

We would like to thank both referees for their valuable comments. We hereby list the comments of the referees and formulate our answers in italic. Changes we made to the manuscript are given in boldface.

## 1 Comments by the first referee

- This paper is like the “curates egg” - good in parts. It raises more questions than it gives answers. It is a mixture of ancient and modern [e.g. Huff curves and Fern copulas]. There is plenty of math offered in describing how to construct a fern copula, which is nicely done after one had read Aas et al. (2009) for guidance (the papers Section 2 gives a nice description of the practicalities of fitting vine copulas), but there is not enough material of how these were chosen/calibrated in the context of the 105 year 10-minute record of rainfall at Uccle. What I found missing was how the choices were made for the ordering of the 3- and 4- dimensional copulas chosen in this paper. How was the non-unique ordering of the fern tree chosen?

*The ordering of the copulas, i.e. the selection of a D-vine, was based on the values of Kendall's tau (as listed in Table 1.) These values show that strongest dependencies exist between the variables W and V, p<sub>d</sub> and W, and V and D. By putting the most dependent pair of variables in the first tree of the vine copulas, we ended up with a D-vine.*

*The method we followed to estimate the parameter value of the Frank copulas consists in calculating Kendall's tau for the different pairs of variables in the tree. Using the relationship between Kendall's tau and the parameter value of the Frank copula, the value for  $\theta$  can be numerically estimated:*

$$\tau_K = 1 - \frac{4}{\theta} \left( 1 - \frac{1}{\theta} \int_0^\theta \frac{t}{e^t - 1} dt \right), \quad (1)$$

*We added this information to the revised paper in Section 4.1, lines 264-267 and lines 277-280*

- Where are the sample copulas? We need more figures - such as sample plots of the material for the copula models. How far are they from Gaussian? How good would an alternative, simpler Gaussian copula have been in competition? It seems that no justification was provided

for the choice. There were no comparisons made with alternative multidimensional probability distribution models; fern and Frank copulas were chosen and that was it.

*We agree that in the paper we restricted ourselves to vine copulas and the Frank family, though we tried to explain why. More validation (as shown below) of the choice will be added to the revised paper. The validation will be restricted to a visual appreciation of the empirical versus Frank copulas based on contour plots. Yet, in this rebuttal we provide the scatter plot of the normalized ranks of the four variables for season 1, which are shown in Figure 1 and a corresponding plot in which the contours of the Frank copulas and the empirical copulas for the three- and four-dimensional vine copulas for the first season is shown in Figure 2.*

*As stated before, we did not intend to select the “best copulas” in the vine copulas but rather wanted to test the framework based on the flexible and easy to fit Frank copula family. As can be seen from Figure 2, probably other copula families could better fit the dependencies between the first two variables ( $p_d$  and  $W$ ) in the first tree, and the third and fourth variable in the second tree ( $W|V$  and  $D|V$ ). However, the goal of our conceptual demonstration is to use a quite easily manageable copula family that has already proven its merits in hydrology. It is not our intention to present the Frank copula as the best copula in this study. This was already addressed in the manuscript: “We are aware that different copula families could be used to describe the dependencies between the different variables (cfr. Vandenberghe et al. [2010b]). Yet, in this conceptual study, we opted to restrict to the Frank copula family to describe the (conditional) bivariate dependencies within the vine copulas, because of its ability to represent positive or negative dependence. Furthermore, this family is frequently applied to describe bivariate hydrological phenomena [Pan et al., 2013]. Alternative families could better fit the different dependencies within the vine copula, however, the search for the best fitting copula was out of the scope of the current study.” We opted to use a vine copula instead of a multivariate copula because of its flexibility to handle multivariate data sets*

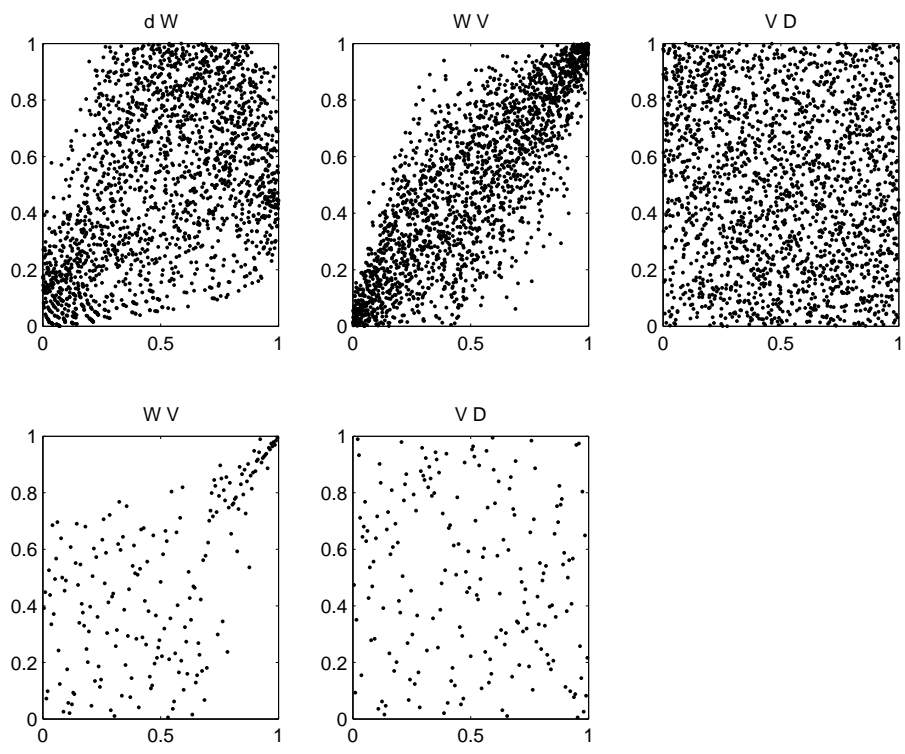


Figure 1: Scatter plots of the normalized ranks of the four (three) variables included in the vine copulas for season 1. Top panel:  $p_d$  vs.  $W$  (left),  $S$  vs  $V$  (middle) and  $V$  vs  $D$  (right). Bottom panel:  $W$  vs.  $V$  (left) and  $V$  vs.  $D$  (right)

