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Natural Hazards and Earth System Sciences
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Discussions

Interactive comment on "On the relevance of extremal dependence for spatial statistical modelling of natural hazards" *by* Laura C. Dawkins and David B. Stephenson

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Key:

- **Reviewer's comment**
- *Our response*
- Additional/edited text in the manuscript

0.1 Main Comments

- **1. a. The authors repeatedly claim the novelty of their approach (ll. 63, 100, 103). As they implicitly note on ll. 63, the main novelty lies in the combination of existing modelling approaches rather than in some fundamental statistical advance. However, conceptually very similar approaches for investigating the appropriate dependence class for spatially remote geophysical extreme events have been implemented before, within a more comprehensive theoretical framework (for example, see Kereszturi et al. 2016). Other than being applied to a different variable, what broad additional insights does the present study provide?**

  Thank you for this comment and very relevant citation. Since reading and responding to all reviewer comments, and reading the suggested literature, we have decided to demonstrate the motivation and novelty of this paper in a new way. In line with the natural hazards theme of the journal, we will focus on developing an approach for, firstly, systematically exploring the dominant extremal dependence class throughout a high dimensional continent wide data set (e.g. windstorm footprint), relevant for the catastrophe modelling of a diverse insurance portfolio for a continent wide natural hazard, and secondly, relevant for natural hazards, how this extremal dependence specification effects the representation of insurance losses. In addition, this loss representation is proposed as an additional, natural hazards relevant, diagnostic for the extremal dependence class. We have not seem any examples in the literature of using the extremal dependence measure of Ledford and Tawn (1996) and Coles (2001) to systematically explore very high dimensional data, nor of bringing this comparison through to natural hazard aggregate losses. Throughout the paper we now use the London-Amsterdam, London-Madrid pairs to introduce the extremal dependence measures and then present a systematic approach for *using the same measures to explore the extremal dependence throughout the high dimensional domain (see response to comment 2 below for this additional analysis). We have rewritten the introduction to reflect this change (see end of comment 1 for revised Introduction).*

- **b. On a related note, the authors suggest that an important result of their work will be to simplify the development and use of models that correctly represent extremal dependence for the variable of interest, removing the need to apply more complex - but more flexible - models which account for the different possible dependence classes (ll. 91-95). There are a number of these models available, including those of Wadsworth et al. (2017) and Huser and Wadsworth (2018). The actual benefits of the approach proposed by the authors are not explicitly described in the manuscript. Are the authors suggesting that the final result stemming from their approach outperforms these models (or that the results are comparable but require less work?) If so a comparison should be provided. Or that the reduction in computational time is so large as to make a difference in practical applications (if so, some indicative figures should be provided)? Or that the ease of implementation of their approach makes it applicable to datasets where other models couldn't be applied? Again, some examples should be provided and the extent/range of validity of this advantage should be discussed. Any one of the above points would be a sound motivation for the present work, but they would need to be explicitly stated and factually supported.**

  Thank you, this is an important point and we agree the motivation for the work needs to be clearer and based within the context of the relevant literature.

As described above, in response to the comments received this motivation has been proposed in a different way.

It is our understanding that, while there is a growing literature in the area of flexible models for extremal dependence which can accommodate higher and higher dimensional data, all such models are still limited by dimensionality. For example Huser and Wadsworth (2018) identify that their model is only feasible in moderate dimensions and note that, with the exception of the specific model used in de Fondeville and Davison (2018), truly high-dimensional inference for spatial extreme-value models has yet to be achieved. Indeed, as noted by de Fondeville and Davison (2018), this dimensionality limitation is true for max-stable models.

Following on from the described re-contextualisation in the above comment, here we aim to model very high dimensional (15000 locations) windstorm hazards data, relevant when modelling natural hazards that effect a large spatial domain (e.g. a whole continent). Therefore, we argue that the application of these flexible models is computational infeasible and instead we must use a systematic diagnostic approach to identify the dominant extremal dependence class throughout the high dimensional data domain, and model the full domain based on this dominant characteristic (e.g. using the model of de Fondeville and Davison (2018) if asymptotically dependent or a geostatsticial Gaussian process or the Gaussian tail model of Bortot et al. (2000), if asymptotically independent). If the high dimensional data characterises both asymptotic dependence and asymptotic independence at different separation distance, we suggest that the conceptual aggregate loss diagnostic can be used to explore how and where this mis-specification of extremal dependence effects the modelled output of interest (the loss).

