambda w_H$ ) and GP distribution (series used for the imple-  
 256 mentation of method 2) and complemented with  $(w_H \times 706 - n_2)$  ordinary skew  
 257 surges (lower than  $u$ ), drawn from the empirical ordinary skew surge distribution.  
 258  $w_H \times 706$  astronomical high tides are drawn from the empirical high tide distri-  
 259 bution. Astronomical high tides and skew surges, assumed to be independent (see  
 260 Appendix C), are summed to generate  $w_H \times 706$  maximum tidal levels. The sub-  
 261 set of  $h_z$  sea levels  $Z_{hist}$  exceeding  $\eta_H$  is then extracted (series used for the im-  
 262 plementation of method 3), as well as the corresponding subset of  $h_x$  skew surges  
 263 larger than  $u$  for the implementation of methods 4 to 6.

#### 264 3.2 Case study

265 Four tide gauges located on the French Atlantic and Channel coasts are used as  
 266 examples for the configuration of the Monte Carlo experiment: Brest, Dunkerque, La Rochelle  
 267 and Saint Nazaire. These tide gauges are selected because of the availability of histor-  
 268 ical information, but also because they cover a variety of situations: i) statistical distri-  
 269 butions of the skew surges and tidal levels, ii) tide/surge ratio (Table 2), iii) tidal am-



**Table 2.** Characteristics of the systematic data set and selected values for the Monte Carlo simulations ( $\hat{\sigma}$ ,  $\hat{\xi}$ ,  $\hat{\lambda}$ ).

Site	Period	$w_S$ (years)	$u$ (m)	$n$	Tide surge ratio*	$\hat{\sigma}$	$\hat{\xi}$	$\hat{\lambda}$
Brest	1953-2017	63.57	0.50	81	22.50	0.09	0.19	1.29
Dunkerque	1959-2016	47.75	0.74	58	15.58	0.14	0.34	1.23
La Rochelle	1941-2016	32.58	0.62	34	17.11	0.08	0.36	1.08
Saint Nazaire	1957-2014	47.56	0.66	53	15.45	0.11	0.12	1.14

\* Ratio of the 98% astronomical high tide to the 98% skew surge quantile (Dixon & Tawn, 1999).

**Table 3.** Characteristics of the historical data sets.

Site	Period	$w_H$ (years)	$\frac{h_x}{\hat{\lambda}}$ (years)	$\frac{h_x}{\hat{\lambda}[1-F_{\hat{\theta}}(u_H)]}$ (years)	$\eta_H$ (m)	$h_z$	$u_H$ (m)	$h_x$
Brest	1846-1952	120	2.33	13.72	8.02	10	0.69	3
Dunkerque	1720-1953	250	6.50	108.42	7.60	8	1.40	8
La Rochelle	1866-1940	80	3.70	13.31	7.15	4	1.00	4
Saint Nazaire	1863-1956	100	4.40	17.62	7.09	5	0.82	5

270 plitude, iv) historical perception threshold level and number of documented historical  
271 events.

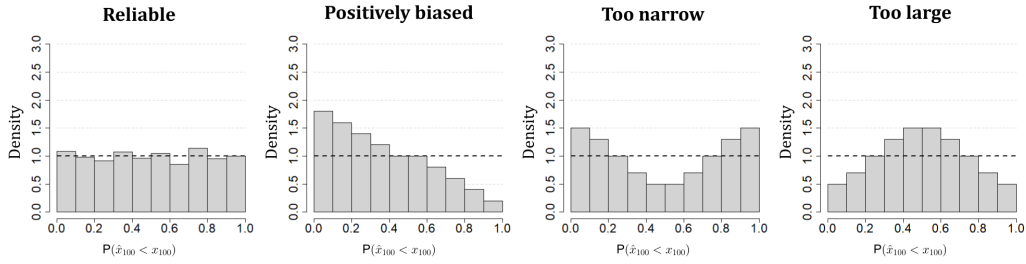
272 The hourly tide gauge data were retrieved from Shom, the French hydrographical  
273 and oceanographical service (data.shom.fr), harmonic analysis is applied on these data  
274 with the R package *TideHarmonics* (Stephenson, 2015), as well as a correction of sea  
275 level rise. Then, hourly astronomical tide levels were processed to extract the series of  
276 corresponding astronomical high tides and systematic skew surge series.

277 The threshold  $u$  for the POT sampling is selected according to the GP parameter  
278 stability criterion (Coles, 2001).

279 Historical sea levels were extracted from Hamdi et al. (2018); Giloy et al. (2018,  
280 2019) for Dunkerque (Table B2) and from Breilh et al. (2014) for La Rochelle (Table B3).  
281 At La Rochelle, the sampling threshold  $\eta_H$  had to be raised to ensure the exhaustive-  
282 ness of the historical record levels and two reported record levels were ignored (see Ta-  
283 ble B3). In fact, the systematic observations started in 1846 and 1863 respectively at Brest  
284 and Saint Nazaire. The complete observed samples were split into systematic and his-  
285 torical samples for the sake of illustration. To test the proposed method, censored sam-  
286 ples of historical record sea levels were extracted at these two stations setting a thresh-  
287 old value of 8m at Brest and 7m at Saint Nazaire (Tables B1 and B4).

288 Table 3 presents the characteristics of the historical samples as well as the consid-  
289 ered duration for the implementation of the various methods. As suggested by Schendel  
290 and Thongwichian (2017), the historical duration  $w_H$  is larger than the time laps between  
291 the first record and the start of the systematic period. The duration considered for the  
292 FAB method  $h_x/\hat{\lambda}$  appears to be extremely reduced. For Dunkerque, the reported his-  
293 torical skew surges are extremely high if compared to the systematic data: 8 values ex-  
294 ceeding  $u_H = 1.40\text{m}$ , when the largest measured value during the systematic period is  
295 1.30m. Some inconsistencies between the historical and systematic data sets at Dunkerque  
296 may be suspected and will be discussed further on in section 4. The observed histori-  
297 cal series are the result of a random drawing. The simulated historical series, based on





**Figure 2.** Possible distributions of  $\mathbb{P}(\hat{x}_{100} < x_{100})$  and conclusions on the reliability of the posterior densities and corresponding credibility intervals.

298 the parameters calibrated on the observed series, may have slightly different character-  
 299 istics on average, especially different numbers of record events (see Table 4).

### 300 3.3 Evaluation methods

301 The RStan package was used to conduct Bayesian MCMC (Monte Carlo Markov  
 302 Chain) inferences based on the formulated likelihood with non-informative priors. The  
 303 results of the inference procedure consist in the posterior densities for the calibrated pa-  
 304 rameters  $\theta = (\sigma, \xi, \lambda)$  and of the corresponding skew surge quantiles, including the max-  
 305 imum likelihood estimates. The evaluation of the various tested methods (see Section  
 306 2.1) was conducted in two steps. The accuracy of the maximum likelihood estimator was  
 307 first verified based on the 100-year quantile estimate (comparison between the quantile  
 308 values  $\hat{x}_{100}^{ML}$  and the real quantile value  $x_{100}$  for the 1000 generated series). The evalu-  
 309 ation will be based on boxplots of the ratio  $\hat{x}_{100}^{ML}/x_{100}$  and classical average performance  
 310 estimation criteria: relative bias, relative standard deviation (RSD) and relative root mean  
 311 square error (RRMSE).

