Increasingly seasonal jet stream drives stormy episodes with joint wind-flood risk in Great Britain

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Abstract

Ignoring a correlation between flooding and extreme winds underestimates risk to insurers or providers of critical infrastructure such as railways or electricity. We explore this potential underestimation for Northwest Europe, illustrated using Great Britain (GB), using an event-based analysis in regional 12 km UK Climate Projections (UKCP18, 1981-1999, 2061-2079 – RCP8.5). We derive a new wintertime (Oct-Mar) set of 3,427 wind events to match an existing set of fluvial flow extremes and design innovative multi-event e*pisodes* (Δt of 1-180 days long) that reflect how periods of adverse weather are actually experienced (e.g. for damage). Results show the probability of co-occurring wind-flow episodes in GB is underestimated 2-4 times if events are assumed independent. Significantly, this underestimation is greater both as severity increases (e.g. 90th to 99th percentile) and Δt reduces, adding the insight that we need to be most concerned about underestimating co-occurrence in the strongest individual or closely consecutive storms ($\Delta t \sim 3$). In the future, joint extremes are twice as likely as in the present. Statistical modelling demonstrates that changes go significantly beyond thermodynamic expectations (i.e. more high flows in a wetter climate). The largest co-occurrence increases are shown to be in mid-winter (DJF) and changes in the north Atlantic jet stream dynamics are demonstrated to be an important driver; particularly in mid-winter it is strengthened and squeezed into a southward-shifted latitude window (45-50°N), conditions typical of high flows and joint extremes impacting GB in present day simulations. More widely, that work highlights that the recipe of driving large-scale conditions (e.g. jet stream state) for a multi-impact 'perfect storm' will vary by country. So, future analyses should work to build area-by-area understanding of how the impact of common drivers varies spatially, which is key to risk mitigation and planning (e.g. diversification, mutual aid across Europe).

Keywords: Jet stream, multi-hazard, seasonality, squeezed, episodes, flooding, extreme wind

1. Introduction

The challenge of multi-hazard risk has long been recognised for storms (e.g., Southern, 1979; White, 1974) and more broadly (Gallina et al., 2016; Hillier, 2017; Kappes et al., 2012; UNEP, 1992; Ward et al., 2022). This co-occurrence of adverse natural events has also recently been framed as 'compound' (e.g., Simpson et al., 2021; Zscheischler et al., 2018). In short the difficulty is that impacts occurring together, colloquially referred to as 'perfect storm', are harder to handle (Hillier et al., 2023) and impacts potentially combine to amplify beyond the sum of the constituent parts.

Inland flooding and extreme winds event cause the largest losses in North-West Europe (Mitchell-Wallace et al., 2017; PERILS, 2024). Illustratively, during 16th-21st February 2022 a sequence of storms named Dudley, Eunice and Franklin inflicted various hazards including flooding and 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 nearly €4 billion in insured losses (Kendon, 2022; PERILS, 2023; Saville, 2022). Similarly, from 3rd-27th Dec 1999 the sequence Anatol, Lothar, Martin caused ~€10 billion insured property damage alone (PERILS, 2024; Roberts et al., 2014).

Strikingly, most of the 98 impactful wintertime (Oct-March) wind or flood incidents in the PERILS database (PERILS, 2024) from 2010 to 2024 affect Great Britain (GB, 73), more than France or Germany (38 or 47, respectively). Moreover, wintertime correlation of proxies for flooding and wind in countries near GB appears similar (Bloomfield et al., 2023; Hillier and Dixon, 2020). This is likely because extra-tropical cyclones typically track eastwards from the Atlantic (e.g., Roberts et al., 2014) and are a key driver of both hazards across NW Europe (Fig. 1), which is illustrated by joint wind-flood events during named storms (e.g., Fink et al., 2009; Kendon and McCarthy, 2015; Liberato, 2014; Matthews et al., 2018). As such GB is a useful sentinel location for studying co-occurring flood-wind impacts in NW Europe.

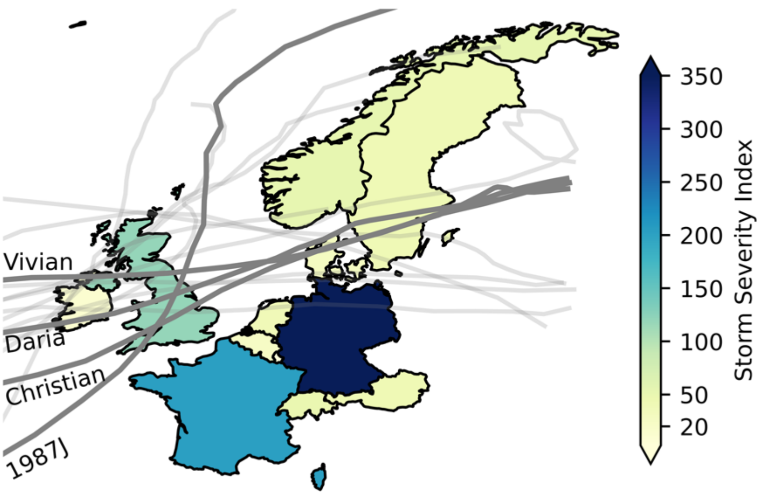

Fig. 1: Indicative map of the distribution of severe wind in NW Europe from a sub-set of 25 storms that caused significant damage in the British Isles from two catalogues (PERILS, 2024; Roberts et al., 2014), for which ERA5 data are available (i.e. pre-2024). 16 pre-2021 tracks are shown where data are available (light grey lines) (CCC, 2022) with 4 illustrative tracks labelled and named (dark grey lines). SSI is the Storm Severity index is v^3 over 98th percentile (see Section 2.1) and is a total per country accumulated over the storms. Map projection: Plate carrée.

Building on initial work establishing that a relationship existed (Hillier et al., 2015; Matthews et al., 2014), there is now strong evidence that floods and extreme wind co-occur in GB on daily to seasonal timescales (Bloomfield et al., 2023; De Luca et al., 2017; Hillier and Dixon, 2020; Jones et al., 2024; Martius et al., 2016; Owen et al., 2021b, a), perhaps controlled by the jet stream characteristics (Hillier and Dixon, 2020). Existing work predominantly uses heavy precipitation as a proxy for flooding (e.g., Vignotto et al., 2021). As reviewed in Bloomfield et al (2023) studies using river flow or impact data, which more directly relate to flooding, are much less common in GB (De Luca et al., 2017; Hillier et al., 2015, 2020) or elsewhere (Küpfer, 2024). Indeed, even globally only three studies assessing dependency use river flow and wind derived from the same underlying climate model, two in GB (Bloomfield et al., 2023, 2024) and one globally for tropical cyclones (Stalhandske et al., 2024). Thus, future change in joint wintertime flood-wind risk remains of interest.

Most recently, two studies have used the UK Climate Projections (UKCP18) to advance understanding of the drivers of the wintertime co-occurrence of potential flooding and extreme wind in GB, present and future. Bloomfield et al (2024) used 30 pre-defined weather types in the regional UKCP18 simulations (12 km spatial resolution) and a GB hydrological model to assess the meteorological drivers of joint wind and high flow extremes. For 1-day windows, using population-weighted severity indices, they found cyclonic weather types typical, and also confirmed the positive phase of the North Atlantic Oscillation (NAO+) as an associated state (Hillier et al., 2020). At a seasonal timescale they also demonstrated a future increase in years that will be both wet and windy. Manning et al (2024) used the convection permitting UKCP18 local (spatial resolution of 2.2 km) to investigate the role of storm track position and jet stream on the co-occurrence of wind and rain extremes. For individual storm events in mid-winter (December-February) they ascribed future change in co-occurrence to predominantly thermodynamic causes (i.e. warmer and therefore wetter) supported by a southerly disposition of the jet stream. Both papers find a 4-fold increase in short-duration joint events (i.e. $\leq$ 1-day) into the future.

This work builds on and adds to these studies in a number of unique ways. Using high flows rather than precipitation, it quantifies the co-occurrence of events (E) within multi-hazard *episodes* (ε) spanning daily to seasonal (i.e. Δt = 1-180 days long) from October to March in the UKCP18 regional data (1981-1999, 2061-2079). It uses high flows as they do not simply arise from precipitation in individual storms, so the causative storm(s) might differ in character as might context (e.g. soil saturation) and associated jet stream dynamics. It examines the role of the jet stream in more detail, primarily by investigating the role of seasonality (i.e. the time-distribution of events within the winter). To do this it employs an accessible index that is widely used to characterise the latitude and strength of the North Atlantic jet (Woolings et al., 2010), with the intention of facilitating future inter-comparison between climate models. Finally, to give real-world relevance, and for technical reasons related to how the severity indices are built for longer time windows (see Section 2.2), it develops an approach (dwECA) using dynamically positioned time windows to reflect how these multi-event windy episodes with high river flows (Δt = 1-180 days) are actually experienced.

To define distinct claims (re)insurers commonly use windows of 72 hours for storms (Δt = 3 days) or 21 days for floods called 'hours clauses' (e.g., Mitchell-Wallace et al., 2017; PERILS, 2023), which insurers will position to encompass the maximum loss possible. More widely, an observer (e.g. an emergency response manager) might say "*It started with the storm on Tuesday, and ended after the last heavy rain on Sunday*". To study individual weather phenomena (e.g. distinct storm) a buffer such as $\pm$24h might be used (e.g., Manning et al., 2024; Martius et al., 2016), but it is less clear how to proceed for an episode containing storms over a longer period (e.g. 14-days), and non-overlapping windows or block maxima (e.g., Bloomfield et al., 2023; Zscheischler et al., 2021) may chop a storm in half. The proposed dynamic time windows for episodes (ε) uses the weather events (E) themselves to define the evident start and end of the adverse conditions. As such, dwECA is intended to align with stakeholder definitions and experience, with insurers providing a motivation to focus on time windows (Δt) of 3 and 21 days. The work has real-world relevance as even in insurance, where natural hazard risk modelling is quite mature (e.g., Mitchell-Wallace et al., 2017), because flooding and extreme wind models of NW Europe are still independently derived, namely based on uncorrelated underlying climate simulations (Dixon et al., 2017; Hillier et al., 2024).

Using the idea of framing multi-hazard risk environments as an in-depth or user focussed case study to cut through complexity (Hillier and Van Meeteren, 2024; Ward et al., 2022) the work is framed by the insurance sector, yet results are more widely applicable. There are four main research questions:

1. Do the most severe extreme winds and flows tend to co-occur or not? Namely, are they asymptotically dependent?
2. How does strength of co-occurrence vary with the time-window (Δt) used to group events into episodes?
3. Can a relatively simply derived metric of jet position be a functional, readily applied tool to distinguish jet states characteristic of co-occurrence?
4. How do future changes in the North Atlantic jet stream influence co-occurrence in simulations of the future?

2. Data & Methods

The workflow in Fig. 2 is used to produce individual events for wind (E_W) and flood (E_F) with timestamps from the same underlying climate model (i.e. UKCP18). Then, from these, multi-hazard *episodes* (ε) are created and analysed. All metrics are calculated during extended winter (October–March) and nationally aggregated. Threshold values are defined at percentiles derived from the present-day climate simulations, then are applied to future climate to understand potential changes.

Existing data and practice (e.g. thresholds, definitions) are adopted to create events and define their severity (Bloomfield et al., 2023; Griffin et al., 2022a, b; Manning et al., 2024). As such, detail is provided in Appendix A. Importantly, the rank correlation between GB aggregated precipitation, high river flows and extreme wind for the simulated present (1981-1999) in UKCP18 closely matches multiple historic weather datasets and river-flows derived from them across time windows from 1 to 180 days (Bloomfield et al., 2023, 2024; Harrigan et al., 2023; Hersbach et al., 2020; Hirpa et al., 2018). Indeed, these correlations have also been verified against impacts on the GB rail network (Bloomfield et al., 2023). Thus, the UKCP18 simulations appear to adequately capture the level of co-occurrence between extreme winds and high flows (detail in Appendix A.1).

