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LETTER

Interactions between apparently 'primary' weather-driven hazards and their cost

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Abstract

A statistical analysis of the largest weather-driven hazards in the UK contradicts the typical view that each predominates in distinct events that do not interact with those of other hazard types (i.e., are 'primary'); this potentially has implications for any multi-hazard environments globally where some types of severe event are still thought to occur independently. By a first co-investigation of long (1884–2008) meteorological time-series and nationwide insurance losses for UK domestic houses (averaging £1.1 billion/yr), new systematic interactions within a 1 year timeframe are identified between temporally-distinct floods, winter wind storms, and shrink–swell subsidence events ($P < 0.03$); this increases costs by up to £0.3 billion/yr (i.e., 26%), although impacts will be spatially variable depending upon the interplay of hazards. 'Memory' required in the environmental system to cause these intra-annual links between event types appears to reside in soil moisture and, tentatively, sea surface temperatures. Similar, unidentified interactions between non-synchronous events are likely worldwide, and the analytical methods we have developed to identify and quantify them are suitable for application to meteorological, geological (e.g., volcanic) and cryospheric (e.g., avalanches) hazards.

1. Introduction

Hazards and the processes driving them (e.g., in the atmosphere) are well studied in isolation, including work to understand their spatial and temporal patterns (e.g., clustering) [1, 2] and impact [3–6]. Multiple hazards impacting the same location (e.g., simultaneous wind and flooding [7, 8]) and their complexities also are investigated [9]. For instance, secondary hazards are considered (e.g., coastal surges produced by storms) and inter-dependencies in impacted systems are recognized (e.g., cascades or hazard chains) [10, 11]. But, there are hazards that are still seen as unrelated to and not triggered by other hazards, which are referred to as 'primary' [11]. Currently primary hazards, which include some of the largest threats (e.g., US Hurricane), are considered independently of each other even in state-of-the-art multi-hazard risk analysis (e.g., for insurance or resilience planning) [3, 9, 12, 13]. Probabilistic multi-hazard risk models known as 'catastrophe models' [14] in (re-)insurance lead methodologies for such analysis [9], but even these quantify primary hazards independently as by definition there is not yet a robust evidence base to do otherwise. However, the physical processes governing apparently primary hazards could be linked in as yet undiscovered ways that cause them to interact at certain temporal or spatial scales. Ignoring any such interaction will lead to a significant mis-estimation of present and future risk (i.e., the impact of the hazard). Specifically, the largest weather-driven hazards are typically still viewed by policy makers and financial institutions as if they do not interact [3, 4, 12, 13]. Thus, the probabilistically modeled impact estimates (i.e., costs) resulting from these 'primary' hazard events are compounded into overall loss estimates as if they occur independently within any given year [9, 12, 15]. Assuming independence will underestimate the severity of 'worst case' years (e.g., a 1 in 250 year combined loss) if hazards tend to co-occur, whilst overstating the risk if hazards tend to occur in different years.

Studying hazard interactions is non-trivial as events for each hazard vary in spatial extent and have drivers of damage (e.g., water depth) that are not directly comparable, but risk (e.g., lives, damage) might serve as a common metric [9, 11]. This paper is the first to examine statistically interactions between 'primary' hazards by quantitatively exploiting insurance loss data, in which houses are effectively 'weather sensors', as a measure common to all the hazards (i.e., £). This measure is used in tandem with traditional meteorological data, and both data sets identify interactions. Most UK households take out insurance to cover against all hazards, and the UK has a long record of environmental observation. It is therefore used as a case study for this global issue.