312 In a second step, the average widths of the computed posterior credibility inter-  
 313 vals for the 100-year quantile are compared and their reliability is evaluated based on  
 314 the rank histogram diagnosis method (Bellier, 2018; Nguyen et al., 2014). For each of  
 315 the 1000 inferences, the exceedance probability  $\mathbb{P}(\hat{x}_{100} < x_{100})$  of the real quantile value  
 316  $x_{100}$  is computed according to the estimated posterior density for the quantile. If the es-  
 317 timated posterior densities are reliable,  $\mathbb{P}(\hat{x}_{100} < x_{100})$  should be uniformly distributed  
 318 over  $[0, 1]$  (Halbert et al., 2016; Gaume, 2018). Figure 2 illustrates how the rank histogram  
 319 can be interpreted.

### 320 3.4 Characteristics of the Monte Carlo simulations

321 Table 4 summarizes the characteristics of the 1000 simulated samples for each case  
 322 study. It seems that the parameters of the Monte Carlo simulations, adjusted on the ob-  
 323 served series, lead to generated series with contrasted characteristics like the number of  
 324 sampled record sea levels or the sampling rate of the historical skew surges exceeding the  
 325 threshold  $u$ . The selected threshold  $\eta_H$  at Brest leads to a large number of sampled his-  
 326 torical sea levels. But due to a large tide/surge ratio, the corresponding samples of skew  
 327 surges exceeding  $u$  represent only a small proportion of the total number of generated  
 328 skew surge exceeding  $u$  for the historical period - on average less than 10%. Dunkerque  
 329 and La Rochelle are considered intermediate cases where smaller average amounts of his-  
 330 torical sea levels are sampled, but the skew surge sampling rate is higher due to a more  
 331 favorable tide/surge ratio - i.e. due to a higher contribution of the skew surges to the  
 332 record levels. Finally, Saint Nazaire appears to be an extreme case, where, due to a rel-  
 333 atively high threshold value  $\eta_H$ , a limited number of record sea levels and skew surges

**Table 4.** Characteristics of the generated historical series of sea levels and skew surges.

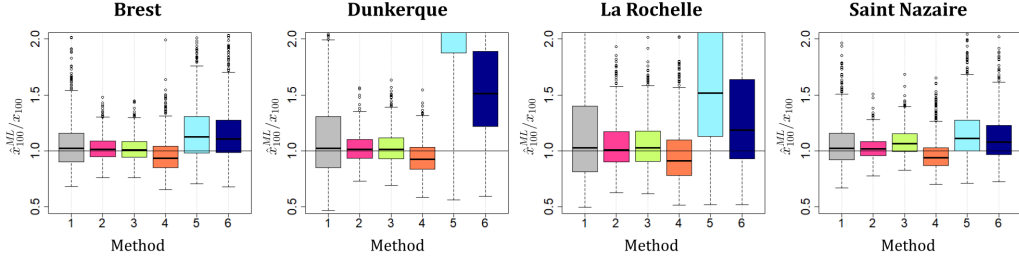
	Brest	Dunkerque	La Rochelle	Saint Nazaire
<b>Generated historical sea levels</b>				
Sampling threshold $\eta_H$ (m)	8.02	7.60	7.15	7.09
Minimum generated value (m)	8.02	7.70	7.24	7.17
Average number of record values	22	7	3	1
Duration of the historical period (years)	120	250	80	100
<b>Generated historical skew surges</b>				
Sampling threshold $u$ (m)	0.50	0.74	0.62	0.66
Minimum sampled value $u_H$ (m)	0.55	1.63	0.90	0.93
Average number of skew surges $> u$	156	308	86	116
Average number of skew surges $> u_H$	26	18	24	28
Average number of sampled values $> u_H$	2	6	2	1
Average skew surge sampling rate (%)	7.63	33.33	8.33	3.57

334 are sampled. A high proportion of the generated historical samples at Saint Nazaire does  
 335 not contain record sea levels exceeding  $\eta_H$  (33%) or skew surges exceeding  $u$  (45%).

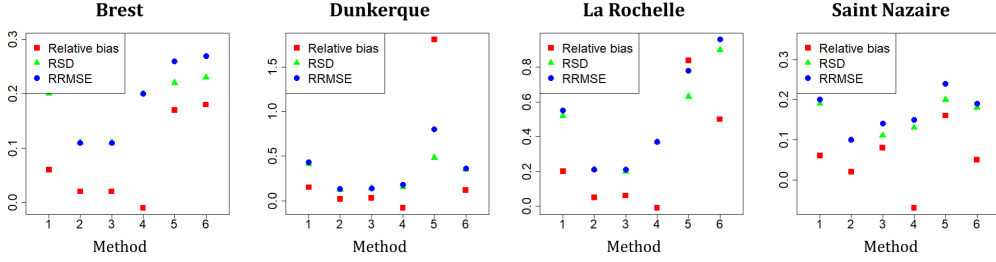
### 336 3.5 Maximum likelihood estimates

337 The evaluation of the various tested inference procedures confirms some anticipated  
 338 results, but also provides some satisfactions and surprises. The hypothesis of exhaustive-  
 339 ness for the sample of skew surges exceeding  $u_H$  during the historical period, on which  
 340 the naive method (method 4) is based, is clearly not reached for the four test cases. The  
 341 average skew surge sampling rates appear largely lower than 100% in Table 4. As a con-  
 342 sequence, method 4 underestimates the 100-year skew surge quantile  $x_{100}$  (see Figures 3  
 343 and 4). Table S1 in the supplementary information provides the numeric values corre-  
 344 sponding to Figure 4 for a more detailed analysis. The magnitude of the bias affecting  
 345 the estimation of the parameter  $\lambda$  (i.e. average number of skew surges exceeding  $u$  per  
 346 year) seems clearly dependent on the skew surge sampling rate for the historical period  
 347 (see Figure 5 as well as S1, S2, S3 in the supplementary information). The estimation  
 348 of the two parameters of the GP distribution is also biased since these parameters control  
 349 the probability of exceedance of the threshold value  $u_H$  appearing in the likelihood  
 350 formulation for the historical period in method 4 (see Table 1). The increase of the amount  
 351 of information used for the inference in method 4 leads nevertheless to a significant de-  
 352 crease of the standard deviation of the  $x_{100}$  estimator, if compared to the method based  
 353 on the systematic data only (method 1). Surprisingly, the balance between bias and re-  
 354 duced standard deviation appears positive for the naive method : for the four test cases,  
 355 the RRMSE of the  $x_{100}$  estimator is significantly lower for the naive method than for  
 356 the method based on the systematic data only (see Figure 4). This remains true, even  
 357 for the Saint Nazaire case study, where a high proportion of historical generated series  
 358 does not contain any recorded skew surges exceeding  $u$ . This issue will be addressed later.

