GC Insights: Open R-code to translate the co-occurrence natural hazards into impact on joint financial risk

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Abstract.

Hydro-meteorological hazard is often estimated by academic and public sector researchers using publicly funded climate models, whilst the ensuing risk quantification uses proprietary insurance sector models, which can inhibit the effective translation of risk-related environmental science into modified practice or policy. For co-occurring hazards, this work proposes as an interim solution open R-code that deploys a metric (i.e., inter-hazard correlation coefficient *r*) obtainable from scientific research, usable in practice without restricted data (climate or risk) being exposed. This tool is evaluated for a worked example that estimates the impact on joint financial risk at an annual 1-in-200 year level of wet and windy weather in the UK co-occurring rather than being independent, but the approach can be applied to other multi-hazards in various sectors (e.g. road, rail, telecommunications) now or in future climates.

1 Introduction

Translating scientific work into improved policy or practice is widely accepted to be desirable yet challenging (Cordner, 2015; Dowling, 2015; Evans, 2006; Margalida et al., 2015; Scott et al., 2018). For hydro-meteorological natural hazards such as flooding or wildfire (Berghuijs et al., 2019; Finney et al., 2011) caused by extreme weather, two main restrictions on data inhibit the effective translation of risk-related environmental science into modified practice in the insurance sector (e.g., Hillier and Van Meeteren, 2024). Firstly, open datasets output by publicly funded weather and climate models (e.g., from Met Office, ECMWF) are large (10s of terrabytes), with users required to have the capability to translate the variables provided into metrics related to extremes. Data might also be released to academics on non-commercial licenses. Secondly, financial risk is quantified using proprietary models and sensitive data (e.g. insurance claims).

During February 2022 the storm sequence 'Dudley', 'Eunice' and 'Franklin' inflicted several hydro-meteorological hazards (snow, landslips, flooding, extreme winds) across the UK and Northwest Europe (Mühr et al., 2022; Volonté et al., 2023a, b), resulting in multi-sector impacts (e.g. road, power distribution) and ~€3-4 billion in insured losses (Kendon, 2022; Saville, 2022). These losses illustrate the importance of considering multi-hazard risk (Kappes et al., 2012; Ward et al., 2022; Zscheischler et al., 2018). In Northwest Europe, flooding and extreme wind cause the largest losses (Mitchell-Wallace et al., 2017), co-occuring on timescales from (sub-)daily to seasonal (Bloomfield et al., 2023; De Luca et al., 2017; Hillier and Dixon, 2020; Owen et al., 2021b, a). This dependency exists in meteorological variables such as precipitation (e.g., Martius et al., 2016) and in impact data: insurance losses and railway delays (Hillier et al., 2015, 2020). Yet, the potential for this multi-hazard relationship is not always considered in (re)insurance risk analysis. Like almost all hazards, European flooding and wind risk are currently modelled separately by catastrophe models (Mitchell-Wallace et al., 2017). Tropical cyclones are the recent exception, with hazards derived from the same climate model (Stalhandske et al., 2024; Verrisk, 2024).

Prior to such a full joint modelling workflow, this paper proposes and evaluates a statistical approach to combine flooding and wind risk models using their per-event hazard values and losses they output. These are small and obtainable datasets. It is the first open code for this task, intended for use by any researcher or practitioner. The approach was developed during a collaborative project 'TOGETHER' (Bank of England, Verrisk, Aon, Met Office, Loughborough University), which led to a modification to the Insurance Stress Tests that regulate UK insurers (Bank of England, 2022).

Research questions:

1. What is the impact of co-occurring wet and windy weather in the UK on insurers' joint annual 1-in-200 year financial risk?
2. How useful is the proposed approach in translating scientific research into insurance industry practice?