2.1. Defining events (E) for each separate hazard

Each event (E) is a grid of the maxima of a hazard driver (e.g. v) during a time-window containing an isolated hydro-meteorological extreme (detail in Appendix A.2). For each event, summary metrics (total area, duration, severity index) are assigned to a single date t_{max}, the individual day during the event when the greatest number of grid cells exceeding the set threshold level. An event's Storm Severity Index, SSI(E) follows Klawa and Ulrich (2003) as given by Eq. (1) and Table 1, detailed in Appendix A.3:

Eq. (1)

$$SSI(E) = \sum_{i=1}^{N_i}\sum_{j=1}^{N_j}\left(\frac{v(E)_{i,j}}{v_{i,j}^{98}} - 1\right)^3 \cdot I_{i,j}$$

$$I_{i,j} = \begin{cases} 0 & \text{if } \; v(E)_{i,j} < v_{i,j}^{98} \\ 1 & \text{otherwise} \end{cases}$$

Table 1: Table of parameters used, with precipitation included for completeness (see Appendix A).

Parameter	**Symbol**	**Units**
Maximum daily 10 m wind gusts at a grid cell *i,j*, and the threshold (98th) percentile taken to define extreme at a grid cell.	$v_{i,j}$, v^{98}	ms^{-1}
Total daily precipitation, and the threshold (98th) percentile taken to define extreme at a grid cell.	p, p^{98}	mm
Daily mean river flow	q	m^3s^{-1}
Day	t	days
Event (e.g. event ID *k* = 1247 for wind). W is for Wind, F is for river flows and P is precipitation.	$E_{W,k}$	-
Multi-hazard *episode* ε, with its type (wind W, high flow F, joint J) and SI percentile exceeded	ε_W^{95}	-

for events within it (75th, 95th, 99th). Also see Fig. 3.		
Event's most extreme day, to which summary statistics (e.g. duration, FSI) are assigned.	t_{max}	days
Temporal limits of an event (i.e. start and end)	t_{start}, t_{end}	days
Length of multi-hazard episode, 'time window'	Δt	days

For, simplicity and to avoid a judgement linking value directly to population density (e.g. consider a wind farm), no population weighting is used. The optimal formulation of SSI (e.g. power-law, exponential, wind threshold, storm duration) is still actively debated. Most pertinently, probabilistic models that account for the uncertainty in how individual assets are damaged (Heneka et al., 2006; Heneka and Ruck, 2008; Pardowitz et al., 2016; Prahl et al., 2012) better approximate losses in Germany across all 2004 wintertime days in 11 years (1997-2007). The exception to this is the costliest days (~10 per year), which are still adequately modelled using cubic excess-over-threshold approach with a 98th percentile (Prahl et al., 2015). Thus, using Eq. (1) is appropriate here. Because recent developments have not been previously reviewed, a detailed justification is in Appendix A.3. The new wind event set is described in Appendix A.4.

Based on the form of SSI, Flood Severity Indices (FSI) have recently been developed (Bloomfield et al., 2023). Only grid cells on the river network are used, again with no population weighting. Thus, each events' flood severity FSI(*E*) is given by Eq. 2 and Table 1.

Eq. (2)

$$FSI(E) = \sum_{i=1}^{N_i}\sum_{j=1}^{N_j}\left(\frac{q(E)_{i,j}}{q_{i,j}^{99.5}} - 1\right)\cdot I_{i,j}$$

$$I_{i,j} = \begin{cases} 0 & \text{if } \ q(E)_{i,j} < q_{i,j}^{99.5} \\ 1 & \text{otherwise} \end{cases}$$

Debate on the form of FSI is expected to continue, so a detailed justification is in Appendix A.3. Pertinently, FSI as configured in Eq. 2 is suitable here as only the most extreme events are selected (i.e. >75th percentile of events). Furthermore, this is 5-6 high flows per year, comparable to the ~7 floods per year in commercial risk models (Hillier et al., 2024).

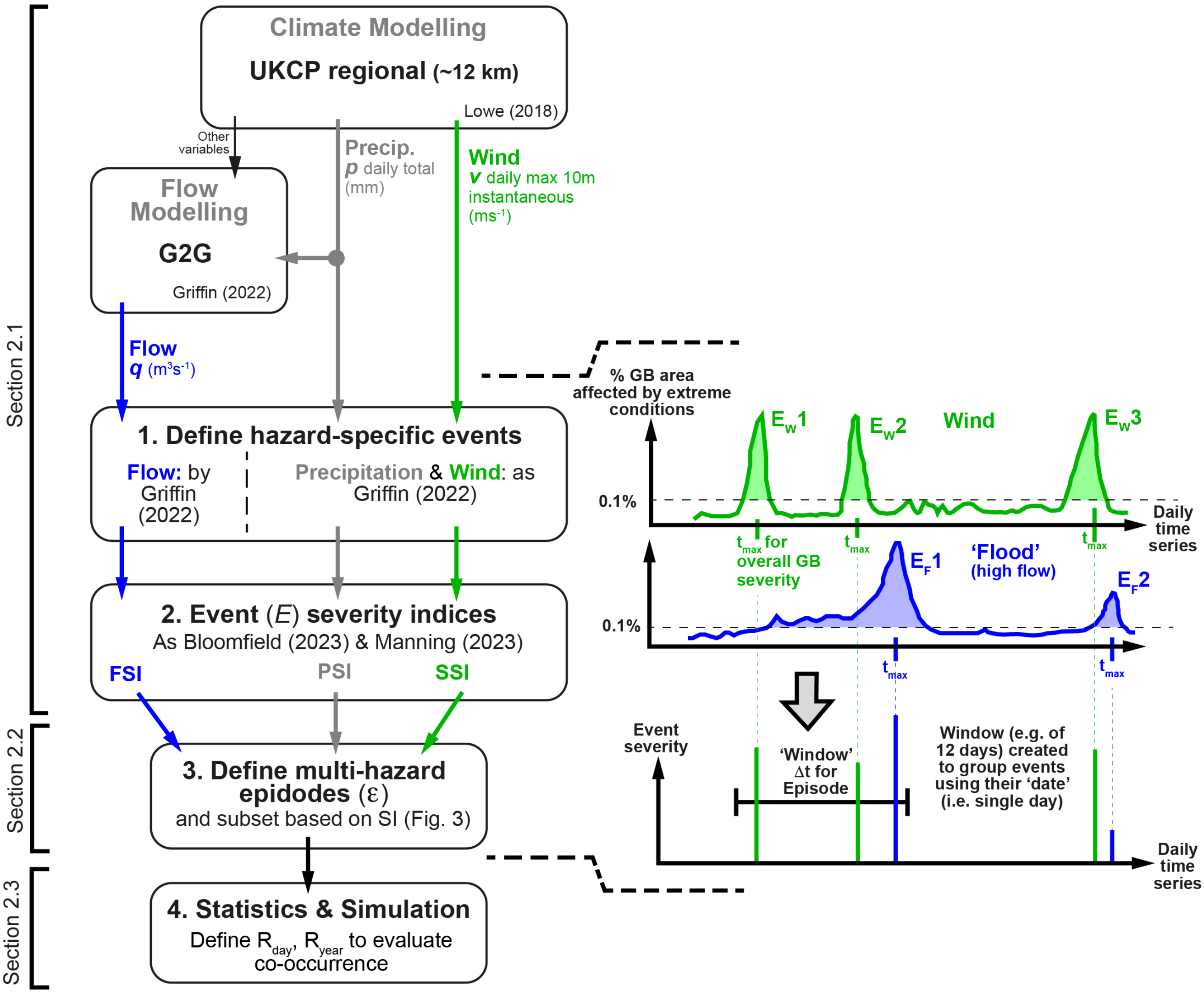

Fig. 2: Workflow used in this analysis, including definitions for some of the variables. Detailed explanation is in main text. For the flow data from Grid-to-Grid (G2G) (Griffin et al., 2022a), 0.1% of the river network is ~20 cells, or > ~20 km². For the UKCP18 data on wind gusts and precipitation 0.1% is of the GB land area is >=2 cells or ~300 km². To find the largest SI to create episodes, FSI and SSI are normalized so that their 95th percentile values are equal (ratio = 1.0). In reality, rare storms might have twice the impact of floods (e.g., Hillier et al., 2024), but sensitivity testing shows that ratios of 0.5 and 2.0 have minimal effect on the episodes defined. Time series are illustrative, not real data. Precipitation is included for completeness (see Appendix A).

2.2. Defining multi-hazard episodes (ε)

Extratropical cyclones cluster in time, with 2 or 3 meteorologically distinct cyclonic systems (Mailier et al., 2006; Vitolo et al., 2009) combining in longer windy periods. Similarly, rainy days occurring in succession might be grouped in episodes (Kopp et al., 2021). Here, this concept is applied to multi-hazards (Fig. 2), adopting the term *episode* (ε) and applying it to mean a grouping in time of hazardous events (*E*) within a selected spatial domain as is established practice when hazards co-occur (e.g., Bloomfield et al., 2023; De Luca et al., 2017; Hewitt and Burton, 1971; Hillier et al., 2015; Kappes et al., 2012). In this case the domain is set to GB. The temporal grouping approach is related to the time-lag method promoted by Claassen et al. (2023) except that the time-lag here might also be due to impact related factors (e.g. time to develop, repair or recovery time, staff fatigue, an organisation's reporting timeframe, an April-March financial year) not just duration and overlap of physical hazard (e.g., Hillier et al., 2023; Hillier and Dixon, 2020; de Ruiter et al., 2019).

Episodes are defined by starting with the event with greatest severity index (SI), placing a window of length Δt days around it positioned to capture other events that create the largest total SI (see Fig. 2), and removing these events. Then, this is repeated until all events are accounted for. Once created, episodes' severity must be quantified.

That flood-wind co-occurrence might be raised by a preponderance of an NAO+ state across a 180-day season (Bloomfield et al., 2024; Hillier et al., 2020) raises the technical question of how to quantify severity for long episodes. This depends on stakeholder and purpose. It is possible to simply sum daily SSI or FSI (Bloomfield et al., 2023), implicitly assuming that each day is independent and additive in its impact (i.e. duration/persistence is significant). Is being flooded at 2.0m depth for 5 days five times more damaging than for 1 day? For an electricity network operator fined by customer minutes lost, it might be (Wilkinson et al., 2022). As the strongest gusts or highest river levels during an event approximate insured damage well (Mitchell-Wallace et al., 2017), an alternative is to use an event-based approach (e.g., Griffin et al., 2022b; Roberts et al., 2014), then sum events' losses. This implicitly assumes a reset between events, ignoring duration (Appendix A.3) and is the (re)insurance approach followed in Fig. 4.

In this paper, however, the main purpose is to study co-occurrence of large events that drive risk. So, episodes (ε) are classified by the severity of their constituent events (Table 1), with thresholds chosen to select potentially impactful events (Section 2.1, Appendix A.3) and mutually exclusive subsets containing roughly equal numbers of episodes (i.e. RPs) (Fig. 3). This classification is *not* a summation. Illustratively, ε_W^{95} contains at least one wind event E_W with an SSI in the top 5% of wind events but no high flow event.

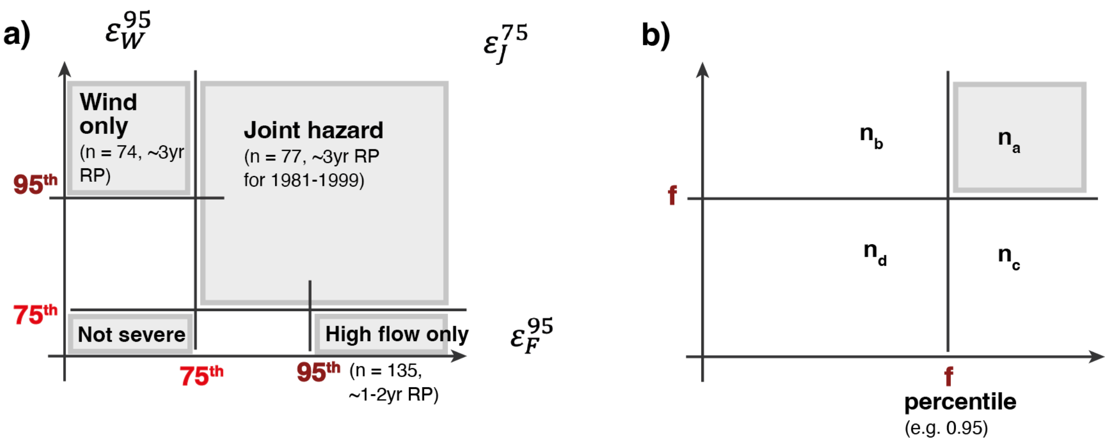

Fig. 3: a) Illustration of subsets and nomenclature used, with numerical detail for Δt = 3 in the present day from Fig. 4a. ε_J^{75} is the subset of all episodes with both hazards jointly having at least one event exceeding the 75th percentile. Also see Table 1. b) Nomenclature used to define U (Section 2.3).

