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ORIGINAL PAPER

Beyond the local climate change uplift – The importance of changes in spatial structure on future fluvial flood risk in Great Britain

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Abstract
Widespread spatially coherent flood events can cause severe damage and disruption. Climate change has the potential to change the severity and frequency of such events. Despite this, assessment of future fluvial flood risk typically gives little to no consideration to potential changes in the spatial structure of future events. To understand the significance of this gap, climate model simulations are coupled with a national hydrological model to identify event spatially coherent present and future flood events. A statistical Empirical Copula is used to generate a large number of unseen events and linked to a national flood risk simulation model. The research finds that including changes in the spatial structure of flood events materially increases projected changes in risk when compared to conventional approaches based on local uplifts alone; increasing the projected change in Expected Annual Damage across Great Britain by a factor of ~ 1.5. The event-based approach is also shown to provide new insights into the extreme distribution fluvial risk including single event damage, damage seasons, and damage years. The results suggest the 1-in-100-year winter flood may increase from £1.3b to £2.1b, and the 1-in-100 year single event damage may rise from £1.1b today to £1.7b by the 2080s given a 4 °C rise in Global Mean Surface Temperature (assuming current adaptation policies continue and no population growth). Consequently, the findings suggest a much greater emphasis is needed on spatial 'flood events' if future risk is to be understood and adaptation responses appropriately framed.

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Graphical abstract

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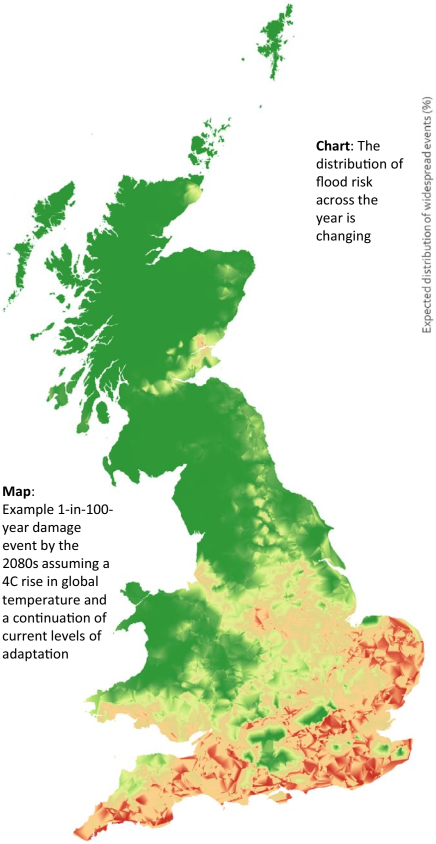
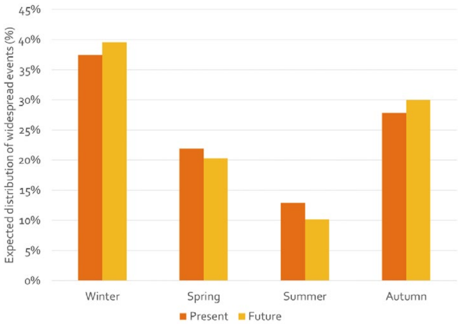


Map: Example 1-in-100-year damage event by the 2080s assuming a 4C rise in global temperature and a continuation of current levels of adaptation

Chart: The distribution of flood risk across the year is changing



This paper explores changes in fluvial flood risk using an event-based climate risk assessment. Unseen events are generated based on the UKCP18 climate outputs and a national hydrological analysis (the G2G model). Flood risk is then assessed using the Future Flood Explorer.

The research suggests the influence of climate change on the spatial structure of fluvial flood events is an important contribution to future increases in flood risk. Conventional approaches relying upon local climate uplifts may significantly underestimate future change.

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Keywords Climate change · Regional climate modelling · Flood risk · Adaptation

Abbreviations

AEP	Annual Exceedance Probability
CCA	Census Calculation Area
CCRA3	The third UK Climate Change Risk Assessment
EAD	Expected Annual Damage
FEH	Flood Estimation Handbook
FFE	Future Flood Explorer
GMST	Global Mean Surface Temperature
PoE	Probability of Exceedance
RCM	Regional Circulation Model
UKCP18	United Kingdom Climate Programme 2018

1 Introduction

Spatially coherent events occur when multiple connected locations are affected by the same or different hazards within a limited time window. Spatially compounding events occur when spatial inter-connectiveness (either through physical or social geography, supply chains or infrastructure networks) exacerbates the impacts beyond those that would be anticipated based on an isolated site analysis. Flood hazards are often coherent at regional (or even larger) spatial scales and have the potential to drive spatially compounding impacts (such as those frequently experienced in Pakistan, including in 2022, in Queensland in 2010/11, and across the UK in 1947 and 1953). Widespread flood events across Great Britain in 2007 (Marsh and Hannaford 2007) and 2014/15 (Met Office 2014) reinforced the early warning of Evans et al. (2004a,b) that '*disruption can quickly lead to widespread and serious consequences*' and *'proactive measures are needed to improve resilience of (infrastructure) networks'*. These events motivated the National Flood Resilience Review (2016) to highlight the importance of such events in driving cascading and escalating risks and the need to develop resilient systems. In parallel, the private sector within Great Britain is increasingly placing a greater emphasis on understanding risk into the future. This includes increased regulatory interest in the resilience of financial institutions to present and future climate related risks (for example, as recognized in the Bank of England Climate Stress Test, Bank of England 2022) and reflects the recognition that reinsurance and lending (particularly mortgage lending) exposes the risk-taker (lender or re-insurer) to the influence of climate change (e.g. CISL 2019; Westcott et al. 2020).

The coming together of climate risk assessment needs within the public and private sectors provides the motivation for this paper. The flood risk assessment method and application set out bring together the advantages of the conventional public and private sector approaches for the first time into an event-based national-scale climate change flood risk assessment that represents the potential changing spatial structure of fluvial flood events in the future. The approach set out supports multiple scenarios of adaptation and socio-economic change (a prerequisite for public sector applications) and the identification of event-based risks today and in future climates (a prerequisite for private sector financial and reinsurance applications and public sector understanding of network resilience).

2 Overview of alternative risk frameworks

Risk concepts are widely used across several disciplines, including finance, investment, insurance, disaster management, adaptation, conflict and peacebuilding. The concepts vary in detail, but all rely on the same basic principle; risk is a function of two components—the chance that a situation arises with the potential to cause harm (*e.g.* a flood hazard) and the magnitude of the harm caused should that situation arise (*i.e.* consequence, such as loss of social well-being, economic output, ecosystem health). Risk therefore can be considered in general terms as a function of both the probability and magnitude of some form of impact. This versatility has enabled the concept of risk to gain significant traction across all decision realms. The ability to help decision makers compare and prioritize alternative courses of actions in a structured and coherent way is the central advantage of a risk-based approach.

Within the context of flooding in the Great Britain (and elsewhere), an understanding of current and future flood risks is now a well establish cornerstone of making good risk-based decisions (e.g. Sayers et al. 2002). The importance of 'understanding risk' was first formalized within national-scale adaptation policy planning as part of the seminal Foresight Future Flooding Studies (Evans et al 2004a; 2004b) and is now embedded in the Climate Change Act (2008) (the 'Act'). The Act places a requirement on the UK Government to undertake *a Climate Change Risk Assessment* (CCRA) undertaken every 5 years to measure progress in adaptation and to gain early insights to future adaptation priorities (with the most recent flood projections given in Sayers et al. (2020). An understanding of present and future Expected Annual Damage (EAD) and other annualized risk metrics have been a central consideration in such assessments and associated national adaptation investment planning (such as the Environment Agency's Long Term Investment Scenarios, LTIS, Environment Agency 2019). Nonetheless, public sector assessments of risk continue to largely ignore present-day spatial correlations (despite investing in related research for some time, e.g. Environment Agency (2011), Lamb et al. (2010)) and typically exclude any consideration of how the spatial structure of flood events may change with climate change.

Outside of the public sector, Catastrophe (CAT) Models often form the basis of present-day risk assessments including, for example, the insurance and financial sectors. CAT models rely upon stochastic event sets to determine a risk profile (the damage conditional on an annual probability of exceedance) as well as expected annual losses across their asset portfolio. Issues of climate change and adaptation have, until recently, played a less central role (e.g. CISL 2019).

Across these domains the approaches currently used can be broadly sub-divided into two main classes, a *'local-dependence framework'* and *'event-based framework'* as elaborated below.

