



HAL
open science

Trend in the Co-Occurrence of Extreme Daily Rainfall in West Africa Since 1950

Juliette Blanchet, Claire Aly, Theo Vischel, Gérémy Panthou, Youssouph
Sané, Mariane Diop Kane

► **To cite this version:**

Juliette Blanchet, Claire Aly, Theo Vischel, Gérémy Panthou, Youssouph Sané, et al.. Trend in the Co-Occurrence of Extreme Daily Rainfall in West Africa Since 1950. *Journal of Geophysical Research: Atmospheres*, 2018, 123 (3), pp.1536-1551. 10.1002/2017JD027219 . hal-01820737

HAL Id: hal-01820737

<https://hal.science/hal-01820737v1>

Submitted on 22 Jun 2018

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Trend in the co-occurrence of extreme daily rainfall in West Africa since 1950

Juliette Blanchet¹, Claire Aly¹, Théo Vischel¹, Gérémy Panthou¹, Youssouph Sané², and
Mariane Diop Kane²

¹Univ. Grenoble Alpes, CNRS, IRD, IGE, F-38000 Grenoble, France

²Physical Sciences Division, ANACIM, Dakar-Yoff, Senegal

Key Points:

- We study the co-occurrence of extreme daily rainfall in Senegal and Central Sahel.
- A change is found in the 80s in both regions but with contrasting results.
- In Senegal, anisotropic co-occurrence is found before the 80s and isotropic co-occurrence afterwards.
- In Central Sahel, anisotropy is found over the whole period, with greater extension after the 80s.
- This provides qualitative indicators on change in size and propagation of the strongest storms.

Corresponding author: Juliette Blanchet, juliette.blanchet@univ-grenoble-alpes.fr

Abstract

We propose in this paper a statistical framework to study the evolution of the co-occurrence of extreme daily rainfall in West Africa since 1950. We consider two regions subject to contrasted rainfall regimes: Senegal and the Central Sahel. We study the likelihood of the 3% largest daily rainfall (considering all days) in each region to occur simultaneously and, in a 20-year moving window approach, how this likelihood has evolved with time. Our method uses an anisotropic max-stable process allowing us to properly represent the co-occurrence of daily extremes and including the possibility of a preferred direction of co-occurrence. In Senegal, a change is found in the 80s, with preferred co-occurrence along the E-50-N direction (i.e. along azimuth 50°) before the 80s, and weaker isotropic co-occurrence afterwards. In Central Sahel, a change is also found in the 80s but surprisingly with contrasting results. Anisotropy along the E-W direction is found over the whole period, with greater extension after the 80s. The paper discusses how the co-occurrence of extremes can provide a qualitative indicator on change in size and propagation of the strongest storms. This calls for further research to identify the atmospheric processes responsible for such contrasted changes in storm properties.

1 Introduction

The Sahelian region is one of the world's region with the strongest signal of climate change over the last sixty years [Hulme *et al.*, 2001; Dai *et al.*, 2004; Gallego *et al.*, 2015]. This African band makes the transition between the dry Saharan Desert towards the North and the wet Sudanian region towards the South. It experiences a monsoon period from June to September with very variable and intermittent rainfalls in the form of storms, called meso-scale convective systems [Mathon *et al.*, 2002]. The occurrence and intensity of these storms condition the hydrology in the region [Lebel *et al.*, 2003; Vischel and Lebel, 2007]. They can lead to situations of either droughts or floods, with large consequences for such a vulnerable population to climate hazard [Tarhule, 2005; Di Baldassarre *et al.*, 2010].

Several studies have shown that the recent climate in the Sahelian region can be divided into three periods [e.g. Lebel and Ali, 2009; Nicholson, 2013]. The first one, from 1950 to 1969, corresponds to a relatively humid period, which was followed by a long and intense drought period between the 1970s and 1980s. Since the 1990s the mean annual rainfall levels have slightly increased with respect to the dry period. This has often led to

48 consider the last two decades as a recovery period [e.g. *Nicholson, 2005; Sanogo et al.,*
49 *2015*]. However annual rainfall remains on average much lower it was during the humid
50 period and it features a strong interannual variability. Moreover the recovery is not con-
51 sistant over the region with some significant contrasts between the Central Sahel (Niger,
52 Burkina, Eastern Mali), which has progressively become wetter, and the Western Sahel
53 (Western Mali, Senegal), which has remained much in deficit [*Lebel and Ali, 2009*]. In the
54 Central Sahel, the strong decadal variability has been associated with significant changes
55 in the amount of rainfall at mesoscale. The rainfall deficit of the dry period is mainly at-
56 tributable to a significant decrease in the frequency of storms with no significant decrease
57 in intensity [*Le Barbé et al., 2002; Bell and Lamb, 2006*]. On the contrary, over the last
58 two decades, the occurrence of storms did not increase significantly compared to the dry
59 period, but the contribution of the most intense storms to the rainfall regime reached un-
60 precedented levels [*Panthou et al., 2014*]. The fact that Sahelian rainfall has turned into
61 a more extreme regime is in phase with the intensification of the water cycle expected at
62 the global scale. The rise in intense storms in the Sahel was recently related to the global
63 warming and is thus likely to be a consistent feature of the Sahelian rainfall regime over
64 the long term [*Taylor et al., 2017*].

65 The present study brings new insight into the evolution of extreme precipitation in
66 the Sahel through the statistical analysis of the co-occurrence of extreme daily rainfall, i.e.
67 of daily rainfall exceeding some large level. The co-occurrence is studied for the period
68 1950-2014 over two contrasted regions in the Western (Senegal) and the Central Sahel.
69 The results lead us to speculate on possible changes in intense storm properties in light of
70 the decadal variability and regional disparities.

71 A suitable theoretical framework for assessing the frequency of rainfall exceeding
72 some large level and their evolution is provided by univariate extreme value statistics
73 [*Coles, 2001*]. *Panthou et al. [2013]* uses this framework to show temporal nonstationar-
74 ity in the local occurrence of extremes in the Sahelian region, i.e. in their marginal dis-
75 tributions. However this gives only indication about the evolution of extreme rainfall *at a*
76 *given site*. The spatial (i.e. surfacic) scale is, by definition, missing. To cope with the spa-
77 tial variability of heavy rainfall, areal data are required, which is often lacking. Thus one
78 usually resorts to the spatial interpolation of point data supplied by raingages [*De Michele*
79 *et al., 2002; Ceresetti et al., 2012; Panthou et al., 2014*], whose quality for representing the
80 most extreme events may be questioned [*Delrieu et al., 2014*].

81 Another way of looking upon the spatial variability of heavy rainfall is to study
82 the probability of different locations to co-experience some extreme event. A suitable
83 framework for this is provided by the theory of max-stable processes for spatial extremes
84 [*de Haan and Ferreira, 2006*]. Max-stable processes have been used recently for studying
85 the co-occurrence in threshold exceedances of wave height [*Raillard et al., 2014*], rainfall
86 [*Thibaud et al., 2013; Huser and Davison, 2014*] or river discharges [*Asadi et al., 2015*].
87 However these studies assume temporal stationarity in the probability of co-occurrent ex-
88 tremes. Nonstationarity in the co-occurrence of extreme temperature has been studied in
89 *Reich et al. [2014]* but considering temporal co-occurrence, not spatial one. In a spatial
90 context, it has been studied in *Westra and Sisson [2011]; Shang et al. [2011]; Zhang et al.*
91 *[2014]* for extreme precipitation by using nonstationary marginal distributions in max-
92 stable processes or in *Nicolet et al. [2016]; Shaby and Reich [2012]* by studying the evo-
93 lution of the max-stable spatial dependence of extreme snowfall and extreme temperature,
94 respectively. However these studies consider concomitance in annual maxima, whose ex-
95 planatory power is rather limited because it only informs on whether large maxima tend
96 to co-occur the same year, without accounting for their timing within the year. Studying
97 trend in the co-occurrence of threshold exceedances aims precisely at overcoming this
98 drawback.

99 The data are presented in Section 2 while Section 3 describes how is modeled and
100 inferred the probability of concomitant exceedances, which is based on an anisotropic
101 max-stable model. Section 4 assesses the probability of concomitant large exceedances in
102 the two regions and their evolution since the 50s in a 20-year moving window approach.
103 Section 5 discusses the results through a possible link between changes in the probability
104 of concomitant exceedances and changes in the properties of extreme storms.

105 **2 Data**

106 Two climatologically contrasted Sahelian regions are used in this study: Senegal
107 and the Central Sahel. The instrumented area in Senegal covers a surface of about $600 \times$
108 600 km^2 , as displayed in Figure 2. The network comprises 38 stations with daily mea-
109 surements since 1950. The instrumented area in the Central Sahel is divided into two net-
110 works. The first one covers about $1200 \times 600 \text{ km}^2$ and straddles Niger, Burkina Faso, Togo
111 and Benin (Figure 2). 44 stations are dispatched over this area, with daily measurements
112 since 1950. The second network is the AMMA-CATCH rainfall network in Niger [*Lebel*

113 *et al.*, 2009]. It covers about $110 \times 120 \text{ km}^2$ in the region of Niamey. It comprises 30 sta-
114 tions with 5' measurements since 1990, which we aggregate at daily scale.

115 We restrict the analysis to the four monsoon months of June-July-August-September
116 (JJAS) and to the period 1950-2014, which is the period presenting the most complete
117 data. The mean percentage of missing data over this period is 4% in Senegal, with a max-
118 imum of 15%, and 3% in the Central Sahel, with a maximum of 12%. Considering all
119 pairs of stations, the mean percentage of days with at least one concurrent missing value
120 is 7% in Senegal and 6% in the Central Sahel. However more and more lack is found
121 since the 90s. The Senegalese network comprises 38 stations with less than 15% of miss-
122 ing data in the 20-year window 1950-1969, but this decreases to 23 stations in 1995-2014.
123 Similarly, the Central Sahelian network comprises 44 stations with less than 15% of miss-
124 ing data in 1950-1969 but 34 such stations in 1995-2014. In the moving window study
125 of Section 4.2, we will only consider, for a given window, the stations comprising less
126 than 15% of missing data over this window, meaning that actually less stations will be
127 used in the most recent period to document co-occurrence. A separate analysis restricted
128 to the stations having less than 15% of missing data on every 20-year window (23 sta-
129 tions in Senegal and 30 stations in the Central Sahel) shows that the results of the present
130 study are not dependent on the evolution of the network though years (not shown). For
131 the small-scale network of AMMA-CATCH, the 1990-2014 period is considered. Within
132 this period, each station has less than 10% of missing data. Due to the shorter measure-
133 ment period, these data will not be considered in the non-stationarity study of Section
134 4.2, but the higher spatial density of the network will provide valuable information of co-
135 occurrence for small interdistances in Section 4.1.