The UK is affected by several apparently 'primary' natural hazards, of which wind damage caused by winter storms (WS), droughts (DR) including the '*gradual catastrophe*' [16] of the shrink–swell effect of clay soils on houses (SS), and flooding (FL) are the most costly to the economy [17, 18]. All can cause severe disruption and/or financial losses [4, 19]. All are mainly driven by meteorological factors, but FL and WS are still considered separately because severe events (e.g., extra-tropical cyclones) are rarely individually responsible for substantial amounts of both FL and WS damage [20]. Inter-hazard linkages can be postulated (e.g., FL ↔ SS), are considered a key unknown in the UK National Climate Change Risk Assessment [21], and we denote them with an arrow (↔). Such interactions can be conceptualized as forming linked risk and hazard systems (figure 1), with risks (i.e., impacts) indicated with a prime (e.g., WS′). However, the hazard linkages are relatively poorly understood [9, 13]. Links might be directly causative, or have a mutual underlying cause. Furthermore, intra-seasonal to inter-annual 'memory' might exist within the system, so linked events need not be synchronous [12]. Financial reckoning across a year (e.g., via annual budgets or insurance contracts) governs the uppermost timescale for linkages relevant to many stakeholders, is a time-window that has not been examined for extreme weather interactions, and is therefore used in our analysis. The spatial resolution of this first intra-annual analysis is national (i.e., UK wide).

To identify and understand hazard interactions within annual time-windows, this paper statistically co-investigates meteorological and loss data. Each dataset is described, including how it is well placed to provide insights into the underlying linkages within the natural environment. Systematic intra-annual interactions are demonstrated to exist between temporally distinct events of multiple types, and initial explanations are offered in terms of causative physical processes previously proposed for related observations. Lastly, brief note is made of how the modified risk estimates may, illustratively, interest decision makers.

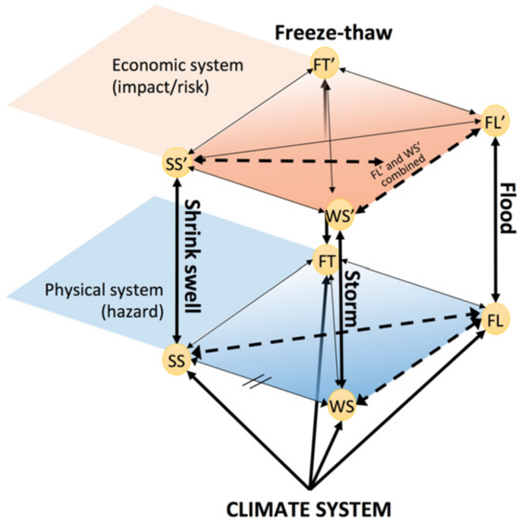

Figure 1. Potential inter-relationships between the climate system, hazards (e.g., FL) and impacts (denoted with a prime, e.g., FL′) in the UK. Potential interactions between the hazards or the risks (thin lines) are poorly understood [21]; see supplementary material for a review. Systematic links identified in this paper are dashed bold arrows, whilst the double bar (on SS ↔ WS) indicates an investigated but unsupported link. Bold arrows indicate previously well-studied links, such as the conversions from each hazard to risk (i.e., vertical bars such as SS ↔ SS′).

2. Data

Annual FL′, WS′ and SS′ financial loss data between 1998 and 2013 are used in the analysis (figure 2). These are compiled from nationwide, spatially aggregated insurance data on losses claimed for damage to UK domestic property that are available quarterly to 2013 from the Association of British Insurers [18]. Since 1998 'weather' losses have been separated from other categories including 'domestic subsidence' (SS′), and the weather losses are sub-divided into 'flood' (FL′), 'storm' (WS′) and 'pipes' which represents freeze-thaw damage due to cold weather (FT′). Before more granular reporting of 'escape of water' in 2004, however, 'pipes' losses were dominated by factors unrelated to weather (e.g., washing machine leaks), leaving this data time-series too short to use. Insurance loss data have several key advantages. They are effectively the output of many houses acting as 'weather sensors', which offer dense spatial coverage whilst being widely distributed, whose output is checked for its quality (e.g., by claims assessors). Furthermore they, by definition, directly record the aspects of each physical process that makes it a hazard, and output in a metric common between hazards (i.e., £). Whilst houses are not evenly distributed in space, leading to an inhomogeneous spatial sample of losses,