To achieve this we use the bivariate measures in the paper as they are quick to estimate and can therefore be used to explore many thousands of pairs of locations, giving a detailed understanding of the high dimensional data.

We have rewritten the introduction to reflect these comments (see end of responses to comment 1).

- **c. As a final note, very little is said in the introduction of the above-mentioned models which account for a broad range of dependency classes (see also references in Huser et al., 2017). There is a growing literature in this subfield, which should be discussed. With the above I don't suggest that the work of the authors is devoid of interest, but they should certainly explain more clearly what the real novelty of the study and what the advantages it will provide to the community are. In my view, it will not be sufficient to alter one or two sentences in the manuscript: this will require a substantial clarification and contextualization effort, and likely some additional analysis to support the claims made.**

We agree with this comment and have now included a thorough review of these very relevant papers within our introduction. As described above, we have re-contextualised the paper to have two clear novelties, relevant for the natural hazards community, 1 - an approach for systematically exploring extremal dependence in very high dimensional natural hazards data (relevant for modelling wide spread impact), necessary since flexible models for extremal dependence are limited by dimensionality, 2 - understanding how specification of extremal dependence class effects the hazard model representation of insured loss using an additional, natural hazards relevant, conceptual loss extremal dependence diagnostic approach. In implementing this re-contextualisation we have rewritten the introduction to describe these aims and reviewed the relevant literature (see

below), developed and applied approaches for systematically exploring the high dimensional domain, requiring substantial additional analysis (see response to comment 2), and introduced a more generic conceptual loss function for broader applicability (see responses to Reviewers 1 & 2). We feel that attempting to apply the approach of Huser and Wadsworth (2018), for example, would be irrelevant here since the aim is to eventually model the full high dimensional data, and rather a thorough discussion of the merits and limitations of such approaches is adequate when combined with the large alterations made to the motivations, methodologies and scope of the paper.

The rewritten Introduction:

Multivariate statistical models are increasingly used to explore the spatial characteristics of natural hazard footprints and quantify potential aggregate losses. For example, such models for European windstorms are used by academics and re/insurers to create catalogues of possible events, explore loss potentials, and benchmark synthetic events from atmospheric models (Bonazzi et al. (2012);Youngman and Stephenson (2016)).

Natural hazards, such as European windstorms, have wide spread effects, often causing insured losses at many locations throughout a continent. Therefore, statistical models for such hazards must accommodate very high dimensional data in order to represent the full hazard domain. For example, Youngman and Stephenson (2016) develop a statistical model for European-wide extreme wind, requiring the representation of over 700 weather stations throughout Europe. Moreover, since natural hazards are rare events in the tail of the distribution, these statistical models must also correctly represent the dependence in the extremes to ensure valid inference and, hence a realistic representation of the hazard's aggregate losses.

When modelling multivariate extremes, variables can be described as being either asymptotically dependent, where large values of the variables tend to occur simultaneously, or asymptotically independent, where the largest values rarely occur together (Coles et al. (1999)). As noted by Wadsworth et al. (2017), examples of modelling joint extremes often assume asymptotic dependence in order to accommodate asymptotically justified extreme value max-stable models, potentially leading to over-estimation of the joint occurrences of extremes, if incorrect. This assumption is common in the field of natural hazard research. Coles and Walshaw (1994) used a max-stable model for the dependence in maximum wind speeds in different directions; Blanchet et al. (2009) to model snow fall in the Swiss Alps; Huser and Davison (2013) to model extreme rainfall and Bonazzi et al. (2012) to model windstorm hazard fields at pairs of locations in Europe. Indeed, Bonazzi et al. (2012) simply base this modelling assumption on being "in line with many examples found in the literature". Therefore, it is important to ask: how valid is this assumption of asymptotic dependence? And how much of an effect might a misspecification of extremal dependence have on the resulting hazard loss representation in the model?

Two approaches for exploring, and correctly representing, extremal dependence are present in the literature. These involve using either a flexible model, able to represent both forms of extremal dependence, or a set of diagnostic measures to identify extremal dependence class prior to model fitting.