136 Daily rainfall in JJAS can be considered as identically distributed. Moreover the
137 little extension (less than 10km large) and short duration (maximum a few hours) of the
138 strong convective cells induce a very strong spatio-temporal variability of rainfall [see
139 Figure 4 of *Vischel and Lebel*, 2007, for example]. This implies in particular that daily
140 amounts can be considered as almost independent from one day to another, as validated
141 in *Ali et al.* [2006] and *Gerbaux et al.* [2009] for reproducing the interannual and intra-
142 seasonal variability of Sahelian rainfields. Serial independence of extremes -which are the
143 main object of this study- can be quantitatively assessed by computing the mean number
144 of consecutive values that exceed high thresholds. Independent exceedances correspond to
145 a mean value of 1 and the closer to 1, the less dependent the exceedances. Using the es-

146 timation method of *Ferro and Segers* [2003], we find that the average mean cluster size is
 147 1.2 in Senegal, 1.14 in Central Sahel and 1.05 for AMMA-CATCH network, which con-
 148 firms that assuming independence of threshold exceedances is reasonable for the three net-
 149 works.

150 As shown in Figure 2, a drawback of the studied networks might be that that none
 151 of them samples uniformly the space and the azimuths. The Sahelian stations are not uni-
 152 formly distributed over the region, with a bigger density of stations close to the Atlantic
 153 coast. Stations of the Central Sahelian network are fairly uniformly dispatched but the re-
 154 gion features a rectangular shape, with a N-S extension more limited than the E-W one.
 155 However a separate analysis performed on a subset of stations distributed quite uniformly
 156 on squared domains in both regions showed that actually the results of this study are quite
 157 robust to the shape and spatial distribution of the networks (not shown).

158 3 Method

159 3.1 Probability of interest

160 Let X_{jt} be the random variable of daily rainfall at station j and day t , for $t = 1, \dots, T$.
 161 Daily rainfalls X_{j1}, \dots, X_{jT} are assumed to be independent and identically distributed, i.e.
 162 to be a random sample of a variable X_j representing daily rainfall a given day at station j ,
 163 with distribution function F_j .

164 Let \mathcal{R} be a given region. We are interested in the probability of concomitant ex-
 165 ceedance across \mathcal{R} , i.e. in

$$\text{pr}(X_j > x_j \text{ for all } j \in \mathcal{R}) \quad (1)$$

166 for x_j s large. Eq. (1) is the probability that a large level is exceeded simultaneously ev-
 167 erywhere across \mathcal{R} , due to a very convective activity making storms to affect all of \mathcal{R} the
 168 same day. By large we mean here larger than the α -quantile of the marginals distributions,
 169 i.e. for $x_j > u_j = F_j^{-1}(\alpha)$ with α large (e.g. $\alpha = 0.97$ in Section 4). Note that knowing (1)
 170 for all x_j large is equivalent to knowing

$$\text{pr}(h_j(X_j) > x_j \text{ for all } j \in \mathcal{R}) \quad (2)$$

171 for all x_j large, with h_j any positive bijective function. It is convenient to consider h_j so
 172 that all $h_j(X_j)$ have the same margins. In particular, with $h_j(.) = -1/\log\{F_j(.)\}$, the trans-

173 formed variables

$$Y_j = h_j(X_j) \quad (3)$$

174 are unit-Fréchet distributed, i.e. $\text{pr}(Y_j \leq y) = e^{-1/y}$. This framework turns out to be conve-
 175 nient to work with for spatial extremes, so in the rest of this paper we will be interested in
 176 the probability of simultaneous exceedance for the transformed variables Y_j , i.e.

$$\text{pr}(Y_j > y_j \text{ for all } j \in \mathcal{R}) \quad (4)$$

177 for all y_j s large. The probability (1) is then simply obtained as (4) taken in $y_j = -1/\log F_j(x_j)$.

178 By transforming the X_j s into Y_j s and studying (4) instead of (1), we assume that the
 179 marginal distributions F_j s are known. Actually, since we are interested in (1) when all x_j
 180 are larger than some large quantile u_j , only the tail of the marginal distribution is needed.
 181 The theory of univariate extremes (*Coles [2001]*) tells us that if u_j is large enough, we
 182 can assume that peaks-over-threshold follow a GPD (Generalized Pareto Distribution), i.e.
 183 that for $x > u_j$

$$F_j(x) = \text{pr}(X_j \leq x) = 1 - (1 - \alpha) \left(1 + \xi_j \frac{x - u_j}{\sigma_j} \right)^{-1/\xi_j}, \quad (5)$$

184 where $\sigma_j > 0$ is the scale parameter and ξ_j is the shape parameter. Thus a first step of
 185 our analysis is to estimate, for each station j , the GPD parameters σ_j and ξ_j based on the
 186 data exceeding the chosen threshold u_j , then use these estimates to transform the data x_j
 187 exceeding the threshold into $y_j = -1/\log F_j(x_j)$. The data below the threshold are set to
 188 $v = -1/\log \alpha$ and tagged as "censored". They will be used to estimate the model (4) in a
 189 censored likelihood approach; see Section 3.2.4.

190 **3.2 Modeling of co-occurrence**

191 **3.2.1 Asymptotic dependence and asymptotic independence**

192 Here we describe how is modeled the probability of co-exceeding some large thresh-
 193 olds (1). This implies modeling the dependence between variables at large levels. Depen-
 194 dence models for extremes can be split into two families [*Davison et al., 2013*]: asymp-
 195 totic dependence models and asymptotic independence models. Asymptotic independence
 196 models assume dependence of variables at moderate levels but independence as the levels
 197 approach the supremum of the support of the distribution. In particular the probability of
 198 one variable being larger than its η -quantile conditionally on another variable being larger

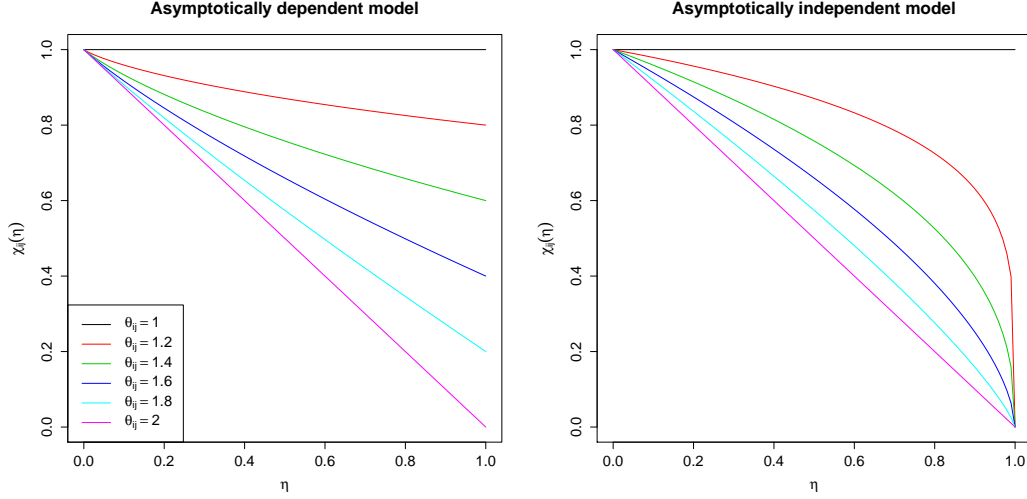
199 than its η -quantile,

$$\chi_{ij}(\eta) = \text{pr}(X_j > F_j^{-1}(\eta) | X_i > F_i^{-1}(\eta)), \quad (6)$$

200 converges to 0 as $\eta \rightarrow 1$, whatever the dependence at sub-extremal levels (provided the
 201 two variables are not almost surely equal), as illustrated Figure 1. The Gaussian depen-
 202 dence model, for example, belongs to this class as soon as its correlation coefficient is not
 203 1, no matter how close to 1 [Coles *et al.*, 1999]. Asymptotic dependence models, on the
 204 contrary, assume that some dependence remains at infinite levels, i.e. that $\chi_{ij}(\eta)$ converges
 205 to a positive value χ_{ij}^+ as $\eta \rightarrow 1$, as illustrated Figure 1. In practice distinguishing between
 206 weakly asymptotically dependent variables (χ_{ij}^+ close to 0) and asymptotically independent
 207 variables reveals difficult [Coles *et al.*, 1999], and this is confirmed on our data. A sepa-
 208 rate analysis revealed that, when considering annual maxima, the asymptotically dependent
 209 Brown-Resnick process (see Section 3.2.2) and the asymptotically independent version of
 210 *Wadsworth and Tawn* [2012] are actually pretty equivalent. Comparison of the values of
 211 CLIC [Davison *et al.*, 2013] in the stationary and non-stationary cases gave preference to
 212 either model depending on the period, in equal proportion, with always very similar val-
 213 ues of CLIC. Indeed the estimated probabilities of co-occurrence, e.g. of $\chi_{ij}(\eta)$ in (6), are
 214 pretty similar whatever model when η lies in the observed range of values, making selec-
 215 tion difficult. Extrapolation at much larger levels obviously differ but according to CLIC
 216 no clear preference is given to either family of models. In this article, we have chosen to
 217 consider the asymptotically dependent case, discarding asymptotically independent mod-
 218 els for the sake of concision, but also because, from a physical point of view, we don't
 219 see why more and more extreme storms should be less and less extended, as assumed by
 220 asymptotically independent models. However we keep in mind that our choice may not be
 221 optimal at extrapolation, and so that estimations of e.g. $\chi_{ij}(\eta)$ might be only valid in the
 222 observed range of values, in which case the choice of model seems to have little impact.

227 3.2.2 *Brown-Resnick model*

228 Let assume that the daily rainfall variables X_{j_s} , or equivalently the Y_{j_s} of (3), are
 229 asymptotically dependent. Following *de Haan and Ferreira* [2006], chapter 9, well-founded
 230 asymptotically dependent models for maxima belong to the family of max-stable pro-
 231 cesses. *Thibaud et al.* [2013] justify that this theory can be used for large exceedances.
 232 Various parametric models of max-stable processes have been proposed in the literature.
 233 The most popular ones are the Smith process, the Schlather process [*Schlather*, 2002], the



223 **Figure 1.** Theoretical conditional exceedance probabilities $\chi_{ij}(\eta) = \text{pr}(X_j > F_j^{-1}(\eta) | X_i > F_i^{-1}(\eta))$ for (left)
 224 an asymptotically dependent model corresponding to a max-stable process with extremal coefficient $\theta_{ij} = 1,$
 225 1.2, 1.4, 1.6, 1.8, 2; (right) an asymptotically independent model constructed as the inverted max-stable process
 226 of the left panel [Wadsworth and Tawn, 2012].

234 Brown-Resnick process [Kablichko et al., 2009], the Geometric Gaussian process [Davison
 235 et al., 2012] and the Extremal-t process [Opitz, 2013]. Few comparative studies exist
 236 in the literature but the overall consensus is to prefer the Brown-Resnick, Extremal-t and
 237 Geometric Gaussian processes towards the Smith and Schlather processes [Davison et al.,
 238 2012; Gaume et al., 2013], with actually very similar performances for the three first ones
 239 but a slightly better robustness of the Brown-Resnick process [Nicolet et al., 2017]. This
 240 lead us to consider the Brown-Resnick process for this study. Alternative options to max-
 241 stable modeling could be to consider generalized Pareto processes [Ferreira and de Haan,
 242 2014; Dombry and Ribatet, 2015; Thibaud and Opitz, 2015].

