This item was submitted to [Loughborough's Research Repository](#) by the author.
Items in Figshare are protected by copyright, with all rights reserved, unless otherwise indicated.

Multi-hazard dependencies can increase or decrease risk

PLEASE CITE THE PUBLISHED VERSION

<https://doi.org/10.1038/s41558-020-0832-y>

PUBLISHER

Nature Research

VERSION

AM (Accepted Manuscript)

PUBLISHER STATEMENT

This paper was accepted for publication in the journal Nature Climate Change and the definitive published version is available at <https://doi.org/10.1038/s41558-020-0832-y>.

LICENCE

All Rights Reserved

REPOSITORY RECORD

Hillier, John, Tom Matthews, Robert Wilby, and Conor Murphy. 2020. "Multi-hazard Dependencies Can Increase or Decrease Risk". Loughborough University. <https://hdl.handle.net/2134/12489755.v1>.

Multi-hazard dependencies can increase or decrease risk

In risk analysis, it is recognised that hazards can often combine to worsen their joint impact, but impact data for a rail network show that hazards can also tend to be mutually exclusive at seasonal timescales. Ignoring this overestimates worst-case risk, so we therefore champion a broader view of risk from compound hazards.

¹John K. Hillier, ¹Tom Matthews, ¹Robert L. Wilby, ²Conor Murphy

¹Geography and Environment, Loughborough University, LE113TU, UK.

²Irish Climate Analysis and Research UnitS (ICARUS), Department of Geography, Maynooth University, Co Kildare, Ireland.

The interplay among natural hazards affects risk globally, and this is expected to evolve as climate changes^{e.g. 1–3}. Conventional modelling has focused on impacts from each hazard in isolation^{4,5}, but this is being transcended by a 'compound event' paradigm for multi-hazards^{3,6}. Over meteorological timescales (hours to weeks), hazards like wind and precipitation extremes can combine to exacerbate total risk^{7–9}. However, infrastructure operators, government agencies, (re)insurance and health services are also interested in aggregated risk over climatological timescales (seasonal to annual). Using Australia and Great Britain (GB) as examples we illustrate that, from this perspective, some hazards tend to be mutually exclusive due to low-frequency modes of variability. Pairwise views of a multihazard environment that target instances where risk is exacerbated^{7–9} might therefore overestimate worst-case risk. This complication is one reason for the ongoing development of multi-variate statistical frameworks to better model hazardous extremes^{10–13}, but cases are under-reported. Thus, we highlight the need for a broader and more holistic view of multihazard risks, applied at spatial scales meaningful to stakeholders, and including the climatological timescales relevant to them. From

this standpoint it becomes clear that hazards can be influenced by modes of atmospheric variability in ways that reduce the likelihood of some hazard combinations, thereby moderating tail-end (that is, worst-case) risk (Fig. 1). How such risk moderation works is explained using an analogy of rolling dice, and by relating hazards to climate modes such as the El Niño-Southern Oscillation (ENSO).

El Niño example

Consider weather-related hazards in Australia. During summer, El Niño tends to reduce the likelihood of tropical cyclones² and flooding⁸, but enhances drought¹⁴ and wildfire¹⁵ risk, whereas La Niña drives the opposite conditions. Under the present climate, there are then two regimes or modes of hazard behaviour which are unlikely to co-occur. Concurrent impacts from both cyclone- and drought-related hazards are unlikely when either mode is active, making severe aggregate impacts from all four hazards less likely than might be expected if the two hazard modes were independent. This creates the possibility that, if a tendency for hazard modes to be mutually exclusive exists but is not accounted for, a focus on damaging extremes (individually^{e.g. 5,15,16} or in pairs/triplets that compound to worsen impacts⁷⁻⁹) may overestimate risk. Numerous oscillatory climate modes (e.g. ENSO, North Atlantic Oscillation) have been related to the activity level of hazards^{2,16}, meaning that cases similar to this Australian example may not be unusual.

Illustration using dice

A probabilistic configuration of multihazards that protects against worst-case combinations can be illustrated by rolling dice. Imagine that flooding and wind damage happen if a six is rolled on a standard die. In traditional risk analysis¹⁷, flooding and extreme winds are treated as independent phenomena, so would have a die each. A ‘worst case’ is when both occur (two sixes), on average 1-in-36 throws. If flooding and wind always happen together, however, only one die is needed and both hazards occur if a six is thrown, 1-in-6 rolls. Thus, assessing such

hazards independently underestimates risk^{7,9,17}. Flooding and wind damage in a tropical cyclone are strongly related⁸ and so close to this specific case. To replicate a situation where flooding and wind never happen together, a rule is introduced that rolling a six on one die dictates (somehow) that the other die must score a one; two sixes are not allowed. Hence, neglecting a relationship in which states are mutually exclusive overestimates worst-case risk.

Where there is a weaker tendency for phenomena to occur together, such as for flooding and wind in extratropical cyclones^{1,7} (Box 1), two similarly loaded dice is a more apt analogy. Both would tend to score high or low such that the chance of two sixes is greater, perhaps 1-in-12. On the other hand, hazards (for example flooding and wildfire in Australia) might tend to be mutually exclusive over a season or year. Then, the loading of the dice would be such that if a six is rolled on the first die the chance of a second six is reduced. This lowers the probability of two sixes, a worst-case impact, to perhaps 1-in-60 throws on average (see Supplementary Discussion 3). These arguments apply to ENSO-driven hazard modes in Australia, and to impactful winter weather in Great Britain.