There is a growing literature in the area of flexible models for extremal dependence, originating from the bivariate tail model of Ledford and Tawn (1996), varying in their merits and limitations. Wadsworth and Tawn (2012) developed a spatial model, involving inverted max-stable and max-stable models, able

to incorporate both forms of extremal dependence. This model, however, requires the estimation of a large number of parameters and is only able to transition between dependence classes at a boundary point of the parameter space. Following this, Wadsworth et al. (2017) explored more flexible transitions between extremal dependence classes and developed a model able to represent a wider variety of dependence structures, although limited to the bivariate case. Huser et al. (2017) went on to develop a flexible extension of the Wadsworth et al. (2017) model using Gaussian scale mixtures, in which the two asymptotic dependence regimes are smoothly bridged between, and estimated from the data. As noted by Huser and Wadsworth (2018), however, this model either makes the transition between dependence class at a boundary point of the parameter space (as in Wadsworth and Tawn (2012)), or is inflexible in its representation of the asymptotic independence structure. Huser and Wadsworth (2018) presents the most recent advancement, in a flexible model able to capture both extremal dependence classes in a parsimonious manner, provide a smooth transition between the two cases and cover a wide range of possible dependence structures, all based on a small number of parameters.

While these models provide a great advantage in terms of flexibility and are growing in their sophistication and applicability to higher and higher dimensions, none are computationally feasible for very high-dimensional datasets (Huser and Wadsworth (2018)), as required for natural hazards modelling over a large domain. Indeed, max-stable models for asymptotic dependence are limited in application to a few dozen variables due to the computational demand of existing fitting methods (de Fondeville and Davison (2018)). Hence, as noted by Huser and Wadsworth (2018), with the exception of the specific high-dimensional peaks-over-threshold model of de Fondeville and Davison (2018), truly high-dimensional inference for spatial extreme-value models has yet to be achieved.

As a result, when aiming to model very high-dimensional data, the alternative, a priori identification of extremal dependences class approach must be taken, and an appropriate model then selected based on this identification. For example the model of de Fondeville and Davison (2018) for asymptotic dependence or a geostistical of multivariate Gaussian model for asymptotic independence.

A number of papers have developed and/or employed diagnostic measures to identify the form of extremal dependence between variables, prior to model fitting. Ledford and Tawn (1996) and Ledford and Tawn (1997) developed a bivariate tail model in which one of the parameters, named the coefficient of tail dependences, is used within a diagnostic approach to help identify the bivariate extremal dependence class. Coles et al. (1999) introduced two extremal dependence coefficients, $\chi(p)$ and $\bar{\chi}(p)$, characterising the conditional probability of a pair of locations exceeding the same high quantile threshold $1 - p$, for which the asymptotic limit as $p \rightarrow 0$ provides a diagnostic of bivariate extremal dependence. Bortot et al. (2000) used pairwise scatter plots and empirical estimates of $\chi(p)$ and $\bar{\chi}(p)$ to diagnose the form of extremal dependence present in a 3-dimensional dataset of sea surge, wave height and wave period in south-west England. They found evidence for asymptotic independence, and hence developed a multivariate Gaussian tail model for their data, derived from the joint tail of a multivariate Gaussian distribution with margins based on univariate extreme value distributions. Similarly, Eastoe et al. (2013) apply the coefficient of tail dependence, the χ and $\bar{\chi}$ measures, and the conditional extremes model of Heffernan and Tawn (2004) to estimate the form of extremal dependence in 3 hourly sea surface elevation maxima at 15 locations, identifying generally asymptotic dependence. Similarly, more recently, Kereszturi et al. (2015) employed the coefficient of tail dependence and χ and $\bar{\chi}$ measures within a comprehensive theoretical framework to assess extremal dependence of North Sea storm severity along four strips of 14 locations within the North

Sea. Kereszturi et al. (2015) noted that, in some cases, these commonly used diagnostics can be inconclusive, and showed how supplementing them with a measure of the dependence for the body of the data increased diagnostic performance.

In all of the above examples these diagnostic approaches are applied to a relatively small number of locations. Here we present an approach for systematically exploring the dominant form of extremal dependence within a high dimensional natural hazards dataset. Specifically, we demonstrate this approach using a large ($\sim$6103 events) and very high-dimensional dataset ($\sim$15,000 locations) of climate model generated European windstorm footprints, described further in Section 2.