243 *Huser and Davison* [2013] derive a closed-form expression for the multidimensional
 244 joint distribution of Brown-Resnick process. In particular, the bivariate distribution func-
 245 tion is given by [Kablichko et al., 2009]:

$$\text{pr}(Y_i \leq y_i, Y_j \leq y_j) = \exp \left\{ -\frac{1}{y_i} \Phi \left(\frac{a_{ij}}{2} + \frac{1}{a_{ij}} \log \frac{y_j}{y_i} \right) - \frac{1}{y_j} \Phi \left(\frac{a_{ij}}{2} + \frac{1}{a_{ij}} \log \frac{y_i}{y_j} \right) \right\}, \quad (7)$$

246 for y_i and $y_j > v$, where Φ is the standard Gaussian cumulative distribution function,
 247 $a_{ij} = \{2\gamma(\|s_i - s_j\|)\}^{1/2}$, with γ the (unknown) semivariogram of an intrinsically Gaussian
 248 process, and $\|s_i - s_j\|$ the distance between stations i and j . Usual practice is to use the

249 isotropic semivariogram,

$$\gamma(\|s_i - s_j\|) = \left(\frac{\|s_i - s_j\|}{\lambda} \right)^\kappa, \quad (8)$$

250 with $\lambda > 0$ and $0 < \kappa \leq 2$ unknown parameters to estimate.

251 Combining (3) and (7) gives that, for any $\eta \geq \alpha$, the probability (6) of one variable
252 being larger than its η -quantile conditionally on another variable being larger than its η -
253 quantile is

$$\chi_{ij}(\eta) = (1 - 2\eta + \eta^{\theta_{ij}})(1 - \eta)^{-1}, \quad (9)$$

254 as illustrated Figure 1.

255 The scalar θ_{ij} in (9) is defined by $\theta_{ij} = 2\Phi\{\gamma(\|s_i - s_j\|)^{1/2}2^{-1/2}\} \in [1, 2]$ and is
256 termed the extremal coefficient. For the semivariogram γ defined by (8),

$$\theta_{ij} = 2\Phi\left(\|s_i - s_j\|^{\kappa/2}\lambda^{-\kappa/2}2^{-1/2}\right). \quad (10)$$

257 Whatever choice of γ , when $\theta_{ij} = 1$, X_i and X_j are completely dependent, and $\chi_{ij}(\eta)$ in
258 (9) is uniformly 1. When $\theta_{ij} = 2$, X_i and X_j are independent and $\chi_{ij}(\eta) = 1 - \eta$. Besides,
259 whatever $\theta_{ij} \in [1, 2]$,

$$\chi_{ij}^+ := \lim_{\eta \rightarrow 1} \chi_{ij}(\eta) = 2 - \theta_{ij}. \quad (11)$$

260 Actually, whatever θ_{ij} , $\chi_{ij}(\eta)$ can be approximated by χ_{ij}^+ with less than 10^{-2} error as
261 soon as $\eta \geq 0.99$, and in particular for the JJAS season as soon as we consider exceedances
262 of the yearly return level. However, let us recall that extrapolation of $\chi_{ij}(\eta)$ beyond the
263 range of observed values is very uncertain for our data because it relies on the assump-
264 tion of asymptotic dependence, which we were unable to clearly validate. Thus, rather
265 than a limit at infinite levels, χ_{ij}^+ will be interpreted in the rest of this article as the con-
266 ditional probability of concomitant large exceedances, the term "large" embracing roughly
267 the range of observed values (i.e. up to about the 100-year return level).

268 **3.2.3 Accounting for anisotropy**

269 According to (10) combined with (9), the Brown-Resnick is an isotropic model of
270 concomitance: any two pairs of stations at the same distance apart have the same condi-
271 tional probability of concomitant exceedance, whatever η . This means that the set of sites
272 s_j such that $\chi_{ij}(\eta) = p$, are circles centered on station i . However assumption of isotropy
273 is often violated for hydrometeorological variables, which tend to show increased depen-
274 dence in the direction of the governing wind fields [Ali et al., 2003; Blanchet and Davison,

275 2011; *Gaume et al.*, 2013; *Nicolet et al.*, 2016]. In order to account for such anisotropy, we
 276 replace in (8) and (10) the isotropic distance by the anisotropic distance defined as

$$\|s_i - s_j\|^2 = (s_j - s_i)' M' M (s_j - s_i) \quad (12)$$

277 where s_i and s_j are 2D-coordinates vectors, s' is the transpose of s and

$$M = \begin{pmatrix} \cos \psi & \sin \psi \\ -b \sin \psi & b \cos \psi \end{pmatrix} \quad (13)$$

278 with $b > 1$ the elongation coefficient and $\psi \in [-\frac{\pi}{2}, \frac{\pi}{2}]$ the angle. Now the set of sites s_j
 279 such that $\chi_{ij}(\eta) = p$ are ellipses centered on station i , with the major axis oriented along
 280 ψ and an elongation (ratio of the major and minor axes) equal to b .

281 3.2.4 Inference

282 Model (7) involves four parameters: λ and κ driving the strength of dependence
 283 along the major axis at a fixed distance, b driving the strength of anisotropy and ψ giv-
 284 ing the direction of major dependence. Assuming temporal independence of the y 's, but
 285 spatial dependence, the log-likelihood of the model is written:

$$\ell(\lambda, \kappa, b, \psi) = \sum_{t=1}^T \log g(y_{1t}, \dots, y_{Nt}) \quad (14)$$

286 where g is the multivariate density of Brown-Resnick model. *Wadsworth and Tawn* [2014]
 287 gives a closed form expression for g , however its computation results in a combinatorial
 288 explosion [*Davison and Gholamrezaee*, 2011; *Castruccio et al.*, 2016]. It is possible to
 289 circumvent this issue by making estimation based on the pairwise log-likelihood [*Varin*
 290 *et al.*, 2011; *Padoan et al.*, 2010]

$$\ell_1(\lambda, \kappa, b, \psi) = \sum_{t=1}^T \sum_{i=1}^{N-1} \sum_{j=i+1}^N \log g_{ij}(y_{it}, y_{jt}), \quad (15)$$

291 where g_{ij} is the bivariate density of (Y_i, Y_j) , i.e. associated to (7), and N is the number of
 292 stations.

293 In applying pairwise likelihood we must account for the fact that exceedances may
 294 occur in both variables, in one variable or in neither, whereas the bivariate density asso-
 295 ciated to (7) is only valid when both variables exceed the threshold v . To do so we apply
 296 the censoring approach described by *Coles* [2001], Section 8.3.1, and used in the context
 297 of threshold exceedances of spatial extremes in *Thibaud et al.* [2013]; *Bacro and Gaetan*

298 [2014]; *Huser and Davison* [2014]; *Raillard et al.* [2014], for example. Writing G_{ij} the bi-
 299 variate distribution, valid only when both variables exceed v , the likelihood contribution of
 300 sites i and j in (15) is:

$$g_{ij}(y_{it}, y_{jt}) = \begin{cases} \partial_i \partial_j G_{ij}(y_{it}, y_{jt}), & y_{it} > v, y_{jt} > v; \\ \partial_i G_{ij}(y_{it}, v), & y_{it} > v, y_{jt} \leq v; \\ \partial_j G_{ij}(v, y_{jt}), & y_{it} \leq v, y_{jt} > v; \\ G_{ij}(v, v), & y_{it} \leq v, y_{jt} \leq v; \end{cases} \quad (16)$$

301 $\partial_i G_{ij}$ denotes the differentiation with respect to y_i in (7). No analytical expression for the
 302 maximum of (15) under (16) is available but maximization may be performed numerically
 303 (e.g. quasi-Newton method).

304 3.3 Workflow

305 Two frameworks are considered in this study. The first one assumes stationarity over
 306 the observation period. The workflow consists of the following steps:

- 307 • For each station j , the empirical α -quantile is computed. The marginal GPD distri-
 308 bution F_j above this threshold is estimated by maximum likelihood.
- 309 • The data x_{jt} exceeding the threshold are transformed into unit-Fréchet variates
 310 $y_{jt} = -1/\log F_j(x_{jt})$. For the data x_{jt} below the threshold, the exact value of y_{jt}
 311 is not necessary since to compute (16) one only needs to know that y_{jt} is in this
 312 case below v .
- 313 • The anisotropic Brown-Resnick model for the region \mathcal{R} of interest is estimated
 314 based on the $\{y_{jt}, j \in \mathcal{R}, t = 1, \dots, T\}$, by maximizing the pairwise log-likelihood
 315 (15) under (7) with censoring (16).

316 This gives one anisotropic Brown-Resnick model for each of the three networks. Deter-
 317 mining the threshold above which this workflow may be applied is a bias-variance trade-
 318 off. Too low a threshold is likely to violate the assumptions of extreme value theory, lead-
 319 ing to bias. Too high a threshold implies too few excesses to estimate the model, lead-
 320 ing to high variance. In this article, the threshold is set to the empirical 97% quantile of
 321 daily rainfall at each station, i.e. $\alpha = 0.97$. This is slightly higher than the thresholds of
 322 *Thibaud et al.* [2013] (90%-quantile) and *Huser and Davison* [2014] (95%-quantile) for
 323 example but we use here longer time-series, so the number of exceedances is roughly sim-
 324 ilar. Setting the threshold to the 95%-quantile leads anyway to similar results (not shown).

325 The second framework considers 20-year moving windows from 1950-1969 to 1995-
 326 2014. The workflow consists of the same steps but applied to each window separately
 327 (i.e. considering only the days t within the window). This means that the threshold is re-
 328 computed for each window and thus different thresholds are used for different windows.
 329 However the models considered here rely on asymptotic theory, so they should apply
 330 equally for any large enough threshold. We checked that using for each window the 97%-
 331 quantile of the entire period does not affect the results, but this implied considering dif-
 332 ferent amounts of data depending on the window, which is not recommended for model
 333 comparison and in particular for what matters uncertainty, so we prefer showing results of
 334 the window-dependent threshold case. Applying the above workflow gives us one Brown-
 335 Resnick model for each network and each window. Given the shortness of its observation
 336 period (25 years), the moving-window framework is not applied to the AMMA-CATCH
 337 network.