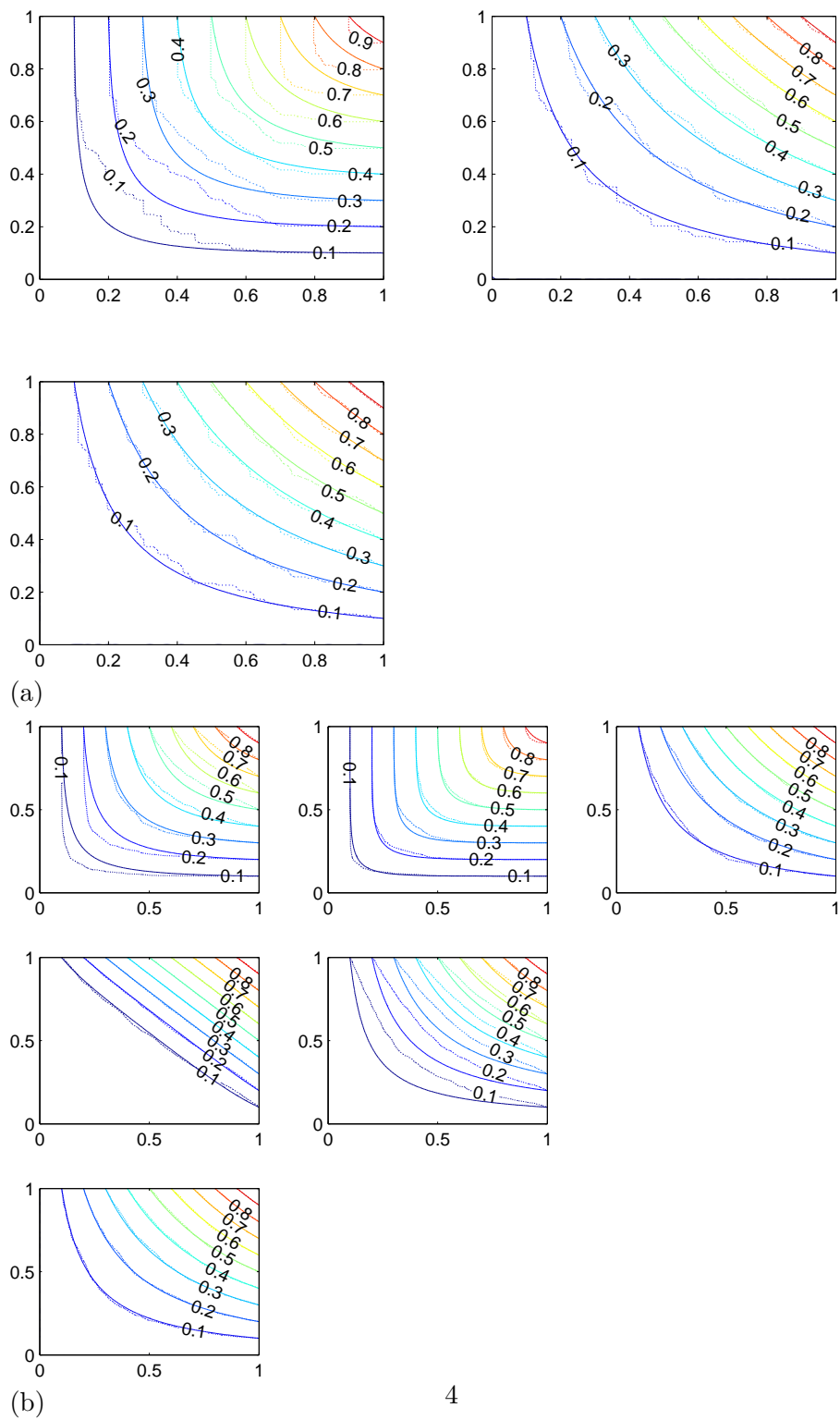


Figure 2: Contour plots of the empirical (dotted lines) and the fitted (solid lines) Frank copulas (solid lines) for the different trees in the three- (a) and four-dimensional vine copulas (b).  $C_{WV}$  and  $C_{VD}$  in the top panel of (a), and  $C_{WD|V}$  in bottom panel of (a).  $C_{p_dW}$ ,  $C_{WV}$  and  $C_{VD}$  in the top panel of (b),  $C_{p_dV|W}$  and  $C_{WD|V}$  in the middle panel of (b) and  $C_{p_dD|WV}$  in the bottom panel of (b).

and the (possible) different dependences therein. Although we admit that we do not fully exploit this flexibility, in future research this can still be accomplished by allowing for the use of different copulas in the vine copula and hence taking into account different dependences such as no, intermediate or strong tail dependencies, (a)symmetries, etc.

