Flood event attribution and damage estimation using national-scale grid-based modelling: Winter 2013/14 in Great Britain

Short title: Winter 2013/14 flood attribution and damage estimation

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Abstract

A sequence of major flood events in Britain over the last two decades has prompted questions about the influence of anthropogenic greenhouse gas emissions on flood risk. Such questions are difficult to answer definitively, as a range of other factors are involved, but modelling techniques allow an assessment of how much the chance of occurrence of an event could have been altered by emissions. Here, the floods of Winter 2013/14 in Great Britain are assessed by combining ensembles of climate model data with a national-scale hydrological model and, for one severely-impacted river basin (the Thames), a detailed analysis of flood inundation and the increased number of residential properties placed at risk. One climate model ensemble represents the range of possible weather under the current climate, while 11 alternative ensembles represent the weather as it could have been had past emissions not occurred. The pooled ensemble results show that emissions are likely to have increased the chance of occurrence of these floods across much of the country, with a stronger influence on longer duration peaks (~10 days or more) than for shorter durations (consistent with observations). However, there is substantial variation in results between alternative ensembles, with some suggesting likely decreases in the chance of flood occurrence, at least in some regions of the country. The influence on flows and property flooding varies spatially, due to both spatial variation in the influence on precipitation and variation in physical properties that affect the transformation of precipitation to river flow and flood impacts, including flood defences. This complexity highlights the importance of using hydrological modelling to attribute hydrological impacts from meteorological changes. Changes in snow occurrence in a warming climate are also shown to be important, with effects varying spatially.

Keywords

Flooding, climate change, inundation, property damage

1 Introduction

It is now widely accepted that climate change will have significant impacts on the hydrological cycle, globally and regionally, and there are increasing signs of hydrological changes having already occurred, rather than just being a concern for the future (Jiménez Cisneros et al. 2014, Blöschl et al. 2017). Detection and attribution of observed hydrological changes to anthropogenic emissions is difficult however, due to the influence of a range of other factors (both anthropogenic and natural) and because available records are often relatively short (Hannaford 2015), making statistical tests prone to uncertainty.

In the UK, there is evidence of observed changes in precipitation, evaporation and river flows, although with varying levels of confidence and little evidence to link them to anthropogenic climate change (Watts et al. 2015). Although there has been little change in annual mean precipitation for England and Wales (since records began in 1766), there have been winter increases and summer decreases, and more recent changes in heavy rainfall (Jenkins et al. 2008). There have also been increases in evaporation (Kay et al. 2013) and decreases in snow (Kay 2016). Each of these is likely to have affected river flows; analyses suggest increases in annual and winter runoff across much of the UK but decreases in summer runoff for England (1961-2011), along with increases in high flow magnitude and duration to the north and west of the UK, although the latter are not always coincident with increases in peak flows like annual maxima (Hannaford 2015).

Floods are one of the most damaging natural hazards, threatening lives and livelihoods worldwide. Floods present a serious natural hazard in the UK, with over 5 million properties considered at risk of flooding from one or more sources (rivers, surface water, coastal) (Thorne 2014). A sequence of major floods has occurred in the UK over the last two decades (Hannaford 2015); Easter 1998 (the Midlands), Autumn 2000 (much of England and Wales), Summer 2007 (central and northern England), November 2009 (north-west Britain), Summer/Autumn 2012 (much of Britain) and, more recently, Winter 2013/14 (southern England; Huntingford et al. 2014) and December 2015 (northern Britain; Barker et al. 2016). This has prompted questions about whether such floods are ‘caused’ by climate change.

While no single weather or flood event can be directly attributed to anthropogenic emissions of greenhouse gases, it is possible to assess how the chance of occurrence has been altered by emissions, via probabilistic event attribution (PEA; Allen 2003). This involves the generation of large ensembles of climate models runs, representing the climate both as it is now and as it could have been had no past anthropogenic emissions occurred. Data from the climate model runs can be analysed directly to investigate weather events (e.g. Northern England/Southern Scotland wet December 2015, Otto et al. 2018; UK cold winter 2010/11, Christidis and Stott 2012), but to investigate a flood event the climate ensembles are used to drive a hydrological model to simulate runoff or river flow. Application of PEA to the Autumn 2000 floods suggested that emissions had increased the chance of occurrence, although with large uncertainty in the amount of increase and variation in the effect on different catchments (Pall et al. 2011, Kay et al. 2011).

In the winter of 2013/14 a series of severe storms led to widespread and persistent flooding across southern England, particularly the Somerset Levels and the lower reaches of the River Thames (CEH 2014). Using PEA, Schaller et al. (2016) showed that anthropogenic emissions gave an increase in January 2014 precipitation over southern England of up to 0.5mm/day in the wettest 1% of the ensemble simulations. This was shown to be due to both large-scale warming (the ability of warmer air to hold more moisture) and local dynamical changes (an increase in the number of January days with a westerly airflow), in the ratio of approximately 2/3 to 1/3; a result confirmed by Vautard et al. (2016) using a different method. Catchment-based hydrological modelling then showed that the rainfall changes led to an increase in 30-day mean flows in the River Thames at Kingston (its most downstream flow gauge), although changes in daily mean flows were much less. Flood risk mapping then showed a small increase in the number of properties at risk of fluvial flooding in the Thames catchment. There was a substantial range of numerical uncertainty in these analyses, reflecting weather variability and climate model uncertainty. Further epistemic uncertainty, relating to approximations made in the analysis of flood impacts, was acknowledged but not quantified.