We introduce the bivariate diagnostic measures of Ledford and Tawn (1996) and Coles (2001) in the context of our approach by initially using them to explore the bivariate extremal dependence in two pairs of locations within the European domain, and subsequently present an approach for systematically applying the same diagnostics throughout the high dimensional domain. We use the simple extremal dependence measure of Ledford and Tawn (1996) and Coles (2001) as they are quick to compute and can therefore be calculated for many thousands of pairs of locations, important when exploring high dimensional data.

In addition, we contribute a further diagnostic, relevant for natural hazards modelling, by presenting an approach for exploring the impact of extremal dependence misspecification on conceptual aggregate hazard loss estimation. We use the Gaussian and Gumbel copula models, representing asymptotic independence and dependence respectively, to model pairs of locations, and quantify the discrepancy between modelled and observed joint conceptual losses. This approach is introduced for one central location, paired with all other locations in the high dimensional domain, and then extended to systematically explore the full domain. In the case where a combination of asymptotic independence and dependence is identified within the domain, this diagnostic is beneficial in understanding how using a model for one form of extremal dependence, necessary due to the high dimensionality of the data, effects this important natural hazards model output, hence providing further justification of the selected dependence model. Indeed, the approaches presented in this paper could be used to explore extremal dependence and develop an appropriate multivariate statistical model for any alternative high-dimensional natural hazard dataset.

The remaining paper is organised as follows. The windstorm hazard dataset used throughout this paper, is described in Section 2. In Section 3 we introduce and apply the extremal dependence diagnostics of Ledford and Tawn (1996) and Coles et al. (1999), firstly to two pairs of locations and secondly to systematically explore the high-dimensional data domain, and contribute a physical explanation for the form of extremal dependence identified in the windstorm hazard fields. Section 4 describes our additional, natural hazards relevant, conceptual aggregate loss extremal dependence diagnostic approach, and finally, Section 5 concludes.

- **2. My second major concern regarding this study is the fact that the results are presented only for two location pairs (with one location common to both). The authors briefly mention the fact that they have tested their results for other locations (ll. 250-252), but this is not substantiated in any meaningful way. Is there a way to systematically test the robustness of the results obtained by the authors across a western European domain, perhaps presenting the results in a form similar to Fig. 7 but for different reference locations or a 2-D version of Fig. 8 showing location on one axis,**

conditional joint loss on the other and density as colours/contours?

Thank you, this is a very important point, especially since now one contribution of the paper is an approach for exploring extremal dependence in very high dimensional data. This point was also made by Reviewer 1, in the context of identifying the dominant class of extremal dependence throughout the domain. We have added this part of the additional analysis at the end of Section 3.3:

When aiming to develop a statistical model for high dimensional spatial data over a large geographical domain, it is essential to systematically explore the dominant extremal dependence class across all locations. Here, we present an approach for doing so, which uses this quick-to-calculate coefficient of tail dependence diagnostic, demonstrated by application to our windstorm footprint data set. We first take a stratified (based on the distribution of locations over longitude and latitude) sample of 100 locations within the European domain. One such sample is shown in [Figure 1 in attachments](a). Since the extremal dependence is likely to decrease with increasing separation distance (Wadsworth and Tawn (2012)) and we hope to understand if asymptotic independence is dominant and hence present at small separation distances, for each of these 100 locations, we estimate the coefficient of tail dependence, η (and the associated 95$\%$ profile likelihood confidence interval) when paired with the 100 nearest locations within the full domain. [Figure 1 in attachments](b) demonstrates how the 100 nearest locations are geographically distributed for one such sampled location in our windstorm footprint dataset. For each pairing, the coefficient of tail dependence is calculated using w as the 0.9 quantile threshold of the structure variable, found to ensure stable estimates of η using diagnostic plots as in [Figure 1 in attachments] (c). The estimated η parameters and confidence intervals for these 100$\times$100 pairs of locations are plotted against separation distance to explore how, throughout the domain, η varies at small separation distances and changes with increasing separation distance, shown in [Figure 1 in attachments] (d). The parameter estimate related to the pair of locations in pink and blue in [Figure 1 in attachments] (b) is shown in pink. This method is repeated many times with 10 such repetitions shown in [Figure 1 in attachments] of the Supplementary Material at the end of the paper, showing very similar results.