Great Britain case study

Given that risk relates to potential for loss, an impact-centric approach^{1,3} is essential. The holistic view advocated here requires consideration of multiple hazards and their dependencies at timescales relevant to stakeholders for their hazard-specific exposure (i.e. assets at risk, Fig. 1a). For instance, wintertime weather-related impacts on the rail network in Great Britain (2006-2018) quantitatively show how such interactions can suppress tail-end risk, mitigating pairwise compound effects (detail in Box 1). In a narrow (bivariate) multi-hazard view, based on the idea that storms might drive concurrent flooding and wind damage^{e.g. 7,8}, the largest losses for these hazards compound substantially, increasing by 28% above those simulated assuming that the damage types are independent (Fig. 2d). This view is appropriate for domestic property (re)insurance where these two hazards dominate¹. However, Network Rail is also exposed to

substantial cold and snow impacts, which themselves compound by +8% during winter. Assuming now that losses are paired, but the pairs are independent given that no published study explicitly suggests otherwise, yields a simulated overall increase of +17%. Figure 2d demonstrates that these calculations would overestimate risk as the total effect of all dependencies acting together on these four hazards results in little net effect (approx. -1%). This occurs because when flooding and wind incidents are prevalent, impacts due to cold and snow are muted. Therefore, a broad multi-hazard approach evidently leads to a very different conclusion from bivariate view(s) (Fig. 1b).

Mutual exclusivity is not self-evident. Storm Ciara (8-10th February 2020) led to disruption from snow, flooding, and wind damage. However, some hazards are more likely under particular synoptic-scale conditions^{e.g. 16,18,19} (weather types²⁰), so if the frequency of a weather type is high over the season the damage from its associated hazards will also be high. Mutual exclusivity arises as the frequency of different weather types trade off against one another²⁰. The greater the difference in hazard likelihood between weather types, and the clearer the seasonal trade-off in their frequency, the stronger this effect will be.

For GB, wintertime frequencies of cyclonic (flood and wind damage^{7,18}) and anticyclonic/northeasterly (cold and snow damage^{5,19}) weather types show strong compensation²⁰ explaining the emergence of ‘hazard modes’ described in Box 1. These modes, however, may not persist in a future climate. Even if the trade-off in circulation types persists, air masses associated with cold and snow hazards may warm sufficiently to no longer yield damage, reducing annual average losses by ~30% (see Fig. 2a). To resolve the effect of such dependencies, and to test simplified hypotheses like this, statistical frameworks for multivariate extremes^{10–13} and/or climate models are needed.

A broader view of compound risk

In summary, dependencies between causative hazards can both compound and suppress risk^{e.g.}
^{1,3,9} (Fig 1b, 2d). Both over and under-estimation of risk is problematic for the systems and
people affected. To neither waste resources nor to be underprepared, scientists, society and
decision-makers need to be alert to both. To date, however, the focus of the modelling
community (especially within climate science) has been on those aspects of dependency that
make outcomes worse. Our contribution highlights that the opposite can also be true (Fig. 1b).
We therefore advocate a broad view of compound risk – a refinement of the established
'compound event' viewpoint that might better serve hazard and risk management communities.

The term 'compound', as applied to risks, developed from its meaning 'make (something bad)
worse; intensify the negative aspects of'^{3,6,17} (see Supplementary Discussion 2). Recently, the
definition has been expanded^{3,6}, but only rarely is a beneficial side-effect³ or reduction of risk
noted as a caveat²¹, and the importance of these tends to be downplayed. We believe that this
wider description, including such positive connotations, is viable as the word compound also
means to 'mix or combine constituents', in this case a mix of hazards. An 'event', however, is an
occurrence rooted in a specific time and place. Thus, perhaps the phrase 'compound event risk'
could be explicitly kept narrow. Conversely, we advocate that 'compound risk' be applied more
holistically to accommodate both compound events^{3,6} that increase impact severity as well as
those impacts that combine within extended timeframes and combine in ways that are mutually
exclusive.

Based on the examples above, situations are likely common globally where multihazard risk is
systematically suppressed with respect to selected narrow (e.g. bi-variate or pairwise)
configurations. We suspect that these are under-diagnosed due to (i) lack of systematic collection
and analysis of impact data, (ii) difficulties in comparing hazards (for example, time-lags
between extreme events, different hazard metrics^{1,17}, time-lags between end-member conditions

like El Niño/La Niña), and lastly (iii) a need for greater awareness that such situations should be identified. The subtle balance between hazards is also non-stationary as climate changes^{e.g. 2,3}, so diagnosis is needed for future climates. Moreover, dependencies are not only between causative hazards, but also embedded in vulnerability and how impacts cascade^{e.g. 3}. Broad, holistic, stakeholder relevant assessments of compound risk for multihazard environments are therefore needed to improve assessments of current and future risk.

Fig. 1: Illustration of plausible effects when the activity of hazard(s) switches between climatologically controlled modes of behaviour, based on Great Britain. a) Impact-centric^{1,3} conceptualisation of the multihazard system. Two hazard modes, each associated with a dominant wind direction (blue arrows), drive six hazards (circles). Rail infrastructure (red) is exposed to all six hazards, whilst (re)insurance (black) is primarily concerned with only two in Mode 2. b) Losses in terms of magnitude and frequency, with rare 'worst cases' on the righthand side (grey band). A conventional view that does not consider dependencies (grey) might underestimate risk if two hazards (for example, flood and wind) compound. However, where exposed assets are subject to hazards driven by two opposing modes (red) compounding effects are suppressed, so care is needed to avoid overestimating risk. Solid arrows represent effect magnitudes seen within the Network Rail loss data (Fig. 2, Box 1), with dashed lines indicating plausible stronger effects.