2.1 Local-dependence framework

The term *local-dependence framework* is used here to refer to an assessment that assumes the probability of the flood hazard to be fully dependent across the area of interest. For example, defences protecting the same floodplain are assumed to experience the same severity of load, say a 100-year return period in-river water level, at the same time. The probability of flood inundation (taking account of the conditional probability of a defence failing or being overtopped) is then determined based on that assumption (e.g. Hall et al. 2003, Gouldby et al. 2008). This assumption may be reasonable at a local scale (*e.g.* a small floodplain) but becomes increasingly in error at larger scales.

A local-dependence framework typically underpins public sector risk analysis and underlies the communication of the probability of flooding, the assessment of risk, and adaptation policy. For example, the communication of the probability of flooding is typically provided through local flood maps that express the Annual Exceedance Probability (AEP) of a given flood depth or velocity (*e.g.* Sayers et al. 2015a). Equally, the national case for investment in flood management considers the local change in probability of flooding for a given investment (e.g. in defences) to determine a change in Expected Annual Damage (EAD), where EAD is routinely determined as (Hall et al. 2003):

$$\boldsymbol{EAD} = \sum_{i} \left(\boldsymbol{P}_{i+1} - \boldsymbol{P}_{i}\right) \times \left(\frac{\boldsymbol{D}_{i+1} + \boldsymbol{D}_{i}}{2}\right) \quad (1)$$

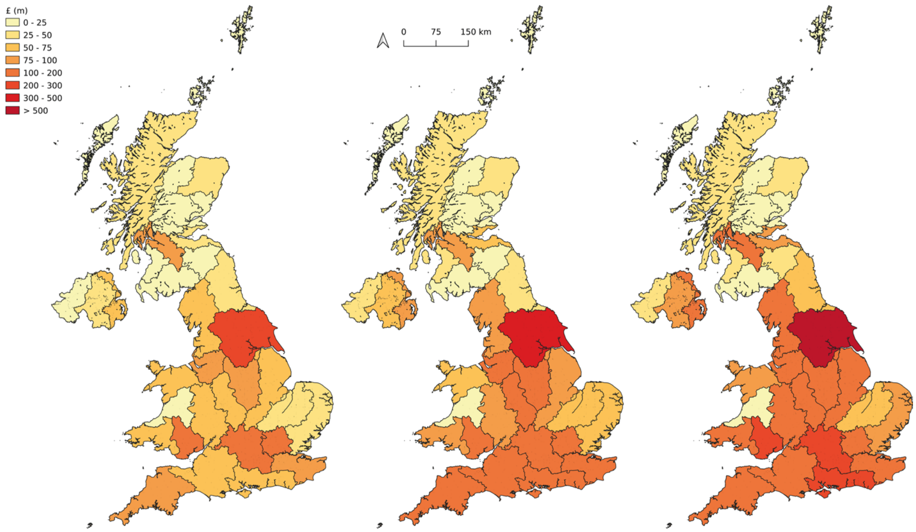

Fig. 1 Expected annual damages by region, assuming current adaptation policies continue to be implemented. Left: 2020s; middle: 2050s and right: 2080s corresponding to a high population growth and rise of 4 °C in Global Mean Surface Temperature by 2100 Source: Sayers et al. 2020

where P_i is the AEP of the load i and D_i is the associated damage.

When computing annual damage in this way, there is an implicit assumption that the damage varies linearly between D_i and D_{i+1}. The error introduced through this process (at a local scale) is readily seen to depend upon the number of AEPs for which damages are available (*e.g.* McGahey and Sayers 2008). It is also typically assumed that local assessments of EAD can be aggregated through simple addition in line with the general principle that an *aggregated* mean is the sum of the local means. This assumption underpins the National Flood Risk Assessment in England (NaFRA; Hall et al. 2003; Gouldby et al. 2008) and the future flood projections in the UK Climate Change Risk Assessment (Sayers et al. 2020). A typical output from this type of analysis is illustrated in Fig. 1.

Expected Annual Damage calculated in this way offers a simple and useful view of risk but does not provide a full picture of the significance of the risk faced. For example, an EAD value dominated by low-probability, high-damage combinations are not the same *'risk'* as one dominated by high-probability, low-damage combinations, even though estimated value may be the same. Understanding the *'risk profile'* (i.e. the relationship between damage and probability) is as important, if not more so, than simply understanding the expected value. An understanding of the risk profile enables low-probability/high-consequence risks and high-probability/low-consequence risks to be distinguished and management actions appropriately tailored.

Local–dependence frameworks can of course be used to provide a local 'risk profile' but these cannot be aggregated to a regional or national scale. This inability reflects the lack of information on the spatial coherence of the AEP assigned to the hazard in different locations. For example, it would be grossly conservative to assume the 1-in-100 year return period storm load occurs at all locations simultaneously and that the 1-in-100 year national damage is simply the sum of the 1-in-100 year damage at all locations. Equally, assuming independence between all locations may dramatically underestimate the likely size of the more severe events (e.g. de Luca et al 2017). Addressing these shortcomings is the central driver of *'event-based'* frameworks used extensively in private sector assessments of risk (and discussed below).

2.2 Event-based frameworks

An *event-based framework* is used here to refer to an assessment of risk based on a spatially coherent event set. A spatially coherent event defines a set of values (of some variable, for example, river level) across a defined area of interest that occur *'at the same time'*. In the context flooding, this does not necessarily mean at the same precise time but during the same event. This is typically defined in the context of *'time window'* that reflects the persistence of flood hazard or the persistence of the potential impacts (e.g. Villarini et al. 2010, Kendon and McGarthy 2015; Barton et al. 2016, Sayers et al. 2015, Zscheischler et al. 2020).

Event-based frameworks are typically used within the financial and reinsurance sectors to explore the probable maximum loss (PML) that may be incurred during a single event across a spatially disparate asset portfolio. This relies on an understanding of the 'risk profile' at the spatial scale of the asset portfolio (a scale that may extend to national or even global scales). Catastrophe (CAT) modelling approaches were developed in the late 1980s to service this need. CAT models first generate stochastic spatial *'hazard event sets'* and assess the damage for each individual event. The event damages are then used to determine an extreme distribution of damage at any scale of aggregation (as well as an EAD, typically referred to in financial sectors as the Annual Average Loss where the 'average' refers to the expected, arithmetic mean, value). In most existing CAT models both the marginal distribution of the extreme hazard variables and their dependence structure are inferred from a blend of observations, weather modelling, and present-day climate modelling. Climate projections are rarely incorporated beyond the application of local uplifts (e.g. increasing river flow, rainfall, or mean sea levels to reflect climate change, see, for example, the Bank of England 2022) or direct use of climate model outputs.

Extending an event-based risk assessment framework to include climate change has several advantages. By better understanding the distribution of losses today and how these may change, an event-based framework provides insights into questions that can help shape the adaptation response:

- What is the national 100-year flood damage today and how might this change in the future?
- What is the chance that many different locations will be affected by severe flooding around the same time (i.e. spatially compounding events)?
- What is the expected flood damage in Winter compared to Summer, and how is this distribution influenced by climate change?

Whilst the local-dependence framework underpinning existing national flood risk assessments are useful in helping prioritize investment decisions, they provide limited insight into these questions. The central disadvantage of adopting an event-based framework, however, is the perceived complexity of the analysis, requiring many thousands of events to be simulated to limit the aleatoric uncertainty in estimate of risk. Many additional simulations are typically then may be required to reflect the system, including, for example, the conditional performance of the defences. This is often problematic if we are interested in exploring multiple climate, socio-economic, and adaptation futures.

2.3 Towards continuous simulation approaches

Continuous simulation-based approaches seek to provide an end-to-end analysis chain of the risk system of interest (including all the sources, pathways and receptors of interest, Sayers et al. 2002). Continuous simulation approaches that operate within a probabilistic risk assessment framework are emerging but remain computationally challenging (e.g. Mitchell-Wallace et al. 2017). These challenges are being overcome in the context of relatively well conditioned problems (such as water resources, Jenkins et al. 2021), selected elements of the flood system (such as hydrological flood simulations (e.g. Smith et al. 2014) and pilot risk assessments (e.g. Falter et al. 2016). Such approaches do not yet offer the capability to undertake credible large-scale risk assessments that reflect the whole system behaviour (including complex source-pathway-receptor relationships) and the influence of adaptation investment choices (such as those explored in Sayers et al. 2020 using a local-dependence framework). This reflects difficulties in representing the full range of interactions within a conventional process-based modelling chain and the associated computational expense (at least in the short term).

3 Method—event-based climate change risk assessment for Great Britain

Given the advantages and disadvantages of the various frameworks outlined above, it is likely spatial event-based approaches will be increasingly used across both private and public sector to explore risk and adaptation decision making. The framework set out below adopts this event-based perspective within a practical form of climate risk analysis, including the influence of changes in the spatial structure of storm events on future risk (a hitherto unexplored influence). The focus of the analysis set out is in the context assessing future changes in fluvial flood risk at the scale of Great Britain. The framework, however, is readily transferable to other risks and geographic contexts.