[Figure 1 in attachments here] - (a) A stratified (based on the distribution of locations over longitude and latitude) sample of locations within the European domain, with stratified grid shown in grey; (b) a demonstration of the 100 nearest locations [turquoise] to one of these sampled locations [blue], with one such point selected at random [pink]; (c) the coefficient of tail dependence diagnostic plot (as in Fig. 4) for wind gusts at the blue location paired with the pink location; (d) the coefficient of tail dependence (estimated using w as the 0.9 quantile threshold of the structure variable) and 95% profile likelihood confidence intervals, for each of the 100 sampled locations paired with their 100 nearest locations in the full domain, plotted against separation distance in kilometres, with the estimate based on the pair of locations in (b) and (c) added in pink.

[Figure 1 in attachments] (d) shows that for small separation distances ($<$180 km) a proportion of pairs of locations have coefficients of tail dependence parameter, η, estimates close to 1, with $\eta = 1$ within the confidence interval, indicating asymptotic dependence. Within the range (0-50 km) 69% of pairs of locations exhibit this behaviour, however this proportion reduces rapidly as separation distance increases, to 30% for locations separated by (50-100 km), 13% for locations separated by (100-150 km) and 3% for locations separated

by (150-200 km). Hence, while there is evidence of asymptotic dependence for some locations in close proximity, even at very small separation distances (50 km) a larger proportion of locations exhibit asymptotic independence. Indeed, here and in [Figure 2 in attachments] of the Supplementary Material, beyond a separation distance of approximately 200km the coefficients of tail dependence parameter estimates drop well below 1, indicating asymptotic independence. Therefore, since separation distances within the domain extend to up to 3500km, we conclude that asymptotic independence is the dominant extremal dependence structure across the spatial domain.

It is important to consider the validity of representing even this small proportion of asymptotically dependent pairs of locations incorrectly as asymptotically independent. To explore this, Bortot et al. (2000) carried out a simulation study in which they fit the Gaussian, Ledford and Tawn (1996) and Gumbel models to bivariate data simulated from three parent populations with different classes of extremal dependence. They conclude that, for asymptotically independent parent populations the Gaussian copula is able to provide accurate inferences for tail probability estimates, out performing the Gumbel copula model, and even for asymptotically dependent parent populations, the estimation error of the Gaussian copula model was deemed to be acceptably small. This suggests that, when data dimensionality prohibits the use of flexible extremal dependence models, such as Huser and Wadsworth (2018), and asymptotic independence is found to be the dominant extremal dependence structure across the spatial domain, using an asymptotically independent model, such as the Gaussian tail model, is preferable over using a model for asymptotic dependence throughout the domain. In Section 4 we present a further, natural hazards relevant, diagnostic approach for further validating this, based on an estimates of the aggregate natural hazard losses.

[Figure 2 in attachments here] - For 10 stratified samples of 100 locations within the European domain: the coefficient of tail dependence (estimated using w as the 0.9 quantile threshold of the structure variable) and 95% profile likelihood confidence intervals, for each of the 100 sampled locations paired with their 100 nearest locations in the full domain, plotted against separation distance in kilometres.

We have also added an equivalent systematic, domain wide, comparison for the conceptual loss part of the paper. Firstly, as an extension of Fig. 7 in the manuscript, by plotting the bias in modelled $\chi(0.1)$, when the Gaussian and Gumbel bivariate models are fit to a stratified sample of 100 location paired with the other 99 locations, against separation distance. Secondly, as an extension of Fig. 8, as you have suggested, a 2-D version in which location is shown on the x axis, expected conditional loss on the y axis, and the difference between the empirical and modelled densities is coloured. This plot is created based on a further stratified sample of 100 location paired with all others in the domain. We have included this first additional analysis and plot after Fig. 7:

We extend this analysis to systematically explore the high-dimensional domain by fitting both the Gaussian and Gumbel models to a stratified sample of 100 locations paired with each of the other 99 locations, and, for each pair, plot the difference between empirical and modelled $\chi(0.01)$ against their separation distance, shown in [Figure 3 in attachments]. This domain-wide comparison indicates that, while the Gaussian model slightly over and under estimates empirical $\chi(0.01)$ at small separation distances, this model consistently outperforms the Gumbel model, which overestimates $\chi(0.01)$ for all separation distance, even very small. This indicates that a majority of nearby locations do not exhibit asymptotic dependence as they are not well represented by the Gumbel

model, further supporting the diagnosed dominance of extremal independence throughout the domain of our dataset.

