Reviewer #2:

GENERAL COMMENTS.

In my opinion, essentially this paper only adds “noise” to the existing Literature: the techniques used have already been published in other works, the only novelty (clearly, not a methodological one) could be the case study, but any new case study must represent a newness over previous ones (otherwise it would be a replica). Most importantly, the work is in general statistically weak, and affected and flawed by fatal errors: the conclusions of the Authors may not be supported by the analyses they carried out. Apparently, the Authors (incorrectly) interpret the results according to their convenience, in order to prove what they want to prove, as shown below. In addition, referencing is often imprecise and/or improper and/or missing: always give credits to whom deserve credits. My recommendation is: REJECTION.

Response to Reviewer 2:

Great appreciation for this comment!

We have taken the review’s suggestions into consideration. Firstly, a nonstationary and stationary GOF tests were implemented for marginal distribution and copula models. In addition, we implement the log likelihood ratio (LR) statistics to check the trend in parameters of distribution, which is more rigorous trend detection method than Mann-Kendall tests (Coles, 2001). We considered more extreme series from more stations in the study area. Because of the insignificant trend denoted by reviewer #1 in the original manuscript, we changed the original 95-th percentile threshold for *Ps* to 0.90. After above modification of extreme values, the significant trend and change point at 5% significance level could be detected in 3 stations by nonparametric tests. Here, we proposed the LR tests to detect the trend in parameter after the Mann-Kendall tests. Some interesting findings are captured. A detailed point-by-point reply has been made as follows.

SPECIFIC COMMENTS.

Line(s) 49–54.

Authors. Copulas, a useful tool for modelling the structure of dependence between hydrological variables regardless of the types of marginal distributions, have been widely used for multivariate frequency analysis + references...

Referee. Historically, the paper by Salvadori and De Michele (2004) was the first one to deal with (copula) multivariate frequency analysis—later works are copies or small variants: this paper is not cited. Please, always give credits to whom deserve credits.

Response: We have added this reference to the revised manuscript.

Line(s) 75–ff.

Authors. There are three kinds of joint return period methods...

Referee. NO. In Literature there are, at least, four kinds of joint return periods. The references given are incorrect. In Salvadori and De Michele (2004) the OR, AND and Kendall cases were first introduced. In Salvadori et al. (2013) a further survival-Kendall approach (not mentioned by the Authors) was outlined. Referencing is often imprecise, almost random: for instance, why citing Jiang et al. (2015) here? It has nothing to do with the original formalization of the four return periods mentioned above. Incidentally, the reference “Salvadori and Michele, 2010” is “Salvadori and De Michele, 2010” (it seems that the Authors wrote the references by hand, instead of using some suitable software...).

Response: we have modified the above statement about the joint return period. And give credits to whom deserve credits at right places. Lines 315-325 in revised manuscript.

Line(s) 95–97.

Authors. Note that following the idea of Rootzén and Katz (2013) we regard the term hydrological risk as the possibility of a certain extreme event occurring and not as a quantification of expected losses.

Referee. Then, probabilistically and statistically speaking (and hydrologically as well!), you should better use the term “hazard” instead of “risk”.

Response: We take the advice by reviewer. And we modified this statement. And also we have changed the title to “Time-varying copula and average annual reliability-based nonstationary hazard assessment of extreme rainfall events.”

Line(s) 126.

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Authors. Detailed information about copulas can be found in Nelson (2007).

Referee. NO. It is Nelsen (2006), not Nelson. For an engineering approach, you may also cite Salvadori et al. (2007). As a strong suggestion, the Authors should carefully check the correctness of all the references (it is easy to do it on the Internet), and add the missing ones.

Response: we have revised the quotation of this reference. Add Salvadori et al. (2007) to revised manuscript as follows: "Detailed information of theoretical derivation about copulas can be found in Nelsen (2006). For the practical guidelines from hydrological point of view, it is recommended to refer to Salvadori et al. (2007)."

Line(s) 138–139.

Authors. ... θ_C^t is the dynamic copula parameter which is a linear function of time.

Referee. The Authors must justify this choice. Please do not reply that "the model was taken from this or that paper": it is not a scientific reason, for a model must be validated on the available data. Also, the results of suitable Goodness-of-Fit statistical tests must be shown.

Response: θ_C^t is set as follows in the revised manuscript:

$$\theta_C^t = \begin{cases} \text{constant} \\ \theta_0 + \theta_1 t \\ \theta_0 + \theta_1 t + \theta_2 t^2 \end{cases}$$

As shown above, both the linear and quadratic models are assumed as the possible function relation between parameter and time, which would consider the linear and nonlinear trend for parameter. We implemented the goodness of fit test for copulas based on Rosenblatt's transformation (Rosenblatt, 1952).

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Lines 271-283: "Rosenblatt's transformation (RT) of the time-varying marginal distribution $U = F_X(x|\theta_X^t)$ and $\mathrm{V} = F_Y(\mathrm{y}|\theta_Y^t)$ of bivariate copula can be defined as follows:

$$\begin{cases} RT_1 = u = \ F_X(x|\theta_X^t) \\ RT_2 = C(v|u,|\theta_C^t) = C[F_Y(\mathrm{y}|\theta_Y^t)|F_X(x|\theta_X^t),|\theta_C^t] \end{cases} \quad (5)$$

Where $C(u|v,|\theta_C^t)$ is just the conditional distribution function of v given by u=$F_X(x|\theta_X^t)$.

According to Rosenblatt, the random variable RT_1 and RT_2 is independent and uniformly in the interval [0,1]. In order to check this assumption, it is convenient to calculate:

$$S_i = [\Phi^{-1}(F_X(x_i|\theta_X^t))]^2 + [\Phi^{-1}(C[F_Y(y_i|\theta_Y^t)|F_X(x_i|\theta_X^t),|\theta_C^t])]^2 \quad i = 1, \dots, n \quad (6)$$

Here, n is just the length of the data; and in this study we let time t be equal to 1,2,…,n. If the random sample $\{S_i\}$ comes from a χ_2^2 distribution, it can accept the NULL hypothesis ($\mathcal{H}_0$: dependence structure between X and Y obey the time-varying copula $C(u,v|\theta_C^t)$). Then the Anderson–Darling goodness-of-fit test based on RT (AD_{RT}) should be used for the above assumption." According to the analysis results, the assumed linear and nonlinear trends of copula parameter can pass the GOF tests based on Rosenblatt's transformation.