The catchment-based PEA study of Kay et al. (2011) showed that it is important to account for variation in catchment response, due to spatial variation in physical catchment properties. Spatial variation in rainfall can also be important, as shown by a PEA analysis of the rainfall that led to flooding in December 2015 (Otto et al. 2018, van Oldenborgh et al. 2015). Schaller et al. (2016) acknowledge that impacts on Winter 2103/14 flows and damages for other rivers than the Thames are likely to differ because of variation in catchment properties and spatial rainfall patterns.

The work presented here uses a national-scale grid-based hydrological model to investigate spatial aspects of the Winter 2013/14 floods, based on the same climate ensembles used by Schaller et al. (2016). The first part of the paper investigates river flows across the whole of Great Britain (GB) using the grid-based hydrological model, looking at the role of snow and providing a first national scale hydrological PEA analysis for the nationally-significant Winter 2013/14 events. The second part re-investigates the Thames basin, looking at both river flows and damage estimates and comparing results to those from the catchment-based modelling of Schaller et al. (2016). The latter PEA study was the first to express attributable risk in terms of the eventual impacts of flooding, represented by the number of properties affected. To make that analysis possible using the available hydrological model simulations, which were for one location on the Thames (Kingston), it was assumed that the impacts throughout the 9,948 km^2 upstream catchment could be determined from the peak flow at Kingston. Although this approximation was lent some support through consideration of the strong spatial and temporal dependence within flood events on the Thames, it is generally more realistic to assess flood impacts using a spatially-distributed analysis of peak flows, inundation and the built environment. Spatially-distributed flood impacts modelling has therefore been applied here for the first time in a PEA study; an important advance that brings the analysis into line with the high level of detail considered in models applied for re/insurance and infrastructure planning. A further advance is that the new analysis accounts for the influence of flood defences.

2 Background and Methodology

2.1 Winter 2013/14 flooding in GB

The meteorological review of Kendon and McCarthy (2015) describes a sequence of storms affecting the UK between mid-December 2013 and mid-February 2014, with a brief period of less stormy but still unsettled weather in mid-January. The storms resulted in the wettest winter (December–February) in Britain since records began, whether measured regionally using gridded precipitation from 1910, or using the average England and Wales precipitation series from 1766. Within this, the gridded precipitation shows that January 2014 was the wettest January in England since records began, and even the wettest calendar month in south-east and central-southern England since records began.

The hydrological review of Muchan et al. (2015), based on data from 104 river flow gauging stations across the UK (index rivers) covered by the National Hydrological Monitoring Program (nrfa.ceh.ac.uk/nhmp), describes how flows were generally declining and below the seasonal average in early December 2013 but increased quickly in some responsive catchments as the storms began in mid-December. Floodplain inundations became more widespread from the end of December, and flows in many rivers in southern, central and eastern England increased substantially in January. Further storms in early February led to further increases in flows, with 500 flood warnings/alerts issued in England and Wales. Over the winter, a majority of index rivers saw total flows exceeding previous winter records, but with few record peak flows; overall, the winter was more exceptional for the duration of the high flows and inundations.

This is confirmed by a wider analysis of gauged flow data from the National River Flow Archive (nrfa.ceh.ac.uk), looking at the rankings of the maximum observed flows for Winter 2013/14 for gauges with at least 40 years of relatively complete data up to 2014 (Figure 1). This shows that, while some catchments did experience record or near-record peaks in daily mean flow during Winter 2013/14, many more catchments experienced record flows at longer durations. Figure 1 also highlights the areas most affected by flooding in Winter 2013/14, which reflect those areas experiencing the highest rainfall totals over the period (Kendon and McCarthy 2015). The Somerset Levels were particularly badly affected, with about 65km^2 flooded and a number of villages cut off for a long period (Muchan et al. 2015, Willis and Fitton 2016). There was also extensive and sustained flooding in the middle and lower Thames (Muchan et al. 2015, Huntingford et al. 2014). According to the Association of British Insurers, between 23 December 2013 and 28 February 2014 there were 18,700 flood insurance claims totalling £451m, about half of which was for homes (ABI 2014). According to Thorne (2014), “the number of properties inundated was surprisingly small given the number and severity of the storms… [but] the societal impacts… were disproportionately large”.

2.2 Hydrological model

The national-scale grid-based hydrological model CLASSIC-GB was developed by combining the runoff-production scheme from the semi-distributed catchment-based model CLASSIC (Climate and LAnd-use Scenario Simulation In Catchments; Crooks and Naden 2007) in a modular framework with a kinematic wave routing module and other modules like a temperature-based snow module (Crooks et al. 2014). CLASSIC was used in the flood attribution studies of Schaller et al. (2016) and Kay et al. (2011), and has been used to investigate historical changes in flow in the River Thames (Crooks and Kay 2015) and the impacts of climate change on floods in catchments across GB (Prudhomme et al. 2013a,b, Kay and Crooks 2014).

CLASSIC-GB requires gridded input time-series of precipitation and potential evaporation (PE), plus temperature (if the snow module is implemented), and can run at spatial resolutions of 1km, 2.5km, 5km or 10km, aligned with the GB National Grid. The routing time-step must be sufficiently short (relative to the spatial resolution) for stability of the routing scheme, but the main model time-step can be a multiple of the routing time-step. Here, CLASSIC-GB uses a 5km spatial resolution, 1-day main time-step and 2-hour routing time-step. Runs at coarser spatial and temporal resolutions are much faster, enabling use of large driving data ensembles (Section 2.3).