[Figure 3 in attachments here] - The difference between empirical and modelled $\chi(0.01)$ for a stratified sample of 100 locations paired with each of the other 99 locations, plotted against separation distance for (a) the Gaussian model and (b) the Gumbel model.

We have then added the second additional plot and analysis after Fig. 8:

Again, we extend this analysis to systematically explore the robustness of these results throughout the high-dimensional domain. To achieve this we carry out the same calculation as in Fig. 8, replacing London as the location of origin, with each location within a stratified sample of 100 locations. For each of these 100 locations, [Figure 4 in attachments] presents the the difference between modelled and empirical relative frequencies of binned ranges of conditional expected joint loss, separately for the Gaussian and Gumbel models, i.e. representing the difference between the modelled and empirical density plots in Fig. 8, but for 100 locations rather than one. [Figure 4 in attachments] (b) identifies that the discrepancy between the empirical and Gumbel estimates of conditional expected joint loss shown in Fig. 8 are consistent throughout the domain, with lower values being under-represented and higher values, even as high as 0.014, over-represented by the Gumbel model. In a similar way, [Figure 4 in attachments] (a) shows that the Gaussian model performs equally well for these 100 locations, with much smaller discrepancy compared to the Gumbel model, as found in Fig. 8.

[Figure 4 in attachments here] - For the 100 sampled locations shown in [Figure 1 in supplementary material] (a), the difference between modelled and empirical relative frequencies of binned ranges of expected conditional joint loss shown on the y axis, for (a) Gaussian model, (b) Gumbel model.

This novel conceptual aggregate loss diagnostic approach supports the use of the Gaussian model when asymptotic independence is found to be the dominant extremal dependence characteristic within a high dimensional natural hazards dataset. In this windstorm footprint application, while the Gumbel model is able to represent some pairs of locations at very small separation distances, where asymptotic dependence is suggested by the coefficient of tail dependence, this model greatly misrepresents the joint tail behaviour and hence the conditional probability of joint loss for a majority of pairs and separation distances. Conversely, the Gaussian model is able to represent the joint tail behaviour relevant for loss estimation for locations within close proximity to each other, as well as further apart.

0.2 Additional Comments

- **3. The title suggests a very broad relevance of the paper. Even though the techniques discussed in the study are general, the analysis effectively focusses on windstorms at three specific locations. As such, the current title is misleading and should be changed to reflect the contents of the study. Alternatively, the approach proposed by the authors should be applied to other geophysical variables and geographical domains.**

  We have now altered the title of the paper to more closely reflect the contributions of the re-contextualised paper and the specific windstorm application,

  to:

  Quantification of extremal dependence in spatial natural hazard footprints: Independence of windstorm gust speeds and its impact on aggregate losses

- **4. l. 124: Please include a reference for how the wind gusts are calculated. This parametrisation is very simple. If it works well, simplicity is obviously good, but a brief discussion of its performance versus alternative approaches should be provided.**

  We have now added two references to the introduction of the paramterisation in Section 2:

  As described by Roberts et al. (2014), the wind gust speeds are calculated from wind speeds in the MetUM model, based on a simple gust parameterisation $U_{gust} = U_{10m} + C\sigma$, where U_{10m} is the wind speed at 10 metre altitude and σ is the standard deviation of the horizontal wind, estimated from the friction velocity using the similarity relation of Panofsky et al. (1977). The roughness constant C is determined from universal turbulence spectra and is larger over rough terrain.

  We then, in combination with a response to Reviewer 2, include a few paragraphs at the end of Section 2 to discuss this parameterisation and the general validity of the MetUM modelled footprints:

  Using model generated windstorm footprints for representing historical storms has benefit in terms of spatial and temporal coverage, however these estimated maximum wind-gust speeds will inevitably differ from the those observed at nearby weather stations. For example, as noted by Roberts et al. (2014), several alternative methods for parameterising wind gust speeds are available (see Sheridan (2011) for a review), which can lead to large differences in estimated gusts (10-20ms^{-1}). The validity of simplistic gust parameterisation stated above was evaluated by Roberts et al. (2014), who found an overestimation in the effect of surface roughness at stations greater than $\sim$ 500 metre altitude, leading to underestimation of MetUM modelled extreme winds in these locations. In addition, within this thorough evaluation of MetUM windstorm footprints, Roberts et al. (2014) identified a slight underestimation in extreme wind gust speeds greater than ~ 25ms^{-1}. This was found to be due to a number of mechanisms including the underestimation of convective effects and strong pressure gradients, leading to the underdevelopment of fast moving storms (Roberts et al. (2014)).