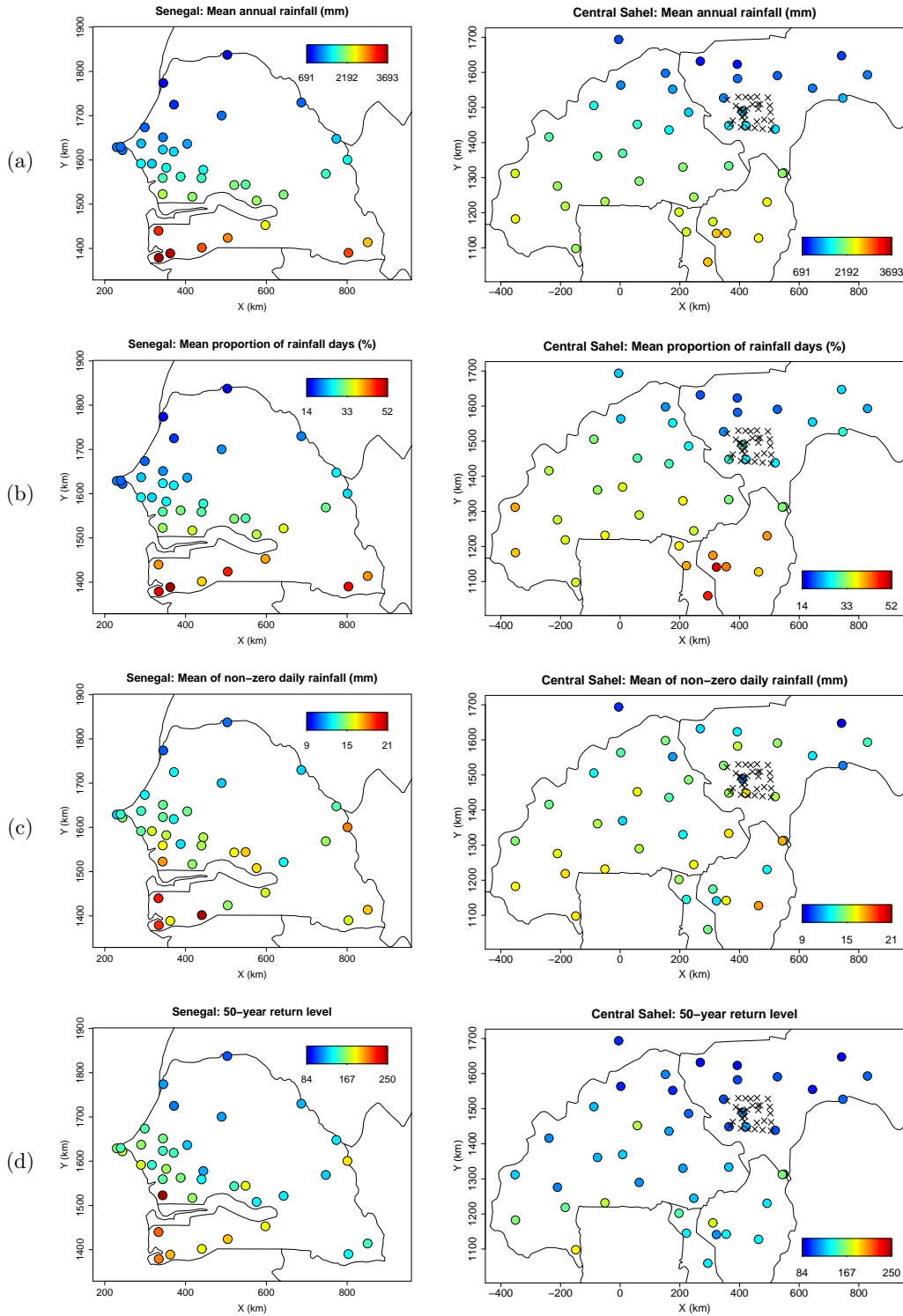
338 4 Results

339 4.1 Stationary case

340 4.1.1 Marginal distributions

341 Although marginal distributions are not the scope of this paper, they are interest-
 342 ing to study to better understand the climatology of rainfall in the region. Figure 2 shows
 343 the maps of (a): mean annual rainfall, (b): mean proportion of rainfall days, (c): mean
 344 of non-zero daily rainfall and (d): 50-year return levels in Senegal and Central Sahel in
 345 JJAS season, for the period 1950-2014. For the three former cases, empirical values are
 346 plotted while the 50-year return level at station j is given by $\hat{F}_j^{-1}(1 - 1/(KL))$, where
 347 $L = 122$ is the number of days in the JJAS season per year, $K = 50$ and \hat{F}_j is an esti-
 348 mate of the marginal distribution F_j at station j . Values for the AMMA-CATCH network
 349 are not shown on this figure because the observation period is much shorter (1990-2014).
 350 Let just note that the average values for AMMA-CATCH network are of the same order as
 351 the values found in Niamey region in Figure 2. For example the mean 50-year return level
 352 for AMMA-CATCH network is around 110 mm.

360 The 50-year return levels (d) in both Senegal and the Central Sahel show a N-S in-
 361 crease, although in Senegal the distance to the ocean seems also to play a role with larger
 362 values when moving closer to the Atlantic West coast. The 50-year return levels in Sene-



353 **Figure 2.** (a): Annual rainfall, (b): proportion of rainfall days, (c): mean of non-zero daily rainfall and
 354 (d): 50-year return level of daily rainfall accumulation (mm) in Senegal and Central Sahel in JJAS season,
 355 for the period 1950-2014. The black crosses in the Central Sahelian map show AMMA-CATCH network.
 356 Coordinates are UTM coordinates.

	Senegal				Central Sahel			
	(a)	(b)	(c)	(d)	(a)	(b)	(c)	(d)
(a)	1.00	0.98	0.76	0.83	1.00	0.96	0.47	0.65
(b)	0.98	1.00	0.64	0.71	0.96	1.00	0.23	0.43
(c)	0.76	0.64	1.00	0.96	0.47	0.23	1.00	0.94
(d)	0.83	0.71	0.96	1.00	0.65	0.43	0.94	1.00

357 **Table 1.** Pattern correlation table of (a): Annual rainfall, (b): proportion of rainfall days, (c): mean of non-
358 zero daily rainfall and (d): 50-year return level of daily rainfall accumulation (mm) in Senegal and Central
359 Sahel in JJAS season, for the period 1950-2014.

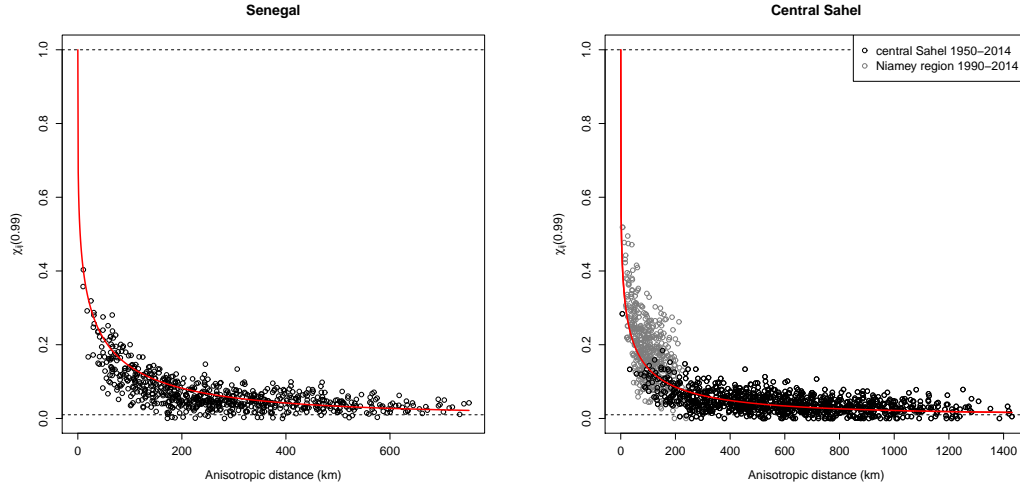
363 gal are on average 20% larger than in the Central Sahel. This superiority applies actually
364 for all $K \geq 1$ year, with greater differences as the return period increases. The 50-year
365 return level map in the Central Sahel shows a similar pattern to the 20- and 100- year re-
366 turn level maps produced in *Panthou et al.* [2012] over the same area but considering an-
367 nual maxima. The fact that it differs from the 50-year return level map of Senegal both in
368 terms of magnitude and shape is a novel result.

369 As shown in Table 1, the proportion of rainfall days (b) explains more the annual
370 totals (a) than the mean of non-zero daily rainfalls (c), as already noted in *Le Barbé and*
371 *Lebel* [1997]; *Le Barbé et al.* [2002]. The return level map of the Central Sahel (d) is
372 more correlated to the proportion of rainfall days (b) than to the mean of non-zero daily
373 rainfalls (c), which is more patchy. This suggests that the N-S increase of extreme rainfall
374 intensity is more driven by the occurrence of the rainfall systems than by their own inten-
375 sity. In Senegal, correlation between the return level map (d) and the proportion of rainfall
376 days (b) is even larger. However the NE-SW gradient of return level maps (d) differs from
377 the N-S gradient characterizing the mean number of rainfall days (b), while the mean of
378 non-zero daily rainfall (c) displays a slight east-west distortion near the coast. This sug-
379 gests that the spatial organization of extreme rainfall in Senegal might be a combined ef-
380 fect of rainfall occurrence and influence of oceanic moisture entries. This additional local
381 oceanic moisture might also explain why extremes are more intense in Senegal than in the
382 Central Sahel.

4.1.2 Co-occurrence of extremes

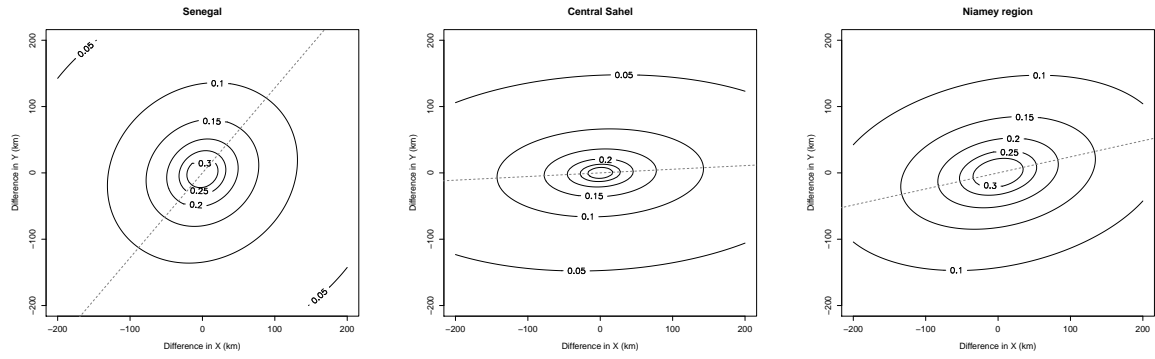
Fig. 3 shows the empirical estimates of $\chi_{ij}(0.99)$, the conditional probability of co-exceeding the 99%-quantile, for all the pairs of stations (i, j) lying in either region. The value of $p = 0.99$ is chosen for illustration with the aim of being far enough in the tail of the distribution while having enough points to make robust empirical estimations. Remind that the 99% quantile corresponds almost to the 1-year return level in JJAS. Estimates are plotted as a function of the anisotropic distance (12) obtained from the estimated Brown-Resnick model of Section 3.2.2 (i.e. with the estimated matrix M in (12)) for the 1950-2014 period. Each plot contains $N(N-1)/2$ points corresponding to the number of pairs of stations. The scatter plot of empirical estimates versus anisotropic distance follows relatively well the curve of $\chi_{ij}(0.99)$ predicted by the estimated Brown-Resnick model, which is given by combining (9), (10), (12) and (13). Let us recall that the model is fitted on the rainfall data directly, and not on the empirical values of $\chi_{ij}(0.99)$ which are uncertain and are only shown here to help judging the quality of the fit. All in all, goodness-of-fit seems satisfactory. Furthermore, in the Central Sahel case, the empirical estimates of the AMMA-CATCH network are also relatively well aligned along the predicted curve, although the estimation is made independently of these data. However the estimated model tends to slightly underestimate the probability of conditional exceedances at very small distance. This may be due to the combination of several factors: first, the fact that AMMA-CATCH network covers a much smaller domain and dependence in the Niamey region may be slightly different than in the whole Central Sahel box. Related to this is the fact that few pairs are located at short distances in the Central Sahel network, and this may induce some bias for estimating the small scale dependence. Add to this the fact that AMMA-CATCH network covers only the most recent period (1990-2015) and co-occurrence of extremes may have changed since 1950. This question will be investigated in Section 4.2.