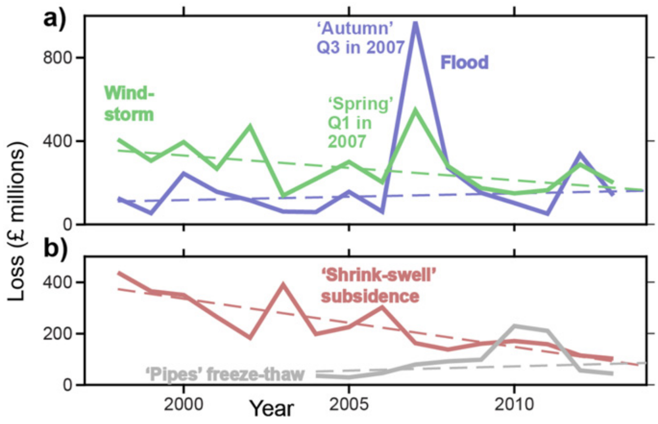

Figure 2. Annualized ABI insurance loss data for 16 years (1998–2013), aggregated nationwide across the whole UK. The robustly fitted trends reflect underlying, gradual changes (e.g., inflation, house design changes, longer-term climatic signals): flood (FL′) is blue; windstorm (WS′) is green; shrink–swell subsidence (SS′) is red; freeze-thaw (FT′) or 'pipes' is gray. Trends are removed before further analysis to focus on inter-annual randomness, and trend fitting is described in Methods.

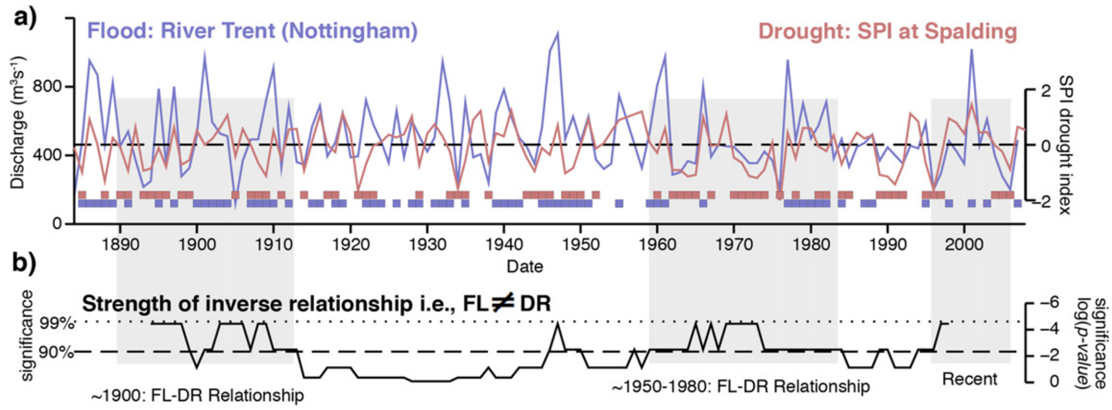

Figure 3. (a) Long historical time series for a 'discharge' measure of FL and the SPI measure of DR, illustrating an inverse relationship ($P < 0.001$) between when 'severe' episodes (colored squares) occur across the whole series (i.e., 1884–2008); i.e., severe FL and DR tend to occur in different years. Half of years are taken as severe (i.e., $f = 0.5$). (b) *Monte Carlo* analysis within a 20 year window that slides along the time-series in 1 year increments, which resolves the non-stationarity in the signal. No FL data are available for 1956–7.

they offer an overall view that is to a first order sufficient to compare to other national-level data.

Meteorological metrics are used that summarize the varied properties of each hazard at a scale that is to a first-order representative of and comparable to annual damage in the UK. Pragmatically, to achieve long time-series, these use published data quantified in a number of ways. Drought's slow arrival is captured in a 12 month average [22], and maximum river flows are used for the largest floods that drive annual FL hazard (e.g., 2007) [19, 23]. Similarly, as the strongest winds drive damage [24, 25] the number of very stormy days is a reasonable measure for WS. Details are given below.