2.3. Statistical simulation for co-occurrence analysis

A variety of options exist to quantify dependency of hydro-meteorological extremes (e.g., Bevacqua et al., 2021; Heffernan and Tawn, 2004; Serinaldi and Papalexiou, 2020), although it is advised to ensure that they are not reinvented or untested (Serinaldi et al., 2022). One well-established approach is using copulas to fit a distribution to data extreme in both variables (e.g., Bevacqua et al., 2017; Manning et al., 2024). This permits smoothed curves to be fitted, but relies upon selecting an appropriate distribution (e.g. Gumbel copula). Alternatively, extremal dependency for wet and windy conditions can be quantified by measures of the co-occurrence of extremes above a given percentile (Hillier et al., 2015; Martius et al., 2016; Owen et al., 2021a). χ (Coles et al., 1999) and uplift in co-occurrence U (De Luca et al., 2017; Hillier et al., 2015) are closely related (Eq. 3, 4) with nomenclature in Fig. 3b.

Eq.3
$$\chi = \frac{n_a}{(1-f)n}$$

Eq. 4
$$U = \frac{n_a}{E[n_a]} = \frac{n_a}{(1-f)^2 n}$$

χ is the probability that one variable is extreme if the other is also extreme, varying between 0 and 1 (e.g., Bloomfield et al., 2023; Vignotto et al., 2021). U is an occurrence ratio, the observed number of co-occurrences divided by the number expected due to chance for independent events (i.e. $E[n_a]$). It is also, therefore, the extent to which one would underestimate the probability of co-occurrence if independence were assumed. Some authors have called U a 'Likelihood multiplication factor' (Ridder et al., 2020; Zscheischler and Seneviratne, 2017). With independent events uniformly distributed over a time period, the significance of U is found with a binomial test (Bevacqua et al., 2021), but $E[n_a]$ can also be simulated directly.

Event Coincidence Analysis (ECA) is a method in time-series analysis to assess if one type of event might be a precursor to another based on an underlying Poisson process (e.g. netCoin or CoinCalc R packages) (Donges et al., 2016; Escobar, 2015; Siegmund et al., 2017). It is unclear to us, with the dynamic positioning of the window and 1 to *n* events potentially within each episode, how to construct this analytically. So, statistical simulation modelling (e.g., Hillier et al., 2015; Ridder et al., 2020) is used to investigate U in UKCP18 by eliminating elements of its temporal structure (Hillier et al., 2015, 2020; Hillier and Dixon, 2020; Zscheischler et al., 2021). In this ECA using dynamic windows (dwECA), two simpler (i.e. less structured) models of events are created, from which episodes are then formed in Section 2.2.

1. R_{day}: For each event, year and day are randomised, a uniform distribution. This is $E[n_a]$, reflecting an Oct-Mar climatology approach (e.g., Champion et al., 2015; Smith and Phillips, 2012; Stephan et al., 2018), or a business-as-usual case in (re)insurance (e.g., Hadzilicos et al., 2021; Hillier et al., 2024).
2. R_{year}: For each event, only year is randomised. All relationships to proximal events within a time-series are broken up to and including inter-seasonal timescales, yet seasonality (i.e. the pattern of frequency as time progresses through a winter) is retained. This avoids pre-supposing a Dec-Feb peak storm season (e.g., Manning et al., 2024; Martius et al., 2016), as this may change in future.

Note that all randomisation is conducted separately within each ensemble member. This is cautious (i.e. perhaps less significant *p*-values) but remains valid even if the 12 ensemble members of UKCP18 are not a truly random sample. Randomisation is repeated 5 times, giving 1140 simulated years in total, 228 for each statistical model run. The chance (*p*-value) of occurrences in UKCP18 occurring in the simplified models can then be assessed by taking each as a null hypothesis H_0 (i.e. Fig. 5, Fig. 6). Here, for episodes, uplift U_ε is the total count of the number events (n_a) over threshold within episodes.

2.4. Jet Stream metrics

One widely used and relatively simple metric of jet position is that of Woolings et al. (2010). This diagnostic uses four low-level wind fields (925-700 hPa) to quantify the latitude and speed of the eddy-driven jet stream. It is zonally averaged over the North Atlantic (0-60°W, 15-75°N), low pass filtered with a 10-day window to remove effects from individual synoptic systems, then the maximum westerly wind speed across the latitudes is taken to locate and quantify the jet. Data used here (McSweeney and Bett, 2020) are taken from the UKCP18 global model, which drives the regional model used in this paper.

3. Results

Visually, on Fig. 4, a first impression is that the number of more severe joint episodes (ε_J) increases in a future climate. This is investigated further for a range of time periods and thresholds (Section 3.1). Then, distribution by month or 'seasonality' is explored (Section 3.2). Finally, the jet stream is examined as a possible cause of the observed patterns (Section 3.3).

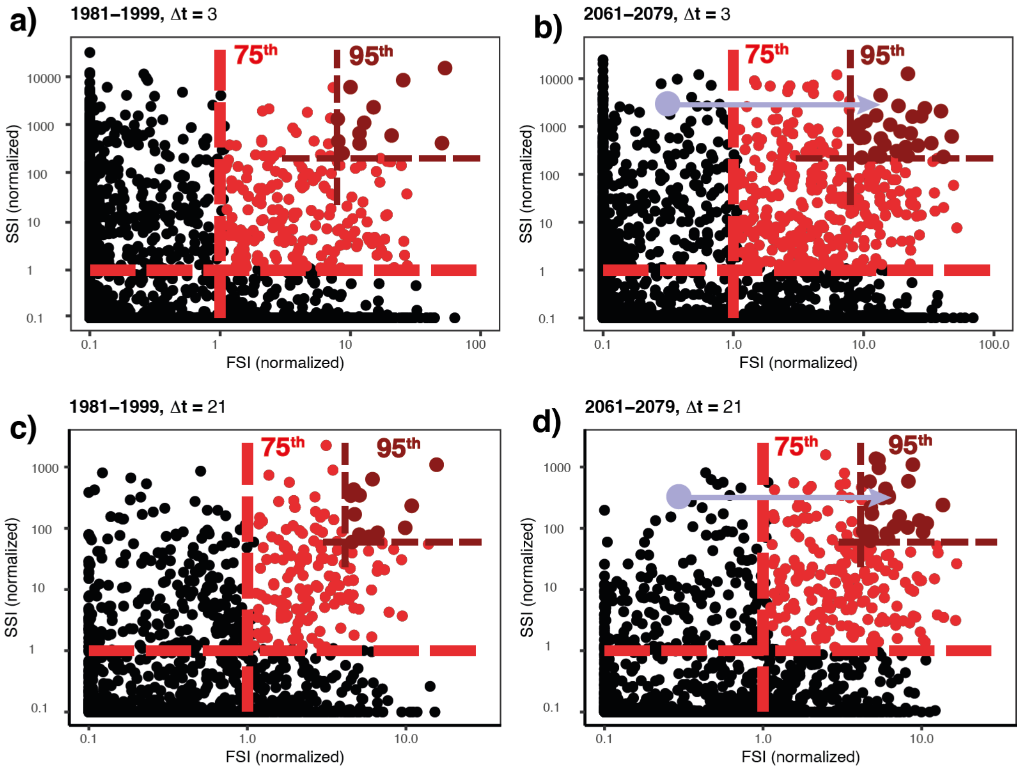

Fig. 4 Scatter plots of the summed severity of potential flooding (FSI) and extreme wind (SSI) for 3-day episodes for a) present and b) future time slices relative to the 75th percentile of these measures. Two thresholds are shown, the 75th percentile (red) and 95th percentile (dark red). Thresholds for 1981-1999 are used in all panels. d) and e) are the same, but for 21-day episodes. Light blue arrows visually highlight the tendency for FSI to increase into the future, which is particularly prominent for Δt = 21.

3.1. Uplift factors

Uplift (U_ε) is the number of times is more common co-occurrences are in UKCP18 than expected for independent events uniformly distributed across Oct-Mar (i.e. R_{day}, pink). Fig. 5a clearly shows two patterns (red lines) for the present.

1. U_ε is broadly two to four for all Δt (1-180 days) and percentiles (75th to 99th), but difficult to detect for seasonal timescales.
2. U_ε is highest for more extreme events (i.e. rarer, larger percentiles) and at shorter time windows (i.e. smaller Δt).

Visually, U_ε is similar in future (Fig. 5b), best seen by comparison to the grey vertical lines which are identical in each panel. As U_ε is relative to a baseline (R_{day}, $E[n_a]$) that accounts for the total of severe events ($n_a + n_b + n_c$) increasing in future, it isolates the potential change in the dependence structure (i.e. level of 'correlation'). Illustratively, for Δt = 3 at the 95th percentile in 2061-2079 (ε_J^{95}), a 104-year return period assuming independence is actually 23 years when accounting for dependence. Return periods (RPs) in Fig. 5c,d are simply calculated for *episodes* (i.e. RP = years/n_ε), and so reflect the increased number of high-flow events in RPs reduced to about half their present value.

For 1-day windows, the act of collapsing events to a single day (t_{max}) will tend to underestimate co-occurrence, as flooding is expected to peak the day after wind given that water takes time (typically up to 24h) to flow into and through GB's rivers (De Luca et al., 2017); daily or storm-based analyses (Bloomfield et al., 2023; Manning et al., 2024) will be less influenced in this particular.