To provide an assessment of future fluvial flood risk the future(s) of interest must be defined. This includes, as a minimum, setting out the assumed: (i) climate change; (ii) socio-economic change; and (iii) approach to adaptation. For the purposes of this paper two climate futures are considered, a 2 °C and 4°C rise in Global Mean Surface Temperature (GMST) by 2100 compared to pre-industrial times. Given the focus on exploring the potential influence of climate driven changes in the spatial structure of fluvial flood events, a simple no population growth future assumption is made.[1] The assumed adaptation future sees a continuation of current policies (as defined by Current Levels of Adaptation assumptions set out in Sayers et al. (2020) covering a portfolio of responses including, catchment management, Sustainable Urban Drainage, forecasting and warning as well as conventional defences).

The framework set out here reflects these assumptions and the typical CAT-Model assessment structure (Fig. 2). This enables the changing spatial event structure that may exist in response to climate change alongside the decision relevant assessment of alternative futures. The methods used to implement each step of the framework are elaborated below.

[1] Extending the analysis to include the UK Shared Socio-Economic Pathways (Merkle et al. 2022) would be straightforward but is excluded for simplicity and clarity.

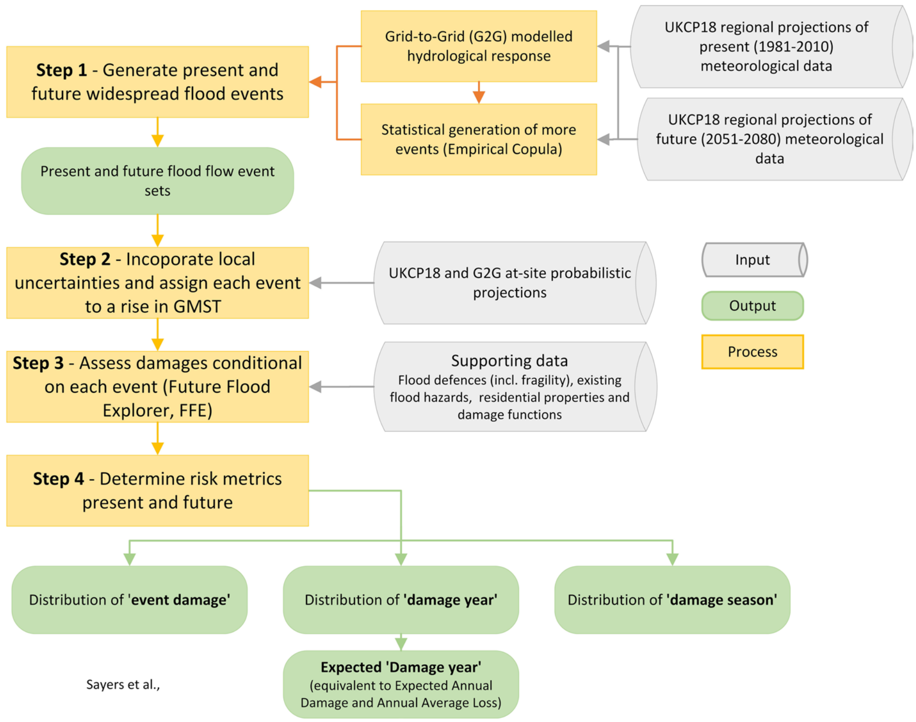

Fig. 2 Framework of the event-based climate change risk assessment for fluvial risk

3.1 Step 1—Generate present and future events

UKCP18 Regional Projections (Lowe et al. 2018) are used to drive Grid-to-Grid (G2G) a national-scale hydrological model (Bell et al. 2009). G2G runs on a 1 km grid and uses a time series of precipitation, temperature, and potential evaporation (PE) from the 12 km Regional Climate Model (RCM) to generate a spatially coherent gridded flow series across Great Britain (Kay 2021a). The baseline results represent the period 1981–2010, which is associated with an estimated rise in GMST of 0.7 °C, compared to pre-industrial era (Morice et al. 2021). The future RCM projections are based on the RCP 8.5 scenario and provide outputs for a 12-member perturbed parameter ensemble (PPE) for the period 2051–2080 (with an associated rise in GMST that varies for each PPE member, Table 1).

The *'observed'* flows are used to identify 'at-site' flood events. An 'at-site' event is assumed to occur when the local flow exceeds the flow expected on two days or fewer per year (on average). This corresponds to a daily probability of exceedance (PoE) of ~ 0.56%, and, assuming a Poisson approximation, an annual probability of exceedance of ~ 86.4% (given the 360-day model year used in UKCP18). The number of G2G cells where the flow exceeds their threshold are summed to provide a proxy of the potential flood footprint at each time step within the present and future periods. It should be noted that the assessed return period events here are subject to sampling uncertainty due to the short 30-year periods of 'observations' from the climate model that form the basis of the extrapolation to

Table 1 Summary of RCM ensemble members. Average rise in GMST up to 2050–2080 relative to pre-industrial levels (1850–1900) from each of the UKCP18-global simulations (GCM) associated with each UKCP18-regional (RCM) simulations (Lowe et al. 2018), and average events per year per RCM ensemble member

GCM/RCM ensemble member	Average rise in GMST from pre-industrial between 2050–2080 (°C)	Mean G2G-modelled events per year (1980–2010)	Mean G2G-modelled events per year (2050–2080)
1	4.19	20	19
4	4.49	20	24
5	4.02	20	20
6	4.16	18	20
7	4.11	20	22
8	3.82	20	20
9	4.64	20	21
10	3.97	20	20
11	4.14	23	24
12	3.98	19	20
13	4.16	20	19
15	3.82	20	22

events with an AEP less than 1% (100-year return period). This is somewhat mitigated by the use of the full ensemble, but each is still based on the same periods. Alongside this is the modelling uncertainty arising from the discrepancy between model and reality, both in the precipitation data and the river flow data. This combines in a non-linear fashion to lead to large uncertainties for the rarest events.

A *'widespread flood event'* occurs when more than 0.1% grid-cells (~20 km^2) exceed their threshold simultaneously. It is assumed that an individual widespread event last for up to 14 consecutive days (if sufficient grid-cells are above threshold). Setting an upper limit of 14 days attempts to avoid the inclusion of consecutive but spatially independent events (Griffin et al. 2022a), as compared to the annual maxima events considered up to a 19-day period in de Luca et al. (2017), although they only found events of up to 16 days.

The limited number of 'observed' widespread events within the climate model and G2G outputs must be extended to a much larger event set for the purposes of the risk assessment. Various methods exist to translate a set of observed events into a simulated event set that includes events unseen in the observed record (e.g. Heffernan and Tawn 2004; Wyncoll and Gouldby 2015; Tawn et al. 2018). In these methods, the analysis typically proceeds by fitting a probability distribution to peak flow data at location B conditional on the flow at another location A being above a threshold and being the most extreme value within the domain (the conditional distribution). Unseen events are then generated by:

- Selecting location A within the domain as the most extreme flow for an event.
- Using the at-site distribution at A to determine the peak flow.
- Using the conditional distribution to determine the flow at location B conditional on the flow at A.
- Together, flows at A and B provide simulated peak flows for a complete event.

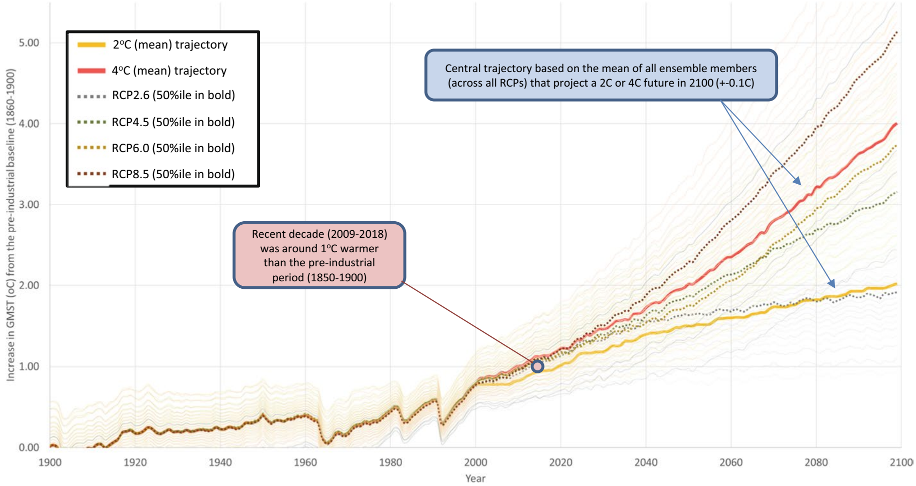

Fig. 3 Rise in global mean surface temperature to 2100 based on UKCP18 probabilistic projections (Met Office Hadley Centre 2018). The figure shows the GMST projections associated with each decile within each RCP (thin lines) and reflects the mean global temperature increase from 1850 to 1900, with the increase by the baseline period of 1980–2010 assumed to be ~ 0.7 °C (as set out by Morice et al. 2021). The adopted projections (highlighted by the thicker lines) represent the mean trajectory for the 2 °C or 4 °C futures and are derived from the UKCP18 probabilistic projections associated with a 2 °C or 4 °C rise by 2100 (± 0.1 °C). Source: Sayers et al. (2020)

The approach used here follows this process and generates new events on a national scale using an Empirical Copula (EC) method (Segers et al. 2017). The use of an EC provides a fast and efficient way to generate widespread flooding events for the whole of Great Britain for all available ensemble members (Griffin et al. 2022b). The approach also preserves the season of each observed and unseen event, a useful insight used later to determine changes in seasonal risk at a national scale.

