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1 **Modelling intersite dependence for regional frequency analysis of extreme**
2 **marine events**

3 Jérôme Weiss ^(1,2), Pietro Bernardara ^(1,3), Michel Benoit ^(1,2)

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40 **Abstract**

41 The duration of observation at a site of interest is generally too low to reliably estimate
42 marine extremes. Regional frequency analysis (RFA), by exploiting the similarity between
43 sites, can help to reduce uncertainties inherent to local analyses. Extreme observations in a
44 homogeneous region are especially assumed to follow a common regional distribution, up to a
45 local index. The regional pooling method, by gathering observations from different sites into
46 a regional sample, can be employed to estimate the regional distribution. However, such a
47 procedure may be highly affected by intersite dependence in the regional sample. This paper
48 derives a theoretical model of intersite dependence, dedicated to the regional pooling method
49 in a “*peaks over threshold*” framework. This model expresses the tendency of sites to display
50 a similar behavior during a storm generating extreme observations, by describing both the
51 storm propagation in the region and the storm intensity. The proposed model allows the
52 assessment of i) the regional effective duration of the regional sample and ii) different
53 regional hazards, e.g., return periods of storms. An application to the estimation of extreme
54 significant wave heights from the numerical sea-state database ANEMOC-2 is provided,
55 where different patterns of regional dependence are highlighted.

56 *Keywords:* regional frequency analysis, pooling, intersite dependence, extremes, significant
57 wave heights

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63 1 Introduction

64 The design of off-shore structures, or coastal protections preventing shoreline areas
65 from marine flooding, particularly requires an accurate estimation of the probability of
66 occurrence of extreme marine events (e.g., extreme storm surges or wave heights). High
67 return levels can be inferred through a local statistical analysis of extremes, from a time series
68 observed at a given site. However, a potential issue is the local duration of observation,
69 generally too low to accurately estimate return levels of interest. For example, wave records
70 from buoys are usually shorter than 20-30 years.

71 Regional frequency analysis (RFA) can help to reduce these uncertainties, by
72 exploiting the information shared by similar sites in a region. When based on the index-flood
73 method [*Dalrymple, 1960*], RFA assumes that extreme observations in a homogeneous region
74 follow a common regional probability distribution, up to a local index representing the local
75 specificities of each site.

76 A possible approach to estimate the parameters of the regional distribution is the
77 regional pooling method [*Bernardara et al., 2011*]. The principle is to pool the data
78 normalized by the local index in a single regional sample, the latter being used to fit the
79 regional distribution. This method is also referred to as the station-year method [*Buishand,*
80 1991] and illustrates the principle of “*trading space for time*”. However, it assumes intersite
81 independence [*Cunnane, 1988; Madsen and Rosbjerg, 1997; Stewart et al., 1999*], which
82 cannot be deemed realistic: indeed, for example, a storm is likely to generate dependent
83 extremes at different sites. Thus, *Dales and Reed* [1989] and *Stewart et al.* [1999] questioned
84 the relevance of regional pooling when intersite dependence is ignored, and showed its
85 approximate nature. Intersite dependence in regional pooling is actually closely related to the
86 concept of regional effective duration [*Bernardara et al., 2011*].

87 The regional effective duration, denoted by D_{eff} , can be defined as the effective
88 duration of observation of the regional sample filtered of any intersite dependence. For
89 example, if the times series recorded in different sites from a given region are considered
90 independent, pooling data from 10 sites, each having 30 years of observation, is equivalent to
91 sample 300 years of “effective duration”. This is not the case in the presence of intersite
92 dependence. At the same time, the highest independent normalized observation in the region
93 is viewed as the largest in D_{eff} years of record. It can be used to both reflect the relevance of
94 RFA to a local analysis and to estimate empirical regional return periods. However,
95 *Kergadallan* [2013] pointed out that one limitation of RFA is the difficulty to evaluate D_{eff} .
96 As an illustration, most of regional pooling studies are based on a simplifying hypothesis. For
97 example, *Hjalimarsom and Thomas* [1992], *Bernardara et al.* [2011] and *Bardet et al.* [2011]
98 assumed D_{eff} as the sum of all the local durations, hence assuming intersite independency.
99 *Dalrymple* [1958] expressed that records cannot be expanded to yield an effective duration
100 equal to the sum of local durations. In this work, it is conversely assumed that D_{eff} can be
101 formulated as the typical local duration, implicitly considering perfect intersite dependence.
102 The actual value is likely to lie between these two extreme cases. A realistic estimation of D_{eff}
103 requires a proper characterization of intersite dependence.

104 A consequence of intersite dependence is a loss of information [*Reed*, 1994]. For
105 example, when a storm impacts several sites, there is redundancy of information because
106 observed extremes stem from the same meteorological event. Several studies assessed the
107 effects of intersite dependence in the framework of RFA. For example, the effective size of
108 samples is reduced [*Bayazit and Önöz*, 2004; *Buishand*, 1991; *Kjeldsen and Rosbjerg*, 2002;
109 *Madsen and Rosbjerg*, 1997; *Rosbjerg and Madsen*, 1996]. *Castellarin et al.* [2008] also
110 observed a decrease of the power of the homogeneity test proposed by *Hosking and Wallis*
111 [1993]. *Stedinger* [1983], *Hosking and Wallis* [1988] and *Rosbjerg and Madsen* [1996]

112 showed that ignoring intersite dependence in RFA leads to an underestimation of the variance
113 of return levels estimates. When at-site distributions are the main interest, *Smith* [1990]
114 suggests to initially ignore intersite dependence and then correcting a posteriori the regional
115 variance.

116 A simple way to take into account intersite dependence is to remove it. Some authors
117 proposed its filtering through a spatial declustering procedure, where events impacting several
118 sites are counted only once. To estimate extreme surges with RFA, *Bernardara et al.* [2011]
119 and *Bardet et al.* [2011] formed the regional sample with the highest observations among
120 extremes occurring within 72 hours in the study area. However, the major disadvantage of
121 such an approach is a significant loss of information on the spatial dynamics of extremes
122 generated by a single storm. Moreover, this approach does not introduce any technique to
123 estimate D_{eff} .

124 Intersite dependence can also be modeled. *Cooley et al.* [2012] and *Bernard et al.*
125 [2013] deplored the lack of an explicit modeling of intersite dependence for RFA.
126 Nevertheless, *Renard and Lang* [2007] and *Renard* [2011] represented the dependence of
127 extreme rainfalls at different sites with elliptical copulas. Extremes at two different sites were
128 also regionally modeled by *Buishand* [1984], through bivariate extreme value theory. An
129 alternative approach, dedicated to annual maxima, was proposed by *Dales and Reed* [1989]; it
130 links distributions of the regional maximum and the typical regional data through an effective
131 number of independent sites.

132 Most of the papers cited above analyzed series of annual maxima. Yet, an alternative
133 way is to consider exceedances over a high threshold with the “*peaks over threshold*” (POT)
134 method [*Davison and Smith*, 1990]. Its superiority over methods based on annual maxima, for
135 both local and regional estimation of extremes, was demonstrated by *Madsen et al.* [1997a],
136 *Madsen et al.* [1997b] and *Arns et al.* [2013]. Besides, the POT framework is more physically

137 appealing to handle intersite dependence. For annual maxima, this one is characterized on a
138 yearly basis, and may thus be difficult to interpret: for example, series of annual maxima
139 observed at two distinct sites can be highly statistically correlated, without necessarily being
140 caused by the same meteorological phenomena. Conversely, the POT framework allows
141 reasoning at the scale of the physical event, provided that the concurrence of observations at
142 different sites can be carefully defined [Mikkelsen *et al.*, 1996; Stewart *et al.*, 1999]. In
143 particular, storms generating extreme observations offer an intuitive framework to deal with
144 intersite dependence in a POT approach. Weiss *et al.* [2014] characterized storms through the
145 gathering of extremes neighbors in space and time, and described a procedure to detect them
146 in the context of marine extremes. These storms allow to naturally define the concurrence of
147 observations at the scale of the physical event.

148 Thus, very few studies addressed the issue of intersite dependence for RFA in a POT
149 framework. Roth *et al.* [2012] used the model of Dales and Reed [1989] by grouping POT
150 data into seasonal blocks. It can be argued, that defining the concurrence of observations
151 through a wide temporal block (the season) may result in a loss of information on both the
152 spatial coverage and the intensity of the physical events generating extremes. Mikkelsen *et al.*
153 [1996], Rosbjerg and Madsen [1996], Madsen and Rosbjerg [1998] and Madsen *et al.* [2002]
154 proposed regional regression models, which are not based on the index-flood procedure used
155 in this paper. Similar to geostatistics, their models explicitly account for intersite correlation,
156 where the concurrence of observations is defined through the overlap of POT data in a short
157 time window. Madsen and Rosbjerg [1997] corrected the variance of the regional distribution
158 parameters with an effective number of independent sites, based on a regional average
159 correlation coefficient. However, in the latter references, although the concurrence of
160 observations is defined in a physically appealing way, only the pairwise dependence is
161 modeled. Moving towards a more global model of intersite dependence indicating, for

162 example, the tendency of sites in a region to behave similarly during a storm, would help to
163 characterize different regional hazards.