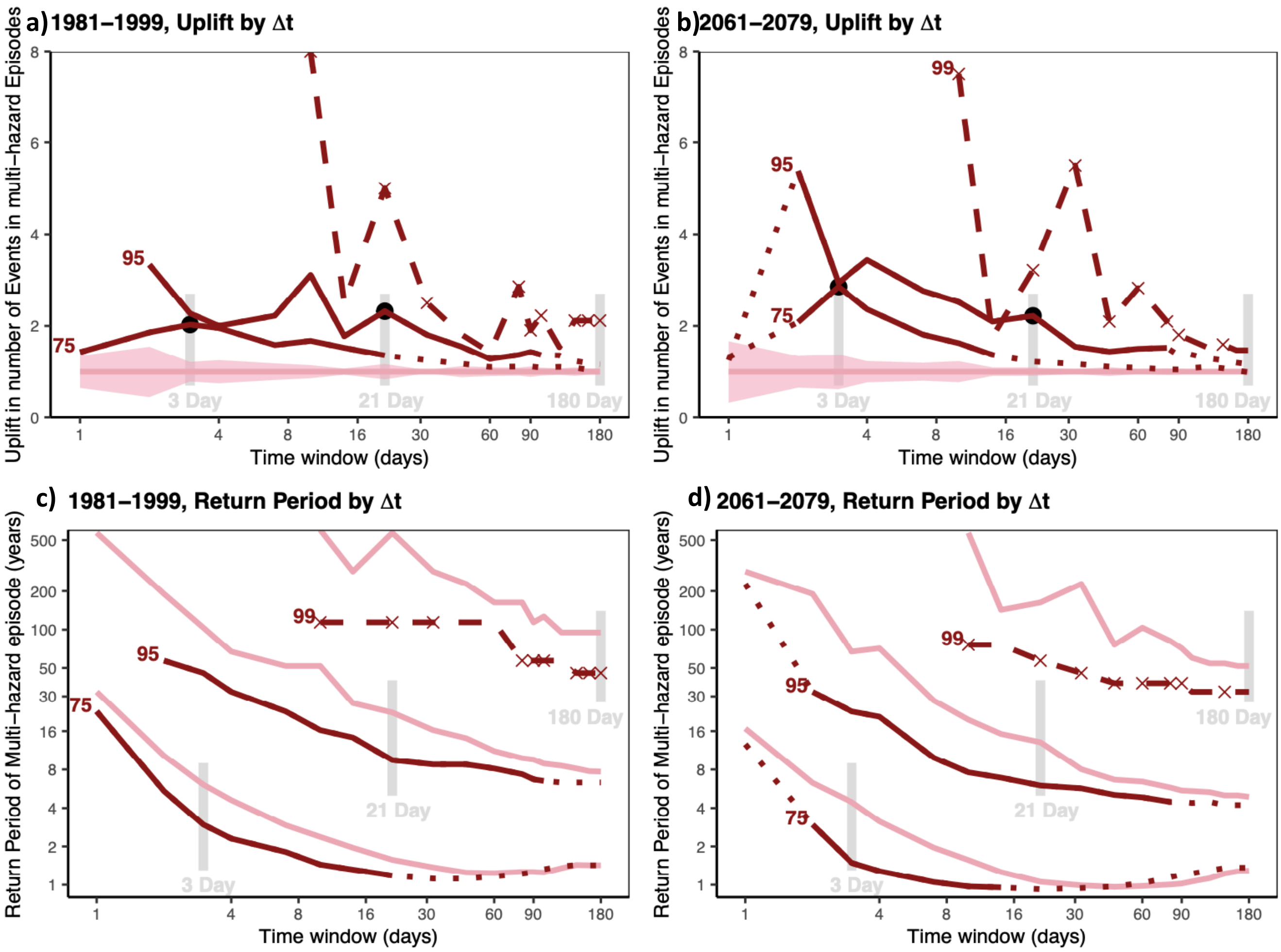

Fig. 5: Enhancement in co-occurrence, for a range of window lengths (Δt) used to create episodes. a) Uplift in number of events involved in multi-hazard episodes (1981-1999) as compared to a baseline of independence (pink line, R_{day}). Solid red lines are statistically significant, unlikely from variability within the independent case (pink shading is 2σ) assessed by simulation. Joint episodes ε_J^{75} are labelled '75', and so on. The Black dots situate the analyses of Fig. 6 within this plot. Dashed line indicates lower subjective confidence as occurrences get low, with x marking statistically significant points. Dotted lines on *Fig. 5* indicate that caution is needed, where *episodes occupy >10% of time because 'remnant' time periods left between already created episodes might start to appear, or where the observation is not clearly different from the baseline (i.e. p > 0.05) because n becomes low or the difference small. c) & d) Return period of multi-hazard episodes at 3 percentiles (75, 95, 99). Note that the grey bars are identically positioned on a) and b), and on c) and d).*

3.2. Seasonality

Distribution by month of the co-occurrence of severe episodes, their seasonality, is explored in Fig. 6 at the key timescales of Δt = 3 and 21 days using ε_J^{75} and ε_J^{95}, respectively. Since a longer window is more likely to contain extreme events, a higher threshold captures sufficient events for Δt = 21. There are three pertinent features:

1. Considered individually (Fig. 6 a,d), both high flows and wind are notably more seasonal in future, more concentrated in December and January. This effect is greater for the higher (95^{th}) percentile.
2. U_ε is 2-3, present and future, aligning with Fig. 5.
3. For Δt = 21, the red line (R_{year}) is only a little below the UKCP18 occurrences (dark red), so at a storm-sequence timescale of weeks (Δt = 21), U can largely by modelled by seasonality (i.e. R_{year}). However, on a shorter timescale (Δt = 3), an additional physical mechanism must be invoked that operates on a shorter time-scale, that of a single storm or storms in fairly rapid sequence (i.e. Δt ~ 2-10 days).

Note that the seasonality effect in this bootstrap modelling (R_{year}, Fig. 6c) arises simply due to more events being placed (e.g. by a broader-scale atmospheric driver) in a restricted timeframe. Illustratively, consider a daily analysis 10 winters of 100 days, containing 50 floods and 50 wind extremes in total. If uniformly distributed (i.e. Poisson randomness), the expected number of co-occurrences is 0.05*0.05*1000 = 2.5 coincidences (e.g., Bevacqua et al., 2021; Hillier et al., 2015). Now, compress these into the central 50 days, the expectation is 0.1*0.1*500 = 5.0 coincidences.

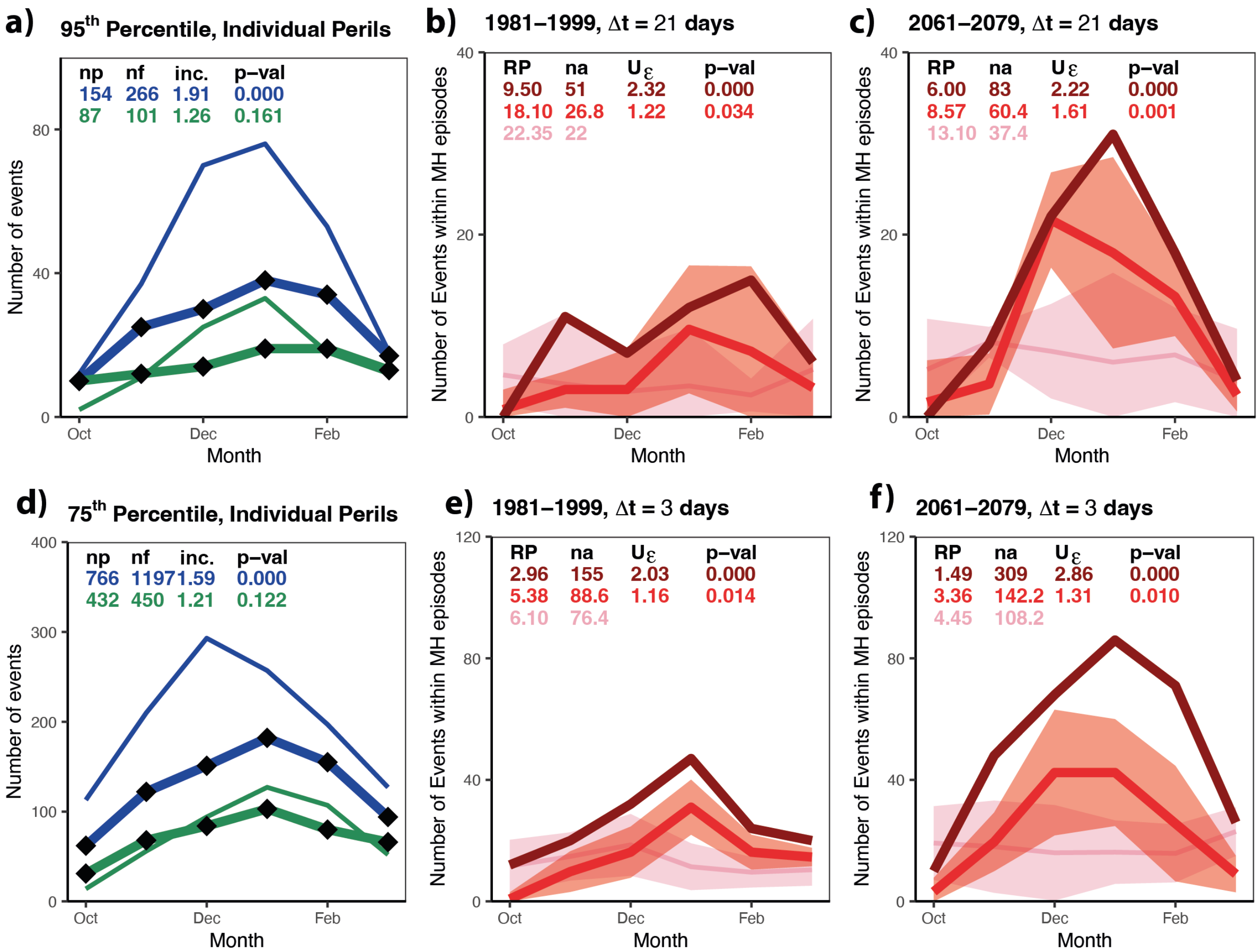

Fig. 6: Seasonality of individual events (E) and multi-hazard episodes (ε). a) Seasonality of events for all high-flows (blue) and extreme wind (green) exceeding the 95th percentile. Thick lines are present day (1981-1999) and thin lines are the future (2061-2079). n_p & n_f are counts for the present and future, respectively. 'inc.' is the mean increase (multiplier) from present to future for the 12 ensemble members with the p-value is assessed using their variability (t-test). b) and c) Number of events in multi-hazard episodes ε_J^{95} from UKCP18 (dark red), simulations with dependency broken but retaining seasonality (red, R_{year} model), and independent phenomena (pink, R_{day} model). Coloured ribbons are 2σ, assessed by simulation. RP is return period of episodes in years, and p-values are calculated using variability of statistical model runs R_{day} and R_{year} (t-test). c) as for b) except for the future climate period. d-f) as for a-c), but for the 75th percentile and Δt = 3.

3.3. *Jet Stream*

Fig. 7 investigates the jet stream as a potential physical mechanism for the uplift U that cannot be explained by seasonality for 3-day episodes (ε_J^{75}) identified in Section 3.2. Jet characteristics for the days of these episodes are plotted, with other subsets (ε_F^{95}, ε_W^{95})(see Fig. 3a) and average values for time blocks (e.g. Dec-Feb) displayed for comparison. Fig. 8 presents a differently derived view, maps of westerly wind velocity anomalies on t_{max} days. Exact consistency between the two is not expected.

A number of features support the reliability and relevance of the main results to follow. First, in Fig. 7 subsets (e.g. ε_J^{75}, ε_W^{95}) are distinct from time blocks and the statistical models (R_{year}, R_{day}). This simply would not happen if there were a mis-match (e.g. in timing) between the metrics of the jet in the global model (McSweeney and Bett, 2020) and extreme weather extracted here from the regional model. Second, the present day trimodal peak in ERA-40/ERA-Interim, matched '*reasonably well*' by UKCP18 (McSweeney and Bett, 2020; Woolings et al., 2010), is present (Fig. 7a,b). Third, on days that severe weather occurs in GB jet-related wind anomalies occur over NW Europe, not elsewhere, (Fig. 8) indicating that the jet metrics (McSweeney and Bett, 2020; Woolings et al., 2010) are relevant to the study area.

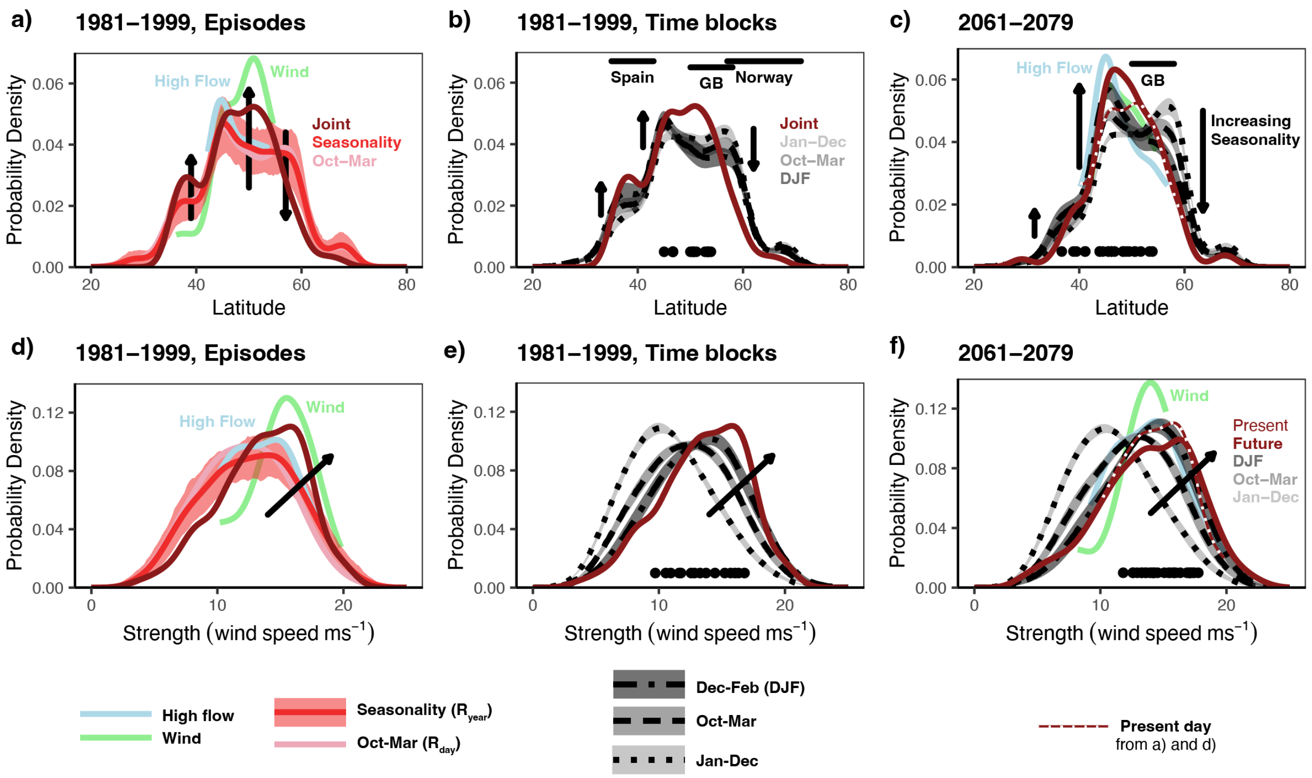

Fig. 7: Jet latitude (top row) and strength (bottom row) in UKCP18 (McSweeney and Bett, 2020) associated with Δt = 3 joint high flow and extreme wind episodes (ε_J^{75}), present and future. Curves are density estimates (Gaussian kernel, σ = 1.0 for strength and σ = 2.0 for latitude), and arrows illustrate trends identified in the data. In panels a) and d), the light red line is sampling preserving the distribution of storms' dates within a season (i.e. R_{year}) and the pink lines are for Oct-Mar (i.e. R_{day}) and the error ribbon is 10^{th}-90^{th} quantiles for these storms as estimated from 100 random realisations. Uncertainty for the selected seasons (b,c,ef) is shown as grey shading and is $\pm 2\sigma$ stderr of the 12 ensembles of UKCP18. For visual clarity, only the parts of the wind and high-flow curves (ε_W^{95}, ε_F^{95}) are shown where they differ notably from the other curves. Dots are the most extreme events (ε_J^{95}). Bars in b) and d) show the latitude ranges of illustrative countries. All days within each episode are used.