In order to allow comparison of the estimated probability of concomitant exceedances in the two region, we plot in Fig. 4 the values of χ_{ij}^+ as a function of the difference in coordinates $(s_j - s_i)$, in the two regions, adding the plot obtained for Niamey region from AMMA-CATCH network. Remind that χ_{ij}^+ is an approximate of the conditional probability of exceeding the K -year return level, for any $K \geq 1$ but $K \leq 100$ to embrace roughly the observed range of levels. For shortness, it is referred below as the conditional probability of concomitant large exceedances. As mentioned in Section 3.2.3, contours of



409 **Figure 3.** Empirical estimates of $\chi_{ij}(0.99)$, the conditional probability of co-exceeding the 99%-quantile,
 410 for all pairs (i, j) lying in (left) Senegal and (right) the Central Sahel, as a function of the anisotropic distance
 411 (12). The red curve shows the values predicted by the estimated Brown-Resnick process for the 1950-2014
 412 period. The horizontal lines at abscissa 1 and 0.01 correspond respectively to cases of complete dependence
 413 and independence. In the Central Sahel case, the gray points show the empirical estimates obtained for the
 414 AMMA-CATCH network covering the period 1990-2014.

422 $\chi_{ij}^+ = p$ delineate circles or ellipses, depending on whether dependence is respectively
 423 isotropic or anisotropic. Fig. 4 shows that a slight anisotropy is found in Senegal. The
 424 conditional probability of concomitant large exceedances is slightly larger in the E-50-
 425 N direction (i.e. bearing 50° anti-clockwise from East, with ψ of (13) estimated to 50°).
 426 Anisotropy is more marked in the Central Sahel region with enhanced concomitance in the
 427 E-W direction ($\hat{\psi} \approx 0$). At a given distance, Senegal shows a slightly larger probability
 428 of concomitance than the Central Sahel. For example there is on average 12% chance that
 429 a location in Senegal receives some extreme rainfall amount a day when extreme amount
 430 is received 100km away (i.e. the average χ_{ij}^+ is 0.12 at 100km distance). In the Central
 431 Sahel, there is on average 9% chance. In Niamey region, we find a marked anisotropy, as
 432 in the Central Sahel case, however the direction of maximum probability of concomitance
 433 is shifted to E-15-N. The dependence is also larger than in the entire Central Sahel region
 434 with e.g. on average 15% chance of conditional large exceedances at 100km distance. As
 435 already mentioned, these differences may be due to the different domains, periods of ob-
 436 servations and spatial scales the two networks allow to document.

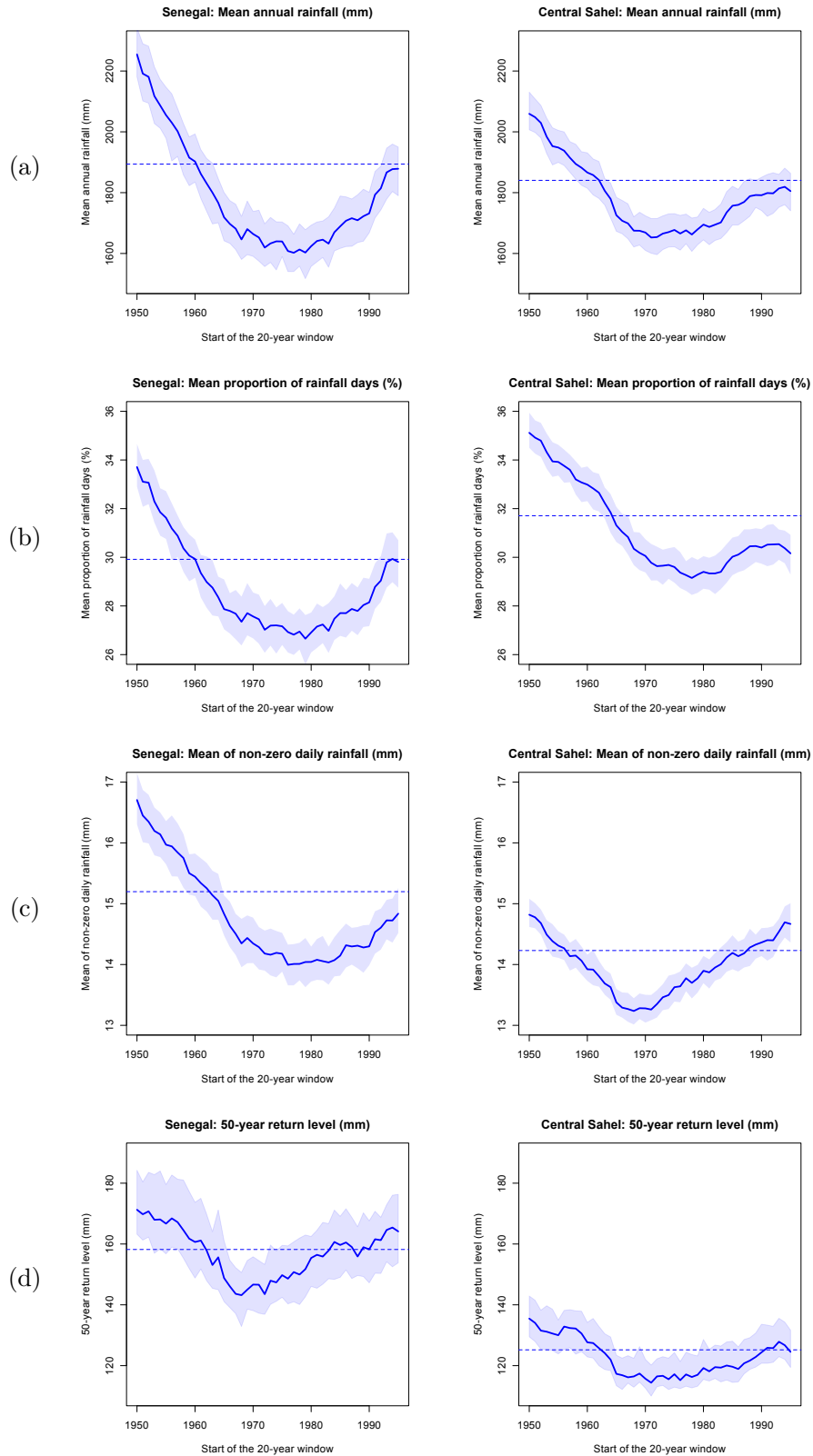


437 **Figure 4.** Values of χ_{ij}^+ , the conditional probability of concomitant large exceedances, under Brown-
 438 Resnick model, as a function of the difference in UTM coordinates ($s_i - s_j$), for sites lying in (left) Senegal,
 439 (middle) the Central Sahel, and (right) the region of Niamey. In the latter case, estimation is based on the
 440 1990-2014 period while in the two former cases it is based on the 1950-2014 period. The gray dotted lines
 441 show the direction of maximum conditional probability of large exceedances, given by ψ of (13).

42 4.2 Moving window case

43 4.2.1 Marginal distributions

44 Fig. 5 shows the evolution of the regional averages of (a): mean annual rainfall, (b):
 445 mean proportion of rainfall days, (c): mean of non-zero daily rainfall and (d): 50-year
 446 return levels, estimated on 20-year moving windows from 1950-1969 to 1995-2014. The
 447 95% confidence intervals are obtained from 200 bootstrap samples, resampling the days
 448 with replacement for each window and each station. Surprisingly contrasting results are
 449 found in Senegal and the Central Sahel for the mean values (a to c). In Senegal, three
 450 periods are found for the mean annual rainfall (a), with a decrease from the 50s to the
 451 70s, followed by a relative stationarity till the 80s and an increase since then. This is in
 452 line with the results of *Lebel and Ali* [2009] and *Nicholson* [2013]. The increase since
 453 the 80s is due to an increase in both the proportion of wet days (b) and the mean rainfall
 454 during wet days (c). Despite the increase in the last decades, the levels of the mean values
 455 (a to c) at the end of the period have barely reached the stationary levels. In the Central
 456 Sahel, two periods are mainly found for the mean values (a to c). A decrease is found
 457 from the 50s to the 70s, as in Senegal, but followed by an increase since the 70s, which is
 458 particularly strong for the mean rainfall during wet days (c).



459 **Figure 5.** Regional averages of (a): mean annual rainfall, (b): mean proportion of rainfall days, (c): mean
 460 of non-zero daily rainfall and (d): 50-year return levels, estimated on 20-year moving windows from 1950-
 461 1969 to 1995-2014, in (left) Senegal, and (right) the Central Sahel. The dashed horizontal lines show the
 462 averages obtained over the whole period. The colored bands show the 95%-confidence intervals obtained
 463 from 200 bootstrap samples.

464 For the 50-year return level (d), similar evolutions are found for the two regions,
 465 with two main regimes. First, a decrease between the 50s and the 70s, with return levels
 466 15% smaller in 1968-1977 than they used to be in 1950-1969. This period of decrease is
 467 followed by a period of increase in both regions since the 70s-80s, particularly in Sene-
 468 gal. The 50-year return levels in Senegal have exceeded the stationary levels since the
 469 80s and almost reached the levels of the beginning of the period. In the Central Sahel,
 470 the stationary levels have barely been recovered so far. These results on extreme rainfalls
 471 evolution in the Central Sahel are coherent with *Panthou et al.* [2013] who found a sig-
 472 nificant decrease of around 10% in the 2-year return level of the periods 1950-1969 and
 473 1970-1990. Over the recent decade, the evolution of the K -year return level in the Cen-
 474 tral Sahel is also in line with the upward trend in daily rainfall maxima shown by *Panthou*
 475 *et al.* [2014].