164 The estimation of extreme events by RFA allows to tackle the open question of the
165 difference between regional and local return period. In particular, note that to estimate the
166 return period of a storm affecting a given area, synoptic variables are usually defined first.
167 *Della-Marta and Pinto* [2009] characterized a storm by the minimum central pressure and the
168 maximum vorticity reached during its track; *Pinto et al.* [2012] used the wind speed
169 maximum; a more general spatial index, reflecting both the magnitude and the spatial extent,
170 was defined by *Della-Marta et al.* [2009], who then estimated the return period from these
171 synoptic variables. By construction, such an estimate corresponds to a “regional” return
172 period, namely the return period of a storm which can occur anywhere in the study area.
173 However, for practical applications (e.g., protection design), a local return period must be
174 estimated. For example, it is clear that a storm whose regional return period is 50 years will
175 not generate everywhere in the area wave heights (or storm surges) corresponding to a 50-
176 year return period. In particular, the link between the regional return period of a storm and the
177 return period of a given observed variable generated by the storm at a particular location
178 remains unknown. Note that *Della-Marta et al.* [2009] showed that regional return periods
179 share up to about half of the variability of the local return periods. In this study, we will show
180 how a proper treatment of intersite dependence can help to describe the relation between the
181 regional and the local return period of a storm.

182 The objective of this paper is to develop a global model of intersite dependence for
183 RFA, specifically dedicated to the regional pooling method and POT data, by reasoning at the
184 storm scale. Distributions of the regional storm maximum and the typical regional storm data
185 are linked through a function of *regional dependence*, describing both the propagation of

186 storms and their regional intensity. The proposed model allows the derivation of different
187 regional hazards and the regional effective duration.

188 The model of regional dependence is developed in section 2, including its implications
189 on the regional pooling method (section 2.4). An application to the estimation of extreme
190 significant wave heights from the numerical database ANEMOC-2 is shown in section 3.

191 **2 Methodology**

192 **2.1 Extraction of storms**

193 To characterize the intersite dependence, it is first necessary to define the simultaneity
194 of observations in space. If data are sampled every hour, the reference for simultaneity can be,
195 for example, the hourly scale. However, as extreme oceano-meteorological conditions can last
196 from several hours to several days, the temporal dimension should be added to describe the
197 spatial dependence. In this paper, the scale of the physical events generating marine extremes
198 (storms) is taken as the reference to define the simultaneity of observations in space.

199 A storm is thus directly characterized through the variable of interest (e.g., wave
200 height or storm surge), being defined as a physical event generating marine extremes in at
201 least one site in the study area. In the literature, the tracking of storms often relies on a nearest-
202 neighbor search in space and time [e.g., *Leckebusch et al.*, 2008; *Renggli et al.*, 2010]. A spatio-
203 temporal declustering procedure is thus employed to detect storms and to reflect their
204 propagation in space and time. In particular, extremes neighbors in space and time are
205 supposed to stem from the same storm. The storm extraction algorithm in the context of
206 marine extremes is described in *Weiss et al.* [2014], trying to reproduce at best the physical
207 dynamics of the storms, while taking into account the spatio-temporal resolution of
208 observations. Moreover, a “double-threshold” approach is employed to separate physical
209 considerations from statistical ones [*Bernardara et al.*, 2014].

210 At a given site, the impact of a storm is characterized by observations exceeding the
 211 “physical threshold” q_p , defined as the p -quantile of the initial time series, with p close to 1. In
 212 order to get independent data at site scale, only the peak value W_s^i is retained to summarize
 213 the storm s at site i (which implies that all other extremes occurring during that storm are
 214 discarded).

215 Only the most intense storm events are now considered for statistical aspects. New
 216 thresholds, denoted u and higher than the quantiles q_p , are selected corresponding to the
 217 occurrence of λ storms per year on average at each site. In particular, if d_i years of data are
 218 available at site i , the $n_i = \lambda d_i$ highest W_s^i are retained to form the n_i -sample X_s^i . The
 219 “statistical threshold” u_i , exceeded on average λ times per year, is then defined as the smallest
 220 observation from X_s^i (minus an infinitesimal quantity). Storms are then statistically redefined:
 221 if site i was impacted by storm s , it is from now on impacted by s if and only if u_i is exceeded.

222 2.2 Regional frequency analysis

223 Extreme events are estimated in this paper from exceedances over a high threshold.
 224 According to *Pickands* [1975], the Generalized Pareto Distribution (GPD) represents the
 225 natural distribution for such exceedances. For ease of notation, the index s denoting the storm
 226 is omitted in this section. For site i , let u_i be the storm threshold which is exceeded on average
 227 λ times per year. The n_i -sample X^i , denoting the exceedances of u_i , is assumed to be drawn
 228 from a GPD: $X^i \sim \text{GPD}(u_i, \alpha_i, k_i)$, where $\alpha_i > 0$ and k_i are, respectively, a scale and a shape
 229 parameter. In particular, the p -quantile of X^i is:

$$x_p^i = \begin{cases} u_i - \alpha_i / k_i (1 - (1 - p)^{-k_i}), & k_i \neq 0 \\ u_i - \alpha_i \log(1 - p), & k_i = 0 \end{cases} \quad (1)$$

230 The right tail of the GPD is bounded when $k_i < 0$, and unbounded when $k_i \geq 0$. The T -year
231 return level, i.e., the value exceeded on average once every T years, is given by $x_{1-1/\lambda T}^i$
232 [Rosbjerg, 1985].

233 A homogeneity hypothesis is required for RFA based on the index-flood method.
234 Observations from sites coming from a homogeneous region are supposed to follow the same
235 regional probability distribution, up to a local index representing the local specificities of a
236 site. In this paper, homogeneous regions are formed following Weiss *et al.* [2014], where
237 typical storm footprints are identified with a clustering algorithm based on a criterion of storm
238 propagation. In particular, sites from a given region are likely to be impacted by the same
239 storms, and any storm impacting a region is likely to remain enclosed in this region.

240 For a homogenous region of N sites, let μ_i be the local index of the site $i = 1, \dots, N$. The
241 normalized variable $Y = X^i / \mu_i$ is supposed to be independent of i , with cumulative distribution
242 function (c.d.f.) F_r . Roth *et al.* [2012] showed that dealing with exceedances over a high
243 threshold necessarily implies that the local index has to be a multiple of this threshold. Here,
244 as in Roth *et al.* [2012] and Weiss *et al.* [2014], μ_i is therefore chosen as the threshold u_i . This
245 implies that $Y \sim \text{GPD}(1, \gamma, k)$, where: i) the regional scale parameter satisfies $\gamma = \alpha_i / u_i$ and ii)
246 the shape parameter $k_i = k$ is constant over the region. From these relationships, $X^i \sim \text{GPD}(u_i,$
247 $\gamma u_i, k)$. For site i , the T -year return level is obtained by multiplying the regional T -year return
248 level by the local index: $x_{1-1/\lambda T}^i = u_i y_{1-1/\lambda T}$.

249 The two regional parameters (γ, k) can be estimated with the regional pooling method.
250 However, as sites in a region are likely to be impacted by the same storms, a strong intersite
251 dependence is expected. If ignored, this may affect the estimation process. Thus, this
252 dependence is firstly modeled as outlined in section 2.3, before the regional pooling method is
253 described in section 2.4.

254 2.3 Modeling of regional dependence

255 2.3.1 *Notations*

256 Let λ_r be the mean annual number of storms in the region and Z_s^i the Bernoulli variable
 257 which is 1 if storm s impacts site i and 0 otherwise. When storm s impacts site i , the observed
 258 normalized extreme with c.d.f. F_r is denoted by $Y_s^i = X_s^i / u_i$. Note that $Y_s^i \geq 1$. The storm s can
 259 be summarized in the region by the multivariate random variable $\eta_s = (\eta_s^1, \dots, \eta_s^N)$, where
 260 $\eta_s^i = Y_s^i Z_s^i$. The storm regional maximum is then defined as $M_s = \max_{i=1, \dots, N} \eta_s^i$. As at least one site
 261 is impacted by the storm s , $M_s \geq 1$.