3.2 Step 2—Incorporate local uncertainties and assign each event to a rise in GMST

The RCMs used to provide the spatial structure of widespread events are few. To provide a more credible assessment of the local changes the results from Step 1 are combined with more detailed at-site analysis. The at-site analysis of flows and their changes uses the probabilistic projections from UKCP18 (Met Office Hadley Centre 2018) and a version of G2G to reflect a wide range of uncertainties in the climate and local hydrological response (Kay et al. 2021b, Rudd et al 2022). A 'time-sampling' approach is used to maximize the number of ensemble members from the probabilistic projections used to assess the change in peak flow (James et al. 2017). This allows all ensemble members associated with a given rise in GMST to be used regardless of when the rise is projected to occur (Fig. 3). The Flood Estimation Handbook methods (FEH, Kjeldsen et al. 2008) are used to translate the 50 percentile changes in peak flow derived for a given GMST rise (as illustrated in Fig. 4 for 4 °C GMST future) to changes in the return period of the in-river water level (using the closest 50m FEH pixel to the G2G river node, Sayers et al. 2020). This process preserves the spatial structure of the event set (derived from the RCMs) whilst maximizing the evidence used to assess local uplifts.

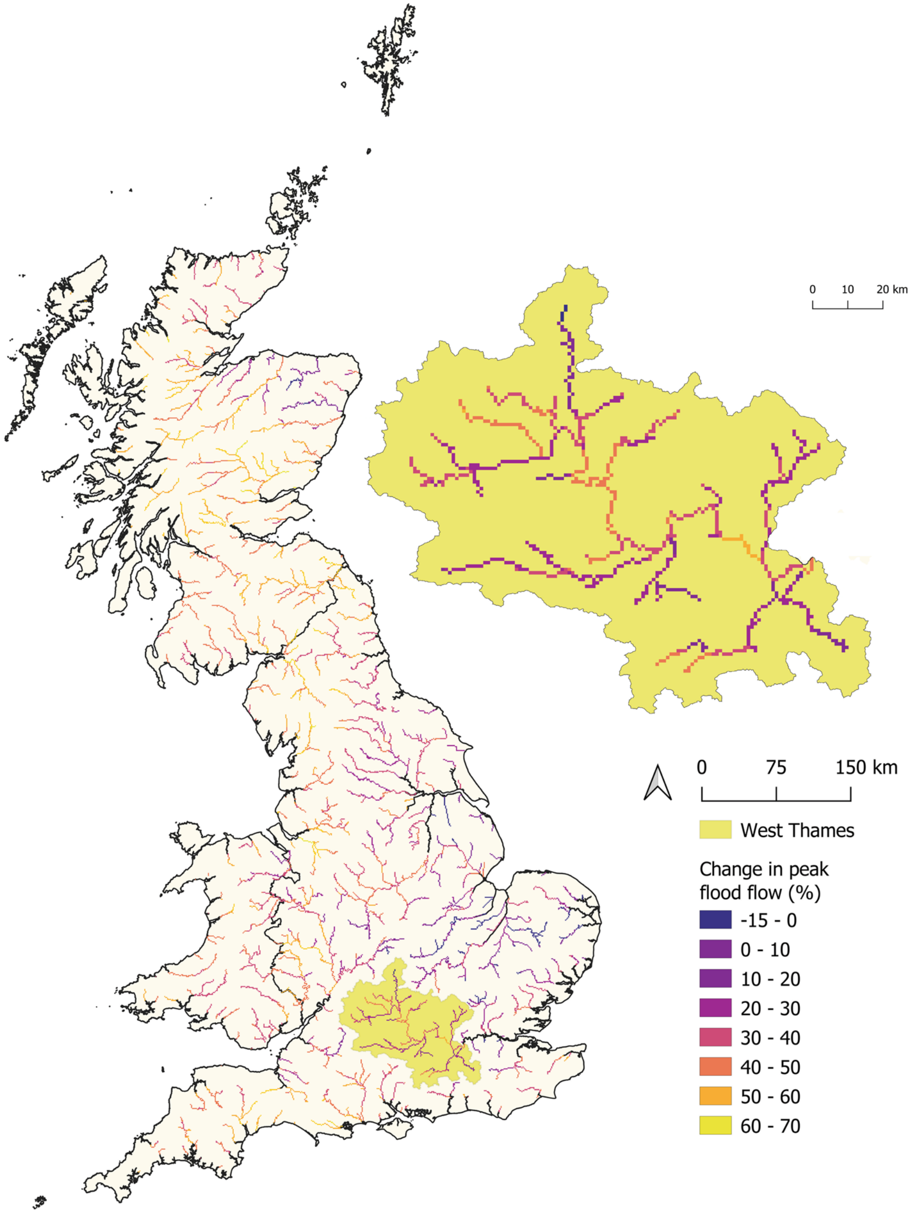

Fig. 4 Changes in peak flows corresponding to a 4 °C rise in GMST by 2100 from pre-industrial times Source: Adapted from Kay et al. (2021b)

3.3 Step 3—Assess damages conditional on each event

The spatial flood hazard events (defined by the return period of in-river water levels from Step 2) provide the boundary conditions to the risk assessment. The Future Flood Explorer (FFE, Sayers et al. 2016, 2020) is then used to relate the return period of the hazard event (at a given river node) to damage (taking account of the performance of flood defences where they exist—including their standard of protection, condition, and fragility—and the associated exposure and vulnerability).

The FFE uses data produced by national leads (such flood defence crest levels and conditions, flood hazard data, and property receptor datasets) to develop an emulation of the present-day flood risk system and manipulates that understanding through metamodeling approaches to assess how flood risk may change in response to climate change, population growth, and adaptation. The FFE relies upon the development and manipulation of Impact Curves (IC) assessed at the scale of 'Census Calculation Areas' (defined using the intersection of river floodplain boundaries and Lower Super Output Area census boundaries, yielding 842,864 CCAs for the UK) and takes account of the Standard of Protection and Condition Grade of the defences that relate to each CCA (Sayers et al. 2015). The local-dependence framework version of the FFE links each CCA to local river point and assessed the EAD for each CCA separately before aggregating the risk (as applied in support of the flood projections in the third UK Climate Change Risk Assessment (CCRA3), Sayers et al (2020). To support the event-based implementation of the FFE, each CCA is associated a river node within the G2G model and an aggregated IC developed. This further enhances computational efficiency of the FFE (reducing the number of Impact Curves to be evaluated by a factor of 100) without loss of fidelity. This process of aggregation does reduce the ease with which adaptation and population assumptions can be modified at a local scale to some extent.

For the purposes of the paper, the assessment of damage used focuses on direct damage to residential properties. This reflects the dominant category of damage within public sector decision making (e.g. Sayers et al. 2016, 2020) but is recognized as a subset of losses incurred during flood events. (For example, loss of well-being, biodiversity impacts, non-residential property damage as well as disruption to supply chains, energy, communities and transport networks and many others are all excluded here.) The focus on residential property, however, provides a well understood focus with well-established methods available to translate exposure to a flood hazard to an economic damage. These methods underpin the implementation of the FFE in CCRA3 and are reused here with some adjustment to enable their use within an event-based framework. This has been done by reconfiguring the Weighted Annual Average Damage (WAAD) relationship (Chatterton et al. 2010, used widely used in the UK to support national assessments, e.g. Environment Agency 2009; Sayers et al. 2020) to provide a Weighted Event-based Average Damage (WEAD) function. The WEAD has been developed by factoring out the probability of the event embedded within the WAAD calculation.