Crooks et al. (2014) tested CLASSIC-GB performance for 54 catchments (representing a range of catchment types), using three measures of fit between simulated and observed river flows. Analyses showed generally very good performance across the full range of catchments. While performance was often better at finer resolutions, improvements when moving from 5km to 1km resolution were generally small, so using the 5km resolution is a good compromise between model performance and speed. Kay et al. (2015) also analysed CLASSIC-GB performance (1km resolution), for 32 catchments across southern GB, using four measures of fit between flow statistics. Analyses showed generally good performance, with that for high flows and flood frequency showing no evidence of bias with respect to catchment properties (area, average annual rainfall, altitude or baseflow index) but a tendency towards under-estimation in catchments in south-west England. This tendency should be borne in mind, but is not considered crucial for flood attribution analysis, which considers differences rather than absolute values. Such biases may be more important for flood damage analyses, due to application of thresholds, but they do not affect the Thames basin damage analysis presented here.

2.3 Winter 2013/14 climate ensemble data

Ensembles of climate data for December 2013 – February 2014 were produced using the weather@home project (Massey et al. 2015), by running the HadRM3P Regional Climate Model (RCM) for Europe (~50km resolution) nested in the HadAM3P atmospheric Global Climate Model (GCM) driven with prescribed sea surface temperatures (SSTs) and sea ice concentration (SIC). Initial conditions are perturbed slightly for each ensemble member, to give a different realisation of the winter weather and so account for natural variability. One ensemble represents the possible weather under the current climate, using observed greenhouse gas concentrations, SSTs and

SIC for 2013/14 (“Actual”, named by the letter ‘a’). A further 11 ensembles represent the possible weather had past anthropogenic emissions not occurred (“Natural”, named ‘e’ to ‘o’). These use pre-industrial atmospheric composition, the maximum well-observed SIC, and estimates of pre-industrial SSTs constructed by subtracting anthropogenic SST change patterns from observed SSTs. Eleven different patterns of SST change were applied based on GCM simulations from 11 CMIP5 models, thus producing 11 Natural ensembles sampling the uncertainty in regional patterns of SST change. Table 1 summarises the ensembles; see Schaller et al. (2016) for further details. An evaluation of the climate model showed that, on average, the “Actual” ensemble realistically represented the strong zonal large-scale circulation seen during Winter 2013/14, and can therefore be used in the context of probabilistic event attribution (Schaller et al. 2016).

The RCM runs provide the daily precipitation and temperature data required to drive CLASSIC-GB, but do not provide PE, which has instead been estimated from monthly mean temperature using the method of Oudin et al. (2005). Precipitation and PE are then converted from the rotated latitude-longitude RCM grid to the 5km CLASSIC-GB grid using area-weighting, with extra weighting based on standard average annual rainfall patterns for precipitation (Kay et al. 2006). Temperature data are lapsed to the CLASSIC-GB grid using altitude information.

CLASSIC-GB is then run with driving data from each ensemble member. To allow spin-up of stores, runs are started in January 2010 using observed driving data; 1km daily precipitation from CEH-GEAR (Tanguy et al. 2015, Keller et al. 2015), 5km Met Office daily minimum and maximum temperature (Jenkins et al. 2008), and 40km monthly PE from MORECS (Hough and Jones 1997). Observed data are used up to 10 December 2013, followed by RCM data from 11 December 2013; the first 10 days of the RCM simulations are not used, to allow the atmosphere to spin up (precipitation in the first few days of the Natural simulations is unrealistically high, but has stabilised after 10 days – see Schaller et al (2016) for further detail). CLASSIC-GB was run both with and without the snow module, to investigate the effects of snow. Note that the spin-up with observed driving data does not allow for any anthropogenic effect on antecedent conditions (see discussion in Section 4).

2.4 Data analysis and damage estimation

From each CLASSIC-GB run, the gridded daily mean flows for 11 December 2013 to end February 2014 are extracted. To analyse flow peaks at a range of durations, the daily time-series for each grid cell are turned into running mean flows for a range of durations (10, 30 and 60 days) and the maximum flow extracted in each case. While it is the shorter duration flow peaks that are important for determining inundated areas, longer duration flow peaks have implications for economic damages (beyond simple counts of properties inundated) as well as for civil emergency response and recovery operations.

The flow maxima are then used to estimate the Fraction of Attributable Risk, FAR=$1-NE/AE$, where AE is the fraction of Actual runs with peak flows exceeding a given threshold, and NE is the fraction of Natural runs with peak flows exceeding the threshold (Allen 2003). A positive FAR indicates that past emissions have increased the chance of peak river flows exceeding the chosen threshold (with a value of 1 suggesting that exceedances may not have occurred without anthropogenic emissions), whereas a negative FAR indicates that emissions have decreased the chance of peak river flows exceeding the threshold. FAR is calculated for each Natural ensemble 'e' to 'o' separately, and for a pooled Natural ensemble ('e-o', giving all members of each separate Natural ensemble equal weight), relative to the threshold given by the 100-year return period flow as simulated by the Actual ensemble. Similarly, FAR is calculated for rainfall accumulations over a range of durations. Regional summaries use the eight areas shown in Figure 3b, which are groupings of river basins based on the Water Framework Directive River Basin Districts.

To estimate property damage within the catchment of the Thames at Kingston (an area of nearly 10,000km^2), peak river flow data simulated using CLASSIC-GB were fed into a model combining flood inundation extents, depths and property locations. This model is a subset of the JBA Risk Management UK Flood Probabilistic Model (JBA Risk Management 2015), which is one of several models used by the insurance industry, and has been adopted by the state-mandated reinsurance scheme Flood Re (Insurance Journal 2015) to provide estimates of damage and financial loss for flood events. It is (in common with comparable products) a proprietary model, however the foundations of the approach are detailed (5m x 5m cell resolution) inundation mapping based on 2D hydrodynamic modelling, using peer-reviewed methodologies that were summarised by Schaller et al. (2016).