359 The results also confirm the suspected biases introduced by the FAB method (method  
 360 5) and reveal other important anomalies. In fact, since an equivalent duration of the his-  
 361 torical period is estimated, the information about the non-exceedances of the threshold  
 362  $u$  during the historical period, which is an important part of the historic information as  
 363 shown by Payrastré et al. (2011), is not evaluated. The historical information is there-  
 364 fore only partly used and limited to the set of a few skew surges reported to have exceeded  
 365  $u$ , that complement the rich series of systematic skew surges. The possible added value  
 366 of the historic data is hence extremely limited in the FAB method. Moreover, the sam-



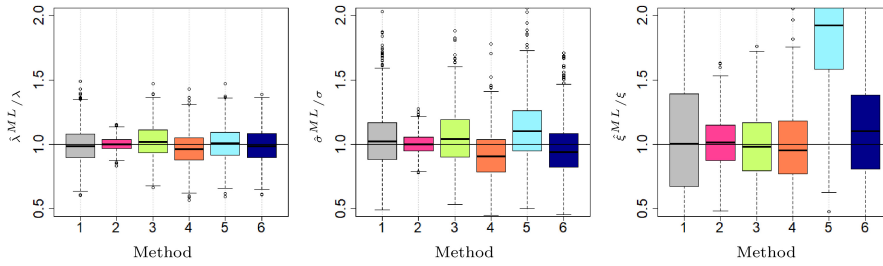
**Figure 3.** Dispersion of the 100-year quantile estimated with the maximum likelihood (divided by the real value), obtained from simulations.



**Figure 4.** Relative bias, RSD and RRMSE on the 100-year quantile estimated with the maximum likelihood at the 4 study sites with the different tested methods.

367 pling process for the historic and systematic surges are different: the sampling thresh-  
 368 hold is higher for the historic surges, especially for locations with low tide/surge ratios  
 369 and highly skewed GP distributions (i.e. large  $\xi$  values). Merging the historic skew surges  
 370 with the systematic sample without further adjustments introduces significant biases in  
 371 the estimates of the parameters ( $\sigma, \xi$ ) of the GP distribution (see Figure 5). As a con-  
 372 clusion, the FAB method cannot really contribute to reduce significantly the inference  
 373 uncertainties and introduces some biases. Its implementation leads to an increase of the  
 374  $x_{100}$  estimation RRMSE if compared to the analyses of the sole systematic data (method 1).  
 375 The proposed adjusted FAB method reduces partly the estimation biases but the effect  
 376 on the estimation RSD remains limited if compared to method 1 (Figure 4). The prin-  
 377 ciples of the FAB method appear as inefficient and statistically inconsistent. Its imple-  
 378 mentation leads to a deterioration in the inference results, if compared to the analyses  
 379 of the systematic data only.

380 In contrast, the proposed method (method 3) appears to perform almost as well  
 381 as the ideal method (method 2). In details, the gain, if compared to method 1, seems  
 382 to be mainly related to a more accurate estimation of the GP shape parameter  $\xi$  (Fig-  
 383 ures 5, S1, S2 and S3 in the supplementary information). These excellent performances  
 384 may be surprising at first sight since many more historical events are evaluated in method 2  
 385 (about 80 to 300 additional historical skew surges) than in method 3 (1 to 22 record sea  
 386 levels) (see Table 4). Moreover, the historical samples used in methods 2 and 3 are partly  
 387 or totally dissociated - i.e. corresponding to different events (see Figure C1). The record  
 388 sea levels included in the inference of method 3 do not necessarily involve the most ex-  
 389 treme skew surges of the historical period. To understand this surprising result, it must  
 390 be firstly considered that the high frequency of skew surges observed during the histor-  
 391 ical period does not provide significant additional information to the one contained in  
 392 the systematic data set. The historical information is mainly encapsulated in the largest  
 393 observed values, that will help constraining the skew surge distribution tail. Payrastre  
 394 et al. (2011) have shown that when including historical information in a statistical in-



**Figure 5.** Dispersion of the parameters estimated with the maximum likelihood (divided by the real values), obtained from simulations at Dunkerque with different tested methods.

395 inference procedure, the length of the documented historical period is a predominant fac-  
 396 tor: "accurate estimates of the values having exceeded the perception threshold are not  
 397 necessarily needed when historical data is used in combination with systematic measure-  
 398 ments ; provided that the theoretical return period of the perception threshold is suf-  
 399 ficiently high, censored (only the values exceeding the threshold are known) or binomial  
 400 censored (only the number of values having exceeded the threshold is known) historical  
 401 data lead to similar inference results". This explains also why the results obtained with  
 402 the proposed method for the Saint Nazaire case study, where a special case of binomial  
 403 censored historic data set is frequently generated (no exceedance of the threshold  $\eta_H$   
 404 or in other words  $h_z = 0$ ), are also satisfactory. It is worth noting that the maximum like-  
 405 lihood estimates of the GP parameters and quantiles appear slightly positively biased  
 406 for all methods except method 4. This bias appears to be more pronounced when inference  
 407 is conducted on a binomial censored sample (method 3 at Saint Nazaire). This ap-  
 408 pears to be a general feature for the ML estimates of the parameters of a GP distribu-  
 409 tion. Indeed, (Hosking & Wallis, 1987) indicated that the ML method leads to biased  
 410 GP parameters estimates when the sample size is not large.

411 The implemented Bayesian inference procedure generates not only best-estimates  
 412 for the quantile values, but also credibility intervals and posterior distributions. The next  
 413 section compares this computed intervals for methods 1 to 4.

### 414 3.6 Posterior credibility intervals

415 The computed credibility intervals confirm the trends observed on the ML estima-  
 416 tors. The added value of the historical information is confirmed by the reduced averaged  
 417 widths of the posterior credibility intervals (Table 5). Without surprise, the widths of  
 418 the posterior credibility intervals for the proposed method (method 3) are larger than  
 419 those for the "ideal" method (method 2), but hence of similar magnitudes, confirming  
 420 that the loss of historical information for proposed method if compared to the ideal case  
 421 is limited, even for the Brest case study with a high tide/surge ratio. Some posterior in-  
 422 tervals based on the naive method (method 4) may have lower widths than the intervals  
 423 based on the proposed method -especially at Dunkerque, but the estimation bias related  
 424 to method 4 should be considered (see next paragraph).

425 Figure 6 shows the rank histograms of the 100-year skew surge quantiles for meth-  
 426 ods 1 to 4 and all of the case studies. The histograms confirm the conclusions drawn from  
 427 the ML estimates. The naive method (method 4) has a clear tendency to underestimate

**Table 5.** Average width of the posterior credibility interval for the 100-year quantile with the Bayesian MCMC procedure for methods 1, 2, 3 and 4.

Site	Average width of posterior credibility interval for $x_{100}$			
	Method 1	Method 2	Method 3	Method 4
Brest	1.15	0.48	0.55	0.95
Dunkerque	6.05	1.10	1.31	1.05
La Rochelle	10.48	1.47	1.60	2.56
Saint Nazaire	1.37	0.46	0.67	0.52