As a comparison with a multivariate Gaussian copula is suggested by the referee, we also employed the multivariate Gaussian copulas (three- or four-dimensional, no vine structure is used) in the same setting as for the vine copulas. We furthermore must stress, that, although goodness-of-fit-tests exist for individual copulas (see, for instance Genest et al. [2009] and Aas and Berg [2009]), obtaining a good fit for the individual copulas does not guarantee a globally optimal fit [Nikololoupoulos et al., 2012]. In this regard, we believe that it is at present better to compare the performance of different copulas and vine copulas by comparing the statistics and extremes of their generated time series to those of the measured time series. Still, for the referee's interest, we also provide contour plots of the three- and four-dimensional Gaussian copulas for the first season for the pairs of variables that are also included in the vine structure, and of the conditional Gaussian copulas  $C_{WD|V}$  of the three-dimensional Gaussian copula and  $C_{p_dV|W}$   $C_{WD|V}$  and  $C_{p_dD|WV}$  of the four-dimensional Gaussian copula for the first season (see Figure 1). A comparison of these contour plots with those of the vine copula, shows that the four-dimensional Gaussian copula more closely fits the contours of the empirical conditional distribution  $C_{WD|V}$ . For the other copulas, similar contour plots are obtained.

We also compared the statistics and the extremes of the time series obtained by the Gaussian copulas with those of the vine copulas. Figure 4 shows the results for aggregation levels of 10 min and 1 h for the vine copulas (cyan) and the multivariate Gaussian copulas (magenta). The comparison of the annual maxima is given in Figure 5. The statistics of the time series generated with the multivariate Gaussian copulas show a slightly better performance compared to those of the vine copulas. We observed that in 19 of the 36 cases (6 aggregation levels, 6 statistics), the cdf of the observed statistics is situated to the right of the bundles for both models. In 17 (resp. 14) cases, the cdf

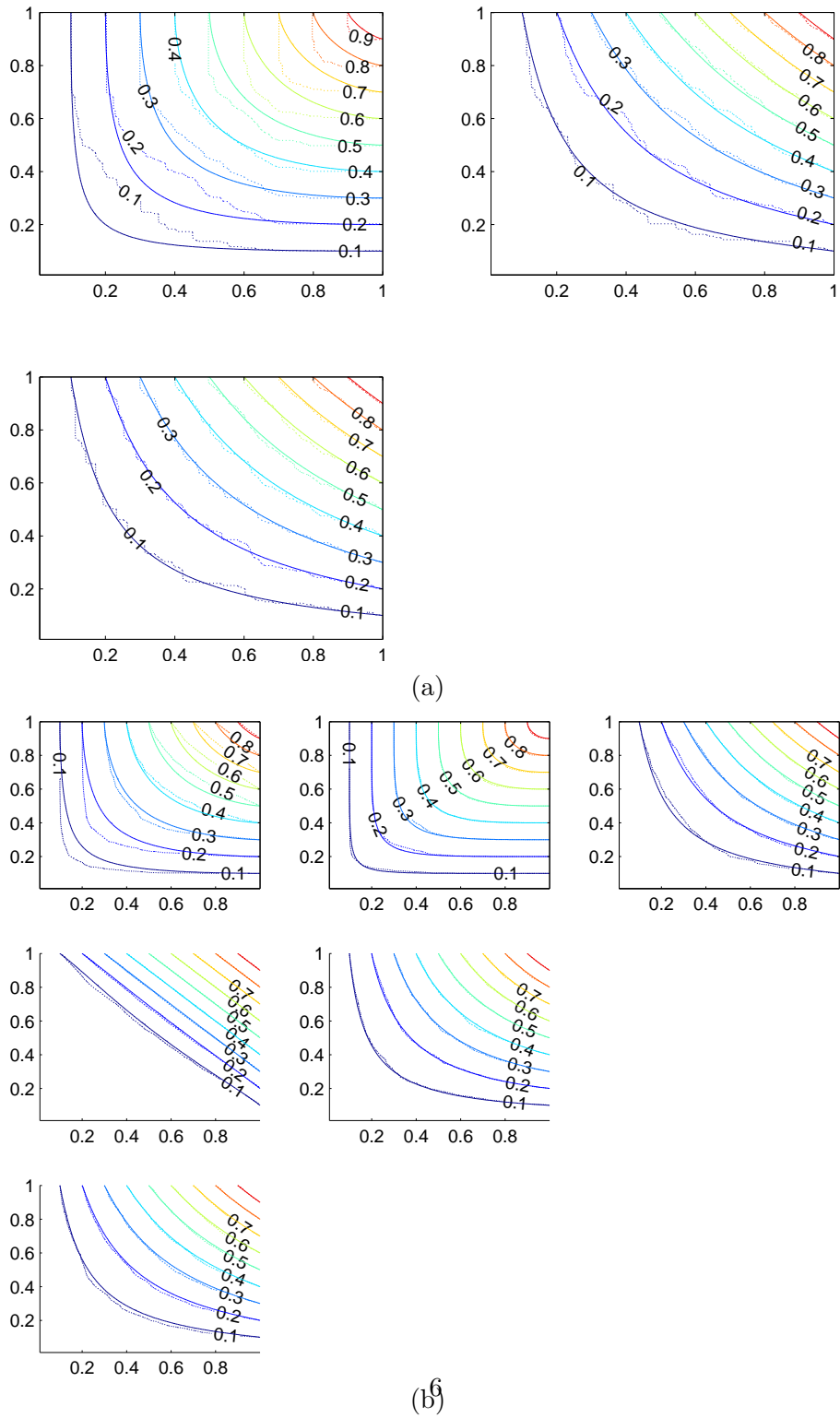


Figure 3: Contour plots of the empirical (dotted lines) and the fitted (solid lines) three- (a) and four- (b) dimensional Gaussian copulas (solid lines) for the pairs of variables that are used in the vine copulas (b).  $C_{WV}$  and  $C_{VD}$  in the top panel of (a), and  $C_{WD|V}$  in the bottom panel of (a).  $C_{p_dW}$ ,  $C_{WV}$  and  $C_{VD}$  in the top panel of (b),  $C_{p_dV|W}$  and  $C_{WD|V}$  in the middle panel of (b) and  $C_{p_dD|WV}$  in the bottom panel of (b).