For each ensemble member simulated using CLASSIC-GB, the peak flow values are interpolated spatially to a set of points placed on the river network. Each peak flow value needs to be represented as an inundation extent and depth in every postcode unit within the Thames catchment. To do this without needing to hydraulically model floodplain inundation for each ensemble member (which would be computationally very expensive) a set of five pre-modelled design floods representing annual exceedance probabilities from 1/20 to 1/1000 are used. The peak flows are converted to return periods, spatially interpolated to the postcode units and then extents and depths at each postcode unit are interpolated from the pre-modelled design floods. This approach is analogous to the development of a river flood 'catastrophe model' applied for estimation of risk across an insured portfolio (see Toothill and Lamb 2017, Figure 3.15, for a summary).

To estimate the number of properties affected in each postcode unit, the Thames subset model includes an input property dataset; developed using population data from the UK census (ONS 2011) combined with property location data purchased from a commercial provider (Rightmove) containing 3.4 million residential properties. Each property is attributed with a postcode unit but the exact footprint of an individual building is not known. This is recognised to be an important source of uncertainty in flood risk assessments (e.g. when comparing flood model predictions with insurance claims data) because even relatively small scale positional uncertainties can affect the number of properties calculated as being within a flooded area, especially at the margins of flooding in densely populated locations. To overcome this, for each individual property and for every ensemble member, many samples are drawn from the range of water depths within that postcode unit. This also accounts for the proportion of the postcode that is predicted to be dry. A property is counted as being flooded if the mean of the sampled depths is greater than 20cm. Flood defence information is included; properties in areas benefiting from flood defences are only assumed to flood if the peak river flow exceeds the standard of protection of the associated flood defence.

3 Results

3.1 National

Maps show that flow FAR values calculated from the pooled Natural ensemble ('e-o') vary considerably across GB, particularly for shorter duration peak flows (Figure 2). For daily peak flows, parts of south-east England show negative FAR while much of western England, Wales and Scotland show positive FAR. For 10-day peak flows, FAR values for parts of north-east England are strongly negative (FAR < -0.5), whereas FAR values are positive for much of the rest of the country (apart from small parts of south-east England, Wales and south-west Scotland for example). For 30-day peak flows, FAR in north-east England is less strongly negative and there are even fewer negative FAR values elsewhere. For 60-day peak flows, FAR in parts of north-east England is still slightly negative but FAR is positive almost everywhere else (apart from a few pixels to the far eastern side of Scotland). In general, FARs are higher for longer durations than for shorter durations.

Boxplots summarising the FAR values calculated from the pooled Natural ensemble ('e-o') highlight the variation in values between different regions of the country (Figure 3). They also illustrate that there is little variation in FAR within some regions (especially in southern England), but a much wider range of FAR in other regions (especially Scotland and northern England).

For parts of eastern Scotland, FAR is strongly positive (>0.5) for all durations (Figure 2 and Figure 3). This is related to changes in flow patterns associated with changes in snowfall and snowmelt in this Highland region; when modelled without the snow module these positive FAR are significantly reduced, becoming negative for longer durations (Figure 3 and Figure 4). A study of future potential changes in peak flows under climate change also highlighted this region of GB as one where changes in snow were likely to have a significant effect on the expected changes in flows (Bell et al. 2016). Although the influence of snow is largest in eastern Scotland and at longer durations, it also has an effect in more southerly regions (e.g. Anglian, SE England and W England) at shorter durations (1- and 10-day), where FAR is typically lower when modelled with snow than without. This was previously shown for the Thames at Kingston for the Winter 2013/14 floods (Schaller et al. 2016) and for eight catchments in England for the Autumn 2000 floods (Kay et al. 2011), and suggests that snow changes are moderating the increases in shorter duration peak flows. The differing effect of snow on flow FARs in E Scotland compared to the rest of the country is likely to be because this is one of the few areas of GB that experiences significant accumulations of snow in the current climate; snow in most areas of GB under the current climate is much more irregular and transient, but would have been more common everywhere in the past (Kay 2016).

Boxplots summarising the FAR values calculated from each Natural ensemble ‘e’ to ‘o’ separately (Figure 5) highlight the large variation between them. The same natural ensemble (‘m’) leads to the highest median FAR value across most regions for all durations, the exceptions being regions in the south and west, where ensemble ‘f’ gives higher FAR at the 10-day duration and ensemble ‘g’ gives marginally higher FAR at the 60-day duration. The natural ensemble with the lowest median FAR value varies more between regions. Ensemble ‘n’ generally gives the lowest FAR in regions towards the south and east (SE England, Anglian and NE England), and ensemble ‘l’ generally gives the lowest FAR in north-western regions (NW England and most of Scotland). In south-western regions (SW England, W England and E Wales) ensembles ‘h’, ‘j’ and ‘l’ all give similarly low FAR values for durations of 1, 10 and 30 days, but ensemble ‘j’ gives the lowest FAR for the 60-day duration.

Comparing the estimated FAR values across GB (Figure 2) with the rankings of observed Winter 2013/14 flows (Figure 1) shows some similarities, in that the FAR values are generally greater for longer durations and the observed flows were more record-breaking at longer durations. However, there appears to be little spatial consistency, especially for daily mean flows: Some areas with positive FARs experienced few record flows (e.g. the far south-west of England, Wales and Scotland) while some areas with negative FARs experienced a number of record flows (e.g. south-east England). While Schaller et al. (2016) showed that the RCM driven by observed boundary conditions was able to represent the large-scale situation of the event reasonably well, these results indicate that the average RCM response in terms of precipitation was different compared to what happened in reality. This is unsurprising as there is only one ‘realisation’ from the weather in the real world, but a distribution of realisations in the model ensembles.