- **5. Section 3.4: Are wind gust speeds really independent Gaussian processes? Can this be tested on the data available to the authors?**

  The reviewer raises a good point. A brief justification has been added to Section 3.4:

  The distribution of each velocity component is expected by the Central Limit Theorem to be close to normally distributed since the net displacement of a particle in turbulence is the result of many irregular smaller displacements. The distribution of each component has zero skewness due to the symmetry of the fluid equations (negative deviations are as likely as positive ones) but can have slightly more kurtosis (i.e. fatter tails) than the normal distribution due to intermittency in the flow. Measurements of velocity components in the

  atmospheric surface layer reveal that the distributions are near to Gaussian (e.g. Chu et al. (1996)).

- **6. Fig. 1. The labels/city names are very difficult to see in print.**

  Thank you for identifying this. We have changed the labelling to including a clearer legend (see [Figure 5 in attachments])

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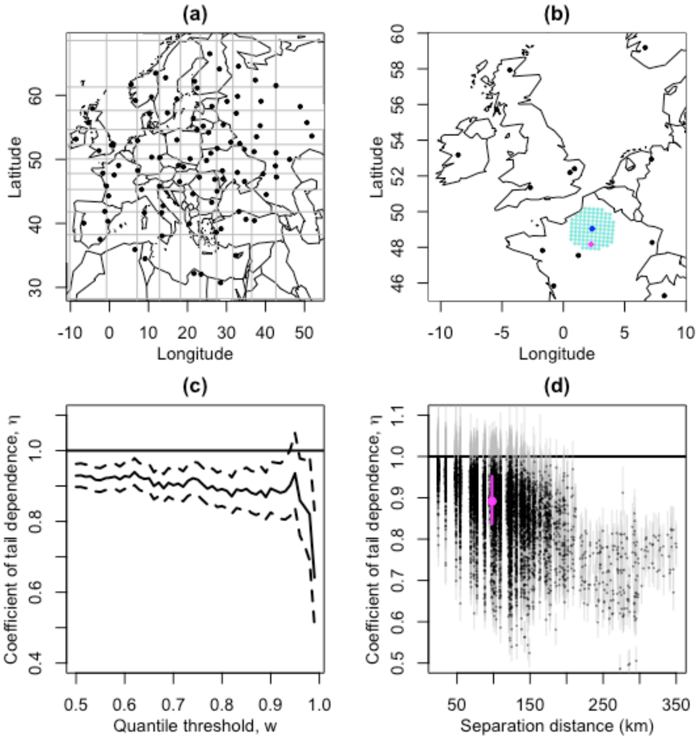
(a)
(b)
(c)
(d)
Latitude
Longitude
Coefficient of tail dependence, η
Quantile threshold, w
Separation distance (km)

Fig. 1.

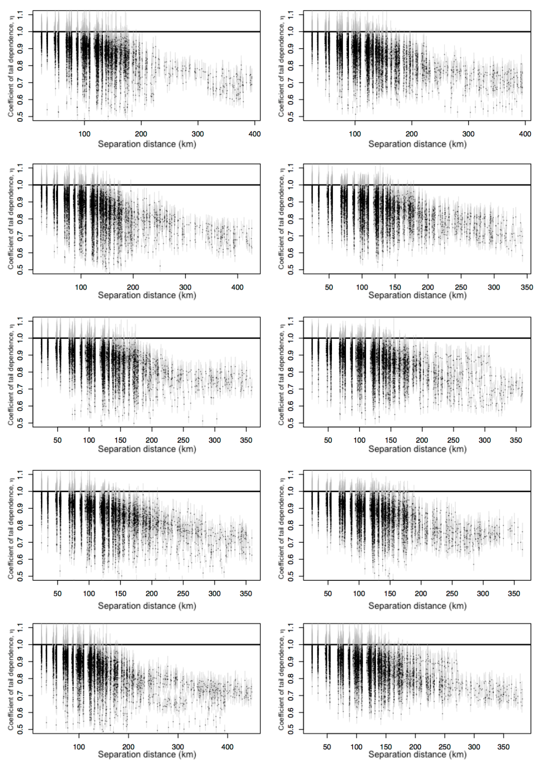
Separation distance (km)

Fig. 2.