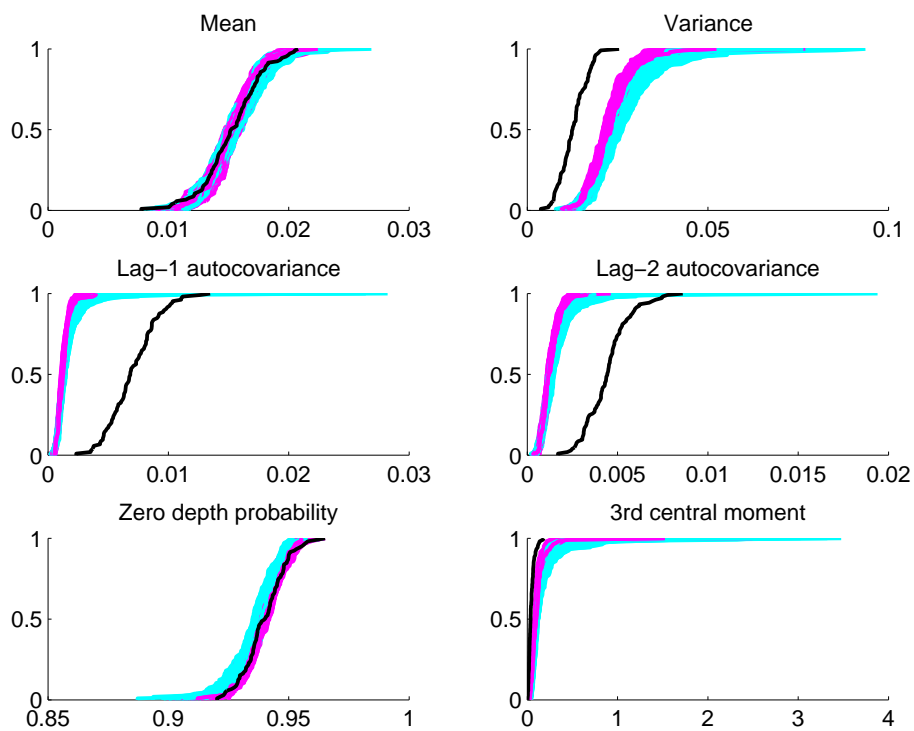
Table 1: Percentage of the observed extremes that are located under, within or above the bundle of extremes obtained by the vine-copula-based model or the Gaussian-copula-based model.

Aggregation level	VC under	GC under	VC within	GC within	VC above	GC above
10 min	100.0	100.0	0.0	0.0	0.0	0.0
1 h	0.0	0.0	81.0	9.5	19.0	90.5
3 h	0.0	0.0	27.6	2.9	71.4	97.1
6 h	0.0	0.0	95.2	3.8	4.8	96.2
12 h	0.0	0.0	100.0	72.4	0.0	27.6
24 h	64.8	0.0	35.2	100.0	0.0	0.0

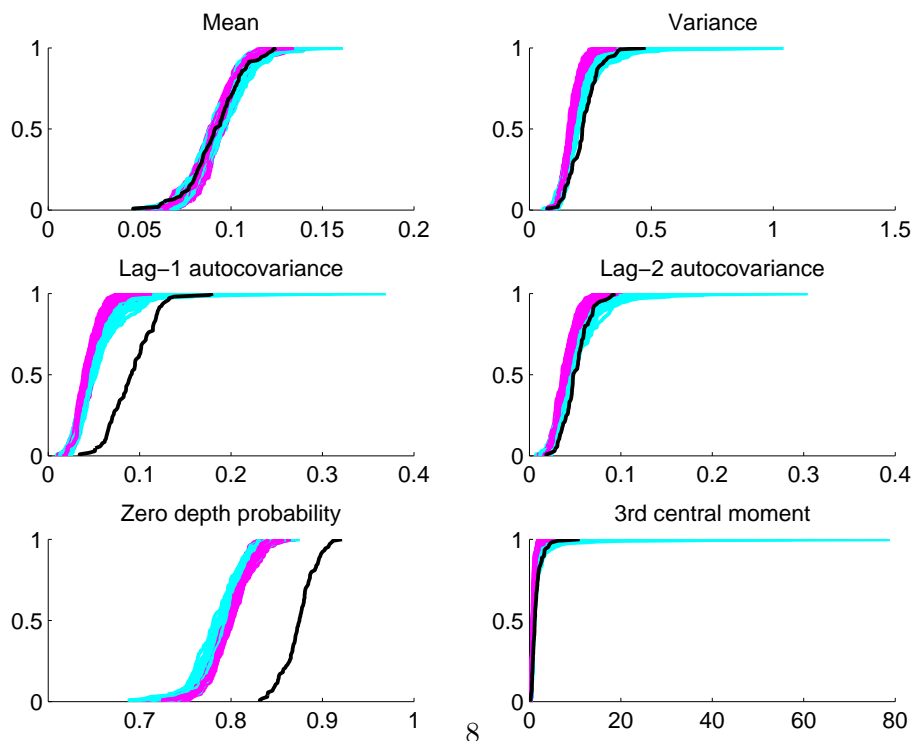
*of the observed statistics is situated to the left of the bundle obtained by the vine-copula-based model (resp. Gaussian-copula-based model). This more or less quantitatively confirms the visual impression of a slightly better performance of the multivariate Gaussian copulas.*