Maps of precipitation FAR (Figure 6) are relatively consistent with those for flow FAR (Figure 2 and Figure 4), in that precipitation FAR values are also generally greater for longer durations, and there is a good amount of spatial consistency. However, for most river points, precipitation FARs are higher than flow FARs for the same duration (Figure 7), reflecting the complexity of the transformation of precipitation into river flows. Similarly, the generally lower correlation between flow and precipitation FARs at the 1-day duration reflects the fact that different catchments, with different physical properties (e.g. area, orientation, geology), respond in different ways to the same climatic inputs, so a high increase in 1-day rainfall in a small ‘flashy’ responsive catchment can cause a high increase in daily peak flow, but to get the same increase in daily peak flow in a more slowly responding catchment would require a more sustained increase in rainfall, typically over a number of days. In particular, the presence of groundwater and its influence in attenuating catchment responses to precipitation is likely to be important in parts of southern and eastern England. [Note that this analysis is not intended to suggest that n-day precipitation peaks lead directly to n-day flow peaks, but is merely assessing the correlation between precipitation FARs and flow FARs for the same set of durations. Also, the analysis for 60-day peaks is more likely to be affected by events being cut off at the end of the 80-day analysis period, which could have the effect of artificially reducing correlations.]

In north-western and eastern Scotland, correlations between precipitation and flow FARs are generally lower than for other regions, even for higher durations, and flow FARs can be much higher than precipitation FARs in some cases, especially at longer durations (Figure 7). This is again because of the influence of extended periods of snow accumulation and melt changing the nature and timing of flow peaks in these more northerly, typically higher altitude, colder regions; correlations are much higher when flows are simulated without the snow module (not shown).

3.2 Thames at Kingston

The maps in Figure 8 show the spatial variation in FAR calculated for peak daily flows across the catchment of the Thames at Kingston, and the variation between the 11 natural ensembles. Table 2 summarises the FAR values for the catchment, in terms of the value at the outlet point and the minimum and maximum values across the whole catchment, for the pooled natural ensemble ('e-o') and for each natural ensemble ('e' to 'o') separately. Table 2 also shows the FAR values for the outlet point estimated from the catchment-based modelling of Schaller et al. (2016). For some natural ensembles the outlet FAR from the gridded modelling is higher than that from the catchment-based modelling, but for other ensembles the opposite is true. This includes the pooled natural ensemble ('e-o'), for which the outlet FAR value is 0.004 from the gridded modelling but 0.032 from the catchment-based modelling. However, both values sit well within the range of uncertainty calculated for the catchment-based modelling (-0.117 to 0.146), so these differences do not appear to be significant.

The gridded modelling shows that flow FAR values vary at a much finer scale than that of the precipitation inputs, for which only ~4 boxes cover the Thames catchment. Also, FAR values upstream in the Thames can be much higher than at the outlet (Figure 8 and Table 2). For the pooled natural ensemble ('e-o') FAR goes up to 0.186, although some tributaries closer to the outlet at Kingston have negative FAR values (down to -0.142). This suggests that damages estimated using gridded modelling should be more reliable than assuming that what happens at the outlet point is representative of the whole catchment (as done by Schaller et al. 2016).

Figure 9 maps the FAR calculated for counts of flooded residential properties aggregated into the 395 postcode districts within the catchment, each of which contains between 2 and 38,733 properties (average 8,774). The results are consistent with the analysis of peak flows: For the pooled ensemble, FAR for flooded properties is greater than zero across much of the catchment, but there are some districts with values below zero. As with the peak flows (Figure 8), the spatial patterns of FAR for flooded properties exhibit considerable variation between ensembles, with some ensembles containing districts for which the FAR indicates considerably stronger influence of past emissions on flood risk, either in terms of an increase or a decrease in likelihood of flooding.

Whilst the FAR results indicate, overall, a slightly increased likelihood of flooding connected with past greenhouse gas emissions, Figure 10 shows the magnitude and uncertainty of this increase in attributable risk, expressed in terms of the difference between the number of properties flooded in the Actual ensemble and each Natural ensemble, and plotted as a function of increasing levels of extremeness within the ensembles (interpreted as a return period in years). A comparable result was presented by Schaller et al. (2016; Figure 5f), based on the simplifying assumption of spatial uniformity, and their headline estimate of 1,000 additional properties at risk is also shown in Figure 10. The new results show a likely increase, attributable to past emissions, in the number of properties at risk of flooding over a wide range of event magnitudes ranging from 20- to 500-year return periods (where the return period estimates are based on the rank position of the simulations within the ensemble). This result is broadly consistent with the earlier analysis of Schaller et al. (2016), but with some important refinements stemming from the new, distributed impacts analysis. Firstly, the amount of increase in attributable risk is smaller than the previous findings, but also within a narrower range of uncertainty. The mean of the pooled ensemble increase (calculated over the range of return periods in Figure 10) is +457 properties, with the individual ensembles ranging between -1,334 (ensemble 'n') and +4,605 (ensemble 'o'). This can be compared with Schaller et al. (2016) estimates of approximately -4,000 to +8,000.

Secondly, whilst there is some variation in the number of properties at additional risk over the range of return periods, both here and in Schaller et al. (2016), the new analysis shows a coherent reduction in the amount of attributable risk (for the pooled ensemble) for return periods between approximately 50 and 300 years, with almost no change attributable to past emissions for return periods between 100 and 300 years. This reduction is observed in most, though not all, of the individual ensembles. It reflects the expected influence of flood defences in the impacts analysis: an increase in river flows will not translate to more properties being flooded if those flows are still contained by flood defence systems. Only a small proportion of properties in the catchment benefit from significant flood defences (see Schaller et al. 2016 Supplementary Information), and hence flood defences have no influence on attributable risk in many parts of the catchment. However, where defences do exist their marginal influence could be significant. This effect is expected to be felt for events that are similar in severity, or somewhat less severe, than the standard of protection of the defence systems, which are typically designed to resist flood flows no worse than a 200-year return period in the Thames catchment (Environment Agency, 2009). For events that are sufficiently extreme to exceed flood defence standards, the marginal influence of those defences (i.e. for an incremental increase in river flow) should diminish. Although the return period scale in Figure 10 is not defined in precisely the same way as the standard of protection of flood defences (owing to the conditional nature of return periods calculated within the simulated ensemble), the pattern in Figure 10 is consistent with the expected influence of flood defences as discussed above.