262 2.3.2 *Distribution of the storm regional maximum*

263 First, note that due to the statistical redefinition of storms at the end of section 2.1, Z_s^i
 264 takes the value 1 with probability λ / λ_r , independently of i . Moreover, by the regional
 265 homogeneity hypothesis from section 2.2, the distribution of η_s^i does not depend on i :

$$\forall x \geq 1, P(\eta_s^i > x) = P(Z_s^i = 1)P(\eta_s^i > x | Z_s^i = 1) = \frac{\lambda}{\lambda_r} (1 - F_r(x)) \quad (2)$$

266 For $x \geq 1$, the distribution of M_s can be obtained through the following decomposition:

$$P(M_s > x) = P(\max_{i=1, \dots, N} \eta_s^i > x) = \sum_{i=1}^{N-1} P(\eta_s^i > x, \max_{j=i+1, \dots, N} \eta_s^j \leq x) + P(\eta_s^N > x) \quad (3)$$

267 Now, as the distribution of η_s^i is independent of i :

$$P(M_s > x) = P(\eta_s^1 > x) [1 + \sum_{i=1}^{N-1} P(\max_{j=i+1, \dots, N} \eta_s^j \leq x | \eta_s^i > x)] \quad (4)$$

268 From (2), this leads to:

$$P(M_s > x) = P(\eta_s^1 > x) \varphi(x) = (1 - F_r(x)) \frac{\lambda}{\lambda_r} \varphi(x) \quad (5)$$

269 where

$$\varphi(x) = 1 + \sum_{i=1}^{N-1} P(\max_{j=i+1, \dots, N} \eta_s^j \leq x | \eta_s^i > x), \quad x \geq 1 \quad (6)$$

270 The distribution of M_s can be thus written in terms of the regional distribution F_r and φ .

271 2.3.3 Characterization of the regional dependence

272 The function φ reflects the regional dependence. Situations of independence and
 273 perfect dependence, illustrating extreme cases of dependence, can be reinterpreted through
 274 equation (6) with $x = 1$. In particular, the region is *regional-independent* ($r - \perp$) if and only if
 275 $\varphi \equiv N$; in that case, a storm impacts only one site in the region, whatever its intensity.
 276 Conversely, the region is *perfectly regional-dependent* ($p - rd$) if and only if $\varphi \equiv 1$; a storm
 277 impacts every site in the region and, whatever its intensity, the generated (normalized)
 278 extremes vary the same way. Between these two extremal situations, φ takes values between 1
 279 and N .

280 By construction, φ relates both the storm propagation in the region and the storm
 281 intensity. It expresses the tendency of sites to display a similar behavior during a storm. The
 282 regional dependence is stronger when φ is small, hence indicating that most of the sites are
 283 impacted by a storm, and are likely to react the same way in terms of normalized extremes.

284 φ is influenced by the number N of sites in the region. In order to compare φ between
 285 different regions, the effect of N can be removed through the following adimensional
 286 function:

$$\Phi(x) = \frac{N - \varphi(x)}{N - 1}, \quad x \geq 1 \quad (7)$$

287 where Φ , lying between 0 and 1, is near to 1 when regional dependence is strong.

288 2.3.4 Assessment of regional hazards

289 A regional hazard is an event occurring at the regional scale, whose probabilistic
 290 description is related to collective risk assessment. The following examples of regional
 291 hazards are expressed in terms of the function of regional dependence φ .

292 A first example is the mean number $\beta_s(x)$ of impacted sites with normalized intensity
 293 larger than $x \geq 1$ when the storm regional maximum is larger than x :

$$\beta_s(x) = E\left[\sum_{i=1}^N \mathbf{1}_{\eta_s^i > x | M_s > x}\right] \quad (8)$$

294 From equation (5):

$$\beta_s(x) = NP(\eta_s^1 > x | M_s > x) = N \frac{P(\eta_s^1 > x)}{P(M_s > x)} = \frac{N}{\varphi(x)} \quad (9)$$

295 In particular, the mean number of impacted sites during any storm is given by $\beta_s(1) = N / \varphi(1)$.
 296 Note that this is coherent with the definitions of *regional-independence* and *perfect regional-*
 297 *dependence*.

298 Another example is the evaluation of the regional return period of a particular storm,
 299 and how it is related to its local return period. Let s be a given storm, and denote by $x \geq 1$ its
 300 corresponding normalized intensity. The *regional return period* of s , T_r , is defined as the
 301 average time between storms impacting *at least one site* in the region with a normalized
 302 intensity greater than x , i.e.:

$$T_r = \frac{1}{\lambda_r P(M_s > x)} \quad (10)$$

303 The *local return period* of s , T , is defined as the average time between storms
 304 impacting *a given site* in the region with a normalized intensity greater than x :

$$T = \frac{1}{\lambda(1 - F_r(x))} \quad (11)$$

305 From (5), T_r and T are related through:

$$T_r = \frac{T}{\varphi(x)} \quad (12)$$

306 2.4 Regional pooling method

307 2.4.1 *Construction of the regional sample*

308 The regional pooling method is used to estimate the regional distribution F_r . However,
 309 due to the presence of intersite dependence, events impacting several sites must be counted
 310 only once. Storms presented in section 2.1 are a convenient way to filter intersite dependence,
 311 as each storm describes the regional footprint of a particular event generating extremes.

312 In particular, the distribution of the storm regional maximum M_s is now assumed to be
 313 the same as the regional distribution F_r . This assumption was implicitly made in *Bernardara*
 314 *et al.* [2011] and *Bardet et al.* [2011], where the regional distribution was estimated from the
 315 highest normalized surges occurred within 72 hours in the region. In other words, the
 316 distribution of the maximum of a regional cluster is identical to the distribution of a generic
 317 element of this cluster. The same assumption is often made in a POT time series framework,
 318 as explained by Anderson in the discussion of the paper by *Davison and Smith* [1990]: “*this*
 319 *apparent paradox is a consequence of length-biased sampling: a randomly chosen*
 320 *exceedance has a disproportionate chance of coming from a large cluster, and in large*
 321 *clusters there tend to be large excesses.*” However, in practice, the validity of this assumption
 322 must be verified. For example, the two-sample Anderson-Darling test [*Scholz and Stephens,*
 323 1987] can be performed at each site i to evaluate the null hypothesis that Y_s^i and M_s have the
 324 same distribution.

325 If n_r independent storms are observed in the region, the regional sample is thus formed
 326 by the n_r -sample of storm regional maxima M_s , and corresponds to D_{eff} years of regional
 327 effective duration.

328 The assumption that the storm regional maximum M_s is the same as the regional
329 distribution F_r depends on the data at hand. When this hypothesis is not verified, the
330 following alternative strategies nevertheless allow to perform a RFA:

- 331 i) Remove sites of which Anderson-Darling p-values are too low (for example, lower
332 than 0.01) to accept this hypothesis. The application of the model of regional
333 dependence and the estimation of F_r can then be performed on the remaining sites.
- 334 ii) Form the regional sample with random (normalized) observations from each storm,
335 instead of using the storm regional maxima M_s . F_r can still be estimated by pooling,
336 directly from this new regional sample. However, the simplified model of
337 dependence (section 2.4.3) is not valid anymore, as φ is not a constant function. It
338 would be possible to update equation (14) by letting the regional effective duration
339 depend on regional quantiles.
- 340 iii) Use another method to perform the RFA, e.g., the regional L-moments method of
341 *Hosking and Wallis* [1997]. The model of regional dependence developed in this
342 paper, dedicated to the pooling method, does not apply anymore in this case.

343 2.4.2 Estimation of the regional distribution F_r .

344 The two regional parameters (γ, k) , see section 2.2, are estimated from the regional
345 sample. Penalized maximum likelihood estimation (PMLE) [*Coles and Dixon, 1999*] is used
346 in this study. The principle is to combine the efficiency of maximum likelihood estimators for
347 large sample sizes and the reliability of the probability weighted moment estimators for small
348 sample sizes. In particular, high estimates of the shape parameter k are penalized. PMLE is
349 implemented in the function `fitgpd` of the POT package [*Ribatet, 2007*], in the statistical
350 computing environment R (R Development Core Team, 2013). Uncertainties on estimates of
351 (γ, k) are here assessed with a bootstrap procedure: 10,000 replications of the (γ, k) values are
352 obtained with PMLE from resamples of the regional sample.

353 2.4.3 *Simplification of the model of regional dependence*

354 The regional pooling method presented in this paper assumes that the distribution of
355 the storm regional maximum M_s is the same as the regional distribution F_r . The model of
356 regional dependence in section 2.3 can thus be simplified. Indeed, from (5), this assumption
357 implies that φ becomes a constant function:

$$\forall x \geq 1, P(M_s > x) = 1 - F_r(x) \leftrightarrow \varphi(x) = \frac{\lambda_r}{\lambda} \quad (13)$$

358 As φ is constant, the way sites react during a storm does not depend on the intensity of the
359 storm. Similarly, *Dales and Reed* [1989] applied their model to rainfall annual maxima and
360 observed that the effective number of sites, summarizing the spatial dependence, did not seem
361 to depend on a particular regional intensity.

362 2.4.4 *The regional effective duration D_{eff}*

363 The pooling procedure yields D_{eff} years of regional effective duration. D_{eff} is closely
364 related to the degree of regional dependence; in particular, D_{eff} is expected to be low when
365 regional dependence is strong.