2 Methods & Data

The innovation is that our approach uses climate science to link risk models *via* Severity Indices (*SI*) recording the magnitude of each hazard, such as $\sum v^3$ for wind (Bloomfield et al., 2023; Klawa and Ulbrich, 2003; Nordhaus, 2010). High and low inter-hazard correlation cases derived from a climate model (Figure 1a) are applied to *SI* values available within risk models (Figure 1b) from the reinsurance industry, without exposing commercial sensitive data.

Correlation is applied at a seasonal timescale because the annual 1-in-200 year return period (RP) loss after reinsurance (i.e. 'net' of insurance companies' own insurance) is a key metric used to calculate insurers' solvency (Hadzilicos et al., 2021). Four statistical methods (e.g. copula) are used exactly as in the Hillier et al. (2023). The calculations are detailed in the R-code provided (Supplementary material). The only inputs needed are a 3-column text file for each model (date, *SI*, monetary loss), with one row per event. No changes are need to the R-code to apply it to other regions of the world or hazard pairs, assuming a correlation coefficient can be determined for the user's data of choice (reanalysis, climate model, emissions pathway).

We use data from two independently derived catastrophe risk models available from Aon. A time-series of 4,731 years is used, with fluvial flood events that have non-zero losses in the UK more frequent (~7 per year) than wind events (~3 per year), and UK-aggregated event losses are approximately log-Normal with tail end wind losses (RP > 100 years) approximately twice that of flood. For wind, correlation ρ between *SI* (sum v^3) and loss per year is in the range ~0.5-0.8, and about half this for flooding (ρ ~0.2-0.3, *SI* is number of events). To test-run the R-code, events derived from the UKCP (Bloomfield et al., 2023; Griffin et al., 2022) have been created to approximate this configuration, but are illustrative only and these outputs should not be interpreted.

To understand the utility of this approach in translating scientific research into reinsurance industry practice, statements were elicited from TOGETHER's collaborators. These data are in Supplementary Material, referenced by company name(s) for quotes or syntheses: illustratively '*The Bank of England's statements are a means of staff sharing views that challenge – or support – prevailing policy orthodoxies. The views expressed here are those of the authors, and are not necessarily those of the Bank of England or its policy committees*' [*Bank*].

3 Quantitative Results

Figure 1d shows the estimated effect that flood-wind co-occurrence has on annual 1-in-200 year financial risk, reporting the difference between the typical assumption (i.e., independence) and a correlated case. As in the Bank of England report (Hillier et al., 2023) the 'high' correlation, Gaussian copula case is considered most realistic, and net of reinsurance (i.e. 'after', light green) is most relevant. Lower gross, yet higher net losses are mainly caused by the flood hazard metric available. The principal result, visually synthesising results from the studies, is that uplift might be as high as ~10-14% for the very specific scenario analysed. It is vital to realise however, that this result should not be over-interpreted, specifically should not be taken to necessarily indicate '*under-capitalisation of any particular firm nor of the sector in general*' [*Aon*].

4 Discussion & Reflections

Quantifying tail risk, severe but rare circumstances, is desirable for a general insurer's risk management. There are potential benefits in shared effort in addressing this complex task yet there is simultaneously the potential for commercial tensions that stem from organisations' differing roles (e.g. insurer, broker, regulator), analogous to many global industries (Ritala, 2012). Such beneficial cooperation between organisations potentially in competition has been labelled 'co-opetition' in 'paradox studies' (Brandenburger and Nalebuff, 1996; Gnyawali and He, 2008; Smith et al., 2017). Various ways of handling this exist (e.g., Stadtler and Van Wassenhove, 2016) although a critical part can be succinctly summarised as '*Partnerships require good networks, time, and trust to develop*' [*Met Office*]. TOGETHER is seen as a successful example of a co-opetition project (Hillier and Van Meeteren, 2024). The finding that co-occurrence might plausibly raise annual joint UK flood-wind losses net of reinsurance by up to ~10% (Figure 1d) is only applicable in this particular analysis but as an indicator that correlated hazards are worth considering it is seen as a valuable contribution [*Aon, Met Office, Bank*], and developing the open source R-code 'tool' is also considered a benefit:

> '*An important step in bringing together publicly funded climate model data and industry-based modelling in a transparent way'* [*Aon*]

But, to what extent is it useful? It is a valuable first step [*Aon*], which can be an informative tool for those insurers who haven't previously captured these dependencies because it is prudent to explore rather than ignore potential dependencies [*Bank*](Hillier et al., 2023). The approach can be applied to any sets of events (e.g., hail, wildfire) from existing models [*Aon*], making it quickly implementable. However, whilst it accounts for uncertainty in one key choices (i.e., dependency structure) there are many other variables, such as in the reinsurance structure or risk model used. Hence, critically, careful interpretive judgement is needed:

> *'Where tools such as this R-code are applied to inform a view of risk, caveats and assumptions should be considered; users should be satisfied a tool is being used in appropriate circumstances.'* [*Bank*]

Illustratively, it would be unwise to apply the headline result to an insurer's unique portfolio. For this reason 'open-source' and 'transparent' are highlighted as key benefits of this approach [*Aon*, *Met Office*]. Possible applications include exploring the sensitivity of peril co-occurrence to different financial structures (e.g. number of reinstatements) [*Bank*]. As independent and open source it also provides a means to benchmark future similar work in this field [*Aon*], and can be applied to different hazards.

Overall, we conclude that our approach is one useful interim solution prior to, and perhaps justifying, more extensive modelling. It is a bridge, deploying a metric (inter-hazard correlation coefficient) obtainable from scientific research, which is usable in practice without restricted data being exposed. More generally, it is an example of embedding environmental science in to practice and policy by identifying a simple, pragmatic means (i.e., r) of estimating the impact on a critical industry-relevant metric. It paves the way for similar methods to be applied within other sectors (e.g. rail, road, power distribution, telecommunications), perhaps for physical climate risk disclosure.