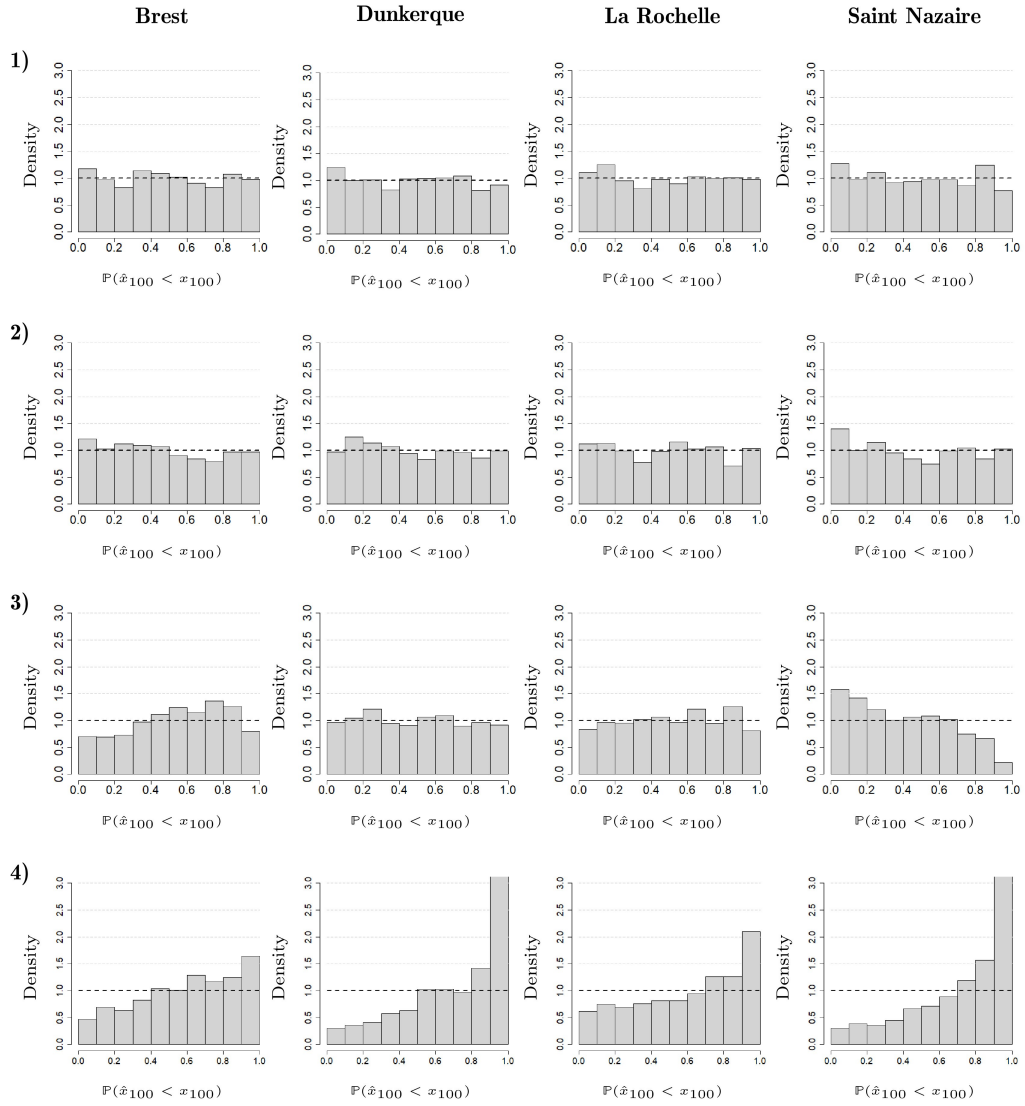
428 the quantile value  $x_{100}$  for all case studies. A slight over-estimation tendency is detectable  
429 for methods 1 and 2, but the computed posterior distributions and the corresponding  
430 credibility intervals for  $x_{100}$  appear overall reliable. As far as the proposed method 3 is  
431 concerned, the over-estimation tendency is clearly marked for the Saint Nazaire case study.  
432 This suggests that the method should ideally be implemented on historical samples in-  
433 cluding some documented historical sea levels. The rank histograms also reveal that the  
434 estimated posterior credibility intervals based on method 3 are too large (the uncertainty  
435 affecting the estimated value is overrated) at stations with large tide/surge ratios: i.e.  
436 stations where the historical record sea level sample does not coincide with the histor-  
437 ical record skew surges. This is visible on the histogram obtained for the Brest case study  
438 and to a lower extent for the La Rochelle case study. The outcome of the Bayesian-MCMC  
439 inference provides a pessimistic assessment of the accuracy of the estimated quantile val-  
440 ues.

441 As a partial conclusion, the conducted tests indicate that the proposed method com-  
442 bining skew surges for the systematic period and sea levels for the historic period is re-  
443 liable and provides inference results that are almost as accurate as those obtained through  
444 in the ideal situation with an inference based on systematic and historical skew surges  
445 (method 2). This is a satisfactory result, but it is important to keep in mind that these  
446 conclusions are valid provided that the underlying statistical model is valid: i.e. skew  
447 surges and astronomical high tides are independent and the distribution of the skew surges  
448 is a GP distribution. It is therefore interesting as a conclusion to evaluate how the pro-  
449 posed approach behaves when implemented on real-world data sets. The next section  
450 presents and analyses the implementation of the method on the data sets available at  
451 the considered tide gauges.

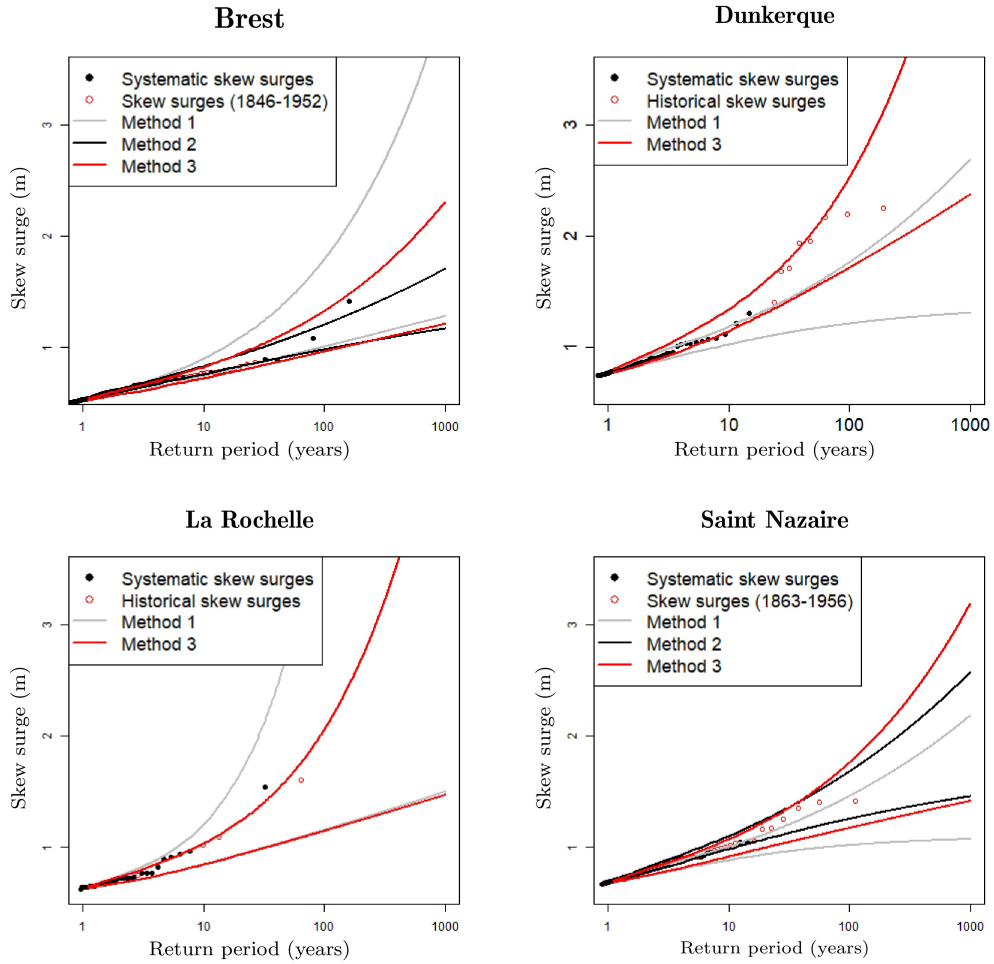
#### 452 **4 Application of the proposed method to the observations**

453 At Brest and Saint Nazaire, complete observed data sets of sea levels and estimated  
454 tides are available. It is hence possible to compare the results of method 3 with those  
455 of methods 1 and 2 at these two stations. At Dunkerque and La Rochelle, the histor-  
456 ical data sets are composed of the observed record sea levels then, only methods 1 and  
457 3 will be implemented. The hypothesis of independence between astronomical high tides  
458 and skew surges was tested and seems to be reasonably valid for all four stations (see  
459 Appendix C).