For 1981-1999 joint severe episodes' (ε_J^{75}, dark red line) jet strength and latitude differ discernibly from conditions at the times of year that they typically occur (i.e. R_{day}, red line and shading in Fig. 7) and from average Oct-Mar conditions (R_{day}); Oct-Mar curves match those for non-severe storms ($\varepsilon_J^{<75}$) very closely, although these are not shown for visual clarity (Fig. 7). Extremes also differ from a jet typical of the mid-winter DJF storm season. Specifically, the four differences are:

1. Days with only high flows (ε_F^{95}) have jet latitude frequency peaks at 45°N, marginally elevated above the seasonal expectation (Fig. 7a). Similar is true for jet strengths (Fig. 7d, Fig. 8b).
2. Potentially damaging winds in isolation (ε_W^{95}) are associated with a strong jet typically focussed on 45-55° latitude range (Fig. 7a,d) with a jet speed anomaly at relatively high latitudes (50-60°N) extending across the Atlantic (Fig. 8a).
3. Jet latitude for joint ε_J^{75} episodes peaks distinctly at 50°N (Fig. 7a,d, Fig. 8c). Self-evidently this is largely due to GB's latitude (Fig. 7b) because storms used here must impact GB, and the southwards displacement in this subset is highlighted with vertical arrows (Fig. 7a).
4. The peak in ε_J^{75} jet latitude is between the ε_F^{95} and ε_W^{95} peaks (Fig. 7a), and their jet strength is intermediate in a progression from the high-flow to wind curves (Fig. 7d, arrow). In map view, the joint ε_J^{75} anomaly is also a blend of those from the individual hazards (Fig. 8a-c). A southerly lobe extending into the mid-Atlantic (20-40°W) is also notable.

Overall, co-occurring events in 1981-1999 appear to be associated with a jet that blends characteristics of the most severe high-flow inducing events (i.e. similar to expectations for the time of year) with the severest wind events. This is true even for the most severe episodes (i.e. ε_J^{95} shown as black dots, *n* = 5 with a RP of 44.8 years).

How does it change for 2061-79? Broadly, most patterns are similar in their character to 1981-1999, but with some important changes in relative magnitudes. The main changes are:

1. In future, jet strength and latitude anomalies (ε_J^{75}, ε_W^{95}, ε_F^{95}) are of higher amplitude with respect to the 1981-1999 levels (Fig. 7, Fig. 8), insensitive to the exact baseline chosen (e.g. R_{year}, non-severe).
2. For jet latitude, the peak for joint extremes (ε_J^{75}) shifts ~3° southwards, as do the conditions for the individual hazards, perhaps caused by the enhanced future seasonality of the jet which shifts southwards in midwinter despite an overall (Jan-Dec) shift northwards (Fig. 7c).
3. DJF jet strength in future becomes very similar to the present-day jet states for joint storms (Fig. 7f).
4. In map view (Fig. 8) anomalies for future wind episodes remain in a similar location, those for high flows expand south and west, and the anomaly for joint hazards like in 1981-1999 shares

characteristics with both; in Europe it extends to Iberia like for high-flows, but across the Atlantic at 50-60°N like wind. This is a switch from a high-flow like pattern to a wind-like one (see Section 4.4).

In short, mean future DJF jet conditions tend to adopt a latitude that characterises high-flows in GB today and a jet strength typical of joint extremes today (Fig. 7c,f). Thus, in future, typical shorter-term ($\Delta t \lesssim 10$ days) midwinter jet states appear like those characteristic of impactful compound storms today, aligning with the observation that ε_J^{75} become more focussed in DJF (Fig. 6). The most severe episodes (ε_J^{95}) reflect this, being twice as frequent with a somewhat stronger and more southerly jet (i.e. *n* = 10, RP 22.4 years, Fig. 7).

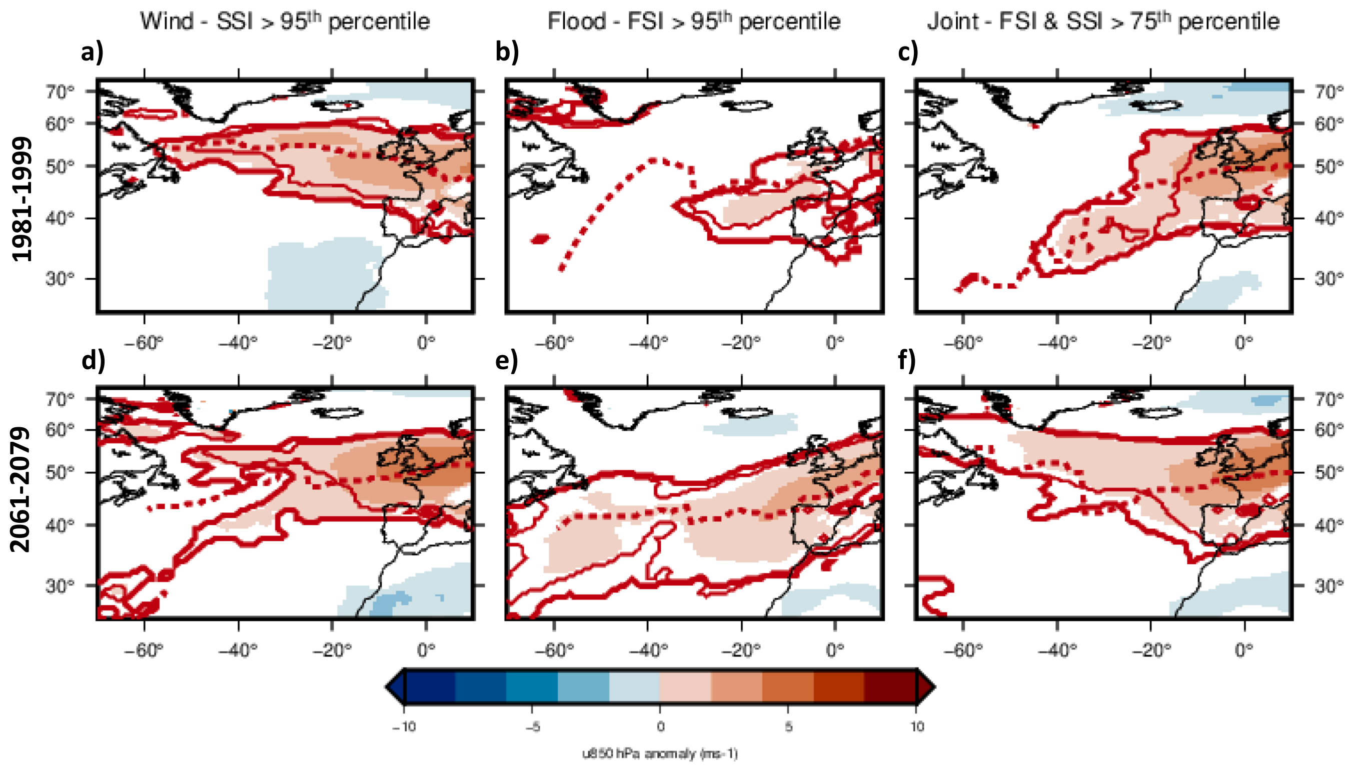

Fig. 8: Plan view of eddy-driven jet anomalies during stormy episodes ($\Delta t = 3$) in comparison to the Oct-Mar climatology. Composites of zonal wind velocity at 850 hPa for (a) dates of wind extremes (ε_W^{95}, n=74), (b) high-flow extremes (ε_F^{95}, n=135), and (c) days where both are extreme (ε_J^{75}, n=77). (a)-(c) are for the present day i.e. 1981-2000, and (d)-(f) are for a future climate. Days used are only the most severe day within an episode (i.e. t_{max}). Solid red lines outline areas where the positive anomaly is significant (p < 0 .05) for one-tailed t-test for difference between means of 12 ensemble members (climatology) and severe episodes. For comparison, thin red outlines are for a DJF climatology, and dashed line is the most significant point at each longitude for a higher-level jet (u250). Hobo-Dyer (i.e. 37.5° standard parallel) cylindrical equal area projection, with -30° meridian. Note that f) is reconciled with Fig. 7c by realising that those data (u maximum) typically occur near NW Europe.

4. Discussion

Co-occurring flooding and extreme wind in GB are part of a complex multi-hazard risk (e.g., Simpson et al., 2021), and this paper considers these hazards using impact-based proxies (Hillier and Dixon, 2020), the UKCP18 dataset and modelled river flows (Griffin et al., 2022b). Its aim is to understand the joint hazard and its drivers. Other complexities, such as interactions between vulnerabilities or exposed infrastructure systems, are not considered. It offers:

1. A first examination of the jet stream for events based on high-flow conditions, not extreme rainfall, in a sentinel location for NW Europe
2. A multi-temporal (Δt = 1-180 days) approach that groups events into multi-hazard *episodes* in a way that is relevant to stakeholders.
3. A new set of 3,427 wind events.
4. An examination of the role of seasonality in how high flows and extreme wind co-occur.
5. An assessment of relatively simple jet stream metrics (Woolings et al., 2010) in this context.

The work fits into a growing consensus on various aspects of potential episodes of joint wintertime flooding and extreme wind in GB. These episodes are typically driven by extra-tropical cyclones (e.g., Hillier et al., 2015; Manning et al., 2024; Owen et al., 2021a; PERILS, 2024), and associated with cyclonic or north-westerly weather patterns in an NAO+ regime (Bloomfield et al., 2024; Hillier et al., 2020). Fig. 5 reinforces an doubling in frequency in future climate projections, and also a x2-4 uplift (U) in co-occurrence over a baseline of independence, a dependency that is not discernibly greater in future (Bloomfield et al., 2023; Manning et al., 2024). The jet stream associated with high river flows is to the south of GB, whilst for wind extremes it is to the north (Fig. 7a), consistent with ETCs being rainy on their northern flank and windy to the south (Manning et al., 2024). And, Fig. 7c shows that potential flooding tends to shift southwards in future (Bloomfield et al., 2024). It is also entirely in line with evidence that GB in future will be wetter (e.g., Lane and Kay, 2021; Lowe et al., 2019) with more frequent and severe high-flows (Collet et al., 2018; Griffin et al., 2022b). Despite being heavily validated, a caveat is that these studies rely on UKCP18, highlighting the need for a multi-model study. An important aspect of the agreement across varied approaches is that it demonstrates, through the episode definition used here, that previous work is applicable to (re)insurance and other stakeholders and their experience of episodes.