Line(s) 143–144.

Authors. It is however possible that the nonstationary behavior may exist in both the marginal and joint distribution function.

Referee. Such an issue was already clearly pointed out and discussed in Salvadori et al.

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(2018), where a similar case study was investigated, and a thorough statistical analysis was carried out. The Authors must mention this fact, and follow the (proper statistical) guidelines outlined in that paper.

Response: We have revised this statement. And we mentioned this fact as:

Lines 134-160. "According to Vezzoli et al. (2017) and Salvadori et al. (2018), a comprehensive statistical analysis which can check the presence of trend and change point should be carried out before we incorporate the nonstationarity into the multivariate hazard assessment. Following the study of Salvadori et al. (2018), the non-parametric change-point statistical tests were implemented to check that whether the marginal or joint distributions are sensitive to changes. These tests can be manipulated in the R package npcp (Kojadinovic, 2017)."

Line(s) 158-Figure 1.

The flow-chart shown in Figure 1 provides wrong indications (see also later comments). In fact, the Authors confuse GoF tests with selection criteria. The flow-chart must be rewritten.

Response: we have revised the flowchart of this study **(Figure 1**) as follows:

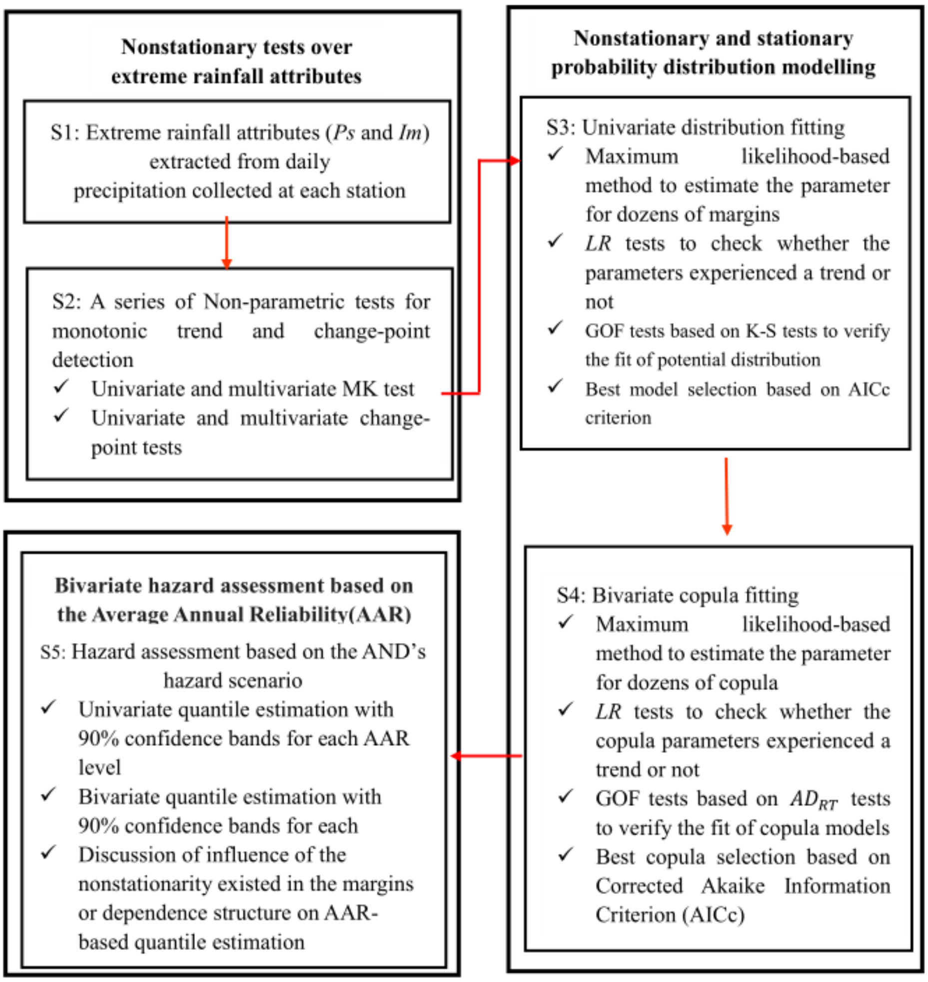

Figure 1. Flowchart of this study

Line(s) 161–164.

Authors. In this part, the Generalized Extreme Value (GEV) distribution was used to... (Cheng and AghaKouchak, 2014).

Referee. This reference makes little sense: the features of the GEV have already been stated and described since decades in other (seminal) works. Please use proper references.

Response: In revised manuscript, five kinds of marginal distribution have been used as candidate distribution. For space limitations, we have deleted the above statement of GEV features.

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Line(s) 166–ff.

Authors. The GEV distribution consists of three control parameters...

Referee. The GEV distribution is well known to hydrologists, there is no need to tell again a story that everybody knows.

Response: we deleted this statement in revised manuscript.

Line(s) 176–179.

Authors. In this study, two kinds of nonstationary GEV models (GEVns-1 and GEVns-2) are developed with the shape parameter being constant. It should be emphasized that modelling the time variance in shape parameter needs long-term observations, which are often not available in practice (Cheng et al., 2014).

Referee. I recently rejected a paper very similar to the present one, where the GEV shape parameter was kept constant. The shape parameter is the most important one, for it rules the generation of extremes. The assumption adopted is definitely questionable: what (extreme) climate change could you really hope to model with a constant shape parameter? Practically, you are trying to model climate changes where the statistics of the extremes do not change with time: it makes little sense. In addition (see also later comments), some estimates of the GEV shape parameter are positive and other negative

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(Table 3). This entails that, in some cases, the corresponding GEV law is upper-bounded, i.e. unable to model an extreme behavior: this is a well known feature of the GEV. I agree that the GEV is the right distribution to be used in your analysis (Block Maxima), but the question is: how can you claim that the phenomenon you are modeling is an extreme one when upper-bounded GEV's are involved? The statistical results seem to tell another story...