Box 1: A case study of compound risk in Great Britain

A case study of weather-related impacts (Fig. 2a, Supplementary Discussion 1) on the rail network in Great Britain (GB) illustrates that interactions may suppress tail-end (i.e. worst) risk, mitigating pairwise compound effects (Fig. 2d). Here, impact is expressed as delays to trains which, when monetized, costs Network Rail an estimated £64.6 million annually. Most (72.5%) of these costs occur in the 'winter' half-year (Oct-Mar). Thus, winter is selected as our temporal domain for a seasonal-scale analysis, which in GB is hydro-meteorologically distinct from summer (see Supplementary Figure 1).

Fig. 2d shows that from a narrow (bivariate) multihazard perspective, the largest losses (i.e. 13 year return period) for flooding (Fl) and wind damage (Wi) compound substantially (+28%). Simulation modelling^{1,10} is conducted to demonstrate that this observation (dark blue line) is not due to chance ($p < 0.05$) by breaking all hazard inter-relationships. In the simulation (see Supplementary Discussion 1), this was achieved by shuffling the years in which losses occur independently for each hazard, and 10,000 of these random realizations are used (dashed line).

However, a wider (multivariate) view yields a distinctly different outcome. When one set of hazards in GB is active, the other main group is typically not. Fig. 2b shows that the categories of loss may be, visually or otherwise, grouped into sub-sets that tend to coincide (that is, are correlated). Specifically, when Fl and Wi incidents are prevalent, impacts due to cold (Co) and snow (Sn) are muted. When summed in pairs (e.g. Sn+Co vs Fl+Wi), there is no overlap between the years in which each pair's top five losses occur ($p = 0.024$, χ^2 test), and an inverse correlation is evident (Fig. 2e). In Fig. 2d, this mutual avoidance expresses itself as the largest losses (i.e. 13 year return period) being suppressed to the level of entirely random selection (dashed line) even as each of the pairs is demonstrated to compound (blue lines). This new observation adds to growing evidence of a seasonal scale Fl-Wi association for GB^{1,7,18}.

186

187 We propose the term 'hazard modes' for sub-sets of partially associated hazards (Fig. 2b). For
188 GB, we hypothesize a simple westerly vs north-easterly driver of the hazard modes (Wi + Fl:
189 westerly, or Sn + Co: north-easterly: Fig. 2c). Low pressure systems (named storms) are
190 associated with westerly and cyclonic synoptic-scale atmospheric patterns¹⁸, and although
191 individual storms are typically viewed as either causing Fl or Wi damage^{4,16} some cause both
192 (e.g. Storm Desmond); particular seasons have also been identified as notably 'wet and
193 stormy'¹⁸. Opposing this behaviour, episodes of extreme wintertime cold or snow in GB are
194 typified by advection of cold air from the north and east, and 'blocking' anticyclonic
195 circulation^{e.g. 5,19}. The wintertime frequency of mobile westerly and cyclonic flows are known to
196 trade off against more stable anticyclonic conditions²⁰. Here we show that the North Atlantic
197 Oscillation is a useful metric to capture these behaviours through its correlations with the hazard
198 modes (Fig. 2f,g).

199

200 **Fig. 2: Winter multihazard impacts in Great Britain.** a) National total winter (October-
201 March) losses for nine hazards affecting Network Rail, of which seven are substantive, i.e.
202 <0.1% of total losses. b) Correlations between the loss classifications; stars denote statistical
203 significance; * < 0.05 (i.e. 95% confidence), ** < 0.01, *** < 0.001. c) Illustration of the
204 proposed 'hazard modes'. d) The effect of interdependencies between hazards upon seasonal loss
205 totals, calculated as the difference between observations (solid lines) and simulation modelling in
206 which randomisation has been used to break any process-based linkages between hazards
207 (dashed line). Larger, rarer losses have greater return periods in this exceedance probability plot.
208 Loss values greater than zero indicate that selected hazard combinations compound, or
209 alternatively are suppressed. Statistical significance of the tendency to compound is computed
210 using the AEP method¹ and simulation. Details of data and simulation methods are provided in
211 Supplementary Information. e)-g) Correlations between losses, and with the North Atlantic
212 Oscillation (NAO). Pearson's r , grey shading is 95% confidence interval for the trendline.