The 1884–2008 flood (FL) series used (figure 3) is from the River Trent. It is one of the longest published continuous series of maximum annual (January–December) discharges for a major river covering Central England (1877-) [23]. The size and location of this river basin make it one of the most reflective of synoptic-scale weather affecting the UK, and it has much lower levels of anthropogenic interference than the River Thames. The Trent series is fully homogenized, with changes in measurement practices accounted for [23]. After 1958 this series is based on gauged flow data at Colwick (Nottinghamshire) on the Trent, which allows a November to October year to be adopted here, better linking the extended meteorological winter [26] and following summer. This is coupled with the second longest reconstructed drought (standardised precipitation index—SPI) series published for the UK (1726-) [22], which is in relatively close proximity at Spalding (Lincolnshire). Pairing up these observations presents a unique set of spatially close but temporally long flood and drought time-series. In the UK, drought is a good proxy for SS [5, 27], and an annualized SPI average is created for 1884 to 2008 from data underlying the published work but adapted to use a November–October year for consistency. Note that negative SPI values indicate drought. A matching synoptic-scale (i.e., nationwide) WS time series is created as the annual (November–October) count of days affected by 'very severe gales' (VSG) as assessed using the UK Jenkinson Gale Index [28]. The publically-available daily index values use reanalysis data (NECP1 and 20CR) [28, 29], and is a verified proxy for storm frequency [6, 20, 29]. Of the three proxies (i.e., FL, WS, SS) a long-term trend is only visually discernable for WS, but is removed for all meteorological series using 50 year boxcar filter.

3. Methods

In order to assess short-term (i.e., intra-annual) co-variability or otherwise for hazards of mismatched characteristics the losses they cause and their occurrence in years are used as common measures for risk and hazard, respectively. Statistical de-trending is used to remove confounding influences (e.g., inflation) from the loss data (section 3.1), and the techniques that have been devised to quantify potential interactions are described in sections 3.2 and 3.3.

3.1. De-trending insurance loss data

Loss data are the 'output' of houses acting as extreme weather sensors by recording damage, but conflate physical (e.g., wind speed) with anthropogenic factors (e.g., demographic shifts, inflation, housing type and quality, type of insurance coverage, and the fraction of households with cover). The non-weather related influences, however, change relatively slowly; that is, more slowly than the 1 year time window relevant to intra-annual interactions between hazards. Pragmatically, these slower changes can be quantified via the approximately steady trickle of losses in more moderate years. So, the data are robustly de-trended (i.e., ignoring outliers) using M-estimation (figure 2) [30]; bisquared weighting, with $c = 4.7$, was used from an initial ordinary least squares estimate. Then, subtracting the trend removes the confounding factors (e.g., increasing exposure) to leave the inter-annual variability that typifies weather hazard and risk [28, 29, 31–33], and these de-trended data are used in all analyses. Clearly, longer climatic trends are also removed. The statistical approach is favoured over the deterministic removal of a trend (e.g., using Gross Domestic Product (GDP)) [31, 34], which may miss some of the factors.

3.2. Monte Carlo method for meteorological data

This *Monte Carlo* method was developed to quantitatively assess interactions in dissimilar, possibly incomplete, meteorological time series. The probability of an association between occurrences of 'extreme' years in any two physical time-series (e.g., figure 3) being non-random (i.e., due to interaction) was determined by *Monte-Carlo* simulation ($n = 10\,000$). What could happen by chance (i.e., without a linkage) was calculated by randomly shuffling the years in which extremes occur, and then counting in how many runs the number of random coincidences equaled or exceed the number observed (the definition of a P value). This is a function of the number of years (n) and fraction (f) of years defined as extreme, with an expectation of $f^2 n$ coincidences on average. A binary approach is compatible with the typical view that severe insurance losses are caused by 'events' over some threshold [9, 12], and the simulation method allows for both an incomplete time-series and selecting only the most extreme portions of it.