4 Discussion and Conclusions

The seemingly high incidence of floods in GB in recent years has prompted increasing questions about the role of climate change. Thus methods like probabilistic event attribution, that can assess the influence of anthropogenic emissions on event occurrence, are becomingly increasingly important. Here, large ensembles of climate model runs, representing both Actual and Natural conditions, have been used to drive a national-scale hydrological model, to assess the influence of emissions on the Winter 2013/14 floods. The results show that emissions are likely to have increased the chance of occurrence of these floods across much of the country (FAR > 0; Figure 2), with the influence on longer duration peaks being greater than that for shorter durations. This is consistent with an analysis of observed flows for the period (Figure 1), which shows that they were more unusual (relative to flows over the preceding 40+ years) at longer durations.

Analyses of flow FAR produced with and without the snow module (Figure 3) show that changes in snow processes are affecting flows differently in different parts of the country. In more northerly regions snow changes are increasing FAR, especially at longer durations, but in more southerly regions and for shorter durations they are decreasing FAR. This highlights the importance of using hydrological modelling, as analyses of precipitation totals do not allow for changes in snowfall and snowmelt, or for the complex effects they can have on flows when modulated by physical catchment properties like topographic distribution (Kay and Crooks 2014). For example, snow melt can occur slowly, with differing timing of melt at different altitudes within a catchment, leading to much reduced peaks, or rapid snow melt, often combined with rainfall, can increase peaks. A review of snow in Britain highlights the complexity of its effects on river flows (Kay 2016).

While flow FAR and precipitation FAR patterns are relatively consistent (especially when the hydrological model is run without the snow module), the precipitation FAR are often higher than the flow FAR, and the correlation between the two varies by region and by duration (Figure 7). This again highlights the importance of using hydrological modelling to attribute hydrological impacts from meteorological changes, to incorporate the complexities of the transformation of precipitation into runoff and river flow. There is variation in the response of different rivers not just because of spatial variation in rainfall patterns but because of variation in physical properties that influence runoff production. Antecedent conditions can also be more influential for some types of catchment (e.g. those with more high permeability bedrock, Kay et al. 2011). Any anthropogenic effect on antecedent conditions is not accounted for here, but is likely to be less influential (i.e. less variable) for winter events than for summer or autumn events for example. Ideally though, the climate ensembles would cover a period prior to the event of interest, in order to include any effects on antecedent conditions.

Similar variation is also visible when the change in risk attributable to past greenhouse gas emissions is translated from the hydro-meteorological domain into impacts of flooding on properties (Figure 9). This variation in patterns of attributable risk can only be explored by using a distributed modelling approach, linking spatially-varying hydrological simulations to detailed, spatially explicit inundation and impacts analysis. Here, such an approach has been demonstrated for the Thames catchment, applying state-of-the-art industry models for flood inundation and impacts analysis, which also include flood defences. Over a range of possible events of increasing severity, the combined modelling suggests a central estimate of +457 properties placed at additional risk because of historical greenhouse gas emissions, within an uncertainty range of -1,334 to +4,605. This number refines earlier estimates of ~1,000 additional properties at risk (range -4,000 to +8,000), with a consistent interpretation that the balance of probabilities indicates an increase in risk attributable to climate change. The attributable change in risk of property flooding varies with the relative severity of events within the ensemble simulation. This variation appears to be in line with the expected influence of flood defences. Flood defences may be able to “absorb” some of the additional risk attributed to climate change, but cannot be relied upon to mitigate the additional risk in its entirety for extreme events, which are nevertheless now shown to be somewhat more likely in the present-day climate than they would have been under pre-industrial conditions.

Uncertainty related to the day-to-day variation in the weather is accounted for through an ensemble approach, with uncertainty in pre-industrial SSTs accounted for through use of SST changes from a range of climate models, resulting in a wide range of FAR values. However, only one GCM/RCM was used for the climate simulations, with one hydrological model; other models may give different results (as for future climate change impacts; e.g. Kay et al. 2009). Ideally a range of climate models would be applied, as this is likely to be the largest source of uncertainty (Vetter et al. 2017, Kay et al. 2009), although Hauser et al. (2017) show that the choice of event attribution method, as well as the data source (GCM), can lead to differing conclusions. Uncertainties in the flood inundation mapping and the sub-postcode location of properties are accounted for via a sampling approach. Flood defences are included, although uncertainties about their actual (as opposed to design) standards and potential for structural failures (e.g. breaching) have not been explored.

While the results presented here and in Schaller et al. (2016) suggest that past anthropogenic greenhouse gas emissions have led to an increased chance of flooding from weather events like those experienced in Winter 2013/14, caution needs to be exercised when inferring how future changes will develop. The modelling study of Rasmijn et al. (2016) suggests that, in a future warmer climate, further changes in atmospheric dynamics will counterbalance the increased atmospheric moisture content, leading to similar precipitation anomalies for the Winter 2013/14 event in the future as in the present day. However, they also suggest that the circulation anomaly of Winter 2013/14 may occur more frequently in future, meaning a likely continued increase in flood risk (unless additional mitigation/adaptation is implemented). This demonstrates the complex and large-scale effects of the atmospheric interactions involved, alongside the complexities of the hydrological processes that transform precipitation into runoff and river flow. Thus detailed and proven climate models and hydrological models are required, along with inundation and damage models, to reliably investigate climate-driven changes in floods and their impacts on people.