460 The implementation results of the methods at Brest and Saint Nazaire appear fully  
461 consistent with the conclusions previously drawn (Figure 7). The adjusted credibility in-  
462 tervals with the proposed method are very similar to those obtained with method 2, even  
463 if they are slightly larger. This is particularly striking for Brest where the historical sea  
464 levels do not represent the events with the largest skew surges. This confirms the con-



**Figure 6.** Uniformity test for the credibility intervals computed with the Bayesian MCMC procedure for methods 1, 2, 3 and 4.



**Figure 7.** 90% posterior skew surge credibility intervals based on the systematic data (grey) and on the historic data with the proposed method (red) and in the ideal case (black). The empirical return periods of the historical records at Dunkerque and La Rochelle were corrected (reduced) according to the skew surge estimated sampling rates (see Table 4).



465 sistency between the observations and the calibrated statistical model: GP distribution  
 466 for the skew surges and independence between skew surges and astronomical high tides.

467 The inclusion of the historical information appears to have contrasted impacts be-  
 468 tween the case studies. For Brest and La Rochelle, the posterior credibility intervals ac-  
 469 counting for the historical information are significantly reduced and totally coherent with  
 470 the intervals based on the sole systematic data sets (Figure 7). This is the expected re-  
 471 sult which reveals an overall good consistency between (a) the systematic observations,  
 472 (b) the historical data sets and (c) the calibrated statistical model. In the case of Saint  
 473 Nazaire, the historical data do not help to reduce the estimation credibility intervals, but  
 474 lead to a modification of the calibrated statistical skew surge distribution. Note that this  
 475 modification remains consistent with the systematic sample - i.e. the observations are  
 476 contained in the revised posterior credibility intervals. This result may be explained by  
 477 the peculiarities of the short systematic sample available at Saint Nazaire, which does  
 478 not contain large skew surges - i.e. skew surges greater than 1m (Figure 7). Since the  
 479 estimated uncertainties (i.e. widths of the posterior credibility intervals) are also related  
 480 to the estimated variability of the skew surge distribution and especially to the magni-  
 481 tude of the parameter  $\hat{\xi}$ , the inclusion of the historical information at Saint Nazaire, lead-  
 482 ing to an increased  $\hat{\xi}$  estimated values, does not result in a reduction of the inference es-  
 483 timation uncertainties. The case of Dunkerque is completely different: even if the length  
 484 of the historical period is considered, the historical record levels and corresponding skew  
 485 surges appear strongly inconsistent with the systematic data set. This inconsistency, re-  
 486 vealed by the inference trials presented herein, remains to be explained.

487 As a conclusion, a final inference test was conducted to confirm the robustness of  
 488 the proposed approach, even in cases where limited information about historical record  
 489 sea levels is available and to verify if the conclusions drawn by Payraastre et al. (2011)  
 490 based on historical river record discharges are also valid for historical record sea levels.  
 491 For the considered case studies, the historical threshold  $\eta_H$  was selected such as there  
 492 is no remaining documented record level exceeding the threshold (i.e.  $h_Z = 0$ , case 3\*  
 493 in Table S2 in the supplementary information). The resulting credibility intervals ap-  
 494 pear to be only moderately affected by this simplification of the historical information  
 495 if compared to case 3. Even the knowledge that a given sea level has not been exceeded  
 496 over a considered historical period (i.e. a given coastal defence structure has never been  
 497 over-topped for instance) is a valuable information, that can efficiently processed with  
 498 the new inference procedure presented herein. This opens new perspectives in coastal  
 499 risk assessments.

## 500 5 Conclusions

501 A new statistical inference procedure is proposed and evaluated to properly inte-  
 502 grate historical sea levels in coastal risk assessment studies. This procedure enables the  
 503 combined analysis of data sets of different nature: skew surges for the recent period and  
 504 sea levels for the historical period. It overcomes a major limitation in the previously pro-  
 505 posed methods to include historical information in sea level frequency analyses. The key  
 506 idea of this new method consists in replacing, in the likelihood formulation, the analytic  
 507 expression of the probability density or cumulative distribution functions related to the  
 508 historical sea level observations, by their numerical approximations (see Appendix A).  
 509 The related R source codes as well as the data files corresponding to the test cases are  
 510 available at: [doi.org/10.5281/zenodo.6260203](https://doi.org/10.5281/zenodo.6260203). Based on the results presented herein,  
 511 some major conclusions can be drawn.

- 512 1. The suggested numerical scheme for the estimation of the historical sea level like-  
 513 lihood as well as its incorporation in the statistical inference procedure are effec-  
 514 tive and reliable. This is particularly well illustrated by the comparison with the  
 515 results of the "ideal" method (method 2).

- 516 2. Unlike the previously published approaches which appear to be biased, the pro-  
517 posed method allows for accurate and reliable estimates of the maximum likeli-  
518 hood quantiles, as well as of their posterior distributions in a Bayesian MCMC in-  
519 ference framework.
- 520 3. The proposed method is almost as accurate as the ideal method - i.e. method based  
521 on a perfect knowledge of the historical skew surges - even in places exhibiting high  
522 tide/surge ratios. This is valid if the hypotheses on which the calibrated statisti-  
523 cal model is based, especially the independence between high tides and skew surge,  
524 are reasonably consistent with the observations. It seems to be the case at Brest.
- 525 4. This last conclusion may appear surprising, since the data set used in the "ideal"  
526 method contains apparently much more information on skew surges, but it is con-  
527 sistent with the conclusions of previous studies dealing with statistical inferences  
528 based on historical records (Payrastré et al., 2011). It seems that the length of the  
529 documented historical period is more decisive than the number or the accuracy  
530 of the documented record events.

531 The proposed approach could be further improved in several ways. First, even if  
532 moderate, some estimation biases remain present: over-estimated credibility intervals in  
533 cases with large tide/surge ratios and over-estimations in the case of binomial censored  
534 historical samples with no exceedance. It would be satisfying if the origin of these bi-  
535 ases were understood and if they could be corrected. Moreover, the possible dependence  
536 between high tides and skew surges, as well as some seasonal features may be considered  
537 in the inference procedure, to increase its pertinence and application range. In fact, the  
538 largest skew surges often occur during winter storms while high tides are observed around  
539 the equinoxes (Tomasin & Pirazzoli, 2008).

540 The method could also be implemented on a larger number of case studies and re-  
541 sults should be compared to those of previous assessments. The possible implementa-  
542 tion of the method on samples with no documented record sea level exceeding the thresh-  
543 old seems to lead to satisfactory results (see the concluding paragraph of Section 4). This  
544 opens new perspectives, especially at sites where little or no historical records are avail-  
545 able. Indeed, any coastal structure with known altitude that has not been submerged  
546 during a considered historical period, may provide valuable information for the statis-  
547 tical inference.