366 First, the two simplistic situations of regional dependence (section 2.3.3) are
367 considered. Let $\bar{d} = \sum d_i / N$ be the mean local duration, where d_i is the local duration of
368 observation at site i and N is the number of sites in the region. If the region is $r - \perp$, a storm
369 impacts only one site in the region. In that case, each observation from any site brings new
370 information, and D_{eff} can be written as the sum of all the local durations: $D_{eff} = N\bar{d}$.
371 Conversely, if the region is $p - rd$, a storm impacts every site in the region. Here, the typical
372 local duration of one site constitutes D_{eff} , as the information from other sites is purely
373 redundant. This can be reflected by taking, for example, D_{eff} as the mean local duration: $D_{eff} =$
374 \bar{d} . It is now assumed that, between these two extremal cases, D_{eff} can be more realistically
375 expressed by:

$$D_{eff} = \varphi \bar{d} \quad (14)$$

376 where φ , lying between 1 and N , is the degree of regional dependence. Note that the situations
 377 of $p-rd$ and $r-\mathbb{1}$ are respectively obtained for $\varphi = 1$ and $\varphi = N$. From equation (13), stating
 378 that $\varphi = \lambda_r / \lambda$, its theoretical value is $D_{eff} = \lambda_r \bar{d} / \lambda$.

379 The mean annual number of storms in the region λ_r can be naturally estimated by $n_r /$
 380 \bar{d} , where n_r is the number of observed storms. An estimate of D_{eff} is then:

$$\hat{D}_{eff} = \frac{n_r}{\lambda} \quad (15)$$

381 Let $n_{r,t}$ be the number of observed storms during year $t = t_1, \dots, t_\tau$ in the region, where t_1 and t_τ
 382 indicate the first and the last year of observation in the region, respectively. The overall
 383 number of observed storms n_r is obtained by summing the $n_{r,t}$ for $t = t_1, \dots, t_\tau$. By assuming that
 384 the $n_{r,t}$ are independent and identically distributed with common mean λ_r and standard
 385 deviation σ_r , the central limit theorem followed by the Slutsky's lemma allow to derive new
 386 confidence intervals for D_{eff} :

$$[\hat{D}_{eff} - z_{1-\alpha/2} \frac{\hat{\sigma}_r \sqrt{\tau}}{\lambda}, \hat{D}_{eff} + z_{1-\alpha/2} \frac{\hat{\sigma}_r \sqrt{\tau}}{\lambda}] \quad (16)$$

387 where $z_{1-\alpha/2}$ is the quantile of order $1-\alpha/2$ of the standard normal distribution, $\hat{\sigma}_r$ is the
 388 empirical standard deviation of the $n_{r,t}$, and τ is the number of years of observation in the
 389 region.

390 Note that (15) can be used even if periods of observations are different, and in the
 391 presence of missing data. This formula also guarantees that $\hat{D}_{eff} \geq \max_{i=1, \dots, N} d_i$, coherently with
 392 what might be expected from the regional effective duration. Besides, it reflects the
 393 importance to extract storms such that their mean annual occurrence λ at the local scale is
 394 common to all sites.

395 As F_r is estimated from D_{eff} years of pooled data, the underlying principle is that any
396 site in the region can be indifferently impacted by a given storm. Parenthetically, with no
397 preferential storm track in the region, the regional pooling method is coherent with the
398 identification of storms footprints to form homogeneous regions. In particular, the regional
399 sample illustrates that, for a generic site, λ storms per year, on average, were observed during
400 D_{eff} years. D_{eff} thus helps to reflect the relevance of RFA to a local analysis. Indeed, pooling
401 enables to estimate extreme events at site i from D_{eff} years of data, compared to d_i years for a
402 local analysis.

403 2.4.5 Evaluation of storm return periods

404 The regional pooling method allows to distinguish between local and regional return
405 periods of normalized storm events (see section 2.3.4 for the corresponding definitions), both
406 at the empirical and theoretical levels. Let s be a given storm from the regional sample, and
407 denote by x its corresponding normalized intensity.

408 Using the Weibull plotting position, its empirical local return period $\tilde{T}_{s,loc}$ is:

$$\tilde{T}_{s,loc} = \frac{D_{eff} + 1}{n_r + 1 - \text{rank}(s)} \quad (17)$$

409 where $\text{rank}(s)$ denotes the rank of s in the regional sample. For example, if s is the most
410 intense storm observed in the regional sample, then $\tilde{T}_{s,loc}$ is about D_{eff} years. Besides, the
411 theoretical local return period $\bar{T}_{s,loc}$ of s is given by equation (11). We recall that $\bar{T}_{s,loc}$
412 corresponds to the theoretical return period of storm s at site scale (i.e., at any site of the
413 region). Using (12) and (13), the theoretical regional return period $\bar{T}_{s,reg}$ is given by:

$$\bar{T}_{s,reg} = \frac{\lambda}{\lambda_r} \bar{T}_{s,loc} \quad (18)$$

414 The empirical regional return period $\tilde{T}_{s,reg}$ is linked with $\tilde{T}_{s,loc}$ through a similar relation.

415 3 Application

416 3.1 Data used

417 ANEMOC-2 (Atlas Numérique d'États de Mer Océaniques et Côtiers - Numerical
418 Atlas of Oceanic and Coastal Sea states) is a numerical sea-state hindcast database covering
419 the Atlantic Ocean over the period 1979-2009 (31 years). It has been developed at Saint-
420 Venant Laboratory for Hydraulics and EDF R&D LNHE [Laugel, 2013]. The simulations of
421 wave conditions have been carried out with the third-generation spectral wave model
422 TOMAWAC [Benoit *et al.*, 1996] forced by wind fields from the CFSR reanalysis database
423 [Saha *et al.*, 2010].

424 The spatial resolution of the so-called “oceanic mesh” of ANEMOC-2 ranges from
425 about 120 km over the Northern part of the Atlantic Ocean down to about 20 km along the
426 European coast and 10 km along the French coast. Note this grid is supplemented by a
427 “coastal mesh” whose resolution is finer on the continental shelf, in the Channel and along the
428 French coast. For the present study, however, only data from the oceanic mesh is used, and
429 only a subset of 1847 nodes amongst the 13426 nodes of the full oceanic mesh is selected, at
430 locations plotted in Figure 1.

431 Among the wave parameters available with an hourly resolution in ANEMOC-2, we
432 consider here the significant wave height, denoted H_s , which is usually the preferred
433 parameter to summarize sea state intensity. TOMAWAC computes this wave height from the
434 zero-order moment of the wave spectrum. Hourly series of significant wave heights H_s over
435 the period 1979-2009 are thus extracted for the 1847 selected sites. The objective here is to
436 apply the proposed methodology i) to characterize the regional dependence over this area and
437 ii) to estimate extreme H_s by the regional pooling method.

438 3.2 Preparation of data for RFA

439 More details for this section may be found in *Weiss et al.* [2014], where the same
440 dataset was used.

441 The physical extraction of storms generating extreme H_s , described in the beginning of
442 section 2.1 with $p = 0.995$, leads to 5939 storms. *Weiss et al.* [2014] performed a sensitivity
443 analysis and found that storms are properly detected when $p = 0.995$. A quick analysis reveals
444 that, on average: i) there are 192 storms per year in the study area, ii) a storm impacts 38 sites
445 and iii) a storm lasts 12.5 hours at site scale. These storms serve to form physically
446 homogeneous regions, by detecting the most typical storms footprints in the study area. The
447 footprints of the storms of 15-18 February 1986, 11-13 December 1990 and 23-24 January
448 2009 (Klaus) are shown in Figure 2.

449 Storms are then statistically redefined, following the methodology presented in section
450 2.1. In particular, $\lambda = 1$ storm per year are now observed, on average, at each site; 1340 storms
451 are thus retained among the 5939 initial ones. Site i is therefore characterized by the sample
452 of H_s over the threshold u_i exceeded on average once per year; the sample size is 31, as 31
453 years of data are available. These thresholds, represented in Figure 3, are also the local indices
454 used for RFA (section 2.2). These storms serve to i) check the statistical homogeneity of the
455 physically homogeneous regions, ii) deal with regional dependence and iii) estimate extreme
456 events with the regional pooling method.

457 RFA can thus be performed on each of the six homogeneous regions delineated in
458 *Weiss et al.* [2014], see Figure 4.

459 3.3 Regional pooling method

460 For each of the six regions, the regional sample is constructed by pooling the observed
461 normalized storm regional maxima, following section 2.4.1. To check whether the storm
462 regional maxima are sampled from the regional distribution F_r , the two-sample Anderson-

463 Darling test is performed. The p-values for the null hypothesis that Y_s^i and M_s have the same
464 distribution, for each site i from a given region, are higher than 0.01 for 95% of all sites.
465 Therefore, it may be reasonably assumed that i) the model of regional dependence can be
466 simplified and ii) F_r can be estimated from the regional sample.

467 3.3.1 Measures of regional dependence

468 For each region, Table 1 provides some measures of regional dependence defined in
469 sections 2.3.3, 2.3.4 and 2.4.4. Note that there are no missing values in ANEMOC-2 data, and
470 periods of observations are the same for all sites (with a common local duration of $d = 31$
471 years).