4.2.2 Co-occurrence of extremes

476
 477 Fig. 6 shows the ellipses of the contours $\{\chi_{ij}^+ = 0.1\}$ predicted by the Brown-
 478 Resnick model estimated on 20-year moving windows for the two regions. Thus each el-
 479 lipse delineates the set of points having 10% chance of exceeding some extreme level a
 480 day when some extreme level is exceeded in the center of the ellipses. To better assess
 481 changes in these ellipses, we also plot in Fig. 6 the length of the minor and major axis of
 482 the ellipses. In order to assess uncertainty in these values, a bootstrap method is applied.
 483 For each window and each region, i) we sample the days with replacement; ii) we estimate
 484 the marginal GPD distributions on the bootstrap data exceeding the threshold u_j used for
 485 the original data (thus the threshold itself does not change along the bootstrap procedure);
 486 iii) we transform the data exceeding the threshold into unit-Fréchet variates; iv) we fit the
 487 anisotropic Brown-Resnick model on these new data. We apply this 200 times, giving 200
 488 bootstrap estimations for each window. The confidence bands in Fig. 6 show the 0.025-
 489 and 0.975-quantile of these estimations.

490 In Senegal, concomitance for the periods 1950-1969 to 1975-1994 is characterized
 491 by a preferred direction in the E-50-N direction, which is also the direction found in the
 492 stationary case (see Section 4.1.2). However concomitance of the largest rainfalls along
 493 this direction was more likely during this period than over all 1950-2014, as shown by the
 494 major axis compared to the stationary case in Fig. 6. This anisotropy can be considered as

495 relatively significant since there is little overlap of the 95% confidence bands of the major
496 and minor axis lengths.

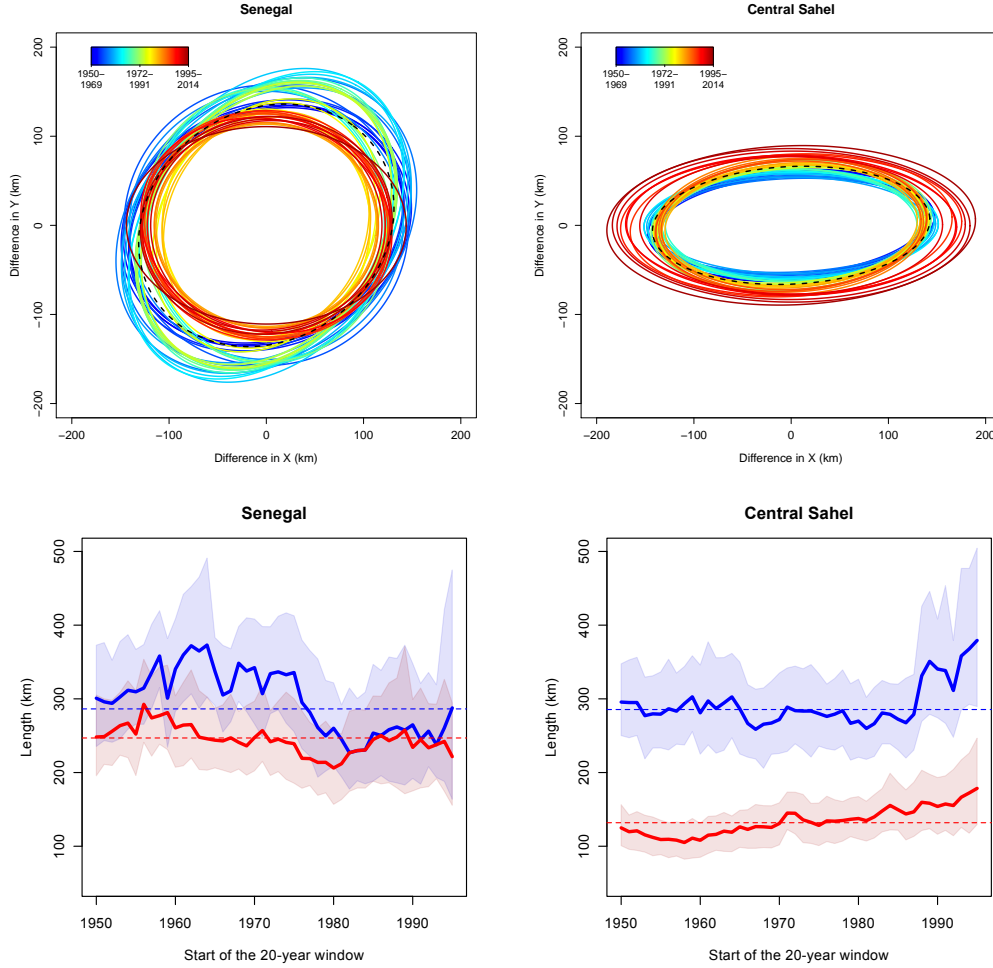
497 For the periods 1976-1995 to 1981-2000, ellipses are less and less elongated, which
498 means that within this period, the preferred direction of concomitance vanished. Finally,
499 from 1982-2001 to 1995-2014, concomitance is characterized by a stability in the shape of
500 the ellipses which are roughly isotropic (i.e. the lengths of the major and minor axes are
501 equal). Thus since the 80s concomitance of extreme rainfall is as likely in any direction
502 but weaker than it used to be, as shown by the red ellipses of Fig. 6.

503 In the Central Sahel, the periods from 1950-1969 to 1981-2000 are characterized by
504 a relative stability in the shape of the ellipses of co-occurrence, with a preferred direction
505 in roughly the E-W direction, as in the stationary case of Section 4.1.2. Judging by the
506 confidence bands in Fig. 6, this preferred direction is highly significant. As for the Senegal,
507 a change in the shape of the ellipses is found in the 80s but surprisingly with opposite
508 consequences. The period from 1982-2001 to 1990-2014 is characterized by a strong enlargement
509 of the ellipses of Fig. 6 in all directions, meaning that, contrary to Senegal,
510 co-occurrence tends to be significantly stronger in all directions these last years.

516 **5 Conclusions and Discussion**

517 In this paper we study the co-occurrence of extreme daily rainfall and its evolution
518 since 1950 in two Sahelian regions: the Western (Senegal) and the Central Sahel. Our
519 approach is based on a max-stable modeling of rainfall threshold exceedances. This allows
520 us to quantify the probability of experiencing concomitant extremes in these regions and
521 to document, in a moving window approach, whether and to what extent this probability
522 has evolved since 1950.

523 Some features of the evolution of extreme rainfall regime appear to be consistent
524 for both studied Sahelian regions. They concern the evolution of the marginal distributions
525 of extreme daily rainfall. A change in the 80s is found with a period of decreasing
526 rainfall intensity between the 50s and the 70s, followed by a period of increasing intensity
527 since the 80s. This confirms previous results found for the Central Sahel by *Panthou*
528 *et al.* [2013] and *Panthou et al.* [2014]. It is also in line with the increasing trend in extreme
529 rainfall detected since 1982 by *Taylor et al.* [2017] over the entire Sahel. However
530 some results show contrasted evolutions between Senegal and the Central Sahel. In Senegal



511 **Figure 6.** Top: Contours of $\{\chi_{ij}^+ = 0.1\}$ estimated on 20-year moving windows in (left) Senegal, and (right)
 512 the Central Sahel. The dotted black ellipses are the contours obtained in the stationary case (see Fig. 4). Bot-
 513 tom: Length of the major (blue) and minor (red) axes of the ellipses delineating the contours $\{\chi_{ij}^+ = 0.1\}$, as
 514 a function of the starting year of the 20-year moving windows. The bands show the 95% confidence intervals
 515 obtained for 200 bootstrap samples. The dotted horizontal lines are the values obtained in the stationary case.

531 gal, a change is found in the 80s in the size and direction of the ellipses delineating the
532 contours of co-occurrence at extreme levels, with preferred co-occurrence in the direction
533 E-50-N before the 80s, and isotropic co-occurrence with lesser extent afterwards. In the
534 Central Sahel, a change is also found in the 80s but with opposite consequences. Ellipses
535 of co-occurrence show a greater extent after the 80s, while anisotropy remains in the E-W
536 direction over the whole period.

537 These contrasts raise several questions about the evolution of extreme precipitation
538 systems. In the Sahel, most of the rainfall is produced by Mesoscale Convective Systems
539 (MCSs). MCSs are often organized in squall lines propagating from East to West. Under
540 particular conditions, organized convective systems can be stationary (long-lasting sys-
541 tems) and may produce large rainfall amounts over a particular location [*Lafore et al.*,
542 2017; *Vischel et al.*, 2017]. Local convection can also occur, but this generally produces
543 less rainfall. We refer to *Laurent et al.* [1998] and *Mathon et al.* [2002] for a review of
544 MCSs climatology in the Sahel.

545 The observed evolution of the ellipses of co-occurrence in extremes can be inter-
546 preted in light of a change in typology of extreme precipitation systems, assuming some
547 link between the two of them. First, one can postulate that anisotropic ellipses correspond
548 to propagative systems, while isotropic ellipses correspond to stationary systems, and that
549 the more elongated the ellipses, the more propagative the system. Second, larger probabil-
550 ities of concomitant extremes (larger minor axis and/or bigger ellipses) can be expected to
551 come from bigger extreme rainfall systems.

552 If these assumptions hold, then the increase in the size of the ellipses since the
553 80s in the Central Sahel would be a consequence of more propagative and slightly big-
554 ger MCSs. This is a plausible hypothesis since the more organized systems in this re-
555 gion [Mesoscale Convective Complex, as defined by *Mathon et al.*, 2002] have such spa-
556 tial characteristics and are very rainy efficient [*Laurent et al.*, 1998; *Mathon et al.*, 2002].
557 The way we interpret the changes in ellipse features is supported by the recent results of
558 *Taylor et al.* [2017]. They show from Infra-Red (IR) satellite data (period 1982-2016) that
559 the trend in extreme rainfall is associated with a significant increasing trend in the verti-
560 cal development of the largest Sahelian MCSs, that are known to propagate faster, and to
561 a smaller extent with a trend in their horizontal extension. This evolution of MCS features

562 is retrieved in Fig. 6 where the trend in the major axis of ellipses in the Central Sahel is
563 more pronounced than the trend in their minor axis.

564 Following the same reasoning in Senegal, the transition between anisotropic to isotropic
565 ellipses could be the manifestation of (i) a transition between a large proportion of prop-
566 agative systems to a large proportion of stationary systems, (ii) a more erratic propagative
567 direction of systems, and/or (iii) more localized but intense convection.

568 The reasons for such a contrasted evolution of extreme rainy system features be-
569 tween Senegal and the Central Sahel still have to be determined. The main drivers of the
570 rainfall intensification in the Sahel have been recently identified by *Taylor et al.* [2017].
571 They incriminate the warming of the Saharan (in link to anthropogenic GHG emissions)
572 since it intensifies convection within MCSs through increased wind shear and intrusion of
573 the hot and dry Saharan air layer at the mid-troposphere. These factors tend to decrease
574 the occurrence of small and localized systems (due to higher convective energy barriers
575 initiating convection) but favor higher development and stronger storms once convection
576 is initiated. While these processes support our results in the Central Sahel, they do not
577 directly explain why storm properties evolved differently in the Western Sahel. *Lebel and*
578 *Ali* [2009] have pointed out the presence of an East-West contrast over the period 1990-
579 2007 with a Western Sahel remaining dryer than the Central Sahel for which a relative
580 increase of mean annual rainfall was observed. This zonal rainfall dipole is also a consis-
581 tent pattern in GCM rainfall projections [*Monerie et al.*, 2012; *Gaetani et al.*, 2017] and is
582 expected to accentuate over the 21st century [*James et al.*, 2015]. The warming of the Sa-
583 hara is also thought to be responsible for this contrast especially through the enhancement
584 of the Saharan Heat Low activity which simultaneously favors air subsidence in the West
585 - preventing deep moist convection - and accentuates monsoon fluxes in the Central Sahel
586 [*Monerie et al.*, 2012; *James et al.*, 2015; *Lavaysse et al.*, 2015].