3.4 Step 4—Determine risk metrics

The results from Step 3 are used to derive a range of risk metrics, including extreme distributions of single *'event damages'*, *'damage years'*, and *'season damages'*, as well as the mean *'damage year'*. The approach to each is set out below.

4 'Event damage'—Extreme values

Event damage refers to the damage incurred during a single event drawn from the event set associated with a given time slice and climate future. Given that it is highly likely that more than one event will occur in any given year (as determined in Step 1), the return period (in years) of single event is determined used the binomial approximation (Eq. 2):

$$\frac{1}{T_D} = 1 - (1 - POE)^{N_{av}} \tag{2}$$

where N_{av} is the average number of events per year for a given RCM and time slice. It computes the probability that, if there were N_{av} events in a year, at least one of them would have a probability of exceedance of less than PoE. The return period (in years) is determined simply as the inverse of the PoE. This is recognized as an approximation but is considered reasonable for return periods greater than 5 years (Sayers et al. 2015).

5 'Damage Year'—Expected and extremes values

To estimate the 'damage year', the G2G-modelled events (Step 1) are used to determine the average number of events per year (N_{av}), for both the present and future climates (Table 1) It is assumed that each event occurs independently, and that the full distribution is adequately represented by a Poisson distribution to allow the number of events in each simulated year (N_y) to be determined, where the probability of $N_y = k$ for $k = 0, 1, 2, \ldots$ is given by Eq. 3.

$$P\left[N_y = k\right] = \frac{e^{(-N_{av})k} \times \left(N_{av}\right)^k}{k!} \tag{3}$$

To determine an extreme distribution of the 'damage years' (for example, the 1-in-5 damage year), damage associated with many event years drawn from a given time slice (present or future) and climate future are estimated using the FFE and the results ranked in descending order of damage. The probability of exceedance for the n^{th} largest event (PoE_n) is then approximated as (Eq. 4):

$$PoE_n = \frac{n}{N_{ey} + 1} \tag{4}$$

where N_{ey} is the number of event years sampled.

A return period in years of a given value 'damage year' is assumed to be the reciprocal of PoE (as above). The damage incurred during each event can be undertaken aggregated at any spatial scale of interest; national, regional, or more locally (assuming the event set is sufficiently complete to be meaningful at the aggregation of interest). This enables the extreme value *'damage years'* to be determined for any region within the model domain. This provides a means for tailoring to outputs to be most useful for a given decision use. For example, to the provide outputs for England only or for the devolved administrations in Scotland and Wales.

The sampled number of events for each year is then drawn from each RCM ensemble member (that relates to the climate future of interest) in turn and the conditional damage for each assessed using the FFE. The expected *'damage year'* is then simply the determined as the arithmetic mean of the damages summed for each *'year'* and equivalent the Expected Annual Damage estimated using local-dependence approaches.

6 'Damage season'—Extreme value summer and winter seasons

Season damage represents the damage incurred during events sampled from a given season. The link between the climate model and the G2G simulations enables the number of events in each season to be recorded. Based on these 'observations' the probability distribution of the events by season can be determined for each RCM ensemble member (i.e. $p_{DJF,}, p_{MAM}, p_{JJA}, p_{SON}$), where:

- DJF = December, January, February (Winter)
- MAM = March, April, May (Spring)
- JJA = June, July, August (Summer)
- SON = September, October, November (Autumn)

This allows the number of events per season ($N_{DJF}, N_{MAM}, N_{JJA}, N_{SON}$) to be sampled for each simulated year (with N_{y} events). This is done by drawing once from the multinomial distribution (Eq. 5) and returning the number of events per season for a given year. This is under the condition that $n_D + n_M + n_J + n_S = N_Y$; otherwise, the probability is zero.

$$P\left[N_{DJF} = n_D, N_{MAM} = n_M, N_{JJA} = n_J, N_{SON} = n_S\right] = \frac{N_Y!}{n_D!n_M!n_J!n_S!} p_{DJF}^{n_D} p_{MAM}^{n_M} p_{JJA}^{n_J} p_{SON}^{n_S} \quad (5)$$

The damage associated with each event drawn from a given season and time slice (present or future) are estimated using the FFE. The damage for each event within each season within a given year is summed to provide a '*damage-season*', with return periods calculated as for *'damage years'*.

7 Results—Event-based climate change risk assessment for Great Britain

7.1 Event damages

The analysis suggests climate change is driving a change in the structure of widespread flood events. A comparison of the distributions of the baseline and future events highlights an increase in widespread events that include a very extreme flows (PoE < 0.01) as well as widespread events than are formed by much more frequent events (Fig. 5). The comparison shows the difference in the national scale results from across all RCM ensemble members (based on the event sets generated using the Empirical Copula set out in Step 1).

The changing structure of the flood events combined with local increases in flow translate to a significant change in the distribution of fluvial damage associated with single extreme events (Fig. 6). The comparison of the damage distribution associated with individual events in the present and future time periods shows a marked increase in damages for events with the same return period in the future (given a 4 °C rise in GMST by 2100, no change in population and a continuation of current adaptation policy). The scale of the

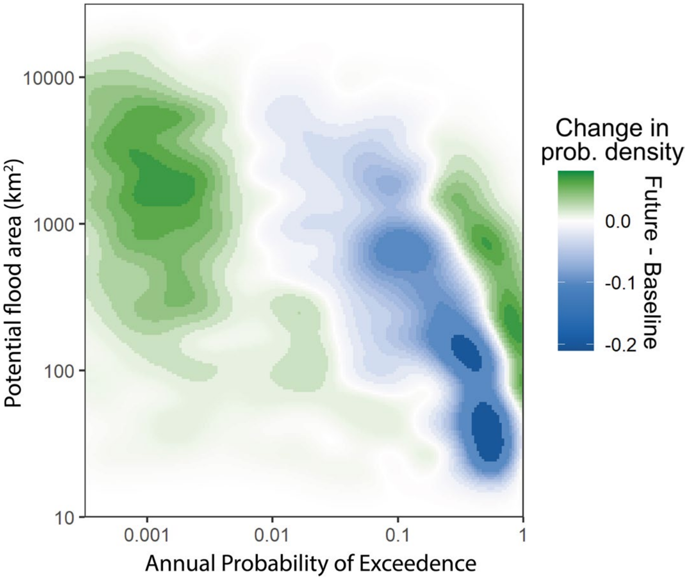

Fig. 5 Heatmap showing the difference in probability density between baseline and future time slices. Positive values (green) indicate more events of this type in the future, and negative values (blue) indicate less events of this type in the future

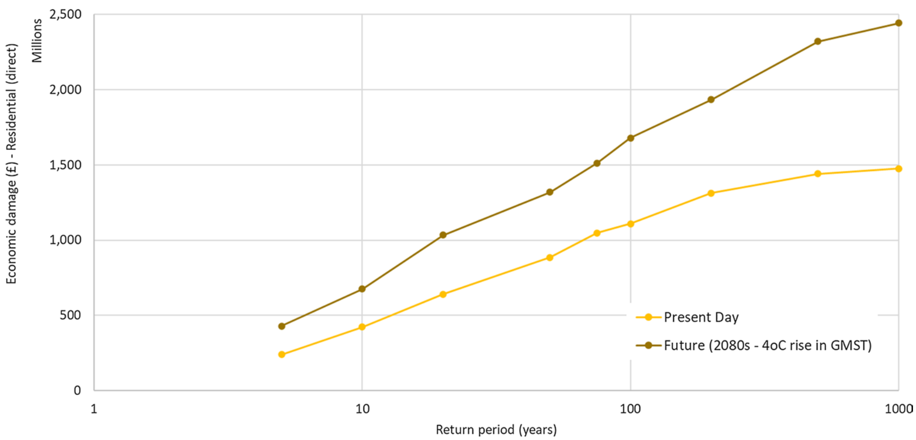

Fig. 6 Single event direct residential property damage by return period. Present and future time slices based on a 4 °C increase (by 2100), no population growth, and assuming a continuation of the current level of adaptation

change increases as the return period of the event increases. This suggests the most damaging events experienced today are likely to become more frequent, and in the future damages from extreme individual events are likely to be much greater than those experienced today. For example, the 1-in-100 year single event is projected to increase from £1.1b to £1.7b by the 2080s.

There is a one-to-many relationship between a given return period *'event damage'* and the events that may generate an equivalent damage. There may be hundreds or even thousands of events that could generate damage equivalent to the 1-in-10 year *'event damage'* (Fig. 7). For example, the event could be more widespread and associated with modest return period flows or more concentrated events and higher flows in locations where the floodplain properties may be poorly protected. The number of events capable of generating a given return period 'event damage' reduces as the return period increases. This reflects the need for each a smaller spatial event in which high fluvial flows coincide with areas of higher exposure and possibly lower defence standards (areas in southern England outside of London), or a much larger spatial event that impacts areas with more moderate exposure and standards. These conditions are met by an increasingly smaller subset of events as the return period of the event damage increases. Example events associated with increasingly larger return period damages are illustrated in Fig. 8 (noting that these are illustrative and alternative events exist for each).