213

214 **References**

- 215 1. Hillier, J. K., Macdonald, N., Leckebusch, G. C. & Stavriniades, A. Interactions between
216 apparently primary weather-driven hazards and their cost. *Env. Res. Lett.* **10**, 104003 (2015).
- 217 2. Steptoe, H., Jones, S. E. O. & Fox, H. Correlations between extreme atmospheric hazards and
218 global teleconnections: Implications for multi-hazard resilience. *Reviews of Geophysics* **55**,
219 50–78 (2017).
- 220 3. Zscheischler, J. *et al.* Future climate risk from compound events. *Nature Climate Change*
221 (2018) doi:10.1038/s41558-018-0156-3.
- 222 4. Lavers, D. A. *et al.* Future changes in atmospheric rivers and their implications for winter
223 flooding in Britain. *Environmental Research Letters* **8**, 034010 (2013).
- 224 5. Bieli, M., Pfahl, S. & Wernli, H. A Lagrangian investigation of hot and cold temperature
225 extremes in Europe. *Quarterly Journal of the Royal Meteorological Society* **141**, 98–108
226 (2015).
- 227 6. Leonard, M. *et al.* A compound event framework for understanding extreme events. *WIREs*
228 *Climate Change* **5**, 113–128 (2014).
- 229 7. De Luca, P., Hillier, J. K., Wilby, R. L., Quinn, N. W. & Harrigan, S. Extreme multi-basin flooding
230 linked with extra-tropical cyclones. *Env. Res. Lett.* **12**, 114009 (2017).
- 231 8. Khouakhi, A. & Villarini, G. Contribution of tropical cyclones to rainfall at global scale. *Journal*
232 *of Climate* **30**, 359–372 (2017).
- 233 9. Wahl, T., Jain, S., Bender, J., Meyers, S. D. & Luther, M. E. Increasing risk of compound
234 flooding from storm surge and rainfall for major US cities. *Nature Climate Change* **5**, 1093–
235 1097 (2015).
- 236 10. Wyncoll, D. & Gouldby, B. Integrating a multivariate extreme value method within a
237 system flood risk analysis. *Journal of Flood Risk Management* **8**, 145–160 (2013).

- 238 11. Serinaldi, F. & Papalexiou, S. M. Random fields simplified: Preserving marginal
239 distributions, correlations, and intermittency, with applications from rainfall to humidity.
240 *Water Resour. Res.* **56**, e2019WR026331 (2020).
- 241 12. Wadsworth, J. L., Tawn, J. A., Davidson, A. C. & Elton, D. M. Modelling across extremal
242 dependence classes. *Journal Of The Royal Statistical Society Series B* **79**, 149–175 (2017).
- 243 13. Bevacqua, E., Maraun, D., Haff, H. I., Widmann, M. & Vrac, M. Multivariate statistical
244 modelling of compound events via pair-copula constructions: analysis of floods in Ravenna
245 (Italy). *Hydrol. Earth Syst. Sci.* **21**, 2701–2723 (2017).
- 246 14. Nicholls, N. The El Niño / Southern Oscillation and Australian Vegetation. *Vegetatio* **91**,
247 23–36 (1991).
- 248 15. Mariani, M., Fletcher, M. S., Holz, A. & Nyman, P. ENSO controls interannual fire activity
249 in southeast Australia. *Geophys. Res. Lett.* **43**, 10891–10900 (2016).
- 250 16. Walz, M. A., Donat, M. G. & Leckebusch, G. C. Large-Scale Drivers and Seasonal
251 Predictability of Extreme Wind Speeds Over the North Atlantic and Europe. *Journal of*
252 *Geophysical Research: Atmospheres* **123**, 11518–11535 (2018).
- 253 17. Kappes, M. S., Keiler, M., von Elverfeldt, K. & Glade, T. Challenges of analyzing multi-
254 hazard risk: a review. *Nat. Hazards* **64**, 1925–1958 (2012).
- 255 18. Matthews, T., Murphy, C., Wilby, R. L. & Harrigan, S. Stormiest winter on record for
256 Ireland and UK. *Nature Climate Change* **4**, 738–740 (2014).
- 257 19. Mayes, J. Regional weather and climates of the British Isles - Part 2: South East England
258 and East Anglia. *Weather* **68**, 59–65 (2013).
- 259 20. Briffa, K. R., Jones, P. D. & Kelly, P. M. Principal component analysis of the Lamb
260 catalogue of daily weather types: Part 2, Seasonal frequencies and update to 1987.
261 *International Journal of Climatology* **10**, 549–563 (1990).

262 21. Gill, M. & Malamud, B. D. Reviewing and visualizing the interactions of natural hazards.
263 *Reviews of Geophysics* **52**, 680–722 (2014).
264

a)

b)

Multi-hazard dependencies can increase and decrease risk

¹John K. Hillier, ¹Tom Matthews, ¹Robert L. Wilby, ²Conor Murphy

¹Geography and Environment, Loughborough University, LE11 3TU, UK.

²Irish Climate Analysis and Research UnitS (ICARUS), Department of Geography, Maynooth University, Co Kildare, Ireland.

Supplementary Information

This document contains supplementary material. There are three main sections. First Supplementary Discussion 1 (S1), relates to the case study of weather-related impacts on the rail network in Great Britain. This expands upon the study contained in main text and Box 1. Within this, sub-sections on data and methods are referred to so that the reader can go into this level of detail if desired. Second, in S2, the widening scope of term 'compound' as applied to risks is more fully documented. Third, in S3, dice games using only standard dice are set out to illustrate the impacts of dependencies, including partial dependency.

Supplementary Discussion 1. Case Study: Compound risk in Great Britain

In the main text and Box 1, a case study of weather-related impacts on the rail network in Great Britain (GB) illustrates that interactions may suppress tail-end (i.e. worst) risk, mitigating pairwise compound effects. The data used in the study are detailed in section S1.1 below, and a formal presentation of the simulation methodology¹ is in S1.2 'Methods'.

S1.1 Data

Weather Related Incident Impact Data (WRIID) is Schedule 8 delay data, manually attributed to nine hazards by Network Rail (NR), who are the owner and infrastructure provider of most of the rail network in GB. WRIID contains 182,000 incidents (2006-2019) that have each been assigned to a hazard and impact location (i.e. the originating site of delays). These data have been used previously for work on heat^{2,3}, but not for multi-hazard analysis. Impact is expressed as delays to trains which, when monetized, costs Network Rail an estimated £64.6 million annually. Most (72.5%) of these costs occur in the 'winter' half-year (Oct-Mar)⁴. Thus, winter is selected as our temporal domain (i.e. seasonal scale), which in GB is hydro-meteorologically distinct from summer^{e.g. 5} (see Supplementary Figure 1).