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Tables

Table 1 Summary of the Actual and Natural climate ensembles for Winter 2013/14.

ID letter	Ensemble set	Number of members	SST source
a	Actual	17220	Observed
e	Natural	7147	Obs – CanESM ΔSST
f	Natural	13823	Obs – CCSM4 ΔSST
g	Natural	7332	Obs – CNRM-CM5 ΔSST
h	Natural	7530	Obs – CSIRO-Mk3 ΔSST
i	Natural	15565	Obs – GFDL-CM3 ΔSST
j	Natural	15335	Obs – GISS-E2-H ΔSST
k	Natural	7159	Obs – GISS-E2-R ΔSST
l	Natural	10964	Obs – HadGEM2-ES ΔSST
m	Natural	7651	Obs – IPSL-CM5A-LR ΔSST
n	Natural	10177	Obs – IPSL-CM5A-MR ΔSST
o	Natural	13210	Obs – MIROC-ESM ΔSST

Table 2 Summary of Thames@Kingston flow FAR values for Winter 2013/14, from the catchment-based modelling of Schaller et al. (2016) and from gridded modelling.

Natural ensemble	Schaller et al. outlet FAR		FAR from gridded modelling		
	Direct estimate	Resampling: median (5^{th}-95^{th} percentiles)	Outlet value	Catchment minimum	Catchment maximum
e-o (pooled)	0.032	0.028 (-0.117 - 0.146)	0.004	-0.142	0.186
e	0.039	0.036 (-0.213 - 0.245)	0.061	-0.149	0.286
f	0.237	0.233 (0.060 - 0.377)	0.182	0.001	0.377
g	0.226	0.222 (0.006 - 0.400)	0.140	-0.106	0.427
h	-0.097	-0.104 (-0.377 - 0.117)	0.003	-0.29	0.109
i	0.009	0.004 (-0.195 - 0.166)	-0.164	-0.248	0.170
j	-0.207	-0.213 (-0.441 - -0.023)	-0.182	-0.417	0.001
k	0.027	0.022 (-0.227 - 0.234)	0.007	-0.189	0.217
l	-0.017	-0.022 (-0.244 - 0.169)	-0.096	-0.178	0.169
m	0.428	0.426 (0.250 - 0.571)	0.372	0.097	0.542
n	-0.193	-0.200 (-0.456 - 0.020)	-0.121	-0.554	0.115
o	0.073	0.069 (-0.130 - 0.235)	0.091	-0.243	0.348