548 Finally, the method was developed for the analysis of coastal sea levels, but the same  
549 principles could certainly be adapted for the statistical analysis of other geophysical vari-  
550 ables.

## Appendix A Estimation of $\tilde{g}_\theta$ and $\tilde{G}_\theta$

The maximum sea level  $Z$  is the sum of a skew surge  $X$  and an astronomical high tide  $Y$ . Both components are supposed to be independents (see Section Appendix C). Hence,

$$\mathbb{P}(Z < z) = \int_{\min(Y)}^{\max(Y)} q(y) \mathbb{P}(X < z - y) dy \quad (\text{A1})$$

where  $q(y)$  is the probability density function of  $Y$ ,  $\min(Y)$  and  $\max(Y)$  represent respectively the lowest and the highest astronomical high tide. The skew surge  $X$  may either be smaller or larger than the systematic threshold  $u$ . Therefore,

$$\tilde{G}_\theta(z) = \mathbb{P}(Z < z) = \mathbb{P}(X \leq u) \mathbb{P}_{X \leq u}(Z < z) + [1 - \mathbb{P}(X \leq u)] \mathbb{P}_{X > u}(Z < z) \quad (\text{A2})$$

Considering that  $\mathbb{P}_{X > u}(X < x) = F_\theta(x)$  and  $\mathbb{P}(X > u) = \hat{\lambda}/706$  and combining equations (A1) and (A2) leads to:

$$\begin{aligned} \tilde{G}_\theta(z) = & \left(1 - \frac{\hat{\lambda}}{706}\right) \int_{\min(Y)}^{\max(Y)} q(y) \mathbb{P}_{X \leq u}(X < z - y) dy \\ & + \frac{\hat{\lambda}}{706} \int_{\min(Y)}^{\max(Y)} q(y) F_\theta(z - y) dy \end{aligned} \quad (\text{A3})$$

The two terms  $q(y)$  and  $\mathbb{P}_{X \leq u}(X < z - y)$  can be estimated based on the observed systematic data set, prior to the implementation of the statistical inference procedure. The distribution of astronomical high tides is defined by the analysis of the predicted high tide values over a saros cycle (18,6 years). To enable the numeric computation of equation (A3), the range of possible values for  $Y$  is split into  $n_T$  intervals  $Y_{k=\{1, \dots, n_T\}}$  of 0.01m width. The vector of length  $n_T$  including the probability values  $\mathbb{P}(Y \in Y_k)$  is computed and the integrals in equation (A3) are approximated by finite sums, leading to:

$$\begin{aligned} \tilde{G}_\theta(z) \approx & \left(1 - \frac{\hat{\lambda}}{706}\right) \sum_{k=1}^{n_T} \mathbb{P}(Y \in Y_k) \mathbb{P}_{X \leq u}(X < z - \text{Med}(Y_k)) \\ & + \frac{\hat{\lambda}}{706} \sum_{k=1}^{n_T} \mathbb{P}(Y \in Y_k) F_\theta(z - \text{Med}(Y_k)) \end{aligned} \quad (\text{A4})$$

where  $\text{Med}(Y_k)$  represents the median high tide value for interval  $k$ .

The term  $\mathbb{P}_{X \leq u}(X < z - \text{Med}(Y_k))$  is estimated based on the empirical distribution of the measured sample of ordinary skew surges (i.e. skew surges lower than the threshold  $u$ ). It is simply equal to the ratio of the number of observed ordinary skew surges lower than  $(z - \text{Med}(Y_k))$  to the total number of observed skew surges lower than  $u$ . Finally, an approximate value of the sea level  $z$  probability density function  $\tilde{g}_\theta(z)$  is deduced from the cumulative density function  $\tilde{G}_\theta(z)$ :

$$\tilde{g}_\theta(z) \approx \left[ \frac{\tilde{G}_\theta(z + h) - \tilde{G}_\theta(z)}{h} \right] \quad (\text{A5})$$

For the computations,  $h$  is set equal to  $0.01z$ .

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**Appendix B Available historical information****Table B1.** Historical information at Brest. In parenthesis, skew surges not exceeding  $u$ .

Date	1856	1877	1882	1888	1899	1913	1928	1936	1939	1940
Sea levels (m)	8.03	8.05	8.03	8.14	8.04	8.02	8.10	8.10	8.07	8.05
Skew surges (m)	(0.44)	0.91	(0.33)	0.72	(0.37)	0.69	(0.48)	(0.38)	(0.48)	(0.32)

**Table B2.** Historical information at Dunkerque.

Date	1720	1763	1767	1807	1808	1846	1846	1953
Sea levels (m)	7.68	7.60	7.76	7.60	8.10	7.96	7.86	7.90
Skew surges (m)	1.68	1.94	1.71	1.40	2.20	1.95	2.25	2.17

**Table B3.** Historical information at La Rochelle. In parenthesis, sea levels not exceeding  $\eta_H$ .

Date	1866	1872	1890	1895	1924	1940
Sea levels (m)	(5.70)	(6.34)	7.30	7.15	7.15	7.40
Skew surges (m)	1.15	1.00	1.02	0.75	1.09	1.60

**Table B4.** Historical information at Saint Nazaire.

Date	1864	1877	1894	1937	1940
Sea levels (m)	7.16	7.24	7.09	7.16	7.12
Skew surges (m)	0.90	1.25	1.35	0.82	1.41

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**Appendix C Settings of the Monte Carlo runs**

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The independence between skew surges and astronomical high tides has to be verified to consider the sea levels as the sum of both components randomly sampled independently. To evaluate the interactions between astronomical high tides and skew surges, Williams et al. (2016) proposed to i) visually analyse the scatter plot of observed astronomical high tides versus the corresponding skew surges (Figure C1), and ii) conduct a Kendall test (Table C1, the test is conducted on the largest skew surge values that are of particular interest here). Both indicate that there is no obvious correlation between astronomical high tides and skew surges. Especially, the skew surges exceeding  $u$ , correspond to diverse levels of high tides.