NR's planning year is April-March, i.e. Q1/Q2 is 'Summer' and Q3/Q4 'Winter' (October-March). The year-end is aligned with the UK hydrological/meteorological year^{4,6} as defined by the National River Flow Archive - <https://nrfa.ceh.ac.uk/>. Thus, assignments in Fig. 2 are for the year in which the winter initiates i.e. 2017 for Oct 2017 to Mar 2108.

Values L_{ij} are winter totals, disaggregated by year i and hazard j . For the time span 2006-2018 there are 13 winters, i.e. $y = 13$ and $i = \{1, 2, \dots, y\}$. There 9 hazards, i.e. $h = 9$ and $j = \{1, 2, \dots, h\}$, giving $n = 117$ data points. These alone are used in the analysis (i.e. Figs 2b, d). Thus, all data in this study are published in Fig. 2a.

In other loss datasets, mis-categorisation of some losses is a recognized issue. For instance, in the Association of British Insurers (ABI) '*General Insurance Statistics*'⁷, some pluvial inundation (surface water flooding) is known by practitioners to be reported as wind damage because it is

associated with stormy weather. This reporting artefact makes it difficult to discern a physically driven component of any correlation between flooding (FI) and wind (Wi)¹. Such an artefact does not appear to be present in WRIID. In winter FI-Wi are dependent ($r = 0.68$, $p < 0.01$, Fig. 2b), but in summer there is no demonstrable relationship ($r = -0.05$, Supplementary Figure 1), and it is difficult to imagine how a reporting artefact might exist in winter and yet be avoided in summer. Other relationships also change (Supplementary Figure 1), suggesting that this inference applies to the other hazards. The summer multi-hazard system, however, is not the subject of this paper.

Supplementary Figure 1: Summertime multi-hazard impacts in Great Britain. Correlations between the loss classifications; stars denote statistical significance - * < 0.05 (i.e. 95% confidence), ** < 0.01, *** < 0.001. Cold, snow and fog losses are negligible in the summer.

S1.2 Methods

Academic literature describing approaches to multi-hazard interactions is limited, mainly applied to combinations of a pair of hazards, and interdependencies between receptors (such as people and infrastructure) are rarely explicitly modelled ^{e.g. 8}.

The method used here combines recently advocated methods. It is designed to be a pragmatic yet powerful approach for gaining insights into compound risk in highly multi-hazard systems (i.e. ≥ 3 extremes), which works even with multiple time-lagged events, varied hazard types and data time-series of limited length. Key elements of the method are using (i) loss data^{1,9,10}, (ii) annual/seasonal time-scales for hazard correlation^{1,9} and (iii) simulation modelling of Aggregate Exceedance Probability (AEP)^{1,11}. These are described below sequentially, along with an explanation of how the correlation matrix is constructed.

Use of loss data: Using loss data is an approach that was recently categorised as 'bottom-up' and strongly advocated¹². Quantitative, impact-centric risk analyses based on observed losses^{1,9,10} or even proxies¹³ are sparse, but the use of losses permits direct comparisons between hazards overcoming a key analytical difficulty encountered by previous multi-hazard analyses (e.g. time-lags between events, different hazard metrics etc.)¹⁴.

Use of a seasonal/annual time-frame: Extended (up to annual) timeframes have been clearly included in major reviews of multi-hazard risk^{14,15}, and seasonal scales for storm prediction (e.g. Tropical Cyclones) have been extensively used^{16–19}, but quantitative analysis of multi-hazard risk on a seasonal scale are relatively rare ^{e.g. 1,9,20}. Typically, compound events involve individual episodes set within a relatively limited timeframe (e.g. <14 days)^{21,22}. One advantage of using

numerous events that occur across a season is in mitigating the aleatory uncertainty (i.e. random noise) in particular events (e.g. impact might depend on whether it is night or day, or the exact time distribution of rain), with these cancelling out with a sum or mean to give a better estimate of tendency with respect to a driver (e.g. climate mode) via the central limit theorem. A second advantage is that antecedence (such as water saturation of the ground) is accounted for, which is important in hazards like flooding²³.

Correlation matrix: Relationships between hazards are expressed (Fig. 2b) in terms of Pearson's correlation coefficient (r), despite known limitations²⁴. Pearson's r is selected for familiarity, simplicity and because the non-parametric calculations in this work regarding Aggregate Exceedance Probability (AEP) curves in Fig. 2d (see 'Simulation modelling' below) account for the net effect of both the dependency structure and marginal distribution of the data^{25,26} (Fig. 2a), which r reflects.

For completeness, Supplementary Figure 2a isolates the dependency structure using Spearman's rank correlation^{24,25}, and Supplementary Figure 2b uses logarithms of the losses to correct for the marginal distribution although this relies on assuming the type of that distribution²⁷, in this case selecting the log-Normal loss distribution²⁸. The proposed hazard modes and clustering structure (i.e. determination of which hazards are most closely related) remain very similar to Fig. 2b even if statistical significances are mainly estimated as lower (e.g. within Mode 2). The other main difference is that the inverse relationship between the two modes is emphasized more strongly (e.g. for Snow and Wind).

R functions `rcorr()`, `corrplot` and `hclust()`²⁹ are used.