*With respect to the annual extremes, a smaller range is obtained, yet the annual extremes of the measured time series are more often underestimated. To that end, we compared how often the 105 observed extremes are situated within the bundle of extremes obtained by the models. Table 1 shows that the observed extremes are better situated within the bundle of the vine-copula-based model, except for an aggregation level of 24 h where the multivariate Gaussian copulas perform better and that of 10 min, where none of both models performs well.*

*Based on these statistics it is clear that the Gaussian copulas do not perform better than the vine copulas, while the vine-copula-based model can be further optimized. Therefore, we decided not to include a comparative study between both types of copulas, as only such a comparison would be fair if both types of models are fully optimized, making it a study on its own. Such a study, which should also investigate the reason why the Gaussian copulas have a lower performance with respect to the extremes, will be performed in the near future.*



(a)



(b)

Figure 4: Comparison of the empirical cumulative distributions of the yearly statistics of the observed time series and the bundle of empirical cumulative distributions of synthetic time series generated by means of the vine-copula-based rainfall model (cyan) and the multivariate-Gaussian-copula-based rainfall model (magenta) for aggregation levels of 10 minutes (a) and 1 hour (b).



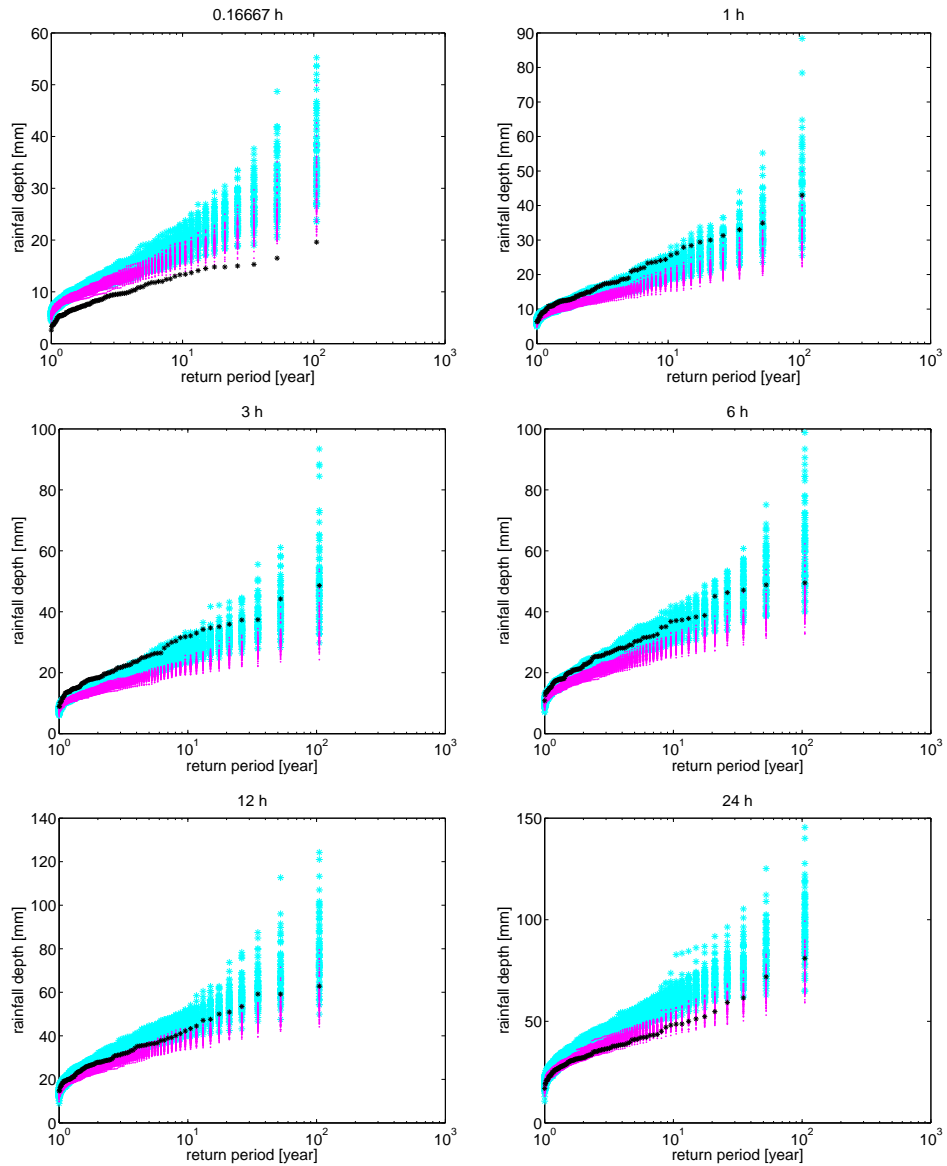


Figure 5: Comparison of empirically derived annual maxima related to the empirical return periods for different aggregation levels on the observed (black asterisks) and ensemble of synthetic time series generated by means of the vine-copula-based rainfall model (cyan) and the multivariate-Gaussian-copula-based rainfall model (magenta).

- I question the complicated (and difficult to follow) method of disaggregating the generated rectangular pulses of rainfall "events". Instead of using Huff curves directly with a strangely unique recipe, why not use a practical alternative (even if the authors are reluctant to go "parametric"!), such as an autoregressive generator or similar. This would provide a sequence of serially correlated pulses, with breaks, then use the seasonal Huff curves to scale the elemental pulses, constrained by the rectangular pulse total, to get the right "shape". There is quite a nice example which does the job, designed by Koutsoyiannis, D. (1994) "A stochastic disaggregation method for design storm and flood synthesis", *Journal of Hydrology*, 156, 193-225, which I reviewed - there will be others.