7.2 Damage years

The distribution of 'damage years' provides an insight into the changing national risk profile that is not visible using local return period-based approaches. The analysis suggests a significant increase in frequency in experiencing extreme damage during a year by the 2080s given a 4 °C climate future (Fig. 9). The present-day 1-in-100-year 'damage year' is projected become ~ 20 year 'damage year' and projects significant increases in the 1-in-100 year 'damage year', increasing from ~ £1.3b to ~ £2.1b. In very rare years, say the 1000 year 'damage year' the damage incurred could rise by ~ 60% (from ~ £2b to ~ £3.1b of direct residential damage).

Insights such as those presented in Fig. 8 cannot be determined using a local-dependence framework; but it is not only the richness of the information that is of interest here. The results also suggest that excluding the changing spatial structure of widespread events can lead to a systematic underestimation of the influence of climate change on risk. For example, as part of the published UK Climate Change Risk Assessment (CCRA3, Climate Change Committee 2021) the supporting flood risk projections (Sayers et al. 2020) use a local-dependence framework together with same underlying data on the present-day flood risk systems (the flood hazard maps, flood defences, and residential properties) as well as the same analysis model as used here but within an event-based framework. A comparison of the Expected Annual Damage from UK CCRA3 and the equivalent metric here (the mean *'damage year'*) reveals interesting similarities and important differences (Fig. 10). The underlying risk model—the Future Flood Explorer (FFE)—and the data on flood defences and receptors are the same in both the CCRA3 and the analysis here. The calculation of the annual expectation of damage is necessarily different in the event-based approach compared to the local-dependence framework and the damage function modified in form but not content from the WAAD to the WEAD (as discussed earlier).

For the present day, it is not necessarily expected that the results would be the same in the two approaches. Although few changes are made in the underlying risk model, the way the EAD is calculated does necessarily vary (the spatial aggregation of the results of local estimates using Eq. 1 to the event-based estimate using Eq. 3). This change may yield some variation in the estimate without implying an error in one or both approaches. The closeness of present-day estimates supports the assumption that the spatial aggregation of EAD

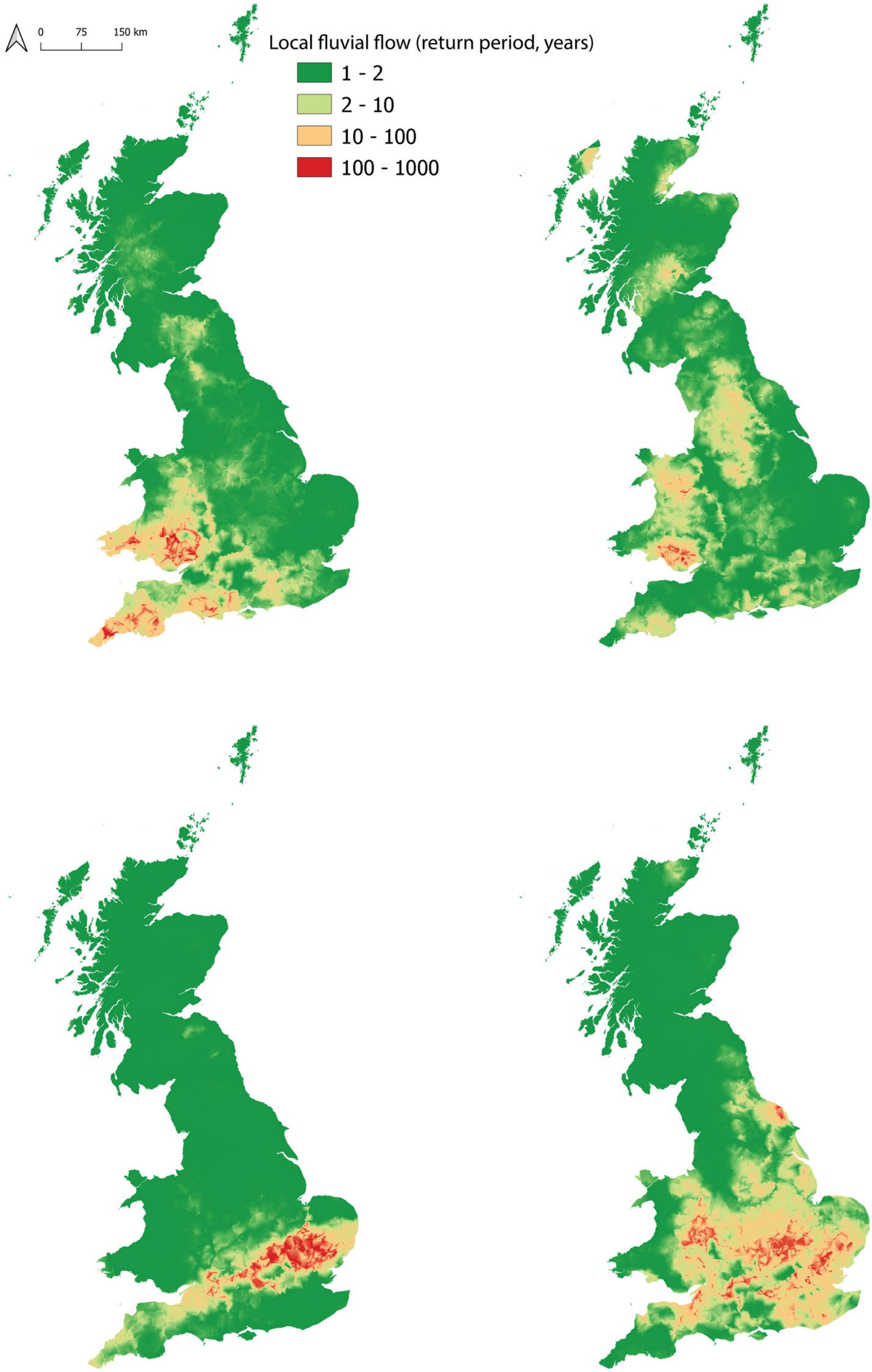

Fig. 7 Example events yielding an equivalent 1-in-10 year damage year for the baseline period. Return period of flood flows shown in years