Supplementary Figure 2: Winter dependency structure between the loss classifications. a)

Spearman's rank, which is a less powerful test but isolates the structure from the marginal

distribution of losses. b) Pearson's r for logarithms of losses. Stars denote statistical significance

- * < 0.05 (i.e. 95% confidence), ** < 0.01, *** < 0.001. The ordering of the hazards is

objectively determined by the clustering algorithm used (see text).

Simulation modelling: The co-occurrence of extremes has been assessed using a null

hypothesis of independence^{21,30} as has the magnitude of a hazard subject to multivariate

drivers¹¹. In considering compound risk¹⁵ however, it is of fundamental importance to ascertain

the difference in impact (e.g. financial cost) between realizations of reality where dependencies

exist and realizations where they do not. But, this is rarely done^{1,8}. We, therefore, use the one

methodology to establish correlation on this basis – the AEP method¹. AEP is exceedance

probability (EP) for aggregate losses, which is directly applicable to the WRIID dataset in Fig. 2a

as L_{ij} are totals from numerous events over a season. The AEP method has six stages:

(1) Select the sub-set of at least two hazards of interest e.g. $h_{\text{sub}} = \{1,2,8\}$, which may be all the hazards, and compute total seasonal observed (i.e. aggregate) losses $AL_i = \sum_j L_{ij}$ where $j \in h_{\text{sub}}$.

(2) Calculate empirical (i.e. observed) AEP values for AL_i , which implicitly contains all interdependencies within the system, albeit potentially masked by unrelated perturbations or 'noise'. These are computed by the standard textbook method³¹. Specifically, sort AL_i in order of descending magnitude, assigning each an index (i.e. row) in the list k . AL_k is then the k^{th} AL_i value in the list. As each year occurs once the probability p of each is $1/y$, the observed exceedance probability EP_k is k/y , and the associated return period (e.g. Fig. 1d) is y/k .

(3) Compute the gradient g_{obs} of exceedance probability (i.e. EP_k) plotted against observed losses (i.e. AL_k). Specifically, a linear model is fitted by ordinary least squares to estimate coefficients in $AL = g \cdot EP + c$. Thus, g_{obs} is a single value quantifying correlation in losses resulting from all interactions at their empirically observed magnitudes.

(4) Conduct 10,000 simulations $m = \{1,2 \dots 10,000\}$ wherein randomisation is used to eradicate any possible dependencies between hazards. In each simulation, for each hazard j separately, losses L_{ij} are randomly re-assigned to a year and denoted L_{ijm} . Then, steps (1) to (3) are repeated for each simulation to generate AL_{im} , AL_{km} and g_m .

(5) Calculate the mean simulated AEP curve with dependencies eliminated, i.e. $\overline{AL_{km}} = \frac{1}{m} \sum_m AL_{km}$. $\overline{AL_{km}}$ vs EP_k can then be compared to the observed AEP curve. Visually this is most effectively performed by plotting the difference between the observed and mean simulated curves (Fig. 2d).

(6) Establish whether or not the observed compounding effect within the subset of hazards could have occurred by chance. The null hypothesis is that there is no compounding effect i.e. $H_0: g = 0$, with an alternative hypothesis that a compounding effect exists i.e. $H_1: g < 0$; x-axis is inverted by use of probability, not the return period. By the central limit theorem the distribution of g is roughly normal, but this test is non-parametric as the simulation-based p-value of g_{obs} is calculated directly. Illustratively, if g for 24 realizations i is smaller than g_{obs} $p = 0.0024$ and the null hypothesis that $g_{obs} = 0$ (i.e. no effect of dependencies) can be rejected. Note that this simulation requires no assumptions about statistical distributions, dependency structure, physical processes, or climate modes.

Supplementary Discussion 2. Defining Compound: Widening scope of term 'compound' as applied to risks

In the Oxford English Dictionary (OED), the word 'compound' has several meanings. When used as a verb, these include to '*mix or combine (ingredients or constituents)*' and to '*make (something bad) worse; intensify the negative aspects of*'. It is conceivable that both of these concepts apply when 'compound' is applied in the context of risk^{12,14,15,32,33}.

In 1971 Hewitt³² characterized a compound hazard as '*several elements acting together above their respective damage threshold*'. In 2010 Kappes¹⁴ distinguished two types of hazard relationship: (1) where one hazard is triggered by another and (2) where the disposition (i.e. magnitude or frequency) of one hazard is altered by another either simultaneously or in a following season. Thus, a typology is formed for '*acting*' and the timeframe of '*together*' is expanded. By 2012, the IPCC definition³³ was extended to include (i) the confluence of multiple

sub-extreme conditions '*combinations of events that are not themselves extremes but lead to an extreme event or impact when combined*', and (ii) when impact is amplified by the extremes (e.g. temperature and wind) combining with underlying conditions (e.g. fuel for a wildfire). However, this detail introduces ambiguities, leading Leonard in 2014¹⁵ to propose a more general definition i.e.