Response: Thanks a lot for this suggestion. We have consider the trend in shape parameter. For all the three parameter (location, scale, shape), three kinds of forms are considered. Here we take the location parameter as an example:

$$\mu_t = \begin{cases} \text{constant} \\ \mu_0 + \mu_1 t \\ \mu_0 + \mu_1 t + \mu_2 t^2 \end{cases} \qquad (2)$$

As stated by reviewer, the GEV can be defined as follows:

$$\mathrm{G}(x) = \exp\left[-\left\{1 + \kappa\left(\frac{x-\mu}{\sigma}\right)\right\}_+^{-\frac{1}{\kappa}}\right] \qquad (3)$$

where Z_+=max{z,0}, σ>0 and μ & κ ϵ $(-\infty, \infty)$. When $\kappa < 0$, it recommends the upper-bounded GEV distribution. We have checked the shape parameter of the best fitted GEV models is always positive (station 2,3,6 in **Table 4(a)-(b)**).

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S1(a). Patterns of the time-varying models for 3-parameter marginal distribution (GEV in this study)

Model	μ	σ	κ
GEV0	constant	constant	constant
GEV1	$\mu = \mu_0 + \mu_1 t$	constant	constant
GEV2	$\mu = \mu_0 + \mu_1 t + \mu_2 t^2$	constant	constant
GEV3	constant	$ln\sigma = \sigma_0 + \sigma_1 t$	constant
GEV4	constant	$ln\sigma = \sigma_0 + \sigma_1 t + \sigma_2 t^2$	constant
GEV5	constant	constant	$\kappa = \kappa_0 + \kappa_1 t$
GEV6	constant	constant	$\kappa = \kappa_0 + \kappa_1 t + \kappa_2 t^2$
GEV7	$\mu = \mu_0 + \mu_1 t$	$ln\sigma = \sigma_0 + \sigma_1 t$	constant
GEV8	$\mu = \mu_0 + \mu_1 t$	constant	$\kappa = \kappa_0 + \kappa_1 t$
GEV9	constant	$ln\sigma = \sigma_0 + \sigma_1 t$	$\kappa = \kappa_0 + \kappa_1 t$
GEV10	$\mu = \mu_0 + \mu_1 t + \mu_2 t^2$	$ln\sigma = \sigma_0 + \sigma_1 t + \sigma_2 t^2$	constant
GEV11	constant	$ln\sigma = \sigma_0 + \sigma_1 t + \sigma_2 t^2$	$\kappa = \kappa_0 + \kappa_1 t + \kappa_2 t^2$
GEV12	$\mu = \mu_0 + \mu_1 t + \mu_2 t^2$	constant	$\kappa = \kappa_0 + \kappa_1 t + \kappa_2 t^2$
GEV13	$\mu = \mu_0 + \mu_1 t$	$ln\sigma = \sigma_0 + \sigma_1 t + \sigma_2 t^2$	constant
GEV14	constant	$ln\sigma = \sigma_0 + \sigma_1 t$	$\kappa = \kappa_0 + \kappa_1 t + \kappa_2 t^2$
GEV15	$\mu = \mu_0 + \mu_1 t$	constant	$\kappa = \kappa_0 + \kappa_1 t + \kappa_2 t^2$
GEV16	$\mu = \mu_0 + \mu_1 t + \mu_2 t^2$	$ln\sigma = \sigma_0 + \sigma_1 t$	constant
GEV17	constant	$ln\sigma = \sigma_0 + \sigma_1 t + \sigma_2 t^2$	$\kappa = \kappa_0 + \kappa_1 t$
GEV18	$\mu = \mu_0 + \mu_1 t + \mu_2 t^2$	constant	$\kappa = \kappa_0 + \kappa_1 t$
GEV19	$\mu = \mu_0 + \mu_1 t + \mu_2 t^2$	$ln\sigma = \sigma_0 + \sigma_1 t$	$\kappa = \kappa_0 + \kappa_1 t + \kappa_2 t^2$
GEV20	$\mu = \mu_0 + \mu_1 t + \mu_2 t^2$	$ln\sigma = \sigma_0 + \sigma_1 t + \sigma_2 t^2$	$\kappa = \kappa_0 + \kappa_1 t$
GEV21	$\mu = \mu_0 + \mu_1 t$	$ln\sigma = \sigma_0 + \sigma_1 t + \sigma_2 t^2$	$\kappa = \kappa_0 + \kappa_1 t + \kappa_2 t^2$
GEV22	$\mu = \mu_0 + \mu_1 t$	$ln\sigma = \sigma_0 + \sigma_1 t$	$\kappa = \kappa_0 + \kappa_1 t + \kappa_2 t^2$
GEV23	$\mu = \mu_0 + \mu_1 t + \mu_2 t^2$	$ln\sigma = \sigma_0 + \sigma_1 t$	$\kappa = \kappa_0 + \kappa_1 t$
GEV24	$\mu = \mu_0 + \mu_1 t$	$ln\sigma = \sigma_0 + \sigma_1 t + \sigma_2 t^2$	$\kappa = \kappa_0 + \kappa_1 t$
GEV25	$\mu = \mu_0 + \mu_1 t$	$ln\sigma = \sigma_0 + \sigma_1 t$	$\kappa = \kappa_0 + \kappa_1 t$
GEV26	$\mu = \mu_0 + \mu_1 t + \mu_2 t^2$	$ln\sigma = \sigma_0 + \sigma_1 t + \sigma_2 t^2$	$\kappa = \kappa_0 + \kappa_1 t + \kappa_2 t^2$

S1(b). Patterns of the time-varying models for 3-parameter marginal distribution (PIII in this study)