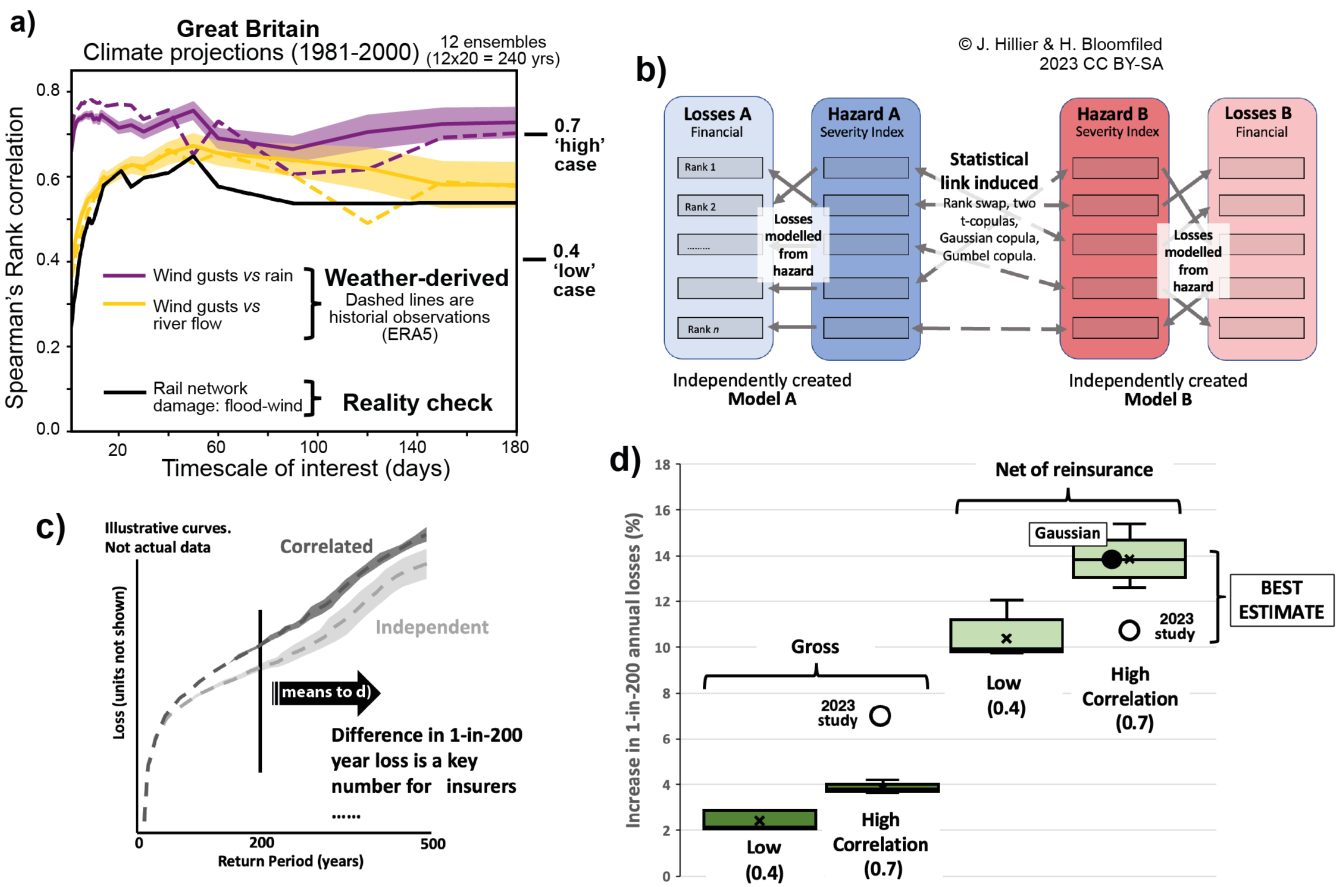

Figure 1 – Pathway from hazard to impact, i.e. effect on losses for very severe events. (a) Wintertime correlation, Spearman's Rank (r_s) within various multi-hazard episode durations for the Oct-Mar season, using severity indices for flooding and extreme wind in Great Britain (Bloomfield et al., 2023). Rain (purple) and river flow (yellow) are related to wind hazard for climate model (UKCP, solid lines) and historical (ERA5, dashed) and rain (purple). Error bands are 95% confidence. (b) Illustration of the method, i.e. statistically linking two independent risk models (red / blue) via their hazard severity indices. (c) Illustrative exceedance probability curves for correlated (dark grey) and independent (light grey) cases, the difference between which is the effect of co-occurrence, with the 1-in-200 return period ($p = 0.005$) of particular interest in insurance (d) Indicative impact of a correlation between flooding and wind hazards on annual losses for the whole UK market at a 1-in-200 year return period. Box plots illustrate the range of answers generated by the five different types of correlation (see b) for each of the four cases analysed: low-gross, high-gross, low-net, high-net. As in Hillier et al (2023) the Gaussian is 'best' and highlighted (black dot) as it best fits annualized hazard data at Site W of Hillier & Dixon (2020). Open circles are from that 2023 study, which used two different catastrophe models.

5 Ethics Statement

Ethical approval was given by the Ethics Review Sub-Committee at Loughborough University.

6 Conflicts of interest

JH is an Executive Editor of *Geoscience Communication*, so the peer-review process was undertaken by independent handling and executive editors. The authors have no other competing interests to declare.

7 Author contributions

JH conceived the work and undertook the analysis. All authors contributed to the drafting, writing and review of the manuscript.

8 Data & Code Availability

The R-code used is openly available, and is in supplementary material to this article, along with guidance and a worked example with idealised data. Data from the proprietary insurance sector models used are not available.

9 Acknowledgements

JH was funded by NERC (UKRI) Knowledge Exchange Fellowships NE/R014361/1 and NE/V018698/1. We are grateful to Aon, Bank of England and the Met Office for their collaboration.

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