472 Storms are, respectively, most and least most frequent in regions 2 and 6, with 25.2
473 and 2.7 storms per year on average. This is explained here by their size: regions 2 and 6 are,
474 respectively, the largest and the smallest in terms of the number of sites. To compare the
475 degree of regional dependence between regions, this size effect can be removed through the
476 adimensional function Φ defined in equation (7). The regional dependence is thus the
477 strongest in region 5, meaning that sites in this region tend to behave highly similarly during a
478 storm: a large proportion of them are impacted, and the normalized extremes are likely to vary
479 the same way. Conversely, the regional dependence is the weakest in region 2. This can be
480 precised by considering the mean number $\beta_s(1)$ of impacted sites during a storm, see equation
481 (9). Indeed, on average, a storm in region 2 only impacts 18.9 sites (4% of the region),
482 whereas a storm in region 5 impacts 56.6 sites (24% of the region).

483 The regional effective duration D_{eff} and its corresponding 95% confidence interval are
484 estimated following equations (15) and (16). For example, pooling data from the 234 sites of
485 region 5 enables to get a regional sample with $D_{eff} = 128$ years of independent observations.
486 Note that taking into account the regional dependence considerably reduces what would be
487 obtained under the assumption of intersite independence (in that case, $D_{eff} = Nd = 7254$ years).

488 Figure 5 shows the evolution of the regional return period T_r against the local return
489 period T for each region, see equation (12). Note that curves for regions 3 and 4 are very close
490 to each other, giving the impression of being superimposed. The simplified model of regional
491 dependence implies that T_r and T are linearly related. For fixed T , T_r is, respectively, the
492 lowest and the highest in regions 2 and 6. For example, Table 1 gives 100_r , i.e., T_r
493 corresponding to $T = 100$ years. $100_r = 3.964$ years in region 2: about every four years on
494 average, a storm in this region causes at least one local 100-year event. Besides, although
495 region 1 is much larger than region 3, note that their 100_r estimates are similar (about 10
496 years). If intersite dependence was assumed, then this quantity would have been, in
497 proportion, much higher in region 3 than in region 1. However, the compensation is due to a
498 stronger regional dependence in region 1. Thus, modeling the regional dependence allows a
499 more realistic assessment of regional hazards.

500 3.3.2 Estimation of extreme H_s

501 For each of the six homogeneous regions, the regional GPD parameters (γ, k) are
502 estimated following the procedure outlined in section 2.4.2. These quantities are given in
503 Table 2, as well as the 100-year regional return level $y_{0.99}$. The shape parameter k is positive
504 (corresponding to an unbounded GPD) in regions 1, 4 and 6, suggesting a higher intensity of
505 extreme H_s . The return level plots for each of the six regional distributions, together with the
506 95% confidence intervals obtained by bootstrap, are given in Figure 6. Note that the plotting
507 position depending on the regional effective duration (equation (17)) is used to represent
508 observations from the regional sample, hence allowing the estimation of empirical return
509 periods (see section 3.3.3 for an application to the most intense storms observed).

510 At-site return levels are obtained by multiplying regional return levels by the local
511 indices. Figure 7 shows the map of the estimated at-site 100-year H_s . Estimates for coastal
512 areas are not shown because, as mentioned in section 3.1, the present analysis uses data from

513 the oceanic model of ANEMOC-2, whose resolution is not sufficient for these coastal areas
514 and which includes only parts of the shallow-water effects. In a follow-up of this study, data
515 from the coastal model may improve the simulated sea states in coastal areas. One can note on
516 Figure 7 that 100-year H_s estimates display a coherent spatial pattern, with lower values near
517 the West European coasts. The highest return levels are obtained for sites located in the north-
518 central part of the study area (up to 29.65 m). Note that these estimates are comparable to
519 those from *Caires and Sterl* [2005] and *Weiss et al.* [2014].

520 Compared to a local statistical analysis, the regional pooling method can help to
521 reduce uncertainties in the estimation of extreme events, at a given site. Indeed, extrapolations
522 from a local analysis would be based here on $d = 31$ years of observations; the regional
523 pooling makes available $D_{eff} > d$ years of data for any site.

524 3.3.3 Return periods of the most intense storms observed

525 From the numeric database ANEMOC-2, storms with the highest normalized intensity
526 were observed on February 1986, February 1979, December 1990, February 1988, December
527 1989 and January 2009, respectively in region 1, 2, 3, 4, 5 and 6. Figure 2 displays these
528 storms which occurred in regions 1, 3 and 6.

529 As an application of section 2.4.5, return periods of these storms are provided in Table
530 3, both at the local and regional scales (empirical and theoretical). For example, in region 3,
531 the empirical local return period $\tilde{T}_{s,loc}$ of the storm of 11-13 December 1990 is estimated at
532 280 years. Its theoretical counterpart is quite close ($\bar{T}_{s,loc} = 367$ years), as indicated by the
533 return level plot for this region (Figure 6). As such a storm was observed only once in 31
534 years of observations in this region, its empirical regional return period $\tilde{T}_{s,reg}$ is logically
535 estimated at 31 years. From equation (18), the model of regional dependence predicts a
536 theoretical regional return period $\bar{T}_{s,reg}$ of 41 years.

537 **4 Conclusions**

538 By exploiting the information shared by statistically similar sites, regional frequency
539 analysis (RFA) can reduce uncertainties in the estimations of high return levels, when at-site
540 durations of observations are short. It is assumed that, in a homogeneous region, extreme
541 observations follow a common regional probability distribution, up to a local index
542 representing the local specificities of a site.

543 The method of regional pooling is employed in this paper, where normalized
544 observations from different sites are gathered into a regional sample to estimate the regional
545 distribution. In particular, this pooling procedure allows to define D_{eff} years of regional
546 effective duration. D_{eff} is actually closely related to the degree of intersite dependence: for
547 example, D_{eff} is expected to be low when the dependence is strong. Intersite independence is a
548 usual assumption in the literature and practice, although unrealistic: a storm is likely to
549 generate dependent extremes at different sites. We have therefore proposed a theoretical
550 frame to model intersite dependence for the regional pooling method.

551 Storms are here identified by detecting physical events generating extremes in at least
552 one site in the study area; their spatio-temporal propagation is taken into account through the
553 gathering of extremes neighbors in space and time. Storms allow to naturally define the
554 concurrence of observations at the scale of the physical event, hence enabling to perform a
555 RFA within a “*peaks over threshold*” framework. These storms represent a convenient way to
556 describe regional dependence. In particular, they are the basis to i) construct the regional
557 sample, by filtering the redundancy of information and ii) model the regional dependence.

558 The distribution of the storm regional maximum is linked to the regional distribution
559 through a function of regional dependence. This function, describing both the storm
560 propagation in the region and the storm intensity, expresses the tendency of sites to display a
561 similar behavior during a storm. The proposed model allows i) a proper evaluation of D_{eff} and

562 ii) the assessment of different regional hazards: for example, the mean number of impacted
563 sites during a storm, or return periods of storms both at the local and regional scales can be
564 theoretically derived.

565 An application to significant wave heights from the numerical sea-state database
566 ANEMOC-2 has been provided to demonstrate the capabilities of the model. Six
567 homogeneous regions, corresponding to the most typical storms footprints were delineated in
568 the North-East part of the Atlantic Ocean. Different patterns of regional dependence have
569 been characterized in this area, before applying the regional pooling method to estimate
570 extreme significant wave heights.

571 Although the proposed example considers significant wave heights, the method can
572 easily be applied to other marine variables. Indeed, it is variable-oriented, in the sense that
573 storms are specifically defined through to the variable of interest only. Moreover, D_{eff} can also
574 be estimated when periods of observations are not the same for all sites, and/or in the
575 presence of missing values. Future works could, for example, apply the proposed model to
576 other marine hazards (e.g., storm surges) to compare how regional dependence manifests
577 compared to significant wave heights.

578

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587 has been extracted from the ANEMOC-2 database. This dataset can be obtained by request
588 addressed to the corresponding author. The use of this data is restricted to research purpose,
589 all industrial or commercial applications being excluded.

590

591 **6 References**

592

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722

723

724 **7 Table captions**

725

- 726 Table 1. Measures of regional dependence for each region (with the number of sites N
727 indicated between parentheses): λ_r is the mean annual number of storms in the region, Φ is
728 the adimensional function of regional dependence, $\beta_s(1)$ is the mean number of impacted

729 sites during a storm, 100_r is the regional return period (in years) of the storm causing at
730 least one local 100-year event (equation (12) with $T = 100$) and D_{eff} is the regional
731 effective duration (in years, along with the 95% confidence interval).

732 Table 2. Parameters of the regional distribution: γ (GPD scale parameter), k (GPD
733 shape parameter), $y_{0.99}$ (100-year regional return level).

734 Table 3. Return periods (in years) of the storms with the highest normalized intensity
735 observed in each region: $\tilde{T}_{s,loc}$, $\bar{T}_{s,loc}$, $\tilde{T}_{s,reg}$ and $\bar{T}_{s,reg}$ are respectively the empirical local
736 return period, the theoretical local return period, the empirical regional return period and
737 the theoretical regional return period.