Model	μ	σ	κ
PIII0	constant	constant	constant
PIII1	$\mu = M * \sin(\mu_0 + \mu_1 t)$	constant	constant
PIII2	$\mu = M * \sin(\mu_0 + \mu_1 t + \mu_2 t^2)$	constant	constant
PIII3	constant	$\sigma = \sigma_0 + \sigma_1 t$	constant
PIII4	constant	$\sigma = \sigma_0 + \sigma_1 t + \sigma_2 t^2$	constant
PIII5	constant	constant	$ln\kappa = \kappa_0 + \kappa_1 t$
PIII6	constant	constant	$ln\kappa = \kappa_0 + \kappa_1 t + \kappa_2 t^2$
PIII7	$\mu = M * \sin(\mu_0 + \mu_1 t)$	$\sigma = \sigma_0 + \sigma_1 t$	constant
PIII8	$\mu = M * \sin(\mu_0 + \mu_1 t)$	constant	$ln\kappa = \kappa_0 + \kappa_1 t$
PIII9	constant	$\sigma = \sigma_0 + \sigma_1 t$	$ln\kappa = \kappa_0 + \kappa_1 t$
PIII10	$\mu = M * \sin(\mu_0 + \mu_1 t + \mu_2 t^2)$	$\sigma = \sigma_0 + \sigma_1 t + \sigma_2 t^2$	constant
PIII11	constant	$\sigma = \sigma_0 + \sigma_1 t + \sigma_2 t^2$	$ln\kappa = \kappa_0 + \kappa_1 t + \kappa_2 t^2$
PIII12	$\mu = M * sin(\mu_0 + \mu_1 t + \mu_2 t^2)$	constant	$ln\kappa = \kappa_0 + \kappa_1 t + \kappa_2 t^2$
PIII13	$\mu = M * \sin(\mu_0 + \mu_1 t)$	$\sigma = \sigma_0 + \sigma_1 t + \sigma_2 t^2$	constant
PIII14	constant	$\sigma = \sigma_0 + \sigma_1 t$	$ln\kappa = \kappa_0 + \kappa_1 t + \kappa_2 t^2$
PIII15	$\mu = M * \sin(\mu_0 + \mu_1 t)$	constant	$ln\kappa = \kappa_0 + \kappa_1 t + \kappa_2 t^2$
PIII16	$\mu = M * \sin(\mu_0 + \mu_1 t + \mu_2 t^2)$	$\sigma = \sigma_0 + \sigma_1 t$	constant
PIII17	constant	$\sigma = \sigma_0 + \sigma_1 t + \sigma_2 t^2$	$ln\kappa = \kappa_0 + \kappa_1 t$
PIII18	$\mu = M * sin(\mu_0 + \mu_1 t + \mu_2 t^2)$	constant	$ln\kappa = \kappa_0 + \kappa_1 t$
PIII19	$\mu = M * \sin(\mu_0 + \mu_1 t + \mu_2 t^2)$	$\sigma = \sigma_0 + \sigma_1 t$	$ln\kappa = \kappa_0 + \kappa_1 t + \kappa_2 t^2$
PIII20	$\mu = M * sin(\mu_0 + \mu_1 t + \mu_2 t^2)$	$\sigma = \sigma_0 + \sigma_1 t + \sigma_2 t^2$	$ln\kappa = \kappa_0 + \kappa_1 t$
PIII21	$\mu = M * sin(\mu_0 + \mu_1 t)$	$\sigma = \sigma_0 + \sigma_1 t + \sigma_2 t^2$	$ln\kappa = \kappa_0 + \kappa_1 t + \kappa_2 t^2$
PIII22	$\mu = M * sin(\mu_0 + \mu_1 t)$	$\sigma = \sigma_0 + \sigma_1 t$	$ln\kappa = \kappa_0 + \kappa_1 t + \kappa_2 t^2$
PIII23	$\mu = M * \sin(\mu_0 + \mu_1 t + \mu_2 t^2)$	$\sigma = \sigma_0 + \sigma_1 t$	$ln\kappa = \kappa_0 + \kappa_1 t$
PIII24	$\mu = M * \sin(\mu_0 + \mu_1 t)$	$\sigma = \sigma_0 + \sigma_1 t + \sigma_2 t^2$	$ln\kappa = \kappa_0 + \kappa_1 t$
PIII25	$\mu = M * \sin(\mu_0 + \mu_1 t)$	$\sigma = \sigma_0 + \sigma_1 t$	$ln\kappa = \kappa_0 + \kappa_1 t$
PIII26	$\mu = M * \sin(\mu_0 + \mu_1 t + \mu_2 t^2)$	$\sigma = \sigma_0 + \sigma_1 t + \sigma_2 t^2$	$ln\kappa = \kappa_0 + \kappa_1 t + \kappa_2 t^2$

Note: M represents the minimum value of the observed time series.

S1(c). Patterns of the time-varying models for 2-parameter marginal distribution containing scale and shape parameter (Weibull, Gamma in this study).

Model	σ	κ
WE0/GA0	constant	constant
WE1/GA1	$ln\sigma = \sigma_0 + \sigma_1 t$	constant
WE2/GA2	$ln\sigma = \sigma_0 + \sigma_1 t + \sigma_2 t^2$	constant
WE3/GA3	constant	$ln\kappa = \kappa_0 + \kappa_1 t$
WE4/GA4	constant	$ln\kappa = \kappa_0 + \kappa_1 t + \kappa_2 t^2$
WE5/GA5	$ln\sigma = \sigma_0 + \sigma_1 t$	$ln\kappa = \kappa_0 + \kappa_1 t$
WE6/GA6	$ln\sigma = \sigma_0 + \sigma_1 t$	$ln\kappa = \kappa_0 + \kappa_1 t + \kappa_2 t^2$
WE7/GA7	$ln\sigma = \sigma_0 + \sigma_1 t + \sigma_2 t^2$	$ln\kappa = \kappa_0 + \kappa_1 t$
WE8/GA8	$ln\sigma = \sigma_0 + \sigma_1 t + \sigma_2 t^2$	$ln\kappa = \kappa_0 + \kappa_1 t + \kappa_2 t^2$

S1(d). Patterns of the time-varying models for 2-parameter marginal distribution containing location and scale parameter (Lognormal function in this study).