'A compound event is an extreme impact that depends upon multiple statistical variables or events'

Here, the emphasis on impact is useful, but the importance of longer timeframes involved is downplayed by use of the word '*event*' rather than '*risk*'. In 2018, Zscheischler¹² emphasizes that '[ignoring] *dependencies can lead to the underestimation of risk*', before defining compound weather/climate events as:

'The combination of multiple drivers and/or hazards that contributes to societal or environmental risk'

This maintains many of the benefits of Leonard's definition and usefully distinguishes drivers (i.e. underlying conditions such as hydro-meteorological extremes), from hazards (i.e. the physical property causing damage such as water depth) and from risk (i.e. impact and its likelihood). It explicitly generalizes previous definitions and continues the expansion of the scope of the term. Rarely, a positive side-effect¹² or reduction of risk is noted as a caveat³⁴, but the importance of these is downplayed. However, there are combinations of drivers and/or hazards that contribute to risk (i.e. losses in Figs. 1, 2) in which the combinations moderate (i.e. suppress) rather than worsen (i.e. compound) risk. Thus, ambiguity is introduced into the term

'compound event hazard/risk'. Either, the definition should be narrowed, or explicit attention is needed to clarify that moderation/mitigation is included within this (or a similar) term such as 'compound hazard/risk', within which an emphasis on the second OED definition (i.e. worsen) is not obligatory.

Supplementary Discussion 3. Dice Games

A series of exercises or 'games', using only standard dice, provide a way to verify our statistical assertions about how full and partial dependency between two hazards affect the likelihood of a 'worst case' where both occur. These directly relate to the examples in the main text, with the difference that an 'event' (e.g. a flood) occurs if the score on the relevant die is defined as 'high' rather than being a six only. The independent case in Game 1 is the baseline to which the other scenarios are compared. All Games are set so that the overall level or hazard (i.e. events of either type occurring) is constant, set at 1-in-3 times that a die is rolled.

(1) Independent hazards: Imagine that flooding and wind damage happen if a 'high' value is rolled on a standard die. In traditional risk analysis¹⁴, flooding and wind are viewed as independent phenomena that have a die each, and a 'worst case' occurs when both happen (i.e. two high values). Define high as when a 5 or 6 is rolled. Then, a worst case happens 1-in-9 times ($\frac{1}{3} \times \frac{1}{3} = \frac{1}{9}$). Roll both dice together a number of times to verify this. Also, verify that overall hazard is set so that a high value occurs 1-in-3 times a die is rolled (i.e. taken individually, count all rolls and all high values).

(2) Completely positively dependent hazards: If flooding and wind always happen together, only 1 die is needed to represent both of them. Define high as when a 5 or 6 is rolled. Verify

that both hazards occur 1-in-3 throws. Verify that, as in Game 1, overall hazard is set so that a high value occurs 1-in-3 times.

(3) Completely negatively dependent hazards: If flooding and wind never happen together, two high values are simply not allowed. No dice are really needed to determine that the chance of a worst case (i.e. both together) is zero however, to complete this analogy, define high as when a 5 or 6 is rolled, and low is when a 1 or 2 is rolled. Roll one die then the other. If both dice are high, swop the second to be equivalently low. If both dice are low, swop the second to be equivalently high. Sixes are swopped to be ones, and visa versa, and fives and swopped with twos. After this manipulation, verify that both hazards never occur together. Verify that, as in Game 1, overall hazard is set so that a high value occurs 1-in-3 times.

(4) Partial positive dependency: Where there is a weaker relationship between phenomena, such as for flooding and wind in extratropical cyclones, two loaded dice are a more apt analogy. This can be replicated with standard dice if they are thrown sequentially so that the second 'knows' what the first has done. 'High' on the first is defined as 5 or 6, and 'low' as 1 or 2. On the second, high is more likely (i.e. 4,5,6) after a high on the first die, less likely (i.e. 6 only) when the first is low, and unaltered for intermediate values. Verify that both hazards occur 1-in-6 times ($\frac{1}{3} \times \frac{1}{2} = \frac{1}{6}$), more than independence (Game 1) yet less than complete dependence (Game 2). Verify that, as in Game 1, overall hazard is still set so that a high value for an individual hazard occurs 1-in-3 times a die is rolled. If desired, a hazard can be randomly allocated to a die before each pair are thrown in sequence (e.g. by flipping a coin), but this does not alter the outcome.

(5) Partial negative dependency: if hazards (e.g. flooding and wildfire) tend to be mutually exclusive within a day, season or year, depending upon the spatial domain considered (e.g. Australia), imagine two dice loaded to reflect this. This loading can be replicated with standard dice if 'high' on one is defined as 6 only, and on the other as 4,5 or 6; decide which before

rolling - dice of different colours may be useful here. Roll both dice together. Verify that both hazards occur 1-in-12 times ($\frac{1}{6} \times \frac{3}{6} = \frac{1}{12}$), more than complete mutual exclusivity (Game 3) yet less than independence (Game 1). Verify that, as in Game 1, overall hazard is still set so that a high value for an individual hazard occurs 1-in-3 times a die is rolled. If desired, a hazard can be randomly allocated to a die before each pair are thrown (e.g. by flipping a coin), but this does not alter the outcome.

References

1. Hillier, J. K., Macdonald, N., Leckebusch, G. C. & Stavrinos, A. Interactions between apparently primary weather-driven hazards and their cost. *Env. Res. Lett.* **10**, 104003 (2015).
2. Ferranti, E. J. S. *et al.* Heat-related failures on South-East England's railway network: insights and implications for heat-risk management. *Weather Climate and Society* **8**, 177–191 (2016).
3. Ferranti, E. J. S. *et al.* The hottest day on the railway network; insights and thoughts for the future. *Meteorological Applications* **5**, 195–208 (2018).
4. Lavers, D. A. *et al.* Winter floods in Britain are connected to atmospheric rivers. *Geophys. Res. Lett.* **38**, L23803 (2011).
5. Svensson, C. *et al.* Long-range forecasts of UK winter hydrology. *Env. Res. Lett.* **10**, 064006 (2015).
6. Wilby, R. L. *et al.* The 'dirty dozen' of freshwater science: detecting then reconciling hydrological data biases and errors. *WIREs Water* **e1209**, 1–19 (2017).
7. ABI. *Data: 'General Insurance Statistics''*. (2014).
8. Ciurean, R., Gill, J., Reeves, H., O'Grady, S. & Aldridge, T. *Review of environmental multi-hazards research and risk assessments*. 86 (2019).