738

739 **8 Figure captions**

740

741 Figure 1. Location of the 1847 sites extracted from the oceanic mesh of the ANEMOC-2
742 sea-state database.

743 Figure 2. Footprints of the storms of a) 15-18 February 1986, b) 11-13 December 1990
744 and c) 23-24 January 2009 (Klaus), where red dots indicate the impacted sites.

745 Figure 3. Map of threshold values of H_s exceeded on average once per year (m).

746 Figure 4. Division into six homogeneous regions.

747 Figure 5. Regional return period T_r against the local return period T for each region, as
748 defined in equation (12). Curves for regions 3 and 4 are superimposed.

749 Figure 6. Return level plots of the regional distributions (crosses represent observations
750 from each regional sample), together with the 95% confidence intervals obtained by
751 bootstrap.

752 Figure 7. Map of estimated 100-year H_s (m).

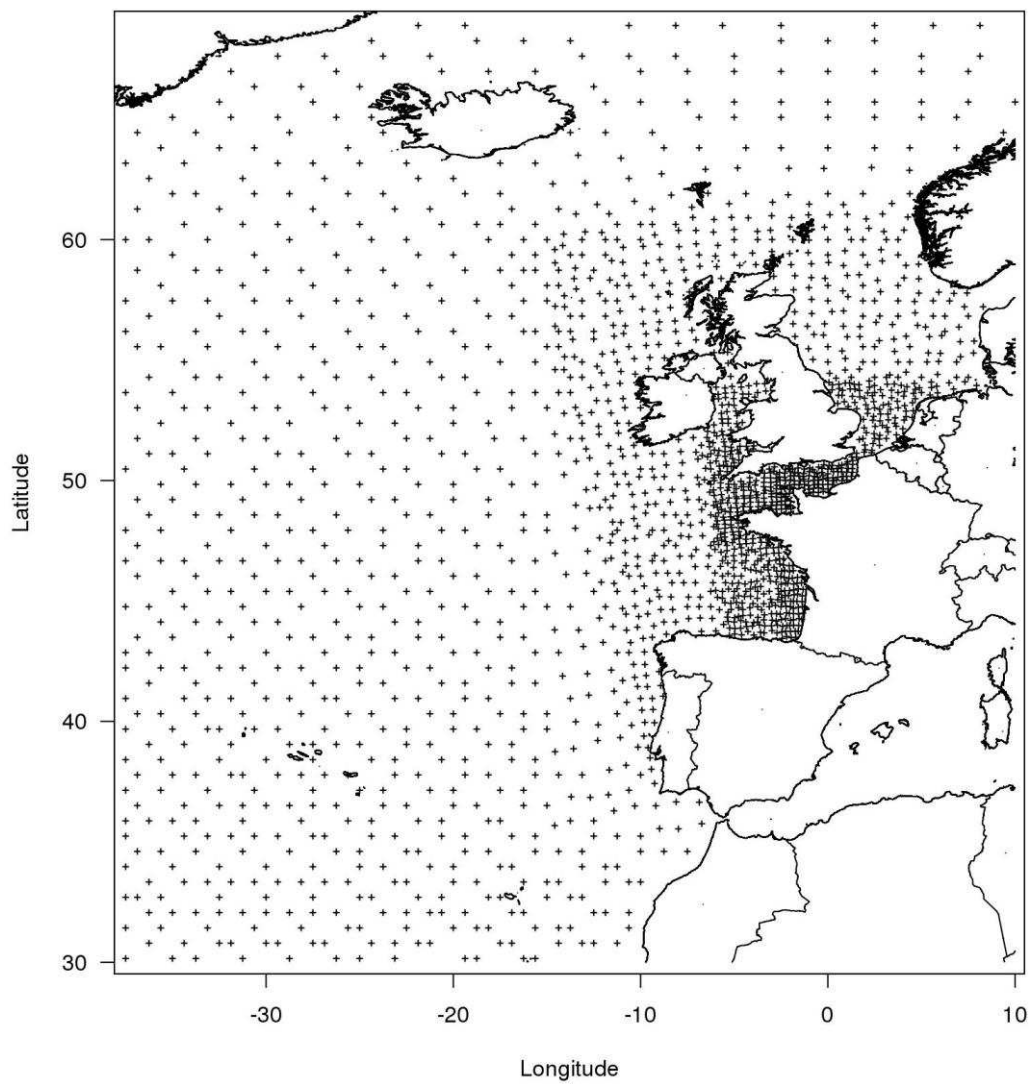


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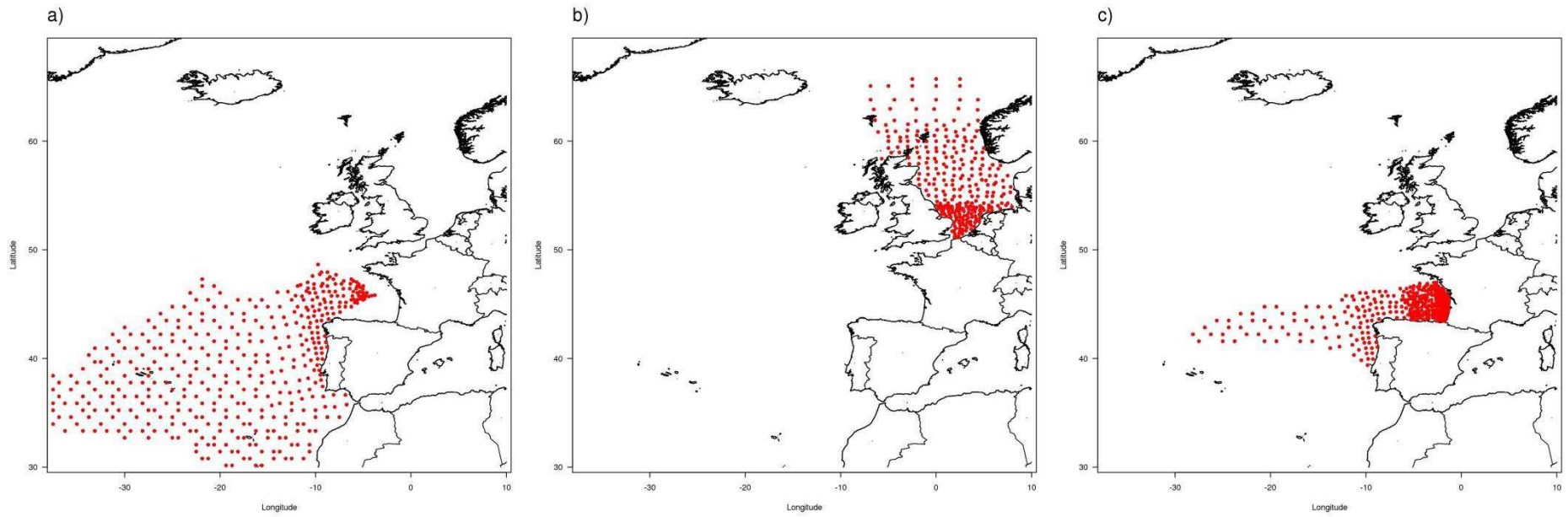


Figure 2. Footprints of the storms of a) 15-18 February 1986, b) 11-13 December 1990 and c) 23-24 January 2009 (Klaus), where red dots indicate the impacted sites.