3.3. Aggregate exceedance probability (AEP) method

The 'AEP method' was developed to quantify the size and significance of interactions between diverse physical processes creating hazards, and involves summing relevant risks (e.g., FL′+WS′). AEP curves (e.g., figure 4(a)) plot the probability that the sum of losses in any one year will exceed a given loss amount. These underpin analysis of natural hazard losses in insurance and re-insurance [3, 4, 15], and are therefore used as the basis for the method proposed below. If the ABI data (figure 2) [18] are plotted in terms of exceedance probability (EP) instead of return period (RP), where $\mathrm{EP} = 1/\mathrm{RP}$, the deviations from losses expected of independent risks plot roughly linearly (figures 4(b) and (d)). This allows the magnitude of the interaction to be summarized by a single metric, the gradient (m) of this line fitted by ordinary least squares. Fitted gradients are shown as dashed lines on figure 4. Each observed gradient then permits an assessment of whether or not an observed potential interaction (e.g., between FL′ and WS′) could occur through chance coincidence by *Monte-Carlo* (MC) simulation ($n = 10\,000$). In each MC realization, for each risk, the year (i.e., 1998–2013) associated with each annualized loss value was randomly shuffled; this eliminates any possibility of a link remaining between the risks when re-combining the losses (e.g., FL′ + WS′) to create AEP curves. These 10 000 'random' realizations give the expected AEP curves (gray lines on figures 4(a), (b) and (d)) and probability distributions of m (figures 4(c) and (e)) for independent risks. This approach both gives loss estimates in a directly relevant form and avoids statistical assumptions (e.g., normality) when calculating P values that quantify the statistical significance of potential interactions. As before, the P value is simply obtained by counting in how many runs simulated random gradients equal or in excess of the observed gradient.

For illustrative purposes possible limiting cases of the strength of each linkage are also created. An entirely 'correlated' case, where one hazard will always tend to co-occur with the other, is modeled by losses for each risk being sorted in descending order before being summed. This pairs the largest annual losses for each hazard. The opposite 'inversely correlated' case, where two hazards always tend to avoid each other, is approximated by listing the losses for one risk in