587 However the way these changes in monsoon circulation might affect extreme rainy
588 systems properties differently in the West and the Central Sahel remains an open question.
589 In addition to these synoptic features, more local processes due to land-ocean interface
590 can also not be excluded to have an influence on storm development and propagation.

591 While the main objective of the present paper was to apply a modern statistical
592 frameworks to characterize the extreme rainfall co-occurrence, the way we interpret the
593 results in light of changes in storm features and atmospheric environment calls for further

594 research. Next work will be to use other datasets from which MCS properties can be in-
595 ferred to confirm the contrasted trends in MCS properties in Senegal and Central Sahel.
596 To that end, the direct analysis of brightness temperature from IR satellite data as in *Tay-*
597 *lor et al.* [2017] or the analysis of IR-derived MCS tracking products [as those proposed
598 by *Fiolleau and Roca, 2013*] might be considered. Further work is also required to better
599 understand the atmospheric mechanisms responsible for the contrasted changes in storms
600 properties. A first option to that end is to make an analytic approach similar to that pro-
601 posed by *Taylor et al.* [2017], including the analysis of regional contrasts in storms proper-
602 ties within the Sahel. A second possibility is to extend the case studies of extreme events
603 such as *Lafore et al.* [2017] and *Vischel et al.* [2017] in Ouagadougou to other locations in
604 the Sahel [see e.g. *Engel et al., 2017*]. Atmospheric simulation experiments, in particular
605 high-resolution convection-permitting simulations, could also be very helpful to find some
606 physical explanations of the observed trends in the co-occurrence of extremes.

607 **Acknowledgments**

608 The research leading to these results has received funding from the NERC/DFID Future
609 Climate For Africa programme under the AMMA-2050 project, grant numbers NE/M020428/1.
610 This work was also supported by the French national programme EC2CO-LEFE "Recent
611 evolution of hydro-climatic hazards in the Sahel: detection and attribution". The AMMA-
612 CATCH rainfall data are freely available at <http://bd.amma-catch.org/> except for the last
613 three years which are subject to restricted access. The other daily data are subject to ac-
614 cess restrictions according to the data policy defined by the National Weather Services in
615 Senegal, Burkina Faso, Niger, Benin and Togo and are not freely available.

616 **References**

- 617 Ali, A., T. Lebel, and A. Amani (2003), Invariance in the Spatial Structure of Sahelian
618 Rain Fields at Climatological Scales, *Journal of Hydrometeorology*, 4, 996–1011.
- 619 Ali, A., A. Amani, T. Lebel, and S. Ibrahima (2006), Utilisation optimale de l'information
620 pluviométrique des MCGA aux échelles hydrologiques au Sahel = Optimal use of GCM
621 rainfall information at the hydrological scale in the Sahel, in *Climate Variability and*
622 *Change - Hydrological Impacts*, pp. 430–435, International Association of Hydrological
623 Sciences press, Wallingford, ROYAUME-UNI, Havana, Cuba.

- 624 Asadi, P., A. C. Davison, and S. Engelke (2015), Extremes on river networks, *Ann. Appl.*
625 *Stat.*, 9(4), 2023–2050, doi:10.1214/15-AOAS863.
- 626 Bacro, J.-N., and C. Gaetan (2014), Estimation of spatial max-stable models using thresh-
627 old exceedances, *Statistics and Computing*, 24(4), 651–662, doi:10.1007/s11222-013-
628 9394-4.
- 629 Bell, M. A., and P. J. Lamb (2006), Integration of weather system variability to multi-
630 decadal regional climate change: The West African Sudan-Sahel zone, 1951-98, *Journal*
631 *of Climate*, 19(20), 5343–5365.
- 632 Blanchet, J., and A. C. Davison (2011), Spatial modeling of extreme snow depth, *Annals*
633 *of Applied Statistics*, 5(3), 1699–1725.
- 634 Castruccio, S., R. Huser, and M. G. Genton (2016), High-Order Composite Likelihood
635 Inference for Max-Stable Distributions and Processes, *Journal of Computational and*
636 *Graphical Statistics*, 25(4), 1212–1229, doi:10.1080/10618600.2015.1086656.
- 637 Ceresetti, D., S. Anquetin, G. Molinié, E. Leblois, and J.-D. Creutin (2012), Multiscale
638 Evaluation of Extreme Rainfall Event Predictions Using Severity Diagrams, *Weather*
639 *and Forecasting*, 27, 174–188, doi:10.1175/WAF-D-11-00003.1.
- 640 Coles, S. (2001), *An introduction to statistical modeling of extreme values*, Springer Series
641 in Statistics, Springer-Verlag, London.
- 642 Coles, S., J. Heffernan, and J. Tawn (1999), Dependence Measures for Extreme Value
643 Analyses, *Extremes*, 2(4), 339–365, doi:10.1023/A:1009963131610.
- 644 Dai, A., P. J. Lamb, K. E. Trenberth, M. Hulme, P. D. Jones, and P. Xie (2004), The re-
645 cent Sahel drought is real, *International Journal of Climatology*, 24(11), 1323–1331,
646 doi:10.1002/joc.1083.
- 647 Davison, A. C., and M. M. Gholamrezaee (2011), Geostatistics of extremes, *Proceedings*
648 *of the Royal Society of London A: Mathematical, Physical and Engineering Sciences*, doi:
649 10.1098/rspa.2011.0412.
- 650 Davison, A. C., S. A. Padoan, and M. Ribatet (2012), Statistical Modeling of Spatial Ex-
651 tremes, *Statistical Science*, 27(2), 161–186, doi:10.1214/11-STS376.
- 652 Davison, A. C., R. Huser, and E. Thibaud (2013), Geostatistics of Dependent and Asymp-
653 totically Independent Extremes, *Mathematical Geosciences*, 45(5), 511–529, doi:
654 10.1007/s11004-013-9469-y.
- 655 de Haan, L., and A. Ferreira (2006), *Extreme Value Theory: An Introduction*, Springer
656 Series in Operations Research and Financial Engineering, 1 ed., Springer-Verlag New

- 657 York, doi:10.1007/0-387-34471-3.
- 658 De Michele, C., N. Kottegoda, and R. Rosso (2002), IDAF (Intensity-duration-area-
659 frequency) curves of extreme storm rainfall: a scaling approach, *Water Science and
660 Technology*, 45(2), 83–90.
- 661 Delrieu, G., A. Wijbrans, B. Boudevillain, D. Faure, L. Bonnifait, and P.-E. Kirstetter
662 (2014), Geostatistical radar–raingauge merging: A novel method for the quantifi-
663 cation of rain estimation accuracy, *Advances in Water Resources*, 71, 110 – 124, doi:
664 <http://dx.doi.org/10.1016/j.advwatres.2014.06.005>.
- 665 Di Baldassarre, G., A. Montanari, H. Lins, D. Koutsoyiannis, L. Brandimarte, and
666 G. Blöschl (2010), Flood fatalities in Africa: From diagnosis to mitigation, *Geophysi-
667 cal Research Letters*, 37(22), doi:10.1029/2010GL045467.
- 668 Dombry, C., and M. Ribatet (2015), Functional regular variations, Pareto
669 processes and peaks over threshold, *Statistics and Its Interface*, 8(1), doi:
670 <http://dx.doi.org/10.4310/SII.2015.v8.n1.a2>.
- 671 Engel, T., A. H. Fink, P. Knippertz, G. Pante, and J. Bliefernicht (2017), Extreme precipi-
672 tation in the west african cities of dakar and ouagadougou - atmospheric dynamics and
673 implications for flood risk assessments, *Journal of Hydrometeorology*, doi:10.1175/JHM-
674 D-16-0218.1.
- 675 Ferreira, A., and L. de Haan (2014), The generalized Pareto process; with a view towards
676 application and simulation, *Bernoulli*, 20(4), 1717–1737, doi:10.3150/13-BEJ538.
- 677 Ferro, C. A. T., and J. Segers (2003), Inference for Clusters of Extreme Values, *Journal of
678 the Royal Statistical Society. Series B (Statistical Methodology)*, 65(2), pp. 545–556.
- 679 Fiolleau, T., and R. Roca (2013), An Algorithm for the Detection and Tracking of Tropi-
680 cal Mesoscale Convective Systems Using Infrared Images From Geostationary Satel-
681 lite, *IEEE Transactions on Geoscience and Remote Sensing*, 51(7), 4302–4315, doi:
682 10.1109/TGRS.2012.2227762.
- 683 Gaetani, M., C. Flamant, S. Bastin, S. Janicot, C. Lavaysse, F. Hourdin, P. Braconnot, and
684 S. Bony (2017), West African monsoon dynamics and precipitation: the competition be-
685 tween global SST warming and CO2 increase in CMIP5 idealized simulations, *Climate
686 Dynamics*, 48(3), 1353–1373, doi:10.1007/s00382-016-3146-z.
- 687 Gallego, D., P. Ordóñez, P. Ribera, C. Peña-Ortiz, and R. García-Herrera (2015), An in-
688 strumental index of the West African Monsoon back to the nineteenth century: An In-
689 strumental Index of the West African Monsoon, *Quarterly Journal of the Royal Meteorolo-*