*We are aware of alternative methods for disaggregation (including an autoregressive generator), however, we did not apply them because we do not see how they could allow for imposing a value of the dry fraction within a storm  $p_d$ , which is drawn beforehand from the vine copulas.*

- Further questions come to mind. What constitutes a break within an event that is not a separation of storms? Can you justify the limit of 24 hours? This seems artificial and constraining - storms don't obey the 24-hour clock for their starting time, although they tend to initiate based on diurnal variation - particularly convective storms in summer rainfall regions.

*The 24 h limit to separate individual, independent storms for this time series has been defined by Verhoest et al. [1997] based on a study similar to the one of Restrepo-Posada and Eagleson [1982]. In this analysis, storms are considered to be independent when their storm arrivals are described by a Poisson process. Hence, the interstorm arrival periods should be exponentially distributed. By repeatedly re-defining storms, i.e. by enlarging the length of a dry period within a storm, and testing the distribution of the intervals to be exponential, the interstorm arrival period was defined. The resulting storms are regarded as being independent in storm duration, depth and intensity. Furthermore, since the methodology developed allows for including long dry periods within a storm (less than 24 hours), we ensure that all dry durations can be modelled. Duration smaller than 24 hours, are obtained through the disaggregation process, while the dry period that last longer than 24 hours are obtained from the vine copulas.*

- This review is choppy and irritable - please excuse me. It comes partly

from the felt need for more explanation combined with a respect for the innovation and bright ideas that are put forward by the authors. However, after all is said and done, the last two sentences of the paper highlight the nature of the incompleteness one obtains in reading it. My recommendation is: moderate revision before resubmission.

- 494 – 23: This choice is not unique; there are other combinations:  $f_{12|3} \cdot f_3$ , or  $f_{23|1} \cdot f_1$   
*In order to stress this, we changed the sentence to: **The joint probability density function (PDF)  $f_{123}$  of a random vector  $(X_1, X_2, X_3)$  can, for instance, be decomposed as follows:***
  
- 500–20: correct the reference  
*The reference has been corrected.*
  
- 501–10: "asserted", not "ascerted"  
*This has been corrected.*
  
- 502–5: "quartile of the storm" - dont you mean "quarter of the storm duration?"  
*This has been corrected.*
  
- 502–10: "duration" instead of "extremity"?  
*Extremity is correct, as Vandenberghe et al. [2010a] refers to the return period of the storm.*
  
- 502–15: "have internal dry 10min intervals" what is the maximum duration of an internal dry period that does not define the end of a storm?  
*This period is, from a practical point of view, restricted to 23 hours, although theoretically a dry duration of 23 hours 40 minutes could be allowed.*
  
- 504–6-17: this paragraph is difficult to understand. Also the limitations are very fussy and artificial - the choice of 10 min & 23h as storm duration limits affects the modelling of 24 hour storms - see 1st and last images in Fig 7

*We changed the paragraph such that it, hopefully, becomes better to understand. The reviewer unfortunately must have misunderstood it, 23 hours is not the maximum duration of a storm, but rather the maximum dry duration within a storm. The duration of the storm itself can take a large range of durations, which can be much more than 24 hours. The paragraph has been changed to:*

**The internal storm structure is then generated as follows. Firstly time intervals having zero rainfall are randomly assigned within the storm such that the sampled value of  $p_d$  is respected. It should be noted that the first and the last interval of the storm cannot have zero rainfall in order to preserve the duration  $W$  of the storm. Furthermore, when the value of  $p_d$  is such that the storm should only contain one wet 10 minute interval (*i.e.*  $p_d$  is close to one), the rainfall depth is evenly divided among the first and last 10 minute intervals. In addition the total length of a dry spell within a storm is constrained to 23 hours, *i.e.* one hour less than the selection criterion, in order to avoid that one storm would result in two different storms when the same storm selection criterion is applied on the simulated rainfall series. It should also be mentioned that storms that have a duration smaller than 40 minutes and for which  $p_d \neq 0$ , are disregarded in the generation of the rainfall series, because of the inability to assure the generation of the imposed quartile storm.**

- 504–18 to 505–20: remove the word "step" from the explanation, because "time b" is an instant, not an interval

*The word "step" has been replaced by "instant"*

- 505–8-20: this passage is difficult to follow - consider revision. I think that in panel (c) of Fig 4, "min" is in the wrong place; it cant be below  $V_{rc}(b)$

*with "min", we mean the smallest increment that can be chosen, the smallest increment is indicated with the line next to min. The resulting value in the Huff curve hence has to be greater or equal to  $V_{rc}(b)$ . We changed the symbol  $V_{rc}$  to  $D_{nc}$  indicating the "normalized cumulative storm depth". We rephrased some sentences in this paragraph in order to make it clearer:*

Time **instant**  $b$  corresponds to the end of a wet period. In **this** third

case, depicted in Figures 6(c) and (d), **the dry period starts at time instant  $b$  and ends at time instant  $c$** . Two sampling strategies are possible, **among which is chosen with equal probability**. It is allowed that a cumulative storm depth is **sampled according to the 10% and 90% Huff curves either at time instant  $b$  or at time instant  $c$** . When the first strategy is chosen (*cf.* Figure 6(c)),  $D_{nc}(b)$  is sampled from the interval  $[\max(D_{nc}(a), H_{10}(b)), H_{90}(b)]$ , the sampled value can hence be smaller **than  $H_{10}(c)$ , which indicates that the generated Huff curve will cross the 10% Huff curve, before reaching time instant  $c$  and will hence not remain between the 10 and 90% boundaries**. When the second strategy is chosen (*cf.* Figure 6(d)),  $D_{nc}(b)$  is drawn from  $[\max(D_{nc}(a), H_{10}(c)), H_{90}(c)]$  **i.e. the sample is chosen according to the 10% and 90% Huff curves at time instant  $c$ . The sampled value can hence be larger than  $H_{90}(b)$ , which indicates that the generated Huff curve will cross the 90% Huff curve before reaching time instant  $b$** .