On this theme, what is an appropriate baseline? Namely, what statistical model (e.g. days of non-severe storms, uniform occurrence in DJF) should be chosen to represent independence between hazards for a particular enquiry? An insurer's standard practice might involve independence across an Oct-Mar season today. Then, illustratively (at Δt = 21) ε_F^{95} has a 1-year RP and ε_W^{95} has a 1-year RP, combining to be a 22-year RP joint episode assuming the R_{day} model, which is reduced 4-fold to a 6 year RP in 2061-2079 accounting for dependence (Fig. 6b,c). If an insurer's modelling correctly includes the individual hazards seasonality, the correction needed would be notably less (Fig. 6). Thus, a fixed timeframe for analysis such as DJF or Oct-Mar (e.g., Zscheischler et al., 2021) should be used with caution, especially since peak months of (co-)occurrence may shift in future, and practitioners and researchers must ensure the statistical approach aligns with the research question posed.

Selected aspects of the results are now discussed.

4.1. Co-occurrence for the most extreme events

The initial estimate of uplift in co-occurrence between extreme winds and high-flow in rivers was ~1.5 times (Hillier et al., 2015). A value of ~2-4 times in UKCP18 for daily data (Bloomfield et al., 2023) is now confirmed visually (Fig. 4) and statistically (Fig. 5, Fig. 6) for episodes like to cause loss (Appendix A.4), and appears robust in that it is not overly dependent on the method, metrics, or time period (1981-1999, or 2061-2079) used in the studies. Less well constrained is whether, in the limit, are these perils are asymptotically dependent or independent? Namely, do the most severe events have a weaker or stronger tendency to co-occur? This is a key question in assessing risk.

For ERA5 wind gusts and precipitation or GLOFAS derived river flow (at daily, weekly, monthly resolution), residual tail dependence ($\bar{\chi}$)(Coles et al., 1999) does not tend to 1.0 as required for asymptotic dependence, but equally gives no indication that correlation disappears into the tail of the distribution, with the same true for monthly Network Rail delay data (Bloomfield et al., 2023; Vignotto et al., 2021). Indeed, in UKCP18 uplift U increases from 2.4 to 3.4 as Bloomfield's threshold increases, an effect previously demonstrated by sensitivity testing (Hillier and Dixon, 2020). Fig. 5 extends this, with systematic increases in U from the 75th to 99th percentile (ε_J^{75} to ε_J^{99}) indicating that more extreme episodes co-occur more strongly (Fig. 5a,b), at least to return periods of up to ~50-100 years (Fig. 5c,d).

Other metrics give a different view. Even as $\bar{\chi}$ or U increase or hold steady with increasing threshold, χ and Spearman's r decrease (Bloomfield et al., 2023; Hillier and Dixon, 2020). Taking this further, for rain and wind, with a Clayton copula best fitting their severity metrics for (UKCP18, 2.2 km) Manning et al (2024) implicitly assume asymptotic independence for the most extreme events. Indeed, by taking parts of two winter seasons and summer (i.e. Jan-Dec) it is possible to find negative correlations at higher thresholds and annual timeframes (Jones et al., 2024). The variety highlights the importance of using measures attuned to each study's purpose. U is a statistic that directly comments on the chance of two extreme events in a season, as in some stress tests for insurers (Bank of England, 2022). It could also be used to force dependency between independently derived (i.e., uncorrelated) event sets at selected percentile(s) (e.g. 75th, 95th, 99th) perhaps with copulas (e.g., Hillier et al., 2023) to better estimate actual likely losses, improving on using one Spearman's *r* value to represent dependency for all events causing notable losses (Hillier et al., 2024). Given these apparent discrepancies, it would be beneficial to further investigate extreme winds and high river flows or flooding, perhaps with larger model ensembles.

4.2. *Co-occurrence across timeframes*

How does strength of co-occurrence vary with the time-window (Δt) used to group events? Previous wind-flow work using Spearman's *r* on regular, non-overlapping periods found it to increase for windows of up to 20-40 days and then hold steady, perhaps decreasing slightly for a whole season (Bloomfield et al., 2023). Fig. 5, however, uses a measure of tail dependency to focus on the severe events (ε_J^{75}) thought to best represent impactful events (Bloomfield et al. (2023), Appendix A.4), and indicates that uplift (U) is highest for shorter time windows. Assuming UKCP18 correctly captures persistence, this overturns the working hypothesis in the initial papers (Hillier et al., 2015; Hillier and Dixon, 2020). These looked at seasonal timescales, as the prevailing yet unpublished view in 2015 was that individual storms were either wet or windy, and took evidence of wet and stormy winters (Kendon and McCarthy, 2015; Matthews et al., 2014) to indicate that co-occurrence might most strongly exhibit on long timescales (Δt = 180). Descriptively and numerically, understanding this trend in strength of dependence with timeframe is useful for stakeholders who might have varied elements of their business to risk assess, from operational (e.g. 3 day or 21 day long event durations in insurance contracts, or railway repairs) to planning (e.g. annual regulatory or budgetary).

Understanding the relative dominance and interplay of the various hydrometeorological processes is less readily achieved. The conceptual, multi-temporal model set out by Bloomfield et al (2023) details evidence for shorter-term (Δt $\approx$ 1-15 days) contributions from storms (i.e. sub-storm to storm clusters) and longer term 'memory', perhaps in GB groundwater or distant conditions (De Luca et al., 2017; Hillier et al., 2015) mediated by atmospheric behaviours captured by weather patterns or the NAO index (Bloomfield et al., 2024; e.g., Hillier et al., 2020). Whilst winters in GB and NW Europe can be undoubtably wet and stormy (Met Office, 2024), the pattern in Fig. 5 adds weight to a case that processes at shorter timescales of a few weeks or less might dominate (i.e. storms, or storm sequences) rather than a set of conditions established for a season (e.g. Arctic sea-ice) dominating. But, any definite statement still seems premature. To aid progression to a process-orientated view, future statistical simulation modelling to split out contributions at the various time-scales (e.g., Hillier and Dixon, 2020) with a consistent metric (e.g. χ, U, r) is needed for high-flows and extreme wind. Meanwhile, a more in-depth look at the jet stream states associated with extreme winds and high flows can also contribute.

4.3. Utility of simple jet stream metrics

Extra-tropical cyclone (ETC) development is closely intertwined with the jet stream (Clark and Gray, 2018; Dacre and Pinto, 2020; e.g., Geng and Sugi, 2001; Laurila et al., 2021). Illustratively, windstorms are located on its poleward side and are more intense when the jet is stronger (Laurila et al., 2021), and ETC clustering is more intense in GB with a strong persistent jet at ~50°N (Pinto et al., 2014; Priestley et al., 2017). So, it was logical for Hillier and Dixon (2020) to propose the jet steam had a role in whether flooding and extreme wind co-occur or not based on an ETCs relationship with the jet.

Practically, calculating an index to quantify the jet stream (Ayres and Screen, 2019; e.g., Woolings et al., 2010; Zappa et al., 2018) is less demanding than cyclone tracking (e.g., Hoskins and Hodges, 2002; Manning et al., 2024). So it is useful to ask if the relatively simply derived metrics for the eddy-driven (lower tropospheric) North Atlantic of jet of Woolings et al. (2010) can be a functional, readily applied tool to distinguish co-occurrence. If so, by being computationally easier than running cyclone tracking algorithms, it should facilitate inter-comparison of this potential driver of co-occurring high-flows and extreme wind between climate models and reanalyses (e.g. CMIP6, ERA5, UKCP18).

Fig. 7 (panels a,b,d and e) clearly shows that the jet steam index of Woolings et al. (2010) is able to distinguish different large-scale jet dynamics associated with joint high-flow and wind events (ε_J^{75}, dark red line), providing an easy answer to the question posed about utility. Specifically, wind (ε_W^{95}) and ε_J^{75} episodes have a stronger jet than high-flows (ε_F^{95}), in accord with analysis of extreme precipitation and expectations that a weaker jet causes ETCs to move more slowly allowing rainfall to persist for longer (Hillier and Dixon, 2020; Manning et al., 2024). Indeed, Fig. 7 demonstrates how statistical significance testing using jet metrics can lend support this idea, augmenting visual analysis (Manning, 2024). In future (2061-2079) latitude illustrates a case where signatures of subsets are similar, with distinctions not clear-cut using only this index (Fig. 7c). So other views, such as on the timing of episodes within a season or their planform distributions of associated high-level wind (Fig. 6, Fig. 8), are also useful to understand the influence of the jet stream.

4.4. Potential influences of the jet stream on future co-occurrence

Do dynamical (e.g. jet stream) or thermodynamic effects most control the co-occurrence? Previous analysis has inferred that the future increase in co-occurrence is a predominantly thermodynamic response (i.e. warmer air can be wetter, and therefore more high FSI events), assisted by southwards displaced cyclone tracks leading to dynamically enhanced temperature (Manning et al., 2024). Fig. 6-8 allows this to be clarified.

First, consider 21 day episodes (Fig. 6a-c), likely associated with storm sequences (e.g., Bloomfield et al., 2023; Dacre and Pinto, 2020; Mühr et al., 2022). For a start, simply doubling the number of high-flow events during Oct-Mar in a wetter future world is insufficient (R_{day}, Fig. 6c). Interestingly, both high-flows and wind extremes become more seasonal, focused into midwinter, particularly and higher percentiles of FSI (Fig. 6a,d, Appendix A). An increased frequency of high flows across winter as a whole is an established idea (Griffin et al., 2022b), but within this the increased seasonality has not been noticed as the only relevant study lacked data over NW Europe (Ridder et al., 2020). Logically this phenomenon forces future co-occurrences to be more focussed in Jan (Fig. 6c,f), and when this more intense seasonality is isolated and modelled (R_{year}) it is nearly possible to explain the UKCP18 events (dark red line). So, at this timeframe, *if* atmospheric drivers distribute extreme conditions correctly by month, thermodynamics are nearly sufficient to explain the increase in co-occurrence in future. Fig. 7b,c demonstrates that mean UKCP18 jet stream latitude becomes more seasonal in future, in wintertime shifting south (equatorwards) and focussing on 45°N to impact GB. A stronger and squeezed future jet is in line with CMIP simulations (Oudar et al., 2020; Peings et al., 2018), so a latitudinally squeezed wintertime jet might be the key dynamical driver of the increasingly seasonal future uptick in joint events. A equatorwards shift is in line with the Polar Amplification Model Intercomparison Project (PAMIP) findings where a sea-ice loss effect outweighs the polewards shift in the jet due to oceanic warming in this 'tug-of-war' (Screen et al., 2022). A northwards historical (1979-2019) shift of the jet stream has been reported in reanalysis products and climate model runs for the present day (inc. UKCP18), inferred from a difference between mean zonal wind velocity (500 hPa) at 40-50°N as compared to 20-30°N (Woolings et al., 2023). This, however, is readily reconciled with our finding of a potential future southerly shift in the jet and that of ETC tracks (Manning, 2024), by considering Fig. 6b,c. In DJF, in the Atlantic at least, there is a *southwards* shift of the jet *into* the 40-50°N bin, increasing typical wind speeds there with respect to that at 20-30°N. So, Fig. 6 provides an additional insight into how broad-scale thermodynamic and dynamic factors combine to explain longer joint high-flow and wind episodes.

For individual or closely consecutive storms ($\Delta t = 3$ days), Fig. 6e,f clearly shows that the number of events alone is insufficient to cause the co-occurrences in UKCP18, particularly in the future, even if enhanced seasonality is accounted for (red line, R_{year}). So, another shorter-term explanatory atmospheric behaviour is needed. Fig. 7 and Fig. 8 suggest that this is the disposition and dynamics of the jet stream. In terms of the latitude and speed of the jet's strongest part, the typical mid-winter jet becomes more like that characteristic of impactful compound storms today (Fig. 7). Fig. 8 adds plan-view information on the jet at the time of high joint FSI-SSI episodes impact GB. In the present, joint episodes (ε_J^{75}) have a jet that typically blends most of the strength of wind events (ε_W^{95}) with the more southerly track of high-flow inducing events (ε_F^{95}). In future, a stronger and more southerly jet is much more prominent for ε_J^{75} episodes (Fig. 7c, Fig. 8e), fitting with the location of extreme precipitation (Bloomfield et al., 2024) and its associated jet (Manning et al., 2024) moving south.