Model	μ	σ
LOGN0	constant	constant
LOGN1	$\mu = \mu_0 + \mu_1 t$	constant
LOGN2	$\mu = \mu_0 + \mu_1 t + \mu_2 t^2$	constant
LOGN3	constant	$ln\sigma = \sigma_0 + \sigma_1 t$
LOGN4	constant	$ln\sigma = \sigma_0 + \sigma_1 t + \sigma_2 t^2$
LOGN5	$\mu = \mu_0 + \mu_1 t$	$ln\sigma = \sigma_0 + \sigma_1 t$
LOGN6	$\mu = \mu_0 + \mu_1 t$	$ln\sigma = \sigma_0 + \sigma_1 t + \sigma_2 t^2$
LOGN7	$\mu = \mu_0 + \mu_1 t + \mu_2 t^2$	$ln\sigma = \sigma_0 + \sigma_1 t$
LOGN8	$\mu = \mu_0 + \mu_1 t + \mu_2 t^2$	$n\sigma = \sigma_0 + \sigma_1 t + \sigma_2 t^2$

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Line(s) 184–186, Eq.s (3)–(4).

You must justify the assumptions/relations implicit in these equations. Why should the position and scale parameters change according to Eq.s(3)–(4)? Did you carry out any valuable/reliable fit? What are the p-Values? And, again, why should the shape parameter be constant instead? Incidentally, these are the same equations used in the paper I recently rejected.

Response: We have taken this advice by considering trend in shape parameters as shown in the former response. Also we have taken the nonstationary K-S tests on the assumed linear and nonlinear trend (**Table 4(a)-(b)**).

Line(s) 191–194.

Authors. Simultaneously, the Deviance Information Criterion (DIC) and Bayes factors (BF) for different stationary and nonstationary models were calculated to select the best fitted marginal model. The minimum DIC value yielded the best performance, while BF smaller than 1 indicated the best fitting.

Referee. This is a typical fatal error of practitioners. These are only selection criteria, not Goodness-of-Fit tests. You must first use (non-stationary) GoF tests to check whether a model is admissible! Otherwise, without first checking the models via suitable GoF tests, you may end up choosing non-admissible ones. This work has no statistical bases.

Response: We have taken this advice by investigating the univariate and bivariate GOF tests as presented in (lines 225-233 and lines 267- 283).

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Line(s) 191–194.

Authors. In multivariate hydrological frequency analysis, two kinds of copulas, named elliptical and Archimedean copulas are widely used in hydrological applications.

Referee. So what? The fact that these copulas were used in other works is not, and cannot be, a scientific justification. This is the usual approach of practitioners that use the copulas provided by Matlab. Given my experience, I do not really think that Nature (especially considering the generation of Extremes) gets stick to just these dependence structures—see also later comments. And, worst of all, you did not even check these copula models via suitable multivariate GoF tests (which are available in Literature, and some certified software is even for free—see below): this work has no statistical bases.

Response: In the revised manuscript, we firstly enrich the kinds of candidate copulas: five kinds of 1-parameter copula (Joe, Frank, Gumbel, Clayton and Gaussian) and five kinds of 2-parameter copulas (Clayton-Gumbel (BB1), Student t, Joe-Gumbel (BB6), Joe-Clayton (BB7) and Joe-Frank (BB8)). In addition, each copula can be rotated at 90, 180 (Survival Copula), 270 degrees. For this study, the rotated copula at 90 and 270 degrees are not considered because of the Kendall's tau values corresponding to each dependence structure of *Ps* and *Im* for each stations are positive (**Table 5(a)**). Considering the trend forms for parameter, almost 100 kinds of copula models are considered. In particular, the BB1, BB6, BB7 and BB8 Copula parameter are set in different parameter intervals of the corresponding copula because of numerically instabilities for large parameters in the R package CDVine (Brechmann and Schepsmeier, 2013). Take the BB1 copula as an example, the parameter interval for two parameters are $(0,\infty)$ and $[1,\infty)$ as usual while in the

CDVine package the parameter interval would be (0,7) and [1,7]. As a result, it is necessary to add constraint functions ($3.5 + 3.5\sin(\theta_0 + \theta_1 t)$ for θ_C^t and $4 + 3sin(\beta_0 + \beta_1 t)$ for β_C^t).

S2(a) Patterns of the time-varying models for 1-parameter bivariate copula model considering different parameter ranges for different copulas

Model	θ
GAU0	constant
GAU1	$\theta = \sin(\theta_0 + \theta_1 t)$
GAU2	$\theta = \sin(\theta_0 + \theta_1 t + \theta_2 t^2)$
GU0/J0/SGU0/SJ0	constant
GU1/J1/SGU1/SJ1	$\theta = 1 + \exp(\theta_0 + \theta_1 t)$
GU2/J2/SGU2/SJ2	$\theta = 1 + \exp(\theta_0 + \theta_1 t + \theta_2 t^2)$
CL0/SCL0	constant
CL1/SCL1	$\theta = \exp(\theta_0 + \theta_1 t)$
CL2/SCL2	$\theta = \exp(\theta_0 + \theta_1 t + \theta_2 t^2)$
FR0	constant
FR1	$\theta = \theta_0 + \theta_1 t$
FR2	$\theta = \theta_0 + \theta_1 t + \theta_2 t^2$

GAU: Gaussian copula; GU: Gumbel copula; J: Joe copula; SGU: survival Gumbel copula; SJ: survival Joe copula; CL: Clayton copula; SCL: survival Clayton copula; FR: Frank copula;