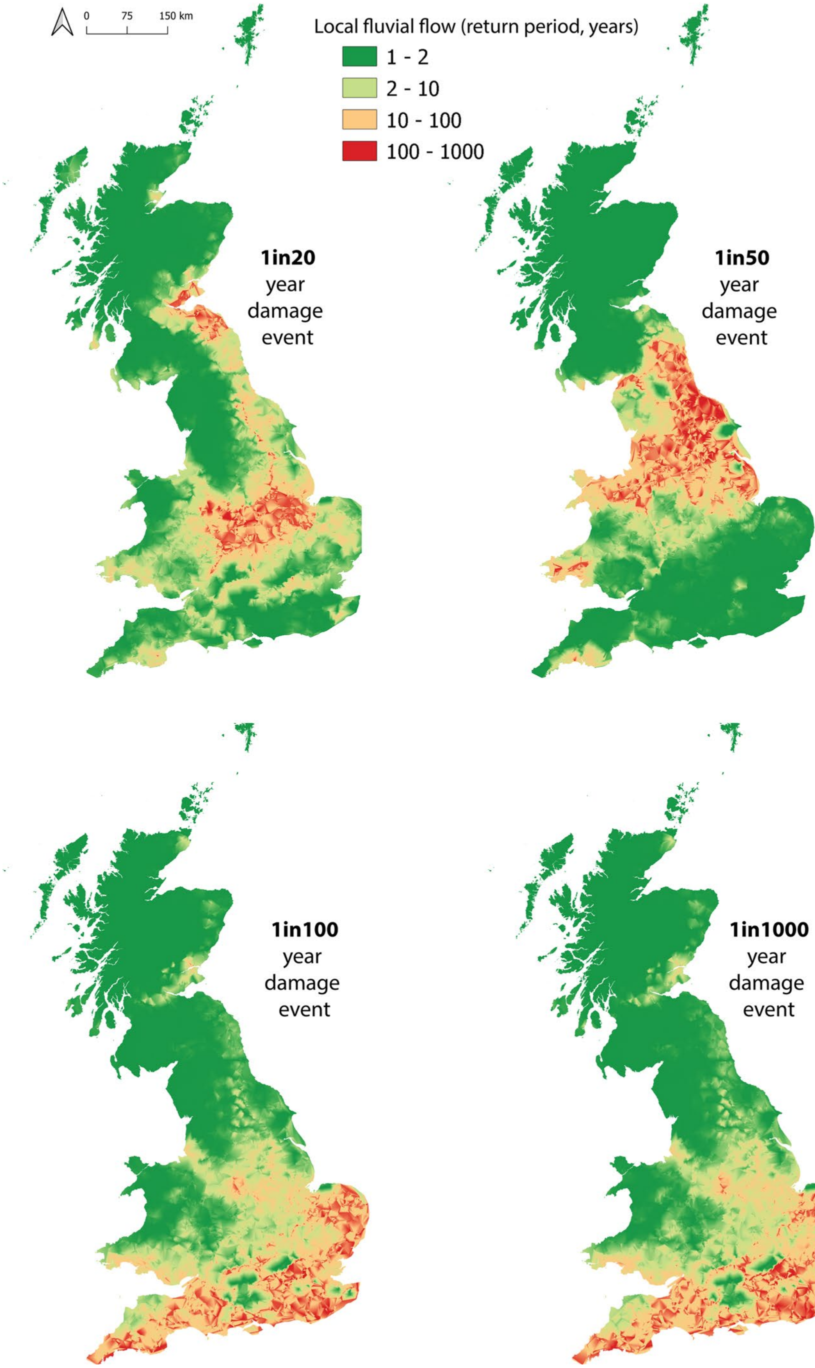

Fig. 8 Example events yielding progressively more extreme fluvial event damages for four return periods for the present-day period. (Top left) 20-year return period, (top right) 50-year, (bottom left) 100-year, (bottom right) 1000-year

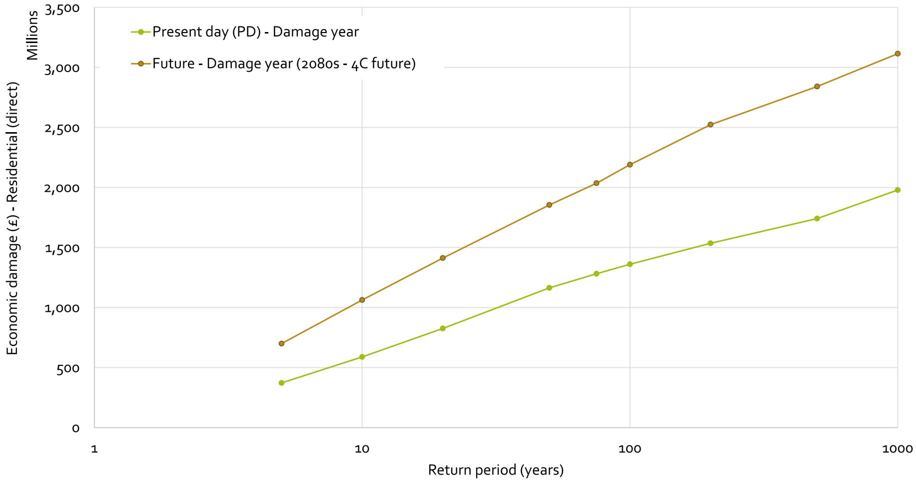

Fig. 9 National fluvial damage year by return period for present and future time slices based on a 4 °C increase, no population growth, and current level of adaptation

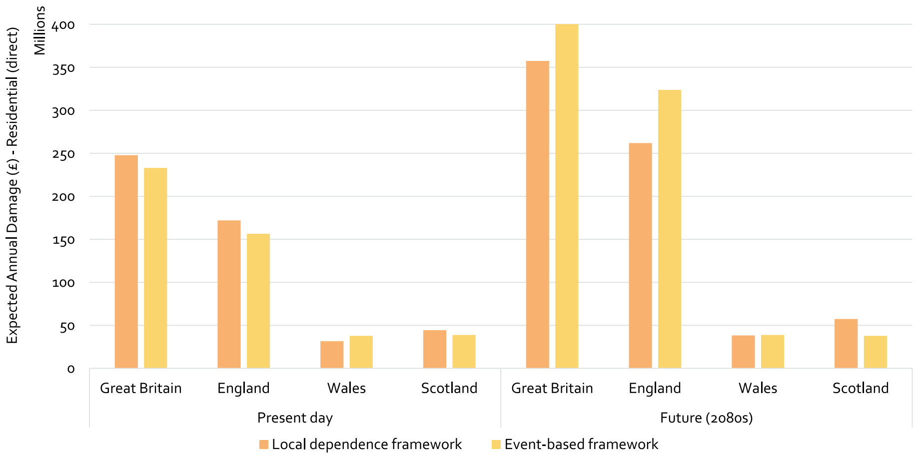

Fig. 10 Comparison of event-based and local-dependence-based estimates of Expected Annual Damages from fluvial flooding for Great Britain, split by epoch and region. Present day refers ~2018. Future refers to the 2080s given a 4 °C rise in GMST, no population growth and a continuation of current levels of adaptation

(determined using a local-dependence framework) is reasonable despite the slight variation at this aggregated scale when compared to the event-based approach.

The difference in the increase in risk is more interesting. The variation in the projected future risk suggests that a local-dependence approach (that fails to reflect the changing spatial structure of widespread events) may understate the increase in risk due to climate change (at least in the context of fluvial flooding as discussed here). For example, the analysis undertaken for the CCRA3 projects a national increase in fluvial flood risk of 44% by the 2080s given a 4°C climate future, no population growth, and a continuation of current levels of adaptation (rising £109m from an EAD of £248m today to £357m by 2080s). Given the same scenario, the event-based analysis here suggests an increase of 60% (rising £167m from an EAD of £233m today to £400m by 2080s). This suggests representing changes in the spatial structure of future events is important; without doing so the impact of climate change on future risk may be underestimated by a factor of ~ 1.5 (rising £167m using the event-based approach compared to £109m using the local-dependence approach).

7.3 Damage season

Figure 11 shows the relative frequencies of different seasonal events across the two time periods and ensemble members. In general, widespread flood events during winter become more common in the future, and summer events less common. There is some variance between ensemble members, but this trend is common across most ensemble members.

The expected *'season damage'* during winter is also projected to increase as reflected in an increase in both frequent and very rare winter seasons (Fig. 12, *top*); with the 1-in-10 year winter *'season damage'* increasing from ~ £0.6b to ~ £1.0b (by 2080s given a 4 °C climate future) and the in 1-in-100 year return period winter 'season damage' increasing from £1.3b to £2.1b. In the summer a more complex story emerges, with the damage associated with more frequently occurring summer seasons increasing (up to the 50-year return period season), but the damage associated with rare summer seasons decreasing with climate change (Fig. 12, *bottom*).

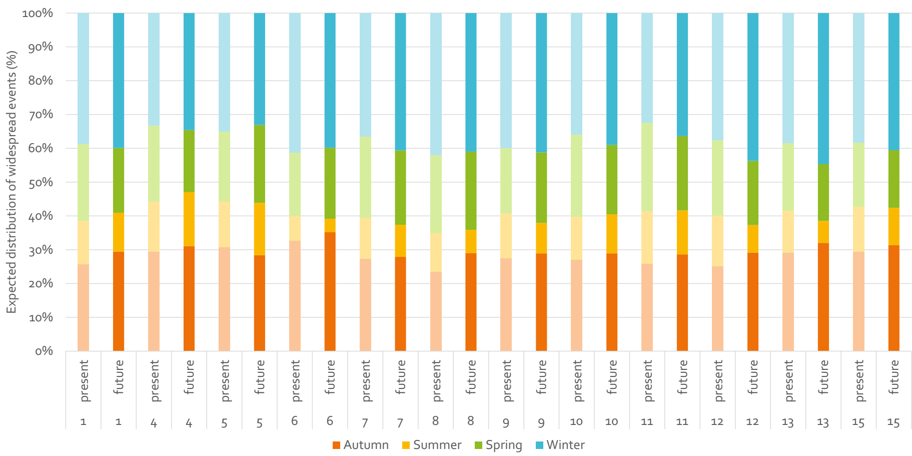

Fig. 11 Probability of seasonal events split by time slice and RCM ensemble member