Future high FSI-SSI episodes (ε_J^{75}) more resemble wind episodes than high-flow (Fig. 8d-f), fitting with a view of a typically rainy wintertime future GB where wind is typically the missing element for a joint event (Bloomfield et al., 2024). Namely, wind becomes the limiting factor rather than flooding as it is now; currently multi-basin high-flows needs multiple storms setting wet antecedent conditions (De Luca et al., 2017), and locally the joint impact footprint's extent is limited by its rain component (Manning et al., 2024). Intriguingly, a southerly jet anomaly during a compound storm's lifetime over the Atlantic (Fig. A1 - Manning et al., 2024) that obtains a very windy signature when impacting GB (Fig. 8d,f) suggests the most severe future events might arise from a jet initially passing over warm southerly water that strengthens and shifts north as it impacts southern GB. So, in a modification to the conclusion of Manning et al. (2024) a relatively equal contribution of dynamics (i.e. jet disposition and seasonality) and thermodynamical (i.e. warmer air carries more moisture) is argued to drive future increases in joint hazard in GB.

Placing an emphasis on dynamics (e.g. jet stream) ties in with a broader, emerging picture of linked multi-hazards across the Atlantic domain (e.g., Röthlisberger et al., 2016). Cold air outbreaks over eastern Canada followed by wind extremes over northern Europe and the British Isles appear associated with an enhanced jet stream (Leeding et al., 2023), whilst January being the dominant month for compound surge and rainfall around GB (Bevacqua et al., 2020) ties to the same timing for wind and riverine high-flows (Fig. 6). Furthermore, clustered ETC are associated with a jet stream anomaly focussed on GB (Dacre and Pinto, 2020; Pinto et al., 2014; Priestley et al., 2017). And, like flow regimes globally, these relationships are likely to change with the climate (e.g., Jiménez Cisnero and Oki, 2014; Li et al., 2024). We therefore advocate a process-orientated approach to co-occurring hazards (e.g., Manning et al., 2024) and highlight that the 'recipe' of driving large-scale conditions (e.g. jet stream state) for a 'perfect storm' will vary by country (Gonçalves et al., 2023; Raveh-Rubin, 2015; Röthlisberger et al., 2016)

5. Conclusions

This study uses novel statistical modelling of dependencies and a jet stream index (Woolings et al., 2010) to understand the co-occurrence of high-flows and extreme wind events in multi-hazard *episodes*, with a focus on 3-day and 21-day durations. The idea of dynamically defined episodes that group events to reflect periods of adverse conditions is defined to reflect lived experience, and extracted using the FSI (Bloomfield et al., 2023, 2024) and SSI indices (e.g., Klawa and Ulbrich, 2003) from the UKCP18 regional 12km dataset which has previously been validated (Bloomfield et al., 2023). The main conclusions are:

- Defining stormy multi-event episodes as they are experienced (i.e. dynamically positioned time windows) produces results that align with previous work, giving stakeholders additional comfort in using published results.
- This said, statistically, it is critical to note that different dependency measures (e.g. χ, U, r, τ) reflect different aspects of distributions of joint extremes, and may even appear contradictory. Also, using fixed timeframe for analysis (e.g. Oct-Mar, DJF) should be used with caution, especially since peak months may shift in future. Statistically modelling seasonality in a month-by-month analysis as done here may be necessary.
- Uplift (U) in co-occurrence is found to increase as severity increases (e.g. 90th to 99th percentile), meaning that evidence is starting to suggest that dependence exists to high return periods, even if not strictly 'asymptotic'. So, ignoring correlation underestimates risk most for the strongest storms.
- Uplift is found to increase as Δt is reduced, highest within insurers' key windows (Δt = 3,21 days), suggesting the importance of atmospheric mechanisms that act to drive co-occurrence at timescales of days to weeks (e.g. storm sequences); see the framework model in Bloomfield et al. (2023). So, ignoring correlation underestimates risk most for individual or closely grouped storms.
- Jet stream metrics (e.g., Woolings et al., 2010) are found to be a useful, easily determined tool to investigate its roles as a driver of co-occurrence.
- Future strong jet streams become increasingly focussed in mid-winter (Dec-Feb) driving the increased seasonality in individual hazards, a larger effect for more extreme events. This broad-scale dynamic effect, combined with thermodynamics (i.e. a warmer, wetter world), explains most of the uplift in future joint events at storm-sequence timescales (Δt = 21 days) and over.
- For individual or closely consecutive storms (Δt = 3 days), altered jet characteristics are also needed to fully explain the uplift in co-occurrence, stronger and displaced southwards as storms impact GB. In short, typical future DJF jet variability closely resembles that of impactful compound storms in GB today highlighting the contribution of the jet changes to the increase in extremes.

Future work will could unpick and quantify the balance between dynamic and thermodynamic effects, ideally using higher resolution data from a variety of climate models. It will be important, however, to build area-by-area understanding of how the impact of common drivers varies spatially to improve risk mitigation and planning (e.g. diversification, mutual aid across Europe). As the jet stream guides storms to one country, another will be spared.

Conflict of interest statement

No conflicts of interest.

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Authors' contributions

The work was conceived by JH with input from HB, PB, LS. Analysis was by JH, with input from HB. Writing and interpretation was led by JH with input from all authors. DK created Fig. 1.

Data availability statement

UKCP18 data are available from the Met Office. Flooding events are from Griffin *et al* (2022a) on the CEDA repository. Wind events will be made available on CEDA.

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Appendix A: Event Sets

A.1 Dataset selection & fields used

This study uses the UK Climate Projections 2018 (UKCP18) regional simulations. On a 12 km grid, over the commonly used EURO-CORDEX domain (Jacob et al., 2014), simulations were run from 1980–2080 using the Representative Concentration Pathway (RCP) 8.5 climate change scenario with 12 member perturbed parameter ensemble (Tucker, et al., 2022). Hourly 10m instantaneous wind gusts and total precipitation were available from the 12 ensemble members for two periods (1981–2000, 2061–2080), and UKCP18-based river flows for these two time periods have been derived (Griffin et al., 2022b) by using the simulated precipitation and temperature, and derived evapotranspiration, to drive the Grid-to-Grid (G2G) hydrological model (Kay et al., 2021). From these daily mean river flows output by G2G on a 1 km grid over GB, a set of high-flow events was created and is openly available (Griffin et al., 2022a). A daily time-series of the area subject to extreme high flows was also provided to the authors.

Thus, UKCP18 is selected as it presents the opportunity for more extreme wind and high-flow events to be analysed than in the observational record, and for future changes to be examined. The UKCP18 simulations are argued to well represent extreme precipitation (Cotterill et al., 2021; Lane and Kay, 2021; Lowe et al., 2018; Tucker, et al., 2022) and wind gusts (Manning et al., 2023) when assessed against lower resolution climate model simulations and gridded historical observations. Importantly, rank correlation between GB aggregated precipitation, high-flows and extreme wind for the simulated present (1981-2000) closely matches the ~30 km resolution ERA5 reanalysis (1979-2021)(Hersbach et al., 2020) and GLOFAS river-flows derived from it using LISFLOOD (Harrigan et al., 2023; Hirpa et al., 2018) across time windows from 1 to 180 days (Bloomfield et al., 2023). In other words, even after higher-resolution verification (i.e. against CAMELS-GB/CHESS-MET), the UKCP18 simulations appear to adequately capture co-occurrence of the extreme wind and high flows (Bloomfield et al., 2023, 2024).

A.2 Defining widespread hazard-specific events

For the present time period, 1981–1999, UKCP18 has 19 complete extended winters over 12 ensemble members, giving 228 simulated seasons designated here by the year they start in (i.e. Oct 1981 – Mar 1982 is '1981'). These contain unrealised yet plausible extremes. Griffin et al. (2022a, b) used the 99.5th percentile of flow across the *whole* year ($q_{i,j}^{99.5}$, Jan-Dec) and required that greater than 0.1% of the area of the GB river network (19,914 grid cells, ~20 km^2) exceed its threshold to constitute being within an event (blue shaded areas in Fig. 2). In addition a 14-day maximum event length was imposed, and events sub-divided if flow dropped to under 1/3 of the lowest of two included peaks which were separated by at least an estimated time-to-peak of storm hydrographs. This is a point-over-threshold approach (e.g., Lechner et al., 1993; Robson and Reed, 1999) and their intention was to isolate hydrologically independent, extreme and widespread events. Here, matching sets of events for extreme wind, and for completeness precipitation, are extracted.

Grids of daily totals of precipitation (p) and maximum 10m wind gust (v) are created, and used to define events (E). Each event is the spatial footprint of the maxima driving that hazard (e.g. v) over a time-window containing an isolated hydro-meteorological extreme.

For wind events, a daily time series for v of the areal fraction of GB where it exceeds its grid cell's 98th percentile ($v_{i,j}^{98}$, Oct-Mar) is first computed (Fig. 2). Then, the temporal limits (t_{start} and t_{end}) of the extreme event days are defined as the first and last day of a period where this areal fraction is at least 0.1% of the whole GB land area (~300 km^2). 0.1% is used for consistency with flooding (Griffin et al., 2022a), and the 98th percentile aligns with a recent consensus for wind impact estimation (e.g., Bloomfield et al., 2024; Klawa and Ulbrich, 2003; Priestley et al., 2018) outlined in Appendix A.3. Thus, based on these thresholds, each event consists of a sequence of consecutive extreme days, with the maximum windspeed (v) across the duration of the event retained at each location to give an event its footprint. No wind event ever exceeds 8 days (95% $\leq$ 3 days, Fig. A1), so the limit of 14 days used by Griffin et al (2022b, a) is not needed. It is likely that clusters of 2 or 3 meteorologically distinct cyclonic systems (Mailier et al., 2006; Priestley et al., 2018; Vitolo et al., 2009) combine within longer wind events. However, the focus here is on periods of disruption as they are experienced.

Precipitation events footprints are created exactly as for wind, except that the sum of precipitation (p) across the duration of the event is retained at each location (i.e. instead of the maximum).

Table 2: Table of thresholds or limits used to define events. These thresholds used (i) in defining events and (ii) calculating severity indices are not to be confused with the percentiles used to distinguish events of differing severity in the Results (e.g. 75th percentile of events once they have been isolated and quantified in terms of a severity index).

Threshold / Limit	**Value**
Percent of river network (q)	0.1%
Percent of GB land area (v, p)	0.1%
Extreme peak river flow (whole year), percentile of daily values.	99.5%

Extreme precipitation (Oct-Mar), percentile of daily values.	98.0%
Extreme daily 10 m max wind gust (Oct-Mar), percentile of daily values.	98.0%
Maximum length of event - from Griffin et al (2022a)	14 days

A.3 Event severity indices

Severity indices are 'impact-based proxies' for hazards such as flooding and wind extremes (Hillier and Dixon, 2020), calibrated against and designed to reflected potential damage (Bloomfield et al., 2023; e.g., Christofides et al., 1992; Heneka and Ruck, 2008; Hillier and Dixon, 2020; Klawa and Ulbrich, 2003).

Storm Severity Indices (SSI) aim to condense the risk associated with a wind event into a single number incorporating factors thought to drive damage such as maximum wind gust (v), area affected and duration (e.g., Christofides et al., 1992; Dorland et al., 1999; Klawa and Ulbrich, 2003). Recently, following Klawa and Ulrich (2003) a form of SSI using v^3 in excess of a 98th percentile minimum threshold beneath which no damage occurs has become well-established as a norm (Bloomfield et al., 2023; e.g., Leckebusch et al., 2008; Osinski et al., 2016; Priestley et al., 2018). Rather than a region defined by a simple (e.g. circular) geometry (Manning et al., 2022, 2024), grid cells over land (e.g., Bloomfield et al., 2023; Pinto et al., 2012) are used to represent GB impact. For simplicity and to avoid a judgement linking value directly to population density (e.g. consider a wind farm), in contrast to Bloomfield et al. (2023), no population weighting is used. Thus, each event's severity SSI(E) is given by Eq. (1):

$$SSI(E) = \sum_{i=1}^{N_i} \sum_{j=1}^{N_j} \left(\frac{v(E)_{i,j}}{v_{i,j}^{98}} - 1 \right)^3 \cdot I_{i,j}$$

$$I_{i,j} = \begin{cases} 0 & \text{if } \; v(E)_{i,j} < v_{i,j}^{98} \\ 1 & \text{otherwise} \end{cases}$$

Two types of model have been used to approximate loss (l) or SSI, power-law ($l = k_1 v^{\propto}$ for $v > v_{\text{thresh}}$) and exponential ($l = k_2 e^{\beta v}$), where k_1, k_2, $\propto$ and β are constants, parameters to be determined by fitting to loss data. In general, the challenge is to approximate data where losses rise steeply above ~32ms^{-1} (Christofides et al., 1992; Dorland et al., 1999; Heneka and Ruck, 2008). Using no threshold an exponential form, which can rise very abruptly, fits postcode district losses for 5 storms better than $\propto$ of 2-4 (Dorland et al., 1999). With a threshold of ~20-24ms^{-1} or the 98th percentile (e.g., Christofides et al., 1992; Klawa and Ulbrich, 2003) v^3 can fit losses for a storm (i.e. within 1-2 days) at district or national resolution, and allow modelling of district level historical losses (e.g., Pinto et al., 2012). This said, the 1999 storms sequence (Anatol, Lothar, Martin) showed losses above 24 ms^{-1} may on occasion rise more sharply for certain domains (i.e. v^4 - v^5 for Denmark, Germany)(MunichRe, 2002).