S2(b) Patterns of the time-varying models for 2-parameter student t copula

Model	θ	β
ST0	constant	constant
ST1	$\theta = \sin(\theta_0 + \theta_1 t)$	constant
ST2	$\theta = \sin(\theta_0 + \theta_1 t + \theta_2 t^2)$	constant
ST3	constant	$\beta = 2 + \exp(\beta_0 + \beta_1 t)$
ST4	constant	$\beta = 2 + \exp(\beta_0 + \beta_1 t + \beta_2 t^2)$
ST5	$\theta = \sin(\theta_0 + \theta_1 t)$	$\beta = 2 + \exp(\beta_0 + \beta_1 t)$
ST6	$\theta = \sin(\theta_0 + \theta_1 t)$	$\beta = 2 + \exp(\beta_0 + \beta_1 t + \beta_2 t^2)$
ST7	$\theta = \sin(\theta_0 + \theta_1 t + \theta_2 t^2)$	$\beta = 2 + \exp(\beta_0 + \beta_1 t)$
ST8	$\theta = \sin(\theta_0 + \theta_1 t + \theta_2 t^2)$	$\beta = 2 + \exp(\beta_0 + \beta_1 t + \beta_2 t^2)$

CG: Clayton-Gumbel copula; SCG: survival Clayton-Gumbel copula;

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S2(c) Patterns of the time-varying models for 2-parameter (survival) Clayton-Gumbel copula (BB1 copula)

Model	θ	β
CG0/SCGO	constant	constant
CG1/SCG1	$\theta = 3.5 + 3.5\sin(\theta_0 + \theta_1 t)$	constant
CG2/SCG2	$\theta = 3.5 + 3.5\sin(\theta_0 + \theta_1 t + \theta_2 t^2)$	constant
CG3/SCG3	constant	$\beta = 4 + 3sin(\beta_0 + \beta_1 t)$
CG4/SCG4	constant	$\beta = 4 + 3sin(\beta_0 + \beta_1 t + \beta_2 t^2)$
CG5/SCG5	$\theta = 3.5 + 3.5\sin(\theta_0 + \theta_1 t)$	$\beta = 4 + 3sin(\beta_0 + \beta_1 t)$
CG6/SCG6	$\theta = 3.5 + 3.5\sin(\theta_0 + \theta_1 t)$	$\beta = 4 + 3sin(\beta_0 + \beta_1 t + \beta_2 t^2)$
CG7/SCG7	$\theta = 3.5 + 3.5\sin(\theta_0 + \theta_1 t + \theta_2 t^2)$	$\beta = 4 + 3sin(\beta_0 + \beta_1 t)$
CG8/SCG8	$\theta = 3.5 + 3.5\sin(\theta_0 + \theta_1 t + \theta_2 t^2)$	$\beta = 4 + 3sin(\beta_0 + \beta_1 t + \beta_2 t^2)$

CG: Clayton-Gumbel copula; SCG: survival Clayton-Gumbel copula;

S3(d). Patterns of the time-varying models for 2-parameter (survival) Joe-Gumbel copula (BB6 copula)

Model	θ	β
JG0/SJGO	constant	constant
JG1/SJG1	$\theta = 3.5 + 2.5sin(\theta_0 + \theta_1 t)$	constant
JG2/SJG2	$\theta = 3.5 + 2.5sin(\theta_0 + \theta_1 t + \theta_2 t^2)$	constant
JG3/SJG3	constant	$\beta = 4.5 + 3.5 * sin(\beta_0 + \beta_1 t)$
JG4/SJG4	constant	$\beta = 4.5 + 3.5 * sin(\beta_0 + \beta_1 t + \beta_2 t^2)$
JG5/SJG5	$\theta = 3.5 + 2.5sin(\theta_0 + \theta_1 t)$	$\beta = 4.5 + 3.5 * sin(\beta_0 + \beta_1 t)$
JG6/SJG6	$\theta = 3.5 + 2.5sin(\theta_0 + \theta_1 t)$	$\beta = 4.5 + 3.5 * sin(\beta_0 + \beta_1 t + \beta_2 t^2)$
JG7/SJG7	$\theta = 3.5 + 2.5sin(\theta_0 + \theta_1 t + \theta_2 t^2)$	$\beta = 4.5 + 3.5 * sin(\beta_0 + \beta_1 t)$
JG8/SJG8	$\theta = 3.5 + 2.5sin(\theta_0 + \theta_1 t + \theta_2 t^2)$	$\beta = 4.5 + 3.5 * sin(\beta_0 + \beta_1 t + \beta_2 t^2)$

JG: Joe-Gumbel copula; SJG: survival Joe-Gumbel copula;

S3(e). Patterns of the time-varying models for 2-parameter (survival) Joe-Clayton copula (BB7copula)

Model	θ	β
JC0/SJC0	constant	constant
JC1/SJC1	$\theta = 3.5 + 2.5sin(\theta_0 + \theta_1 t)$	constant
JC2/SJC2	$\theta = 3.5 + 2.5sin(\theta_0 + \theta_1 t + \theta_2 t^2)$	constant
JC3/SJC3	constant	$\beta = 37.5 + 37.5sin(\beta_0 + \beta_1 t)$
JC4/SJC4	constant	$\beta = 37.5 + 37.5sin(\beta_0 + \beta_1 t + \beta_2 t^2)$
JC5/SJC5	$\theta = 3.5 + 2.5sin(\theta_0 + \theta_1 t)$	$\beta = 37.5 + 37.5sin(\beta_0 + \beta_1 t)$
JC6/SJC6	$\theta = 3.5 + 2.5sin(\theta_0 + \theta_1 t)$	$\beta = 37.5 + 37.5sin(\beta_0 + \beta_1 t + \beta_2 t^2)$
JC7/SJC7	$\theta = 3.5 + 2.5sin(\theta_0 + \theta_1 t + \theta_2 t^2)$	$\beta = 37.5 + 37.5sin(\beta_0 + \beta_1 t)$
JC8/SJC8	$\theta = 3.5 + 2.5sin(\theta_0 + \theta_1 t + \theta_2 t^2)$	$\beta = 37.5 + 37.5sin(\beta_0 + \beta_1 t + \beta_2 t^2)$