- 507–3: 6a not 6b  
*This has been changed.*
- 507–10: "lag-2 covariances" - between what variables?  
*We changed lag-2 covariances to lag-2 autocovariances.*
- 507–13: "With respect to" instead of "W.r.t."  
*This has been changed.*
- 507–29: consider replacing "seems to perform well" with "has promise"!  
*Thank you for this nice way of phrasing. We adapted the text with: holds promise.*
- 508–8: "and does not need any calibration" - not as such, but the Huff curves are a limitation/constraint. The choice of Frank copulas is a matter of convenience? Couldnt we have some plots? How poor would the choice of Gaussian copulas be? At least they would replace the very involved vine copulas. True, that would remove much of the reason for the paper, but the choice seems a touch one-sided.  
*We hereby refer to our previous answers (see above) with respect to*

*the choice of the Frank copulas and the performance of the Gaussian multivariate copula.*

- 520: Fig 3 please add labels of 10% and 90% or mention "upper" and "lower curves" in the caption?  
*This has been changed.*

- 521: Fig 4 this is very difficult to follow - the explanation in the text and in the caption need improvement. It would be helped if a selected set of 24h time series of wet 10m pulses [separated by dry 10m periods if appropriate] were shown in a companion figure, so that readers could weigh up the choice of model.

*We changed the text (see the revised manuscript, changes are indicated in boldface) such that the method is described clearer. However, we are not convinced that showing a time series will clarify the method, as the reader will only see a sequence of wet and dry pulses.* The caption of Fig. 4 has been changed to:

**Illustration of the generation of an internal storm structure. The part of the Huff curve that is already generated (up to time instant a) is indicated by a thick solid line. The value at time instant b needs to be determined. Four cases are possible: sampling in between two consecutive wet periods (a), sampling at the end of a dry period (b), sampling at the end of a wet period followed by a dry period with a selection on the basis of the current time instant (c) and with a selection on the basis of the last time instant in the dry period (d).**

## 2 Comments by the second referee

- The manuscript describes a rainfall model based on vine-copula for simulating the dependence structure of four variables: storm volume, storm duration, dry duration after the storm, and the fraction dry within the storm. The analyzed case study consists on fitting the model on a long rainfall time series (105 years) and comparing simulated and observed data.

The topic is particularly interesting since rainfall simulators are pivotal for several hydrological models. The paper is well written, easy

to read and understand, so I am glad to suggest to publish it.

*Thank you.*

- I have some minor comments to share with the authors listed in the following.
- Introduction. This section could be improved. In the present form it reviews five issues: importance of rainfall simulator, types of rainfall simulators, copulas for rainfall analyses, multivariate copulas, summary of the paper. While the general structure is appropriate, each sub-section could be better described and reviewed. The first sub-section (from pag. 490 line 14 to page 491 line 6) is too vague. It could be removed or it should be clearer. From the practical point of view, in my opinion, rainfall simulators are pivotal for continuous rainfall-runoff models to overcome the drawbacks of event-based approach, so maybe this issue could be underlined.

*We further stressed the advantage of continuous time series of precipitation for deriving extreme statistics of hydrological variables (e.g. discharge) compared to an event-based approach:*

**The corresponding rainfall volume, obtained from e.g. intensity-duration-frequency (IDF) curves is then assigned to the design storm according to a temporal rainfall pattern or internal storm structure [Chow et al., 1988].**

**However, this approach has an important drawback as it does not properly account for the antecedent wetness state of the catchment [Verhoest et al., 2010]. Yet, this initial condition regulates the fractioning of the incident rainfall into runoff and infiltration and thus determines the fluvial response of a catchment to the imposed rainfall event. It was shown by Verhoest et al. [2010] that, because of this, the return period of the rainfall event may differ significantly from that of the corresponding discharge. In order to account for the antecedent soil moisture condition within the catchment, one can alternatively work with continuous rainfall models that provide input to rainfall-runoff models. As the latter models continuously update the soil moisture state, they therefore**

**provide continuous estimates of the antecedent wetness state within the catchment.**

- Page 491 lines 7-15. This paragraph could be clearer.

We changed the paragraph on page 491, lines 7-15 such that is clearer to the reader:

**The variables that characterize a storm, i.e. the storm intensity, duration and volume, mostly exhibit some kind of mutual dependence: a long storm duration is more likely to be associated with a low storm intensity than with a high one.**

**It is therefore of utmost importance to construct joint probability distribution functions whenever frequency analysis studies, e.g. to analyse extremes, need to be carried out. Yet, the marginal probability distribution functions of these storm variables usually do not exhibit the same type of parametric distribution and are largely skewed [Vandenberghe et al., 2010b], i.e. there is a large deviation from the normal distribution. These characteristics complicate the identification of the joint probability distribution functions in order to calculate the probability of occurrence of a storm with a specific duration and intensity. The introduction of copulas in hydrology facilitated this task.**

- Concerning the multivariate copula review, vine-copula is an hot-topic now and there are some papers published in the last two years that should be mentioned, i.e.: Gräler, B. Modelling skewed spatial random fields through the spatial vine copula (2014) *Spatial Statistics*, 10, pp. 87-102. Xiong, L., Yu, K.-X., Gottschalk, L. Estimation of the distribution of annual runoff from climatic variables using copulas (2014) *Water Resources Research*, 50 (9), pp. 7134-7152. so I would devote more lines here for providing literature review compared to the standard copula that is well known.