At a daily timescale a 98th percentile threshold (i.e. ~7 times per year) arises as, in practice, relatively little damage occurs below this level (~20 ms^{-1}) in the flat areas of UK and German (Klawa and Ulbrich, 2003; Palutikof and Skellern, 1991). Of course some places, such a mountains, are windier (Heneka et al., 2006; e.g., Hewston and Dorling, 2011) but both nature (e.g. trees) and the built environment appear to adapt to this recurrence level. Klawa and Ulbrich (2003) illustratively note that winds at List (island of Sylt) exceed 20ms^{-1} 1-in-5 days to no noticeable detriment, and building regulations (e.g. UK, Germany, Netherlands) require greater resilience in windier areas (e.g., Böllman and Jurksch, 1984; Chandler et al., 2001; Dorland et al., 1999; Hill et al., 2013). Whilst a higher percentile might be appropriate for higher frequency data (6-hourly, 99th) (Manning et al., 2024), damage on 2% of days (i.e. 98th percentile) is not wildly different from the number of UK storms, which are named (i.e. 7-8 per/year) when the Met Office believes it has '*potential to cause disruption or damage*' (Met Office, 2024).

Probabilistic models account for the uncertainty in how individual assets are damaged (Heneka et al., 2006; Heneka and Ruck, 2008), for instance using a power-law and replacing the threshold with a function describing the probability of damage (Pardowitz et al., 2016; Prahl et al., 2012). This better approximates losses in Germany across all 2004 wintertime days in 11 years (1997-2007), although the costliest days (~10 per year) are still adequately modelled using cubic excess-over-threshold approach with a 98th percentile (Prahl et al., 2015). Thus using Eq. (1) is appropriate as these 'extremes' are the focus of this paper, particularly as ranks rather than absolute SSI values are primarily evaluated. Moreover, sensitivity testing indicates limited sensitivity of patterns of correlation (e.g. spatial) to are largely choice of threshold (Hillier and Dixon, 2020), something borne out by the convergence of results for recent UK flood-wind research that have employed a spectrum of methodological choices (see Section 4.1).

Storm duration has been argued to influence losses (e.g., Christofides et al., 1992), but statistical studies have found that it does not improve models and may risk 'over-fitting' (Dorland et al., 1999), so in line with the Klawa and Ulbrich (2003) such potential influences (e.g. precipitation, duration) are not included here. We also note that v^3 is theoretically related to kinetic energy flux (e.g., Pinto et al., 2012) and to the dissipation of kinetic energy in the surface layers of a storm (Bister and Emanuel, 1998; Businger and Businger, 2001; Emanuel, 1998, 2005). However, we discount this as any justification for a cubic relationship between economic loss and v, other than perhaps as for the presence of non-linearity. Simply, for cubically increasing losses over a threshold (e.g., Christofides et al., 1992; Dorland et al., 1999) a cubic relationship that starts at zero velocity, as kinetic energy must, does not fit them well (Prahl et al., 2015).

Based on the form of SSI, Flood Severity Indices (FSI) have recently been developed (Bloomfield et al., 2023, 2024). Only grid cells on the river network (e.g., Bloomfield et al., 2023) are used, again with no population weighting. Thus, each events' flood severity FSI(*E*) is given by Eq. 2:

$$FSI(E) = \sum_{i=1}^{N_i} \sum_{j=1}^{N_j} \left(\frac{q(E)_{i,j}}{q_{i,j}^{99.5}} - 1 \right) \cdot I_{i,j}$$

$$I_{i,j} = \begin{cases} 0 & \text{if } \; q(E)_{i,j} < q_{i,j}^{99.5} \\ 1 & \text{otherwise} \end{cases}$$

The 99.5th percentile is inherited, for consistency, from Griffin et al (2022a). It is largely arbitrary, intended to yield sufficient data points for statistical analysis (Bloomfield et al., 2023; Griffin et al., 2022b). It is less than the 2-year return period 'rule of thumb' for bank-full discharge (i.e. 99.9th percentile), although the work this derives from (Williams, 1978) is highly equivocal (i.e. 1-32 year range) due to factors such as basin characteristics, local climate and flood defences (Berghuijs et al., 2019; e.g., Tian et al., 2019). The cubic power is removed as it is not required with, as for SSI, justification of this functional form of FSI being through validation, replicating losses and capturing known floods (Bloomfield et al., 2023). Historical FSIs are highly correlated ($r = 0.74$, $p < 0.05$) with infrastructure loss data on an annual timescale, and FSI captures 28 of 34 wintertime floods (1980-2020) in the Chronology of British Hydrological Events (Black and Law, 2004). This said, lots of small FSI 'events' occur where no flooding was historically recorded. Also, without a threshold non-linearity (i.e. $SI^{\sim 5}$) improves the fit of one proxy to losses (Hillier and Dixon, 2020), so debate on the form of FSI is expected to continue.

FSI as configured in Eq. 2 is suitable here as only the most extreme events are selected (i.e. >75th percentile of events). This is 5-6 high flows per year, comparable to the ~7 floods per year in commercial risk models (Hillier et al., 2024).

A Precipitation Severity Index (PSI) is used for consistency, despite severity perhaps being an incorrect term as rain itself rarely does damage directly (Manning et al., 2024). PSI is defined as for SSI, except that a cubic relationship is omitted as there is no justification for the additional complexity. PSI(E) for each event is given by Eq. 3:

$$PSI(E) = \sum_{i=1}^{N_i} \sum_{j=1}^{N_j} \left(\frac{p(E)_{i,j}}{p_{i,j}^{98}} - 1 \right) \cdot I_{i,j}$$

$$I_{i,j} = \begin{cases} 0 & \text{if } p(E)_{i,j} < p_{i,j}^{98} \\ 1 & \text{otherwise} \end{cases}$$

A.4 Description of Event Sets

A set of high-flows events (Griffin et al., 2022b, a) has been created for the UKCP18 12-member perturbed parameter ensemble (PPE) of the Hadley Centre 12km Regional Climate Model (RCM) (Murphy et al., 2019; Tucker, et al., 2022). Thus, to mirror this, UKCP18 was used to generate wind (*n* = 3,427) and precipitation (*n* = 14,502) events across mainland Great Britain for baseline (winters 1981-1999) and future (winters 2061-2079) time-slices. The wind event set is broadly aligned to other such sets in its construction methods (Lockwood et al., 2022; Osinski et al., 2016; Roberts et al., 2014), and the data been validated for the purposes of examining hazard co-occurrence (Appendix A.1). Summary metrics are created for these event footprints (total area, duration, SI) and assigned to a single date t_{max}, the individual day when the greatest number of grid cells exceed the set threshold.

First consider the size and number of events at the present time. There are 7-8 wind events per year in 1981-1999 on average, each tending to affect a large area (i.e. up to 60% of GB) but be relatively short-lived (< 5-day). This contrasts longer-duration yet more localized fluvial flooding (Fig. A1a). These properties match what is typical of these event types (e.g. Mitchell-Wallace et al., 2017). No wind event ever exceeds 8 days, so the limit of 14 days used by Griffin et al (2022b, a) is not needed. Extreme precipitation is more common than wind with 31-33 events per year, as is flooding at 13-16 events per year.

The relative frequency of events is statistically dictated, depending upon the size of each phenomenon and the parameters (e.g. thresholds) used to extract events. The spatial length-scale of correlation (i.e. floods are typically smaller) increases their number, counteracted somewhat by them lasting longer and the higher percentile. Imagine an idealised scenario wherein windstorms hit the whole UK, whilst floods impact 10% of its area (e.g. in 10 uncorrelated areas). Now, for a 98th daily percentile, every 1 in 50 days all WS points will peak at the same time giving 1 event. For flood, this will happen separately in the 10 areas, giving 10 events. The higher percentile (i.e. 99.5th vs 98th) used for flooding will reduce this by four times, giving 2.5 events in 50 days. Also, by lasting longer, the flood events might merge more readily, reducing their number.

The events in 2061-2079 have some differences to 1981-1999. Fig. A1 echoes the finding of Griffin et al (2022b) that flooding is expected to be more frequent (+18% here) and heavier tailed with larger extreme events (Fig. A1a) and somewhat more seasonal with a focus in mid-winter (DJF), but also identifies a potential shift to a slightly earlier peak in future (Fig. A1b). Considering all events, neither precipitation nor wind events increase in number significantly into the future (*t*-test between means of ensemble members), and echoes the muted changes in climatology (e.g., Manning et al., 2022, 2024). It differs, however, from true extremes are examined in papers (Bloomfield et al., 2023) or the main text. Illustratively, increases for Oct-Mar are +59% for the 75th percentile of FSI, +91% for the 95th percentile of FSI in Fig. 6a,d, both of which are significant (p < 0.01).

Only the top quarter of events defined are focussed upon (i.e. most severe quarter, >75th percentile). For wind events there are 7-8 per year in total, which roughly reflects the Met Office's named storms 2015-2023 (7.4/yr)(Met Office, 2024). Thus, 1-2 per year are focussed upon, comparable to the ~3 per year used in insurance industry risk modelling (Hillier et al., 2024). There are 15 high flow events per year, and taking the top quarter gives ~4 notable high-flow events, comparable to the 6-7 floods per year in a commercial model (Hillier et al., 2024).

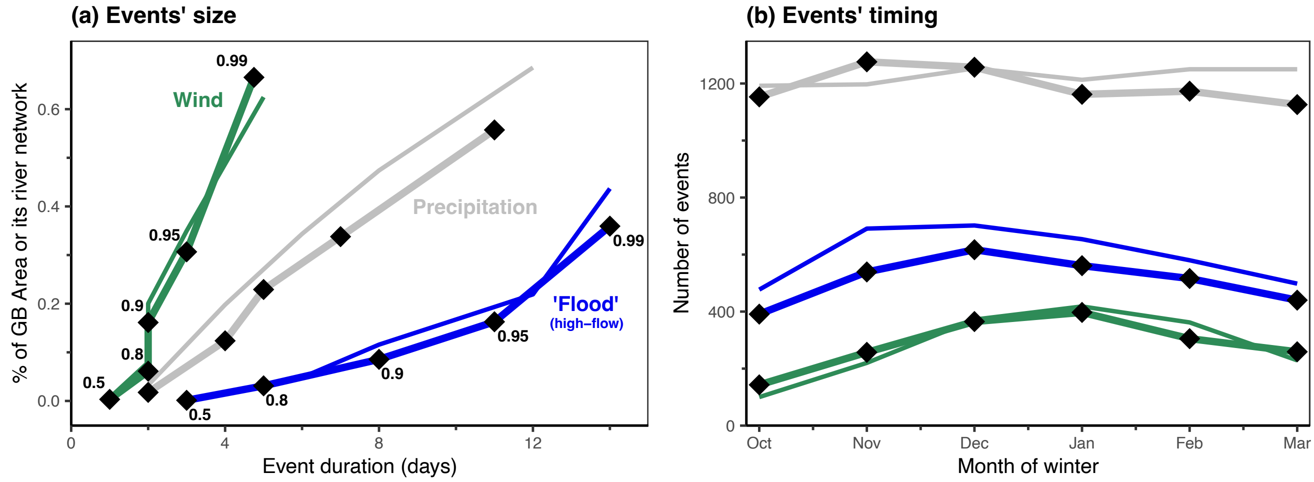

Fig. A1: (a) Size and duration of events created for Wind, Precipitation and Flood. 'Flood' events are high-flow events created by Griffin et al (2023). Percentiles are shown from 50th to 99th, calculated separately for duration and area (i.e. this is not a joint distribution). Present day (thick lines) and future (thin lines) are similar if all the events are considered. (b) Seasonality of the events.