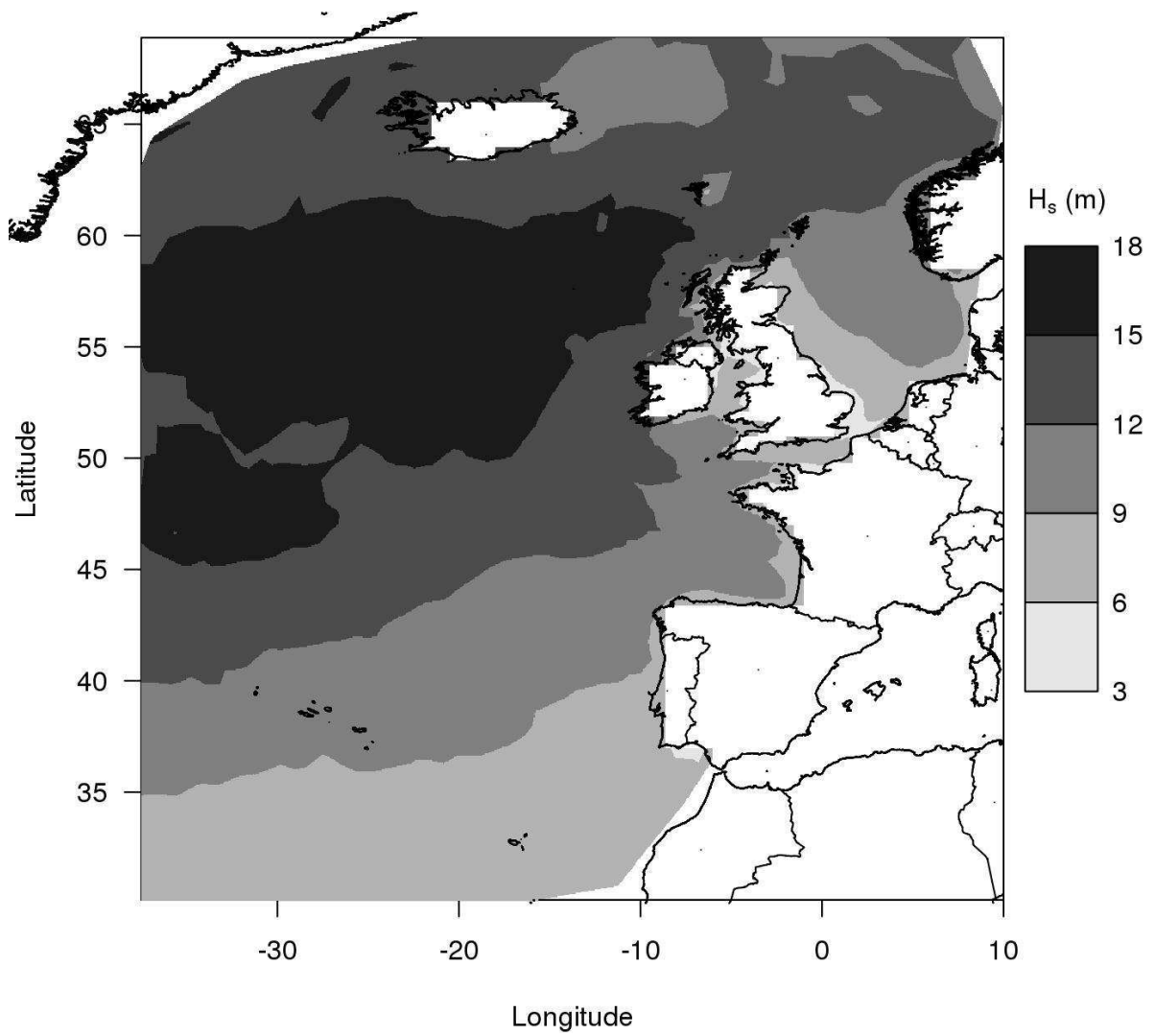


Figure 3. Map of threshold values of H_s exceeded on average once per year (m).

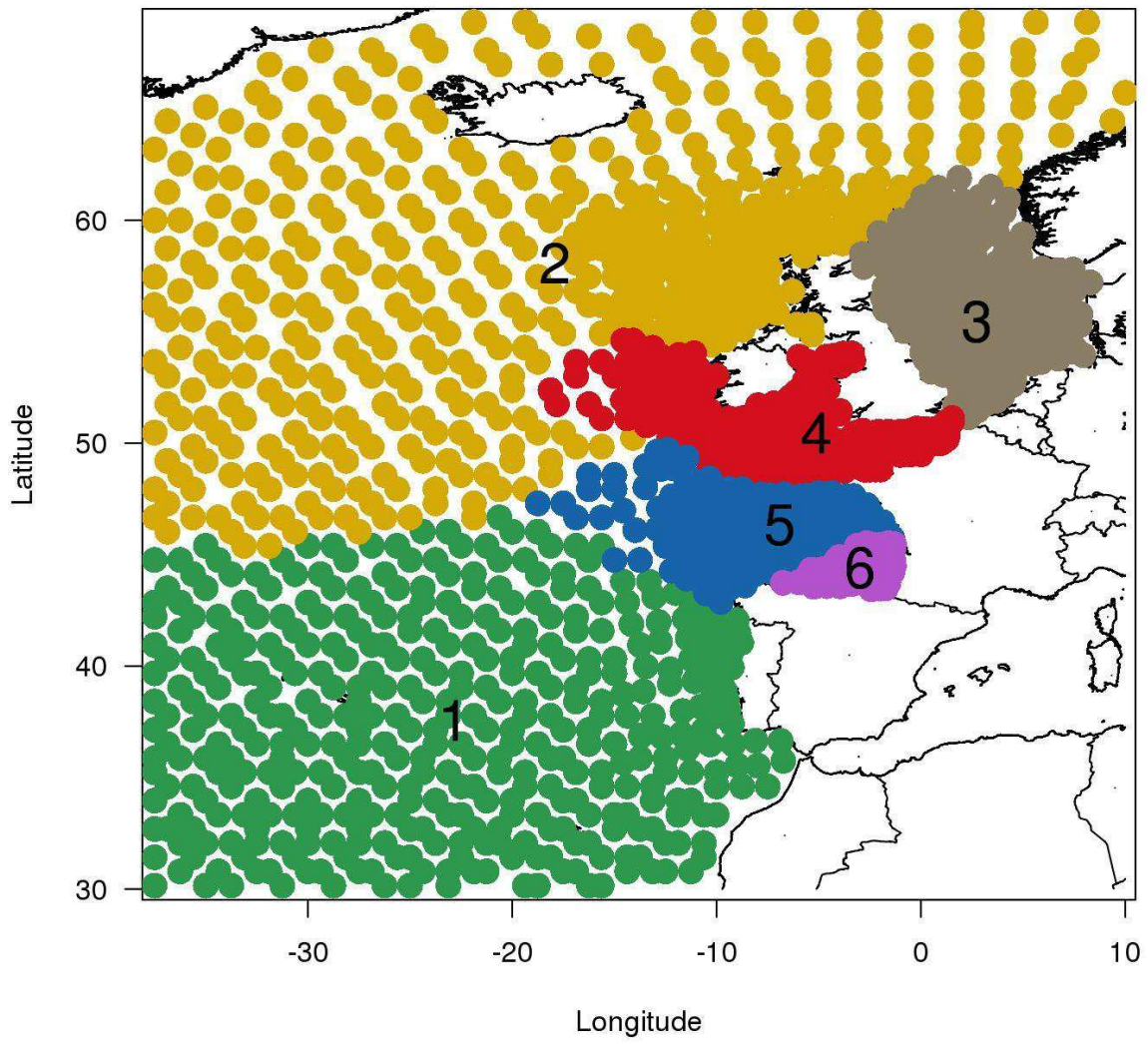


Figure 4. Division into six homogeneous regions.