9. Palin, E. J. *et al.* Skillful Seasonal Forecasts of Winter Disruption to the U.K. Transport System. *Journal of Applied Meteorology and Climatology* **55**, 325–344 (2016).
10. Dimitriou, K., McGregor, G. R., Kassomenos, P. A. & Paschalidou, A. K. Exploring winter mortality variability in five regions of england using back trajectory analysis. *Earth Interactions* **20**, (2016).
11. Wyncoll, D. & Gouldby, B. Integrating a multivariate extreme value method within a system flood risk analysis. *Journal of Flood Risk Management* **8**, 145–160 (2013).
12. Zscheischler, J. *et al.* Future climate risk from compound events. *Nature Climate Change* (2018) doi:10.1038/s41558-018-0156-3.
13. Zscheischler, J. *et al.* A few extreme events dominate global interannual variability in gross primary production. *Env. Res. Lett.* **9**, 035001 (2014).
14. Kappes, M. S., Keiler, M., von Elverfeldt, K. & Glade, T. Challenges of analyzing multihazard risk: a review. *Nat. Hazards* **64**, 1925–1958 (2012).
15. Leonard, M. *et al.* A compound event framework for understanding extreme events. *WIREs Climate Change* **5**, 113–128 (2014).
16. Walz, M. A., Donat, M. G. & Leckebusch, G. C. Large-Scale Drivers and Seasonal Predictability of Extreme Wind Speeds Over the North Atlantic and Europe. *Journal of Geophysical Research: Atmospheres* **123**, 11518–11535 (2018).
17. Vecchi, G. A. *et al.* On the seasonal forecasting of regional tropical cyclone activity. *Journal of Climate* **27**, 7994–8016 (2014).
18. Camargo, S. J., Sobel, A. H., Barnston, A. G. & Klotzbach, P. J. The influence of natural climate variability on tropical cyclones and seasonal forecasts of tropical cyclone activity. in *From Science to Mitigation, World Scientific Series on Asia-Pacific Weather and Climate* 325–360 (World Scientific, Singapore, 2010).

19. Patricola, C., Saravanan, R. & Chang, P. The Impact of the El Nino–Southern Oscillation and Atlantic Meridional Mode on Seasonal Atlantic Tropical Cyclone Activity. *Journal of Climate* **27**, 5311–5328 (2014).
20. Matthews, T., Murphy, C., Wilby, R. L. & Harrigan, S. Stormiest winter on record for Ireland and UK. *Nature Climate Change* **4**, 738–740 (2014).
21. De Luca, P., Hillier, J. K., Wilby, R. L., Quinn, N. W. & Harrigan, S. Extreme multi-basin flooding linked with extra-tropical cyclones. *Env. Res. Lett.* **12**, 114009 (2017).
22. Khouakhi, A. & Villarini, G. Contribution of tropical cyclones to rainfall at global scale. *Journal of Climate* **30**, 359–372 (2017).
23. Berghuijs, W. R., Harrigan, S., Molnar, P., Slater, L. & Kirchner, J. W. The relative importance of different flood-generating mechanisms across Europe. *Water Resour. Res.* **55**, 4582–4593 (2019).
24. Embrechts, P., McNeil, A. & Straumann, D. Correlation and dependency in risk management: properties and pitfalls. in *Risk Management: Value at Risk and beyond* 176–223 (Cambridge University Press, Cambridge, UK., 1998).
25. Genest, C. & Favre, A.-C. Everthing you always wanted to know about copula modelling but were afraid to ask. *Journal of Hydrologic Engineering* **12**, 347–368 (2007).
26. Coles, S., Heffernan, J. & Tawn, J. Dependence measures for extreme value analyses. *Extremes* **2**, 339–365 (1999).
27. Teugels, J. L. & Vandewalle, B. Statistical Analysis of Catastrophic Events. *Lecture notes in Economics and Mathematical Systems* **581**, 105–117 (2006).
28. Clemente, A. & Romano, C. A copula-extreme value theory approach for modelling operational risk. in *Operational Risk Modelling and Analysis: Theory and Practice* 360 (2004).
29. Murtagh, F. & Legendre, P. Ward’s hierarchical agglomerative clustering method: which algorithms implement Ward’s criterion? *Journal of Classification* **31**, 274–295 (2014).

30. Zscheischler, J. & Seneviratne, S. I. Dependence of drivers affects risks associated with compound events. *Science Advances* **3**, e1700263 (2017).
31. Mitchell-Wallace, K., Jones, M., Hillier, J. K. & Foote, M. *Natural Catastrophe Risk Management and Modelling: A Practitioner's Guide*. (Wiley, 2017).
32. Hewitt, K. & Burton, I. *Hazardousness of a place: a regional ecology of damaging events*. (Toronto Press, Toronto, 1971).
33. Seneviratne, S. I. *et al.* Changes in climate extremes and the impacts upon the natural physical environment. in *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation* 109–230 (Cambridge University Press, Cambridge, UK., 2012).
34. Gill, M. & Malamud, B. D. Reviewing and visualizing the interactions of natural hazards. *Reviews of Geophysics* **52**, 680–722 (2014).