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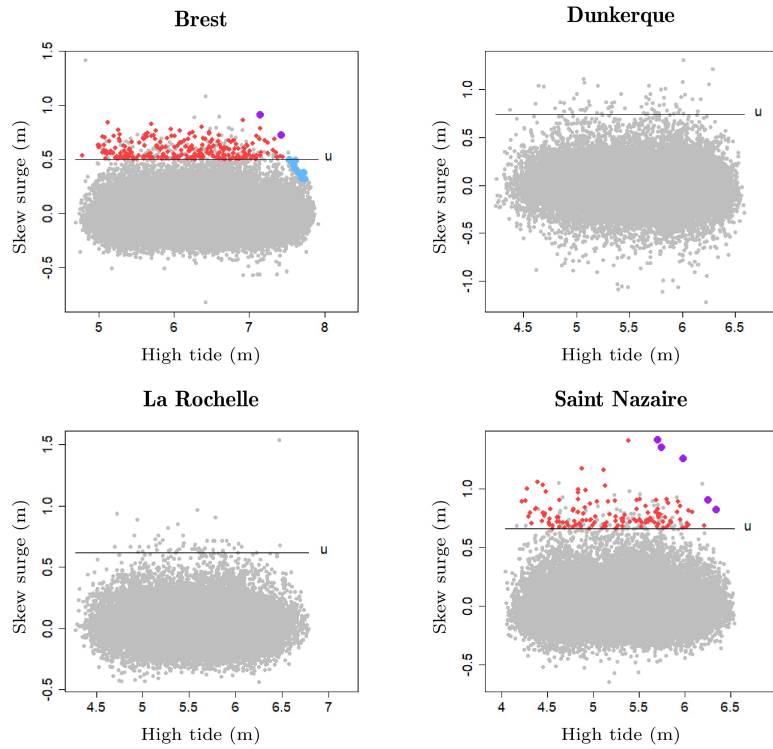
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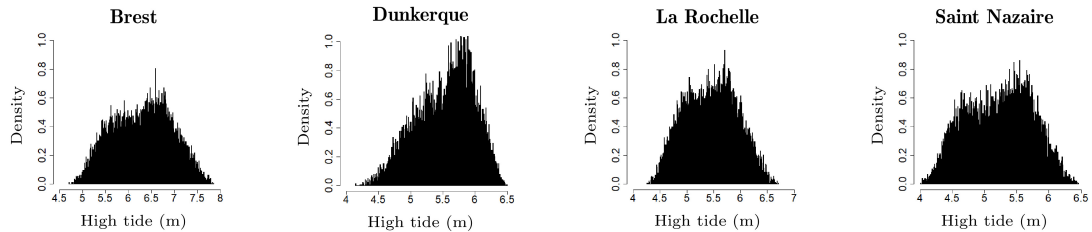
It is worth noting that the sample of historical events valuated in method 3 is a sub-set of the sample of events used in method 2 at Saint Nazaire. It furthermore includes 3 of the 4 largest observed skew surge events. At Brest, a station with a large tide/surge ratio, the samples used for the implementation of the two methods are almost totally different : they have only two events in common including only one of the largest observed skew surges.



**Figure C1.** Scatter plot of the high tide / skew surge samples. For Brest and Saint Nazaire, the red points represent the historical sample used in method 2 (ideal case), the blue points represent the historical sample used in method 3 (proposed method) and the purple points represent the observations common to both historical samples.

**Table C1.** Kendall's  $\tau$  and p-value (5%) for the top 1% skew surges.

Site	$\tau$	p-value
Brest	-0.023	0.257
Dunkerque	-0.009	0.806
La Rochelle	-0.021	0.628
Saint Nazaire	-0.45	0.65



**Figure C2.** Empirical distributions of astronomical high tides.

598 The empirical distributions of astronomical high tides for the four case studies are  
 599 shown in Figure C2. The number  $n_T$  intervals used to describe these distributions in the  
 600 numerical implementation (see Appendix A) depends on the range of high tide values  
 601 at each station: 4.70m to 7.86m at Brest (317 intervals), 4.14m to 6.49m at Dunkerque  
 602 (237 intervals), 4.26m to 6.71m at La Rochelle (247 intervals), 4.00m to 6.46m at Saint  
 603 Nazaire (247 intervals).

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#### 608 References

- 609 Aelbrecht, D., Benoit, M., & Allilaire, J. (2004). Renforcement de la protection contre  
 610 l'inondation du front de Gironde sur le site du Blayais : apports conjoints  
 611 des modélisations physique et numérique. *La Houille Blanche*(3), 37–44. doi:  
 612 10.1051/lhb:200403004
- 613 Andreewsky, M., Kergadallan, X., Bernardara, P., Benoit, M., Gaufres, P., & Trmal,  
 614 C. (2014). Comparaison de différentes méthodes d'estimation des niveaux  
 615 extrêmes en site à fort et à faible marnage. *La Houille Blanche*, 26–36. doi:  
 616 10.1051/lhb/2014035
- 617 Arns, A., Wahl, T., Haigh, I. D., Jensen, J., & Pattiaratchi, C. (2013). Estimating  
 618 extreme water level probabilities: A comparison of the direct methods and  
 619 recommendations for best practise. *Coastal Engineering*, 81, 51–66. doi:  
 620 10.1016/j.coastaleng.2013.07.003
- 621 Batstone, C., Lawless, M., Tawn, J., Horsburgh, K., Blackman, D., McMillan, A., ...  
 622 Hunt, T. (2013). A UK best-practice approach for extreme sea-level analysis  
 623 along complex topographic coastlines. *Ocean Engineering*, 71, 28–39. doi:  
 624 10.1016/j.oceaneng.2013.02.003
- 625 Bellier, J. (2018). *Prévisions hydrologiques probabilistes dans un cadre multivarié:  
 626 quels outils pour assurer fiabilité et cohérence spatio-temporelle?* (PhD Thesis).  
 627
- 628 Benito, G., Lang, M., Barriendos, M., Llasat, M. C., Francés, F., Ouarda, T., ...  
 629 Bobée, B. (2004). Use of systematic, palaeoflood and historical data for the  
 630 improvement of flood risk estimation. review of scientific methods. *Natural  
 631 Hazards*, 31(3), 623–643. doi: 10.1023/B:NHAZ.0000024895.48463.eb
- 632 Breilh, J.-F., Bertin, X., Chaumillon, e., Giloy, N., & Sauzeau, T. (2014). How fre-  
 633 quent is storm-induced flooding in the central part of the bay of biscay? *Global  
 634 and Planetary Change*, 122, 161–175. doi: 10.1016/j.gloplacha.2014.08.013
- 635 Bulteau, T., Idier, D., Lambert, J., & Garcin, M. (2015). How historical information  
 636 can improve estimation and prediction of extreme coastal water levels: applica-