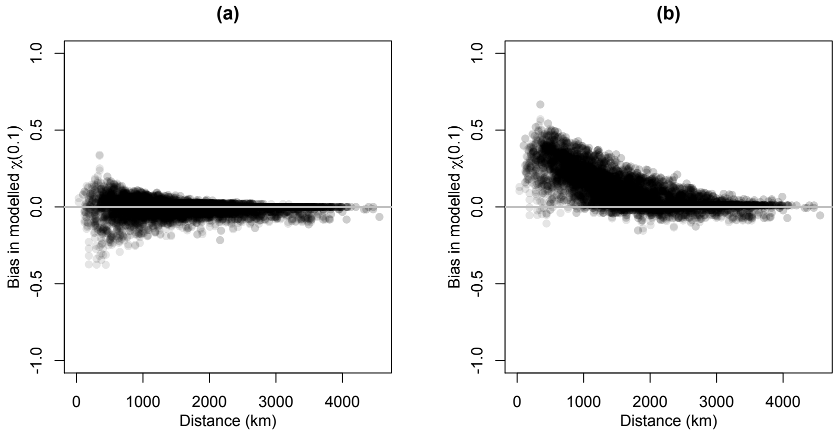
(a)
(b)
Bias in modelled χ(0.1)
1.0
0.5
0.0
-0.5
-1.0
0
1000
2000
3000
4000
Distance (km)

Fig. 3.

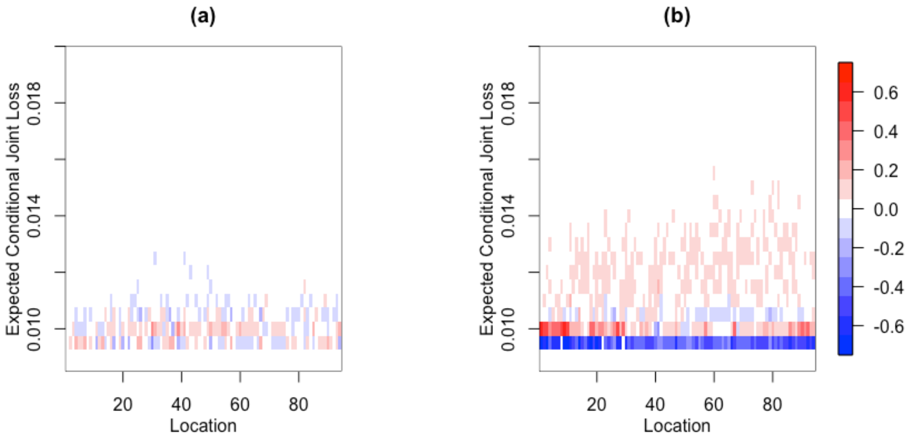
(a)
(b)
Expected Conditional Joint Loss
0.010
0.014
0.018
20
40
60
80
Location
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6

Fig. 4.

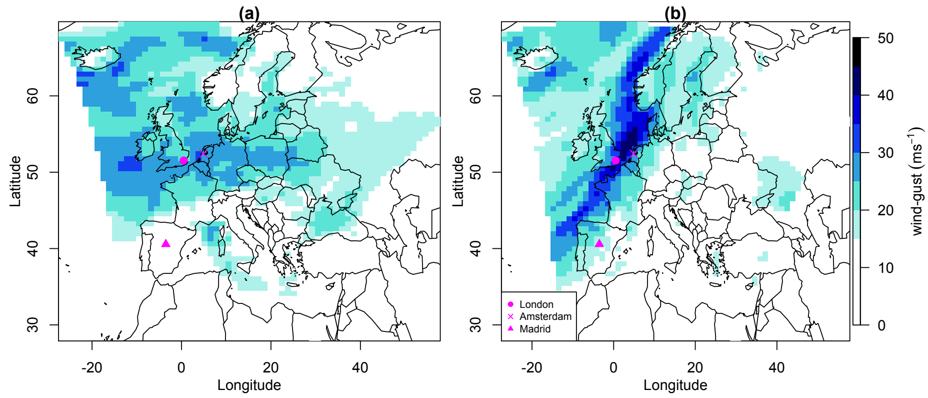
(a)
(b)
Latitude
Longitude
London
Amsterdam
Madrid
wind-gust (ms^{-1})

Fig. 5.