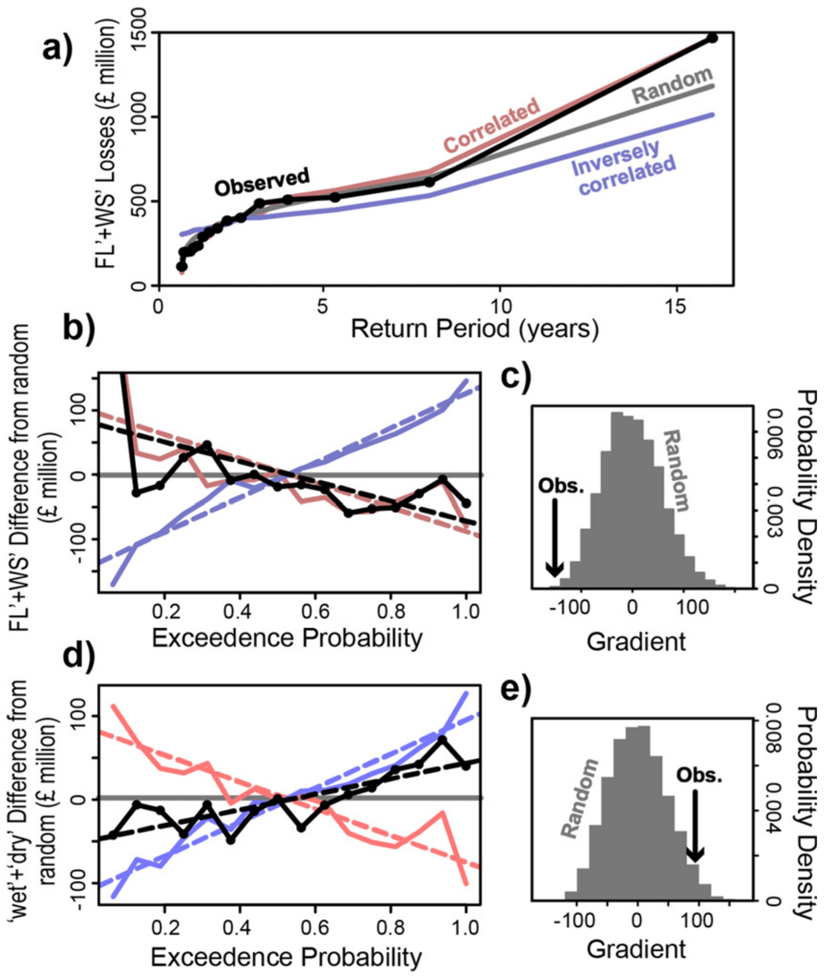

Figure 4. Probability–loss curves for pairs of risks. (a) Aggregate exceedance probability (AEP) plot [15] for FL′+WS′ data, showing observed data with respect to three models where the two risks are entirely 'correlated' (i.e., interact and amplify), are entirely 'inversely correlated' and demonstrate opposing behaviors (i.e., severe in different years), and are 'random' with no association or interaction. (b) as in (a) but in terms of exceedance probability and as differences from the random model, with OLS trend lines fitted (dashed lines). The gradients for the 10000 realizations of the random model are compared to the observed in (c). (d) and (e) are for 'wet' (i.e., FL′+WS′) and 'dry' (i.e., SS′) losses.

ascending order whilst keeping the other in descending order to pair the largest losses with the smallest.

4. Results

The analyses performed give insights into intra-annual 'relationships' between hazards, strictly in terms of a tendency to co-occur or not within a year, and risks in terms of whether larger annualized losses tend to occur together or not. The 'AEP method' developed (see Methods) demonstrates that relationships between FL′↔WS′ ($P = 0.0003$) and WS′↔SS′ ($P = 0.03$) very likely exist, and it quantifies their effect on losses (see figure 4). The FL′↔WS′ relationship increases annual losses with respect to the 'random' model (i.e., interactions eliminated) by £282 million for the 16 year RP event, and exists ($P = 0.03$) even with this largest event in 2007 excluded. To be explicit, if FL and WS tend not to occur together, annualized aggregated losses for one (e.g., FL′) are lower in years when the other (e.g., WS′) is higher; thus, the sum of these two (FL′ + WS′) is higher in 'worst case' years than if there was no relationship. Conversely, WS′ and SS′ tend not to occur together, reducing 16 year RP combined losses by £43 million. When the two 'wet' weather risks are combined (i.e., FL′ + WS′) their relationship to 'dry' SS is significant ($P = 0.025$, figure 4(e)), reducing 16 year RP losses by £42 million. Note that, since the links between these losses and their causative hazard are extremely well established (figure 1 and supplementary material), linkages in the losses indicate matching linkages in the underlying hazards and their driving physical processes.

Taking the SPI drought index as a proxy for SS, and annual maximum discharge in the River Trent as a proxy for FL, the 16 year loss time series can be situated in a long temporal context (i.e., 1884–2008). *Monte Carlo* simulation (see Methods) of the whole time-series together (1884–2008) demonstrates an inverse relationship ($f = 0.5$, $P < 0.001$) between the years in which 'severe' episodes of FL and DR tend to occur (figure 3), in agreement with the 'wet' ↔ 'dry' relationship seen in the loss data. Considering 20 year windows in isolation ($f = 0.5$) demonstrates that the relationship is stronger at some times, specifically between 1890–1910 and 1960–1980 (figure 3b). No significant relationship is observed for WS ↔ SS, whatever fraction of years is defined as severe (f). The most extreme FL and WS (i.e., $f = 0.3$) have a tendency to occur in the same years for the period of highest-quality data (1958–2008), observed with >90% confidence ($P = 0.084$); extreme FL and WS coincide seven times, compared to an expectation of 4.5 times. Similarly, the 30% lowest flows and WS counts coincide more frequently than expected ($n = 7$), so simulated together a relationship between extremes of FL and WS very likely exists ($P = 0.027$).