JC: Joe-Clayton copula; SJC: survival Joe-Clayton copula;

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S3(f). Patterns of the time-varying models for 2-parameter (survival) Joe-Frank copula (BB8 copula)

Model	θ	β
JF0/SJF0	constant	constant
JF1/SJF1	$\theta = 4.5 + 3.5sin(\theta_0 + \theta_1 t)$	constant
JF2/SJF2	$\theta = 4.5 + 3.5sin(\theta_0 + \theta_1 t + \theta_2 t^2)$	constant
JF3/SJF3	constant	$\beta = \frac{1 + 1e - 4}{2} + \frac{1 - 1e - 4}{2}\sin(\beta_0 + \beta_1 t)$
JF4/SJF4	constant	$\beta = \frac{1 + 1e - 4}{2} + \frac{1 - 1e - 4}{2}sin(\beta_0 + \beta_1 t + \beta_2 t^2)$
JF5/SJF5	$\theta = 4.5 + 3.5sin(\theta_0 + \theta_1 t)$	$\beta = \frac{1 + 1e - 4}{2} + \frac{1 - 1e - 4}{2}\sin(\beta_0 + \beta_1 t)$
JF6/SJF6	$\theta = 4.5 + 3.5sin(\theta_0 + \theta_1 t)$	$\beta = \frac{1 + 1e - 4}{2} + \frac{1 - 1e - 4}{2}sin(\beta_0 + \beta_1 t + \beta_2 t^2)$
JF7/SJF7	$\theta = 4.5 + 3.5sin(\theta_0 + \theta_1 t + \theta_2 t^2)$	$\beta = \frac{1 + 1e - 4}{2} + \frac{1 - 1e - 4}{2}\sin(\beta_0 + \beta_1 t))$
JF8/SJF8	$\theta = 4.5 + 3.5sin(\theta_0 + \theta_1 t + \theta_2 t^2)$	$\beta = \frac{1 + 1e - 4}{2} + \frac{1 - 1e - 4}{2}sin(\beta_0 + \beta_1 t + \beta_2 t^2)$

JF: Joe-Frank copula; SJF: survival Joe-Frank copula;

Line(s) 203–205.

Authors. The Gaussian copula was not used in this study because of its deficiency in describing dependencies of extremes (Renard and Lang, 2007).

Referee. The Authors are clearly considering the concept of Tail Dependence. Well, also the Frank family has no tail dependence, while the Clayton family only has lower tail dependence (possibly, of no interest here), the Gumbel family only has upper tail dependence, and the Student family has both lower and upper tail dependence (but they must be equal, and, most of all, they both must exist at the same time!). There are more suitable families of copulas for modeling extremes: again, the ones used by the Authors are simply those provided by Matlab, as (unfortunately, too) many practitioners do, preventing a reliable/valuable investigation and modeling of the phenomenon of

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interest.

Response: As shown in the former response, we have enriched the kinds of candidate copulas.

Line(s) 208, Eq. (5).

Again, as above, you must justify the assumptions/relations shown in this equation. Why should the copula parameter change according to Eq. (5)? Did you carry out any investigation? What are the p-Values?

Response: We implemented the goodness of fit test for copulas based on Rosenblatt's transformation (Rosenblatt, 1952).

Line(s) 212–214.

Authors. The Corrected Akaike Information Criterion (AICc; Hurvich and Tsai, 1989) was employed to make a goodness-of-fit...

Referee. NO.This a typical fatal error of practitioners. The AIC (corrected or not) is only a selection criterion, not a GoF procedure. You must first show that a copula is statistically admissible, e.g. via suitable Monte Carlo Cramer-von Mises or Kolmogorov-Smirnov tests, as in the R package "copula". Then, and only then, you may compare (only) the admissible copulas (if any) and select the "best" one according to some suitable criterion (e.g., the AICc, the BIC, the NLL, etc...).

Response: We implemented the goodness of fit test for copulas based on Rosenblatt's transformation which can also be used to implement GOF tests for nonstationary copula.

Line(s) 214–216.

Authors. Obviously, the presence of nonstationarity in the copula parameter was determined by comparison of the AICc value.

Referee. This sentence is obscure. Are you saying that, since the non-stationary model performs better, then the phenomenon is non-stationary? If so, this makes no statistical and philosophical sense. It looks like you are using your models to "decide" how the real world should work: this is contrary to every scientific principle. This work is also bugged from an epistemological perspective.

Response: We make the LR tests which is a statistical test to check whether the trend in the parameter. If value of the LR tests is smaller than 5%, it recommends the trend existed in the parameter at 5% significance level. And then AICc criterion is used as model selection criterion.

Line(s) 217–ff., Sec. 2.3.

Authors. "2.3. Joint return period and risk analysis based on KEN's and AND's methods"

Referee. Multivariate failure probabilities have been well mathematically formalized in Salvadori et al. (2016), by originally defining and exploiting suitable Hazard Scenarios and copulas' relations. The Authors must take this work into serious account, and mention it.

Response: we have made multivariate hazard assessment based on the Average Annual Reliability (AAR) in the revised manuscript. And we also added the reference Salvadori

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et al. (2016) when we wanted to use the joint exceedance probability under AND scenario.

Line(s) 241, Eq. (7).

See the more general approach and discussion in (Salvadori et al., 2016, Eq.s (33)-(35)).

Response: we have made multivariate hazard assessment based on the Average Annual Reliability (AAR) in the revised manuscript. So this formula has been deleted.

Line(s) 262, Eq. (11).

Why in Eq. (11) the parameters of the marginals F_X ,F_Y, used as arguments in the copula C, do not vary with time?

Response: it is an error of formula definition. We have taken this suggestion**.**

Line(s) 268–269.

Authors. The most likely event at the T 0 -year level can be calculated as (Graler et al., 2013)...

Referee. NO. The Most Likely technique was first introduced in Salvadori et al. (2011): always give credits to whom deserve credits. In addition, it is not the only possible one, as shown in the same paper (viz., the Component-wise Excess method). Moreover, further approaches are outlined in Corbella and Stretch (2012) and Salvadori et al. (2014). Why was the Most Likely approach chosen in this work?