- 690 *logical Society*, 141(693), 3166–3176, doi:10.1002/qj.2601.
- 691 Gaume, J., N. Eckert, G. Chambon, M. Naaim, and L. Bel (2013), Mapping extreme
692 snowfalls in the French Alps using max-stable processes, *Water Resources Research*,
693 49(2), 1079–1098, doi:10.1002/wrcr.20083.
- 694 Gerbaux, M., N. Hall, N. Dessay, and I. Zin (2009), The sensitivity of Sahelian runoff
695 to climate change / Sensibilite au changement climatique du ruissellement au Sahel,
696 *Hydrological Sciences Journal*, 54(1), 5–16, doi:10.1623/hysj.54.1.5.
- 697 Hulme, M., R. Doherty, T. Ngara, M. New, and D. Lister (2001), African climate change:
698 1900-2100, *Climate Research*, 17(2), 145–168.
- 699 Huser, R., and A. C. Davison (2013), Composite likelihood estimation for the Brown-
700 Resnick process, *Biometrika*, 100(2), 511–518, doi:10.1093/biomet/ass089.
- 701 Huser, R., and A. C. Davison (2014), Space-time modelling of extreme events, *Journal*
702 *of the Royal Statistical Society: Series B (Statistical Methodology)*, 76(2), 439–461, doi:
703 10.1111/rssb.12035.
- 704 James, R., R. Washington, and R. Jones (2015), Process-based assessment of an ensemble
705 of climate projections for West Africa, *Journal of Geophysical Research: Atmospheres*,
706 120(4), 1221–1238, doi:10.1002/2014JD022513.
- 707 Kabluchko, Z., M. Schlather, and L. d. Haan (2009), Stationary Max-Stable Fields Associ-
708 ated to Negative Definite Functions, *The Annals of Probability*, 37(5), pp. 2042–2065.
- 709 Lafore, J.-P., F. Beucher, P. Peyrillé, A. Diongue-Niang, N. Chapelon, D. Bouniol, G. Ca-
710 niaux, F. Favot, F. Ferry, F. Guichard, E. Poan, R. Roehrig, and T. Vischel (2017), A
711 multi-scale analysis of the extreme rain event of ouagadougou in 2009, *Quarterly Jour-
712 nal of the Royal Meteorological Society*, doi:10.1002/qj.3165, qJ-17-0033.R2.
- 713 Laurent, H., N. D’Amato, and T. Lebel (1998), How Important is the Contribution of the
714 Mesoscale Convective Complexes to the Sahelian Rainfall?, *Journal of Physics and
715 Chemistry of The Earth*, 23, 629–633.
- 716 Lavaysse, C., C. Flamant, A. Evan, S. Janicot, and M. Gaetani (2015), Recent climatolog-
717 ical trend of the Saharan heat low and its impact on the West African climate, *Climate
718 Dynamics*, pp. 1–20, doi:10.1007/s00382-015-2847-z.
- 719 Le Barbé, L., and T. Lebel (1997), Rainfall climatology of the HAPEX-Sahel region dur-
720 ing the years 1950-1990, *Journal of Hydrology*, 188-189, 43–73.
- 721 Le Barbé, L., T. Lebel, and D. Tapsoba (2002), Rainfall Variability in West Africa during
722 the Years 1950-90, *Journal of Climate*, 15, 187–202.

- 723 Lebel, T., and A. Ali (2009), Recent trends in the Central and Western Sahel rainfall
724 regime (1990-2007), *Journal of Hydrology*, 375(1-2), 52–64.
- 725 Lebel, T., A. Diedhiou, and H. Laurent (2003), Seasonal cycle and interannual variability
726 of the Sahelian rainfall at hydrological scales, *Journal Of Geophysical Research*, 108,
727 doi:10.1029/2001JD001,580.
- 728 Lebel, T., B. Cappelaere, S. Galle, N. Hanan, L. Kergoat, S. Levis, B. Vieux, L. Descroix,
729 M. Gosset, E. Mougin, C. Peugeot, and L. Seguis (2009), AMMA-CATCH studies in
730 the Sahelian region of West-Africa: An overview, *Journal of Hydrology*, 375(1–2),
731 3 – 13, doi:https://doi.org/10.1016/j.jhydrol.2009.03.020, surface processes and water
732 cycle in West Africa, studied from the AMMA-CATCH observing system.
- 733 Mathon, V., H. Laurent, and T. Lebel (2002), Mesoscale Convective System Rainfall in the
734 Sahel, *Journal of Applied Meteorology*, 41, 1081–1092.
- 735 Monerie, P.-A., B. Fontaine, and P. Roucou (2012), Expected future changes in the
736 African monsoon between 2030 and 2070 using some CMIP3 and CMIP5 models under
737 a medium-low RCP scenario, *Journal of Geophysical Research: Atmospheres*, 117(D16),
738 n/a–n/a, doi:10.1029/2012JD017510.
- 739 Nicholson, S. (2005), On the question of the “recovery” of the rains in
740 the West African Sahel, *Journal of Arid Environments*, 63(3), 615 – 641, doi:
741 https://doi.org/10.1016/j.jaridenv.2005.03.004, special Issue on The Greening of the Sa-
742 hel.
- 743 Nicholson, S. E. (2013), The West African Sahel: A Review of Recent Studies on the
744 Rainfall Regime and Its Interannual Variability, *ISRN Meteorology*, 2013, 1–32, doi:
745 10.1155/2013/453521.
- 746 Nicolet, G., N. Eckert, S. Morin, and J. Blanchet (2016), Decreasing spatial depen-
747 dence in extreme snowfall in the French Alps since 1958 under climate change, *Jour-
748 nal of Geophysical Research: Atmospheres*, pp. n/a–n/a, doi:10.1002/2016JD025427,
749 2016JD025427.
- 750 Nicolet, G., N. Eckert, S. Morin, and J. Blanchet (2017), A multi-criteria leave-two-out
751 cross-validation procedure for max-stable process selection, *Spatial Statistics*, 22(Part 1),
752 107 – 128, doi:https://doi.org/10.1016/j.spasta.2017.09.004.
- 753 Opitz, T. (2013), Extremal processes: Elliptical domain of attraction and a spec-
754 tral representation, *Journal of Multivariate Analysis*, 122, 409 – 413, doi:
755 http://dx.doi.org/10.1016/j.jmva.2013.08.008.

- 756 Padoan, S. A., M. Ribatet, and S. A. Sisson (2010), Likelihood-Based Inference for Max-
757 Stable Processes, *Journal of the American Statistical Association*, 105(489), 263–277,
758 doi:10.1198/jasa.2009.tm08577.
- 759 Panthou, G., T. Vischel, T. Lebel, J. Blanchet, G. Quantin, and A. Ali (2012), Extreme
760 rainfall in West Africa: A regional modeling, *Water Resources Research*, 48, W08,501,
761 doi:10.1029/2012WR012052.
- 762 Panthou, G., T. Vischel, T. Lebel, G. Quantin, A.-C. F. Pugin, J. Blanchet, and A. Ali
763 (2013), From pointwise testing to a regional vision: An integrated statistical ap-
764 proach to detect nonstationarity in extreme daily rainfall. Application to the Sahe-
765 lian region, *Journal of Geophysical Research: Atmospheres*, 118(15), 8222–8237, doi:
766 10.1002/jgrd.50340.
- 767 Panthou, G., T. Vischel, T. Lebel, G. Quantin, and G. Molinié (2014), Characterising the
768 space-time structure of rainfall in the Sahel with a view to estimating IDAF curves, *Hy-
769 drology and Earth System Sciences*, 18(12), 5093–5107, doi:10.5194/hess-18-5093-2014.
- 770 Raillard, N., P. Ailliot, and J. Yao (2014), Modeling extreme values of processes observed
771 at irregular time steps: Application to significant wave height, *Ann. Appl. Stat.*, 8(1),
772 622–647, doi:10.1214/13-AOAS711.
- 773 Reich, B. J., B. A. Shaby, and D. Cooley (2014), A Hierarchical Model for Serially-
774 Dependent Extremes: A Study of Heat Waves in the Western US, *Journal of Agricul-
775 tural, Biological, and Environmental Statistics*, 19(1), 119–135, doi:10.1007/s13253-013-
776 0161-y.
- 777 Sanogo, S., A. H. Fink, J. A. Omotosho, A. Ba, R. Redl, and V. Ermert (2015), Spatio-
778 temporal characteristics of the recent rainfall recovery in West Africa, *International
779 Journal of Climatology*, pp. n/a–n/a, doi:10.1002/joc.4309.
- 780 Schlather, M. (2002), Models for Stationary Max-Stable Random Fields, *Extremes*, 5(1),
781 33–44, doi:10.1023/A:1020977924878.
- 782 Shaby, B. A., and B. J. Reich (2012), Bayesian spatial extreme value analysis to assess
783 the changing risk of concurrent high temperatures across large portions of European
784 cropland, *Environmetrics*, 23(8), 638–648, doi:10.1002/env.2178.
- 785 Shang, H., J. Yan, and X. Zhang (2011), El Niño-Southern Oscillation influence on winter
786 maximum daily precipitation in California in a spatial model, *Water Resources Research*,
787 47(11), n/a–n/a, doi:10.1029/2011WR010415, w11507.

- 788 Tarhule, A. (2005), Damaging Rainfall and Flooding: The Other Sahel Hazards, *Climatic*
789 *Change*, 72(3), 355–377, doi:10.1007/s10584-005-6792-4.
- 790 Taylor, C., D. Belusic, F. Guichard, D. Parker, T. Vischel, O. Bock, P. Harris, S. Janicot,
791 C. Klein, and G. Panthou (2017), Frequency of extreme Sahelian storms tripled since
792 1982 in satellite observations, *Nature*, 544(7651), 475–478, doi:10.1038/nature22069.
- 793 Thibaud, E., and T. Opitz (2015), Efficient inference and simulation for elliptical Pareto
794 processes, *Biometrika*, 102(4), 855–870, doi:10.1093/biomet/asv045.
- 795 Thibaud, E., R. Mutzner, and A. C. Davison (2013), Threshold modeling of extreme spa-
796 tial rainfall, *Water Resources Research*, 49(8), 4633–4644, doi:10.1002/wrcr.20329.
- 797 Varin, C., N. Reid, and D. Firth (2011), AN OVERVIEW OF COMPOSITE LIKELI-
798 HOOD METHODS, *Statistica Sinica*, 21(1), 5–42.
- 799 Vischel, T., and T. Lebel (2007), Assessing the water balance in the Sahel: Impact of
800 small scale rainfall variability on runoff. Part 2: Idealized modeling of runoff sensi-
801 tivity, *Journal of Hydrology*, 333(2-4), 340–355.
- 802 Vischel, T., G. Panthou, P. Peyrillé, R. Roehrig, G. Quantin, T. Lebel, C. Wilcox,
803 F. Beucher, and M. Budiarti (2017), Precipitation extremes in the West African Sahel:
804 recent evolution and physical mechanisms, in *Tropical Climate Extremes: Natural Vari-*
805 *ability and Trends*, Synthèses, elsevier ed.
- 806 Wadsworth, J. L., and J. A. Tawn (2012), Dependence modelling for spatial extremes,
807 *Biometrika*, 99(2), 253–272, doi:10.1093/biomet/asr080.
- 808 Wadsworth, J. L., and J. A. Tawn (2014), Efficient inference for spatial extreme value
809 processes associated to log-Gaussian random functions, *Biometrika*, 101(1), 1–15, doi:
810 10.1093/biomet/ast042.
- 811 Westra, S., and S. A. Sisson (2011), Detection of non-stationarity in precipitation ex-
812 tremes using a max-stable process model, *Journal of Hydrology*, 406(1–2), 119–128,
813 doi:http://dx.doi.org/10.1016/j.jhydrol.2011.06.014.
- 814 Zhang, Q., M. Xiao, V. P. Singh, and Y. D. Chen (2014), Max-stable based evalu-
815 ation of impacts of climate indices on extreme precipitation processes across the
816 Poyang Lake basin, China, *Global and Planetary Change*, 122, 271 – 281, doi:
817 https://doi.org/10.1016/j.gloplacha.2014.09.005.