- tion to the Xynthia event at La Rochelle (France). *Natural Hazards and Earth System Sciences*, 15, 1135–1147. doi: 10.5194/nhess-15-1135-2015
- 637  
638  
639 Coles, S. (2001). *An introduction to statistical modeling of extreme values*.
- 640 De Zolt, S., Lionello, P., Nuhu, A., & Tomasin, A. (2006). The disastrous storm of  
641 4 November 1966 on Italy. *Natural Hazards and Earth System Sciences*, 6(5),  
642 861–879. doi: 10.5194/nhess-6-861-2006
- 643 Dixon, M. J., & Tawn, J. A. (1994). Extreme sea-levels at the UK A-class sites: site-  
644 by-site analyses.
- 645 Dixon, M. J., & Tawn, J. A. (1999). The effect of non stationarity on extreme sea  
646 level estimation. *Journal of the Royal Statistical Society: Series C (Applied  
647 Statistics)*, 48, 135–151. doi: 10.1111/1467-9876.00145
- 648 Frau, R., Andreewsky, M., & Bernardara, P. (2018). The use of historical informa-  
649 tion for regional frequency analysis of extreme skew surge. *Natural Hazards  
650 and Earth System Sciences*, 18(3), 949–962. doi: [https://doi.org/10.5194/  
651 nhess-18-949-2018](https://doi.org/10.5194/nhess-18-949-2018)
- 652 Gaal, L., Szolgay, J., Kohnov, S., Hlavcova, K., & Viglione, A. (2010). Inclu-  
653 sion of historical information in flood frequency analysis using a Bayesian  
654 MCMC technique: a case study for the power dam Orlk, Czech Repub-  
655 lic. *Contributions to Geophysics and Geodesy*, 40, 121–147. doi: 10.2478/  
656 v10126-010-0005-5
- 657 Gaume, E. (2018). Flood frequency analysis: The bayesian choice. *Wiley Interdisci-  
658 plinary Reviews: Water*, 5(4). doi: 10.1002/wat2.1290
- 659 Gerritsen, H. (2005). What happened in 1953? The Big Flood in the Netherlands  
660 in retrospect. *Philosophical Transactions of the Royal Society A: Mathematical,  
661 Physical and Engineering Sciences*, 363(1831), 1271–1291. doi: 10.1098/  
662 rsta.2005.1568
- 663 Giloy, N., Duluc, C.-M., Frau, R., Ferret, Y., Bulteau, T., Mazas, F., & Sauzeau,  
664 T. (2018). La base de données TEMPETES : un support pour une expertise  
665 collégiale et interdisciplinaire des informations historiques de tempêtes et de  
666 submersions.. doi: 10.5150/jngcgc.2018.093
- 667 Giloy, N., Hamdi, Y., Bardet, L., Garnier, E., & Duluc, C.-M. (2019). Quantifying  
668 historic skew surges: an example for the Dunkirk Area, France. *Natural Haz-  
669 ards*, 98(3), 869–893. doi: 10.1007/s11069-018-3527-1
- 670 Haigh, I. D., Nicholls, R., & Wells, N. (2010). A comparison of the main methods  
671 for estimating probabilities of extreme still water levels. *Coastal Engineering*,  
672 57, 838–849. doi: 10.1016/j.coastaleng.2010.04.002
- 673 Halbert, K., Nguyen, C. C., Payrastre, O., & Gaume, E. (2016). Reducing un-  
674 certainty in flood frequency analyses: A comparison of local and regional  
675 approaches involving information on extreme historical floods. *Journal of  
676 Hydrology*, 541, 90–98. doi: 10.1016/j.jhydrol.2016.01.017
- 677 Hamdi, Y., Bardet, L., Duluc, C.-M., & Rebour, V. (2015). Use of historical infor-  
678 mation in extreme-surge frequency estimation: the case of marine flooding on  
679 the la rochelle site in france. *Natural Hazards and Earth System Sciences*, 15,  
680 1515–1531. doi: 10.5194/nhess-15-1515-2015
- 681 Hamdi, Y., Garnier, E., Giloy, N., Duluc, C.-M., & Rebour, V. (2018). Analysis  
682 of the risk associated with coastal flooding hazards: a new historical extreme  
683 storm surges dataset for Dunkirk, France. *Natural Hazards and Earth System  
684 Sciences*, 18, 3383–3402. doi: 10.5194/nhess-18-3383-2018
- 685 Hosking, J. R., & Wallis, J. R. (1987). Parameter and Quantile Estimation for the  
686 Generalized Pareto Distribution. *Technometrics*, 29(3), 339–349. doi: 10.1080/  
687 00401706.1987.10488243
- 688 Kergadallan, X., Bernardara, P., Benoit, M., & Daubord, C. (2014). Improving  
689 the estimation of extreme sea levels by a characterization of the dependence of  
690 skew surges on high tidal levels. *Coastal Engineering Proceedings*, 1, 48. doi:  
691 10.9753/icce.v34.management.48



- 692 Kolen, B., Slomp, R., & Jonkman, S. N. (2013). The impacts of storm Xynthia  
693 February 2728, 2010 in France: lessons for flood risk management. *Journal*  
694 *of Flood Risk Management*, 6(3), 261–278. doi: [https://doi.org/10.1111/](https://doi.org/10.1111/jfr3.12011)  
695 [jfr3.12011](https://doi.org/10.1111/jfr3.12011)
- 696 Liu, J. C., Lence, B. J., & Isaacson, M. (2010). Direct joint probability method for  
697 estimating extreme sea levels. *Journal of Waterway, Port, Coastal, and Ocean*  
698 *Engineering*, 136, 66–76. doi: 10.1061/(ASCE)0733-950X(2010)136:1(66)
- 699 Mazas, F., Kergadallan, X., Garat, P., & Hamm, L. (2014). Applying POT methods  
700 to the Revised Joint Probability Method for determining extreme sea levels.  
701 *Coastal Engineering*, 91, 140–150. doi: 10.1016/j.coastaleng.2014.05.006
- 702 Nguyen, C., Gaume, E., & Payrastre, O. (2014). Regional flood frequency anal-  
703 yses involving extraordinary flood events at ungauged sites: further de-  
704 velopments and validations. *Journal of Hydrology*, 508, 385–396. doi:  
705 10.1016/j.jhydrol.2013.09.058
- 706 Ouarda, T., Rasmussen, P., Bobée, B., & Bernier, J. (1998). Utilisation de  
707 l’information historique en analyse hydrologique fréquentielle. *Revue des sci-*  
708 *ences de l’eau / Journal of Water Science*, 11, 41–49. doi: 10.7202/705328ar
- 709 Outten, S., Wolf, T., Mangini, F., Chen, L., & Nilsen, J. E. (2020). *Re-assessing ex-*  
710 *treme sea level events through interplay of tides and storm surges* (Tech. Rep.).  
711 doi: 10.5194/egusphere-egu2020-8000
- 712 Payrastre, O., Gaume, E., & Andrieu, H. (2011). Usefulness of historical informa-  
713 tion for flood frequency analyses: Developments based on a case study. *Water*  
714 *Resources Research*, 47. doi: 10.1029/2010WR009812
- 715 Pugh, D. T., & Vassie, J. M. (1978). Extreme sea levels from tide and surge proba-  
716 bility. *Coastal Engineering Proceedings*, 1, 52. doi: 10.9753/icce.v16.52
- 717 Pugh, D. T., & Vassie, J. M. (1980). Applications of the joint probability method  
718 for extreme sea level computations. *Proceedings of the Institution of Civil En-*  
719 *gineers*, 69, 959–975. doi: 10.1680/iicep.1980.2179
- 720 Reis, D., & Stedinger, J. (2005). Bayesian MCMC Flood Frequency Analysis With  
721 Historical Information. *Journal of Hydrology*, 313, 97–116. doi: 10.1016/j.  
722 [jhydrol.2005.02.028](https://doi.org/10.1016/j.jhydrol.2005.02.028)
- 723 Schendel, T., & Thongwichian, R. (2017). Considering historical flood events in  
724 flood frequency analysis: Is it worth the effort? *Advances in Water Resources*,  
725 105, 144–153. doi: 10.1016/j.advwatres.2017.05.002
- 726 Stephenson, A. (2015). *Tideharmonics: harmonic analysis of tides*.
- 727 Tawn, J. A. (1992). Estimating probabilities of extreme sea levels. *Applied Statis-*  
728 *tics*, 41, 77. doi: 10.2307/2347619
- 729 Tawn, J. A., Vassie, J. M., & Gumbel, E. J. (1989). Extreme sea levels; the joint  
730 probabilities method revisited and revised. *Proceedings of the Institution of*  
731 *Civil Engineers*, 87, 429–442. doi: 10.1680/iicep.1989.2975
- 732 Tomasin, A., & Pirazzoli, P. A. (2008). Extreme Sea Levels in the English Chan-  
733 nel: Calibration of the Joint Probability Method. *Journal of Coastal Research*,  
734 4, 1–13. doi: 10.2112/07-0826.1
- 735 Williams, J., Horsburgh, K. J., Williams, J. A., & Proctor, R. N. F. (2016). Tide  
736 and skew surge independence: New insights for flood risk. *Geophysical Re-*  
737 *search Letters*, 43, 6410–6417. doi: 10.1002/2016GL069522