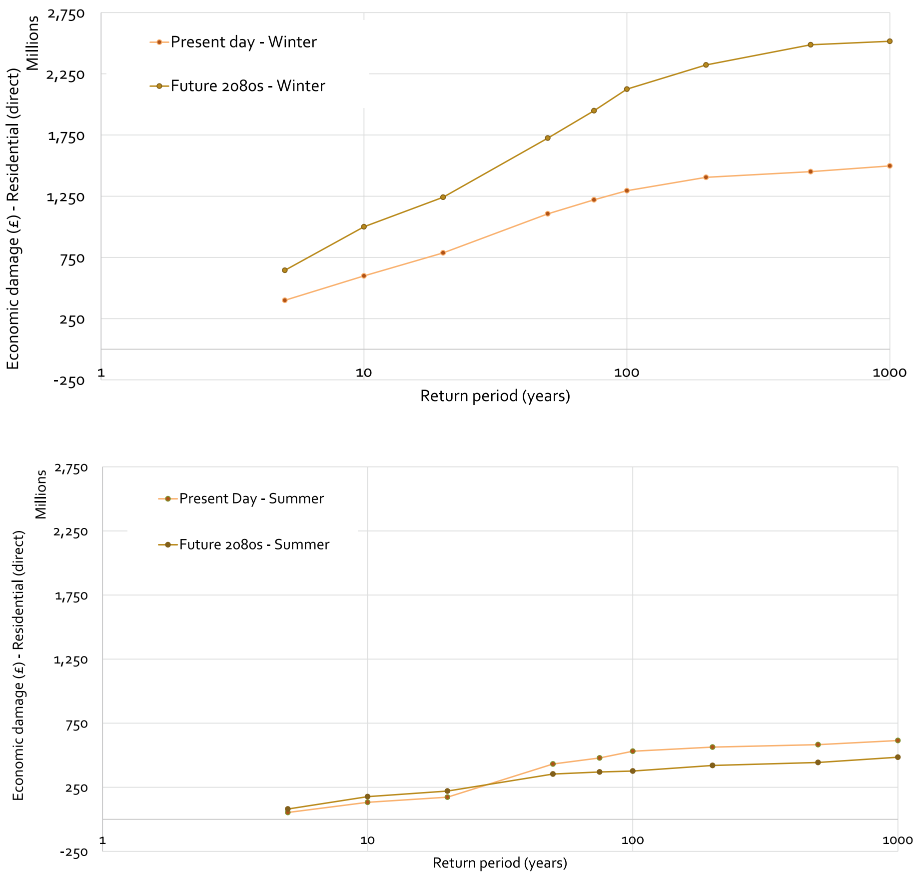

Fig. 12 Present and future *'season damage'* for winter (top) and summer (bottom), based direct residential property damage given a 4 °C climate future, no population growth, and current level of adaptation

7.4 Challenge of convergence

The computation effort needed to achieve convergence of the 'damage year' estimates increase with rarity (return period) of the damage year of interest (Fig. 13). For example, convergence of the 1-in-10 year *'damage year'* occurs within 10,000 event year samples (*i.e.* ~ 200,000 simulated events in the FFE), whereas the 1-in-1000 year *'damage year'* fails to converge even after 100,000 event years (*i.e.* ~ 2,000,000 simulated events). This is intuitively credible, as one would expect ten times fewer 1-in-1000 year 'damage years' to be observed than 1-in-100 year *'damage years'*, so it is expected that convergence would take on the order of ten times longer. The variation in the mean 1-in-1000 year damage year is small after ~ 50,000 event years (*i.e.* 1,000,000 simulated events) and can considered converged at this point from a practical perspective.

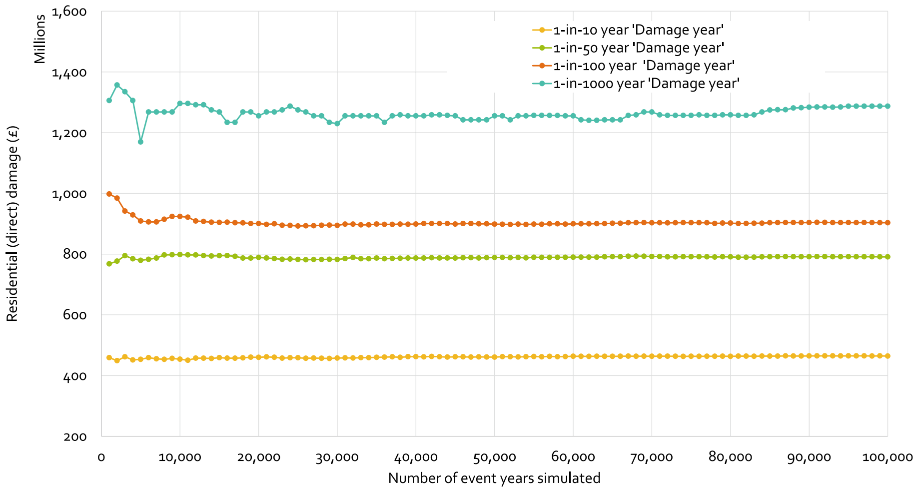

Fig. 13 Convergence of the damage year by return period for Great Britain. Residential direct damages only for Great Britain using present-day event set

8 Discussion and conclusions

The research suggests that the future spatial structure of widespread fluvial flood events may be different from today. Such changes have the potential to materially increase projected increases in risk when compared to local-dependence approaches to climate change risk assessment that rely on local climate uplifts and ignore this influence. The difference could be significant. The analysis suggests that excluding changes in the spatial structure of future events may mean the increase in fluvial flood risk is underestimated by a factor of ~ 1.5 (with the caveat that the analysis here is based a single GCM driving a single RCM and then the twelve ensemble members used to drive one national-scale hydrological model). This is the central finding of the research and reinforces the need to better understand the more subtle influences of climate change in general, and specifically our understanding of the changing structure of *'flood events'*.

Adopting an event-based approach to climate change risk assessment supports a richer insight into the influence of climate change on future risk than is possible using a local-dependence framework. The ability to explore changes in *single event damages*, *seasonal damages*, and *damage years* (including both expected values and changes in the extreme distribution of risk) provides a rich evidence base to support better adaptation choices. Understanding the spatial nature of events is also a prerequisite to understanding how infrastructure networks, emergency response provision, and any other connected may be influenced as impacts cascade, and potentially escalate, through multiple location experiencing flooding *'at the same time'*; an understanding that is central to developing resilience within connected systems. These insights are not possible with a local return period-based analysis.

The transition to an event-based climate risk assessment is a natural evolution of existing approaches that brings together the best of public and private sector methods. Doing so will require highly efficient risk simulation models capable of exploring multiple climate futures (using multiple GCM and RCM outputs) as well as alternative adaptation portfolios and socio-economic change projections. Some models do exist to support this (such as the Future Flood Explorer as used here) but continued development will be needed to address increasingly complex adaptation questions. For example, it is now generally accepted that the notion of a single 'design' storm is not necessarily an appropriate basis for planning (the *'single design storm is dead',* Sayers et al. 2015). Temporally compounding events, driven by storm sequences and clusters, are important over multiple timescales. The insights here in the changing 'season damage' also provide some insight. There is a projected increase in winter damage across all return periods, for example, with the in 1-in-100 year winter *'season damage'* projected to increase from £1.3b to £2.1b. In the summer a more complex story emerges, with the damage associated with more frequently occurring summer seasons increasing (up to the 50-year return period season), but the damage associated with rare summer seasons decreasing with climate change. Fully capturing the temporally compounding influence of a series of events, however, will require the temporal sequencing of present and future events (and their influence on risk) to be much better understood.

The analysis presented is an initial analysis. Multiple further strands of research remain to be explored. The inclusion of multiple sources of flooding (allowing the coherent consideration of coastal and pluvial alongside fluvial flooding), the extension to temporal sequences on defence performance and risk, and the influence of alternative GCMs RCMs, and hydrological models on the findings are all obvious development areas. The event-based analysis has clear links to assessment of connected infrastructure as well as climate stress tests within the financial sector where coherent (in time and space) risks are important considerations. Exploring alternative adaptations within an event-based risk assessment framework offers multiple opportunities to identify adaptation pathways that manage the risk profile across different spatial scales. It also enables intra-year variations within the system to be considered, for example, to reflect summer and winter property occupancy or variations in the influence of a flood on agricultural damages depending on the season.

Debate continues around the accuracy of any flood risk assessment and validating any probabilistic risk assessment remains challenging. Although not the focus here it is recognized that assessments based on events provides a useful foundation for a more meaningful comparison between observed and models outcomes. Continuing to compare modelled assessments and real events will be important in prioritizing future research in a meaningful way.

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Author contributions PS developed the concept of the research and drafted the paper. SC developed the implementation within the Future Flood Explorer, the maps, and reviewed the draft manuscript. AG developed the spatial hazard event set and edited the draft manuscript. AK provided the hydrological modelling to identify hazard events within the climate models. Lisa Stewart managed the UKCEH inputs and edited draft manuscript. JL and DB supported the development of the concepts and climate inputs. All authors provided edits and review comments on the paper.

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Data availability The Grid-to-Grid event sets for this study can be found in the Environmental Informatics Data Centre (Griffinet al. 2002c). The projects of flood risk associated with the UK CCRA3 can be found on Climate Change Committee webpages.

Declarations

Conflict of interest The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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