5. Discussion

The biggest (i.e., £282 million in 2007) and most robust risk intra-annual interaction is therefore apparently between FL′ and WS′. Its existence even without the eye-catching association in 2007 (figure 2(a)) indicates that it is pervasive throughout the loss time series (1998–2013). However, it is at least partially a reporting artefact; some insurers report pluvial flood losses as WS′. So, the results demonstrate the effectiveness of the AEP method at extracting relationships, but cannot prove a systematic FL ↔ WS linkage between hazards because the FL′ and WS′ series cannot generally be decoupled reliably. In 2007 the quarterly loss data show a winter-summer separation between FL′ and WS′ (figure 2(a)), so this association cannot be explained by 'leakage' between the loss categories. However, this is a single year unambiguously linking the losses, and thus hazards. In contrast, the 1958–2008 meteorological data provide evidence of a systematic FL ↔ WS hazard linkage for more extreme years ($P = 0.027$), with coincidences such as 2007 occurring about ×1.5 more than expected by chance. This hypothesis is supported by 2013/4 (December–February), which was both prone to flooding and exceptionally stormy [20, 29]. Furthermore, the high WS index in 2007 associated with flooding that did not severely impact the Trent [19] suggests that a national analysis will reveal the relationship more strongly still. A systematic, long-term, intra-annual FL ↔ WS hazard link has not been reported before for the UK, but is not surprising as extra-tropical cyclones can cause both high wind speeds and extreme precipitation. Although individual cyclones impacting the UK rarely cause both significant FL and WS damage, sequences of multiple strong cyclones as in 2013/4 could lead to conditions (e.g., saturated soil) favouring flooding [20], perhaps via associated atmospheric rivers [26] and possibly driven by teleconnections to anomalies such as in the western Pacific warm pool [35] or the simultaneous influence of extreme temperature gradients between the North American continent and sea-surface temperatures in the Northwest Atlantic [36]. That worst-case combinations of FL and WS (e.g., 2007, 2013/2014) are ~1.5 times more likely than previously thought may interest those planning resource provision for emergency response.

Loss data, showing a pattern mirrored in the longer-term meteorological proxies of hazard (1884–2008), demonstrates for the first time that a link between 'dry' drought-related SS′ [5] and the 'wet' risks (i.e., FL′+WS′) likely exists. Thus, an intra-annual linkage between these hazards likely exists in the UK; this result complements longer-period (e.g., decadal) FL ↔ DR relationships that have been identified using proxy data, for instance in Mediterranean regions [37]. Physically, it is easy to imagine saturated ground both facilitating flooding [20] and deterring SS damage that is caused by extended periods (e.g., 12–18 months) drying of the top ~1 m of soils susceptible to volumetric change [27, 34]. This previously unacknowledged 'dry' ↔ 'wet' hazard interaction modifies annual losses by £42 million, which is ±7% of total (i.e., FL′ + WS′ + SS′) annual average UK insured losses, a figure that may equate to a commercially significant amount of money for stakeholders with large high-value portfolios of assets (e.g., insurers, national infrastructure providers). Since the hazards have differing spatial distributions [5, 6, 19], our results show that future impacts on portfolios of assets (e.g., houses) will depend critically on both their geographic distribution and the interplay of hazards.

6. Conclusions

It can be concluded that major hazards in the UK previously viewed as independent in fact interact, and that these interactions significantly alter their annual combined impacts and how bad worst-case years are. Most widely, however, this paper demonstrates the utility of loss data (e.g., insurance losses, repair costs, travel-time increase) in assisting investigations into intra-annual interaction between diverse processes driving hazardous weather-related events. The *Monte Carlo* approach proposed and the AEP method, which is a novel adaptation of an analytical tool from insurance, are suitable for application to meteorological, geological (e.g., volcanic, earthquake) and cryospheric (e.g., avalanches) hazards. Future opportunities could be analyses including European storms [31] or tropical cyclones [32], or perhaps an assessment of landslides, debris flows and flooding in an Alpine environment [33]. Quantifying the strength of observed linkages in the environmental processes driving hazard is an indicator of where to direct future investigations, a constraint on climate and risk models, and provides a basis for better models to assist policy makers concerned with future resilience to climate change [12].

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Author contributions: JH and NM conceived the work. JH devised and conducted the statistical analyses, NM cleaned data, and NM and GC advised on meteorological processes and data. AS reviewed existing literature. All authors discussed the results and wrote the paper.

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