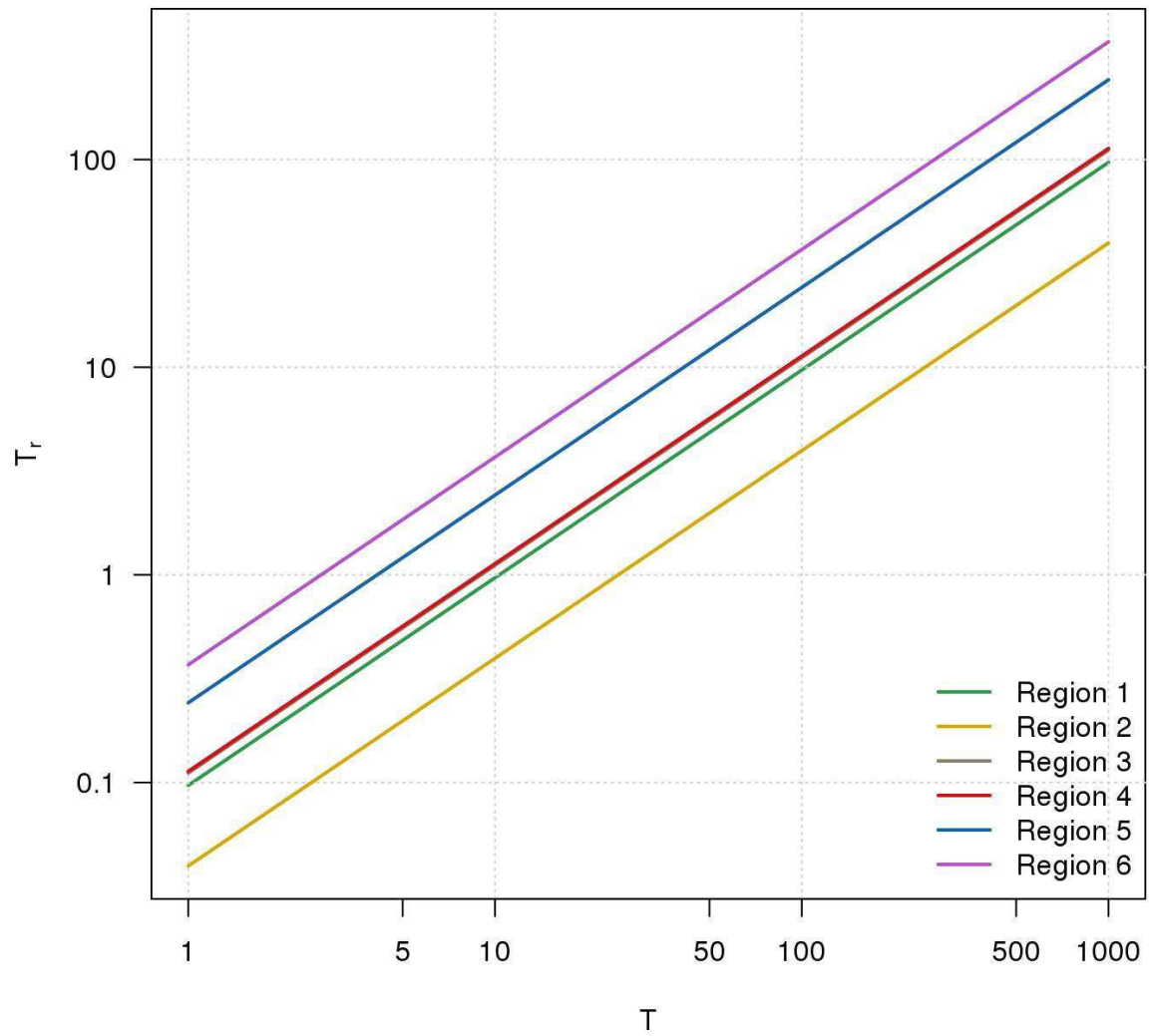


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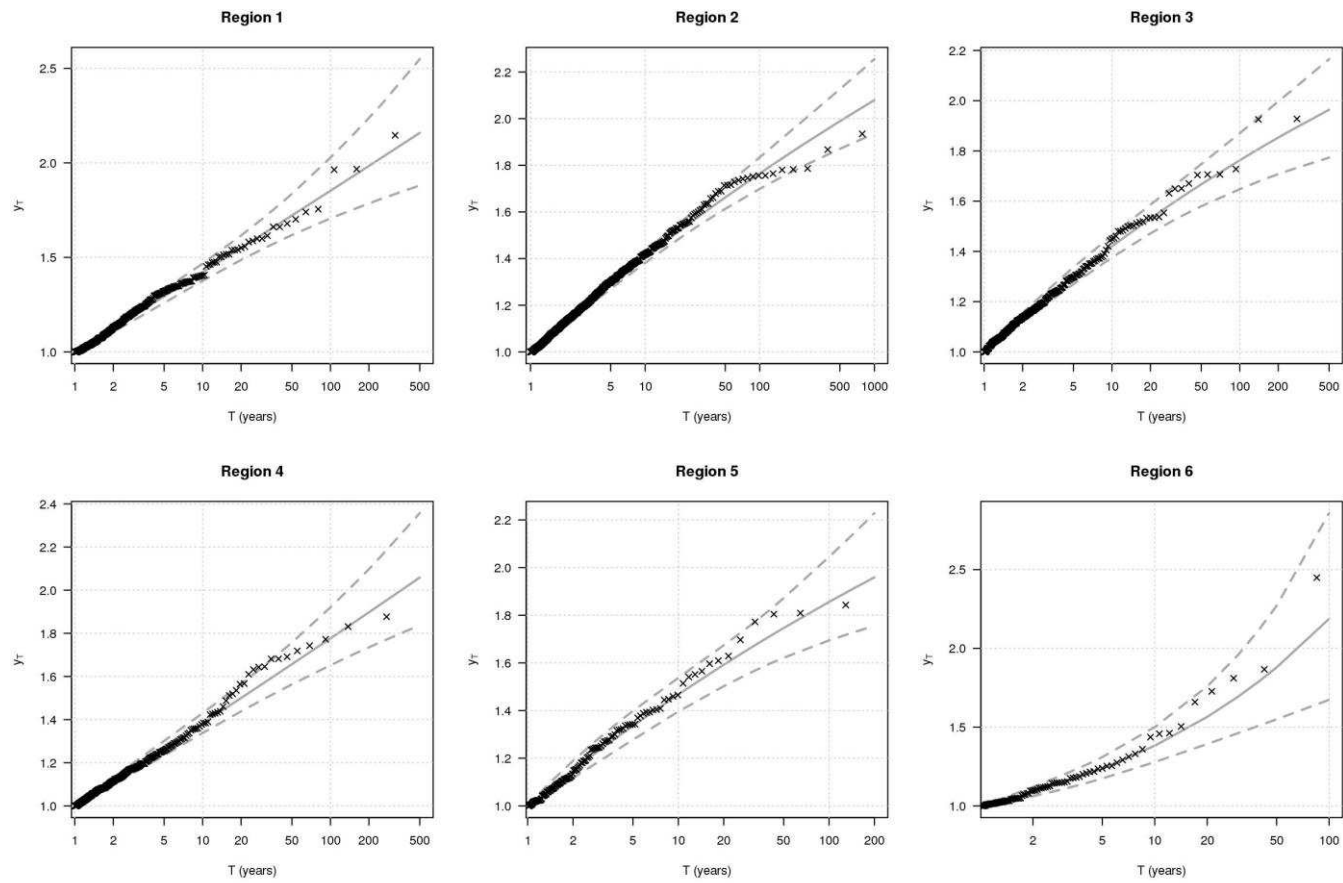


Figure 6. Return level plots of the regional distributions (crosses represent observations from each regional sample), together with the 95% confidence intervals obtained by bootstrap.

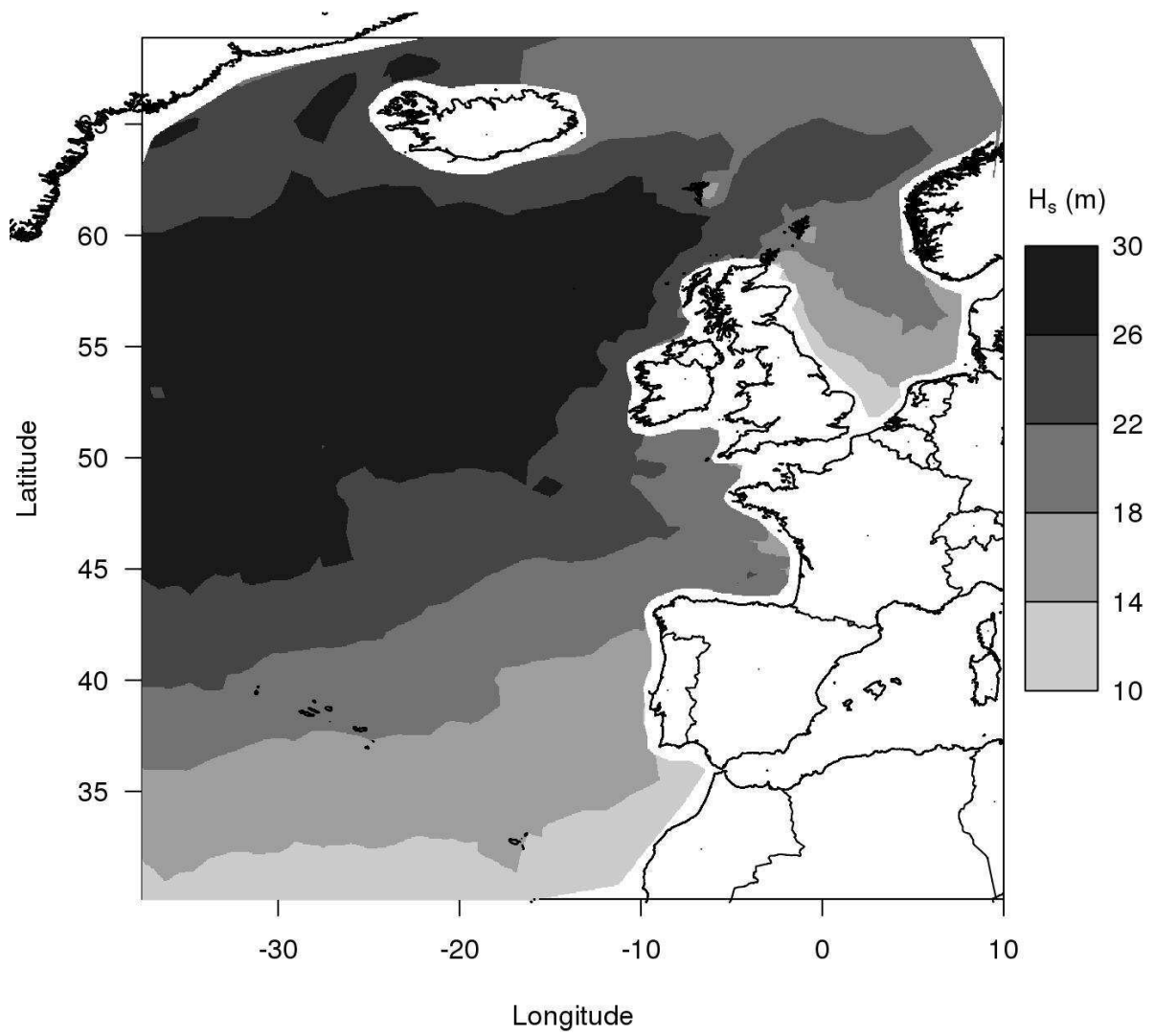


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