Response: We have added the suggested reference to the manuscript. In order to

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simplify the process of generating the extreme rainfall quantiles at each ARR level, the most-likely technique was implemented by choosing a certain quantile pair which has the largest joint probability than other combinations at the same level (Salvadori et al., 2011). And we proposed the algorithm to capture the numeric solution for the bivariate quantiles (shown in 332-349).

Line(s) 289, Eq. (17).

In Eq. (17), why is the modulus used? Obviously ΔR will always be positive. And even in this latter case, there is no quantification of any “scale” on which ΔR should be evaluated (when is it large? when is it small?). Such a number tells nothing to me.

Response: we deleted the formula because of adopting the ARR-based quantile estimation from hydrologic design.

Line(s) 330–331.

Authors. As shown in Figure 3, concurrences of univariate and bivariate trends, the nonstationarities in rainfall extremes can be detected at several stations...

Referee. This is simply because you use a 10% critical α-level, entailing a large probability of rejecting the Null Hypothesis of non-stationarity. For instance, at a standard 5% level, no one of the Univariate and Multivariate MK tests would fail, only two (at most three) out of 12 of the Univariate Pettitt tests would fail, and only one out of 6 of the Multivariate Pettitt tests would fail. In turn, the conclusions of the Authors are definitely questionable: in my opinion, in general, there is no clear statistical

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evidence of non-stationarity (not to say if the standard 1% level were used, for in this case stationarity would be fully supported). Apparently, the Authors manipulate statistics according to their convenience, in order to show what they want to show.

Response: We considered more extreme series from more stations in the study area. Because of the insignificant trend denoted by reviewer #1 in the original manuscript, we changed the original 95-th percentile threshold for *Ps* to 0.90. After above modification of extreme values, the significant trend and change point at 5% significance level could be detected in 3 stations by nonparametric tests. And there is no station which can exhibit concurrences of univariate and bivariate trends, the nonstationarities according to the results in revised manuscript. The significance level of 5% is just the minimum standard. And it is not right and statistical objective to manipulate statistics according to our convenience, in order to show what we want to show. We have deeply realized the seriousness of the problem and corrected it in revised manuscript.

Line(s) 353–354.

Authors. The location parameter (μ) and scale parameter (σ) are regarded as time variant, while the shape parameter κ is time invariant...

Referee. As above, it is a dream to try and model time-variation of extremes using a constant shape parameter: it is the only one that matters in these kind of analyses. In addition, why should the other parameters vary according to Eq.s (3)–(5)? Simply because the same relations were used in other papers (again, without justification)? This paper has no scientific objective grounds.

Response: as shown above, we have incorporate the potential trends into shape parameter. And K-S based GOF tests were conducted to verify its rationality.

Line(s) 356–358.

Authors. Despite the exception of Im for station 4, the shape parameter κ for most fitted models was in the interval of [-0.3,0.3]...

Referee. Tables 3 provide little statistical information, for no suitable confidence intervals are shown: this may have considerable consequences regarding the conclusions drawn by the Authors in later sections. In fact, they did not carry out any Monte Carlo analysis, and hence their results do not take into account the estimates' uncertainties (as if the Authors were stating the absolute Truth). To be clear, no confidence bands are plotted in later figures. This is not a scientific way of proceeding: the Authors must provide plots such as the ones shown in Salvadori et al. (2018), which may give an idea of the uncertainties at play (which may be huge, especially when a GEV is used, and may completely change the interpretation of the results, as I suspect). In addition, as above, some of the fitted values of the shape parameter would imply that the corresponding GEV is Upper Bounded, entailing that the corresponding variable cannot be an Extreme one. Furthermore, the fact that the range of the shape parameter is "in accordance with previous studies" is not significant and relevant at all (also given the fact that the range is quite large).

Response: The parametric bootstrap (Efron and Tibshirani, 1993) method was implemented for parameter estimation and quantile estimation based on ARR level. It can provide a confidence bands (90% in this study) of parameter or the quantile estimation.

Line(s) 359–360.

Authors. The best fitted model was selected by performing the minimum DIC criterion combined with the Bayes factor (BF) test.

Referee. Again, you did not show that it is an admissible one! This work has no statistical bases. Line(s) 380–382.

Authors. Table 4(a)-(b) illustrates the results of best fitted copula, based on the minimum AICc and maximum logllikelihood value (LL).

Referee. Again, AIC and LL are not GoF criteria: the chosen models can be non-admissible! This work has no statistical bases.

Response: These two comments are replied by taking K-S based GOF tests for marginal distribution and A-D with Rosenblatt's transformation for copula models.

Line(s) 433–435.

Authors. Although the copula model for station 5 was stationary, it was regarded as a nonstationary model because of the marginal nonstationary GEVns-2 model for Ps or Im, which existed at other stations.

Referee. This makes no sense. The Authors do not understand the basic fact that the

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dependence structure is independent of the marginals (as stated by Sklar's representation Theorem): even if the marginals are non-stationary, the copula may be stationary. The introduction of non-stationary copulas is arbitrary, without any justification: you cannot manipulate the results in this way!

Response: we have deleted this nonsense statement as suggestion.

Line(s) 440–ff.

Authors. Figure 5 shows isolines of Kendall return period and AND-based return period...

Referee. Given the uncertainties mentioned above (not considered by the Authors), I strongly suspect that the interpretation of the results shown in Figure 5 could be quite different if suitable confidence bands were plotted. This work lacks of elementary statistical bases.

Response: The parametric bootstrap (Efron and Tibshirani, 1993) method was implemented for parameter estimation and quantile estimation based on ARR level. It can provide a confidence bands (90% in this study) of parameter or the quantile estimation.

Line(s) 537–ff., Sec. 4.6.

In the light of the objections given above, the "Further discussion" section (4.6) makes no sense.

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Response: we have modified the further discussion after we revised the manuscript as reviewer 2 suggested.

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