*Thank you for this suggestion. We included both references in the overview and added some references to finance, as vine copulas are also becoming more popular in that domain:*



The use of vine copulas is becoming popular in finance (see e.g. [Nikololoupoulos et al., 2012, Zhang, 2014, Mendes and Accioly, 2014]) and geophysics and hydrology (see e.g. [Gräler, 2014, Xiong et al., 2014, Gyasi-Agyei and Melching, 2012, Gräler et al., 2013]).

- Concerning the Huff curve, the citation of Candela et al., 2014 should be included in the Section 4.2, while here, briefly, the Huff curve should be defined. Section 2 Authors should make the effort to make lighter this section. I would suggest to include an appendix where all the equations are listed. At the same time I would remove all basic equations about copula that are well known or in any cases available in many other papers (for sure, Eq. (1), (2), (3))

*We included a short definition of the Huff curve in this paragraph:*

*In a second submodel, the intrastorm-generating-model, the intrastorm variability is obtained based on Huff curves [Huff, 1967], **which plot the normalized cumulative storm depth against the normalized time since the beginning of a storm.***

*The reference to Candela et al., 2014 was, however, moved to Section 3 (instead of Section 4.2., as suggested by the referee) as the explanation of a Huff curve is given in that section:*

**As the storm characteristics  $V$ ,  $W$  and  $D$  do not reveal any information on the internal storm structure, and  $p_d$  only gives partial information, Huff curves, as derived in Vandenberghe et al. [2010a] are employed to provide statistical information on the internal structure. The idea to use Huff curves for generating an internal storm structure has also been adopted by Candela et al. [2014]. Huff or mass curves present ...**

*Concerning the equations in Section 2, we opted to include the basic equations as more explanation about copulas was asked in a recent review of another paper and we therefore conclude that copulas are not yet broadly known in the hydrological community. Concerning the equations used in the vine structure, we think that these equations are important to understand how vine copulas are constructed and used in simulations. As the first referee states that this Section “gives a nice description of the practicalities of fitting vine copulas”, we believe that*

*it is better to keep these equations in Section 2 instead of moving them to an appendix.*

- Section 4.1 The a priori choice of Frank copula seems in contradiction with the choice to adopt the vine-copula. However, I understand that the best fitting copula issue is out of the scope of the paper. At the same time two questions arise: which is the impact on final results, in practice, of the best copula selection? authors in the conclusions say that the approach is data driven and does not need any calibration, however a four-dimensional copula is fitted on the observed data....is there not a risk that with 105years the fitting is reasonable while in the common situation (50years) the number of parameters to be estimated are too numerous? these issues should be at least mentioned in the conclusion as future work.

*We changed the sentence "and does not need any calibration" to:*  
**and is easier to calibrate than other rainfall generators as e.g. the commonly used Modified Bartlett Lewis model as, once the structure of the vine copula is determined, the calibration is reduced to estimating the parameters of the bivariate copulas.**

*We do not expect that fitting a 4D vine copula (which requires 6 parameters, as 6 bivariate copulas need to be fitted) will be problematic in situations where one possesses of e.g. only 50 years of rainfall data. In such situation, one would still have ca. 1000 storms (per season) on the basis of which 6 parameters will need to be determined. In criteria such as Akaike's information criterion (AIC), which takes into account the model complexity, the number of parameters of the model does not matter in comparison to the value of the log-likelihood (first term in the AIC), if the number of data points ( $N$ ) is much larger than the number of parameters ( $p$ ) to be fitted. For fitting a three-dimensional vine copula, however, one would possess of only ca. 100 storms (per season) on which 3 parameters will need to be determined. For these vine copulas, one could expect that finding the best copula can be more problematic, although in that case one could reduce the 24 hour criterion to delineate individual storms, to enlarge the data set on which the vine copulas can be fitted. Reducing this limit will not influence the modelled rainfall series, since all dry durations can be modelled. Durations smaller than 24 hour are now obtained through the disaggregation process, while dry periods that last longer than 24 hours are obtained from the vine copulas. We added this in the conclusions:*

It should also be noted that we possess of an exceptional long time series of rainfall data on which the vine copulas are determined. If one would follow the same approach and search for the best-fitting copula family on a more commonly shorter time series of e.g. < 50 years of rainfall data, one could be faced with difficulties as, the number of storms per season may become too small for fitting the copulas.

We also added a line that future research will reveal whether copulas that better fit the data can improve the performance of the vine copulas:

**Also, it should be investigated whether including other bivariate copulas in the vine copulas can further improve the performance of the vine-copula-based model.**

- Concerning Figures, often in paper where copula and time series are applied, a plot with the comparison among observed and simulated data is included since it is highly communicative. So, I would suggest to include a matrix plot for the four-dimension copula visual assessment and a spot (not all 105 years...but only short window) of the time series.

*We don't believe that such a figure would give much information, as our rainfall generator is not used to predict future rainfall. It is a stochastic model, which generates rainfall time series that should, hopefully, obey the properties of the observed rainfall time series (e.g. statistics, extremes). Yet, this does not mean that e.g. rainfall peaks and dry periods will occur at the same instances as in the observed time series. In this regard, showing a spot of simulated versus observed rainfall will not add information to the reader, but rather could cause confusion.*

## References

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