Figures

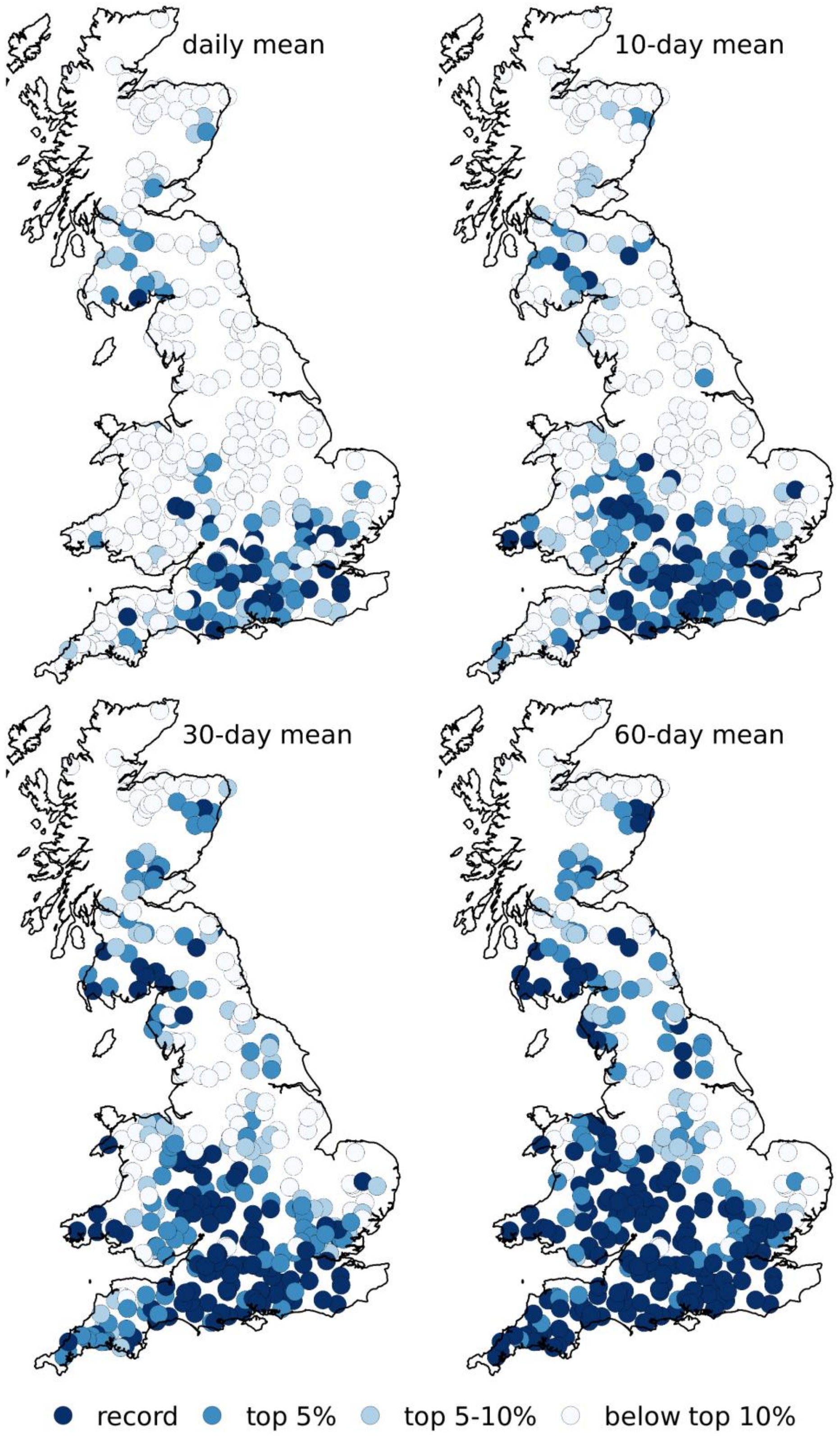

Figure 1 Maps showing the ranks of the maximum observed flows over December 2013–February 2014, for 1-, 10-, 30- and 60-day mean flows, for 342 gauges with at least 40 years of available data up to 2014.

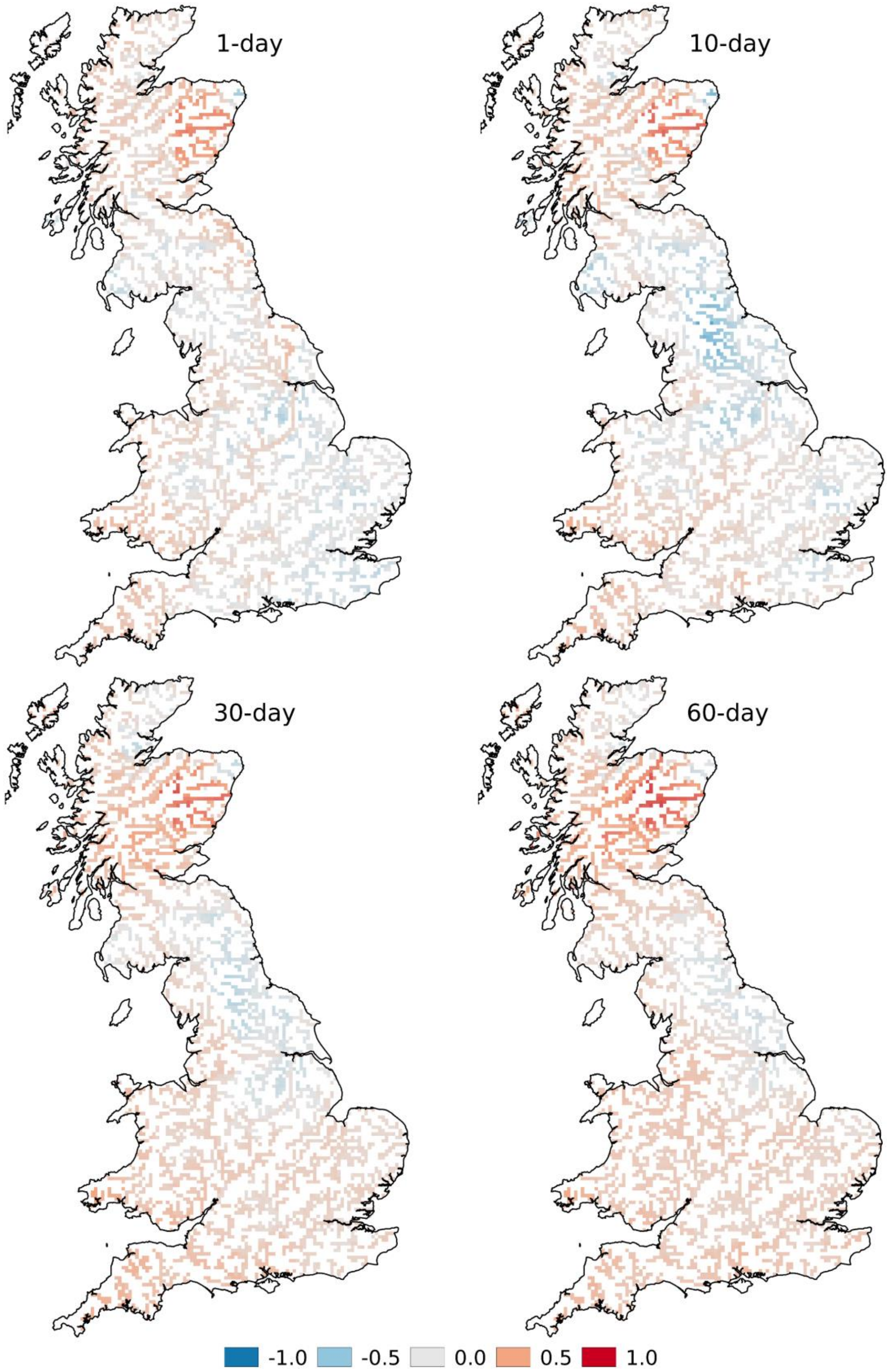

Figure 2 Maps of FAR values (using the pooled Natural ensemble), for 1-, 10-, 30- and 60-day mean flows. The legend shows the colours used for specific FAR values; colours are interpolated for intermediate values.

Figure 3 a) Boxplots summarising the range of FAR values for the 5km grid boxes within eight regions across GB (using the pooled Natural ensemble), for 1-, 10-, 30- and 60-day mean flows, when modelled with and without the snow modules. The boxes show the 25th-75th percentile range (with the black line showing the median), the whiskers show the 5th and 95th percentiles, and additional markers show minima and maxima. b) Map showing the eight regions of GB. Also shown is the catchment of the Thames@Kingston (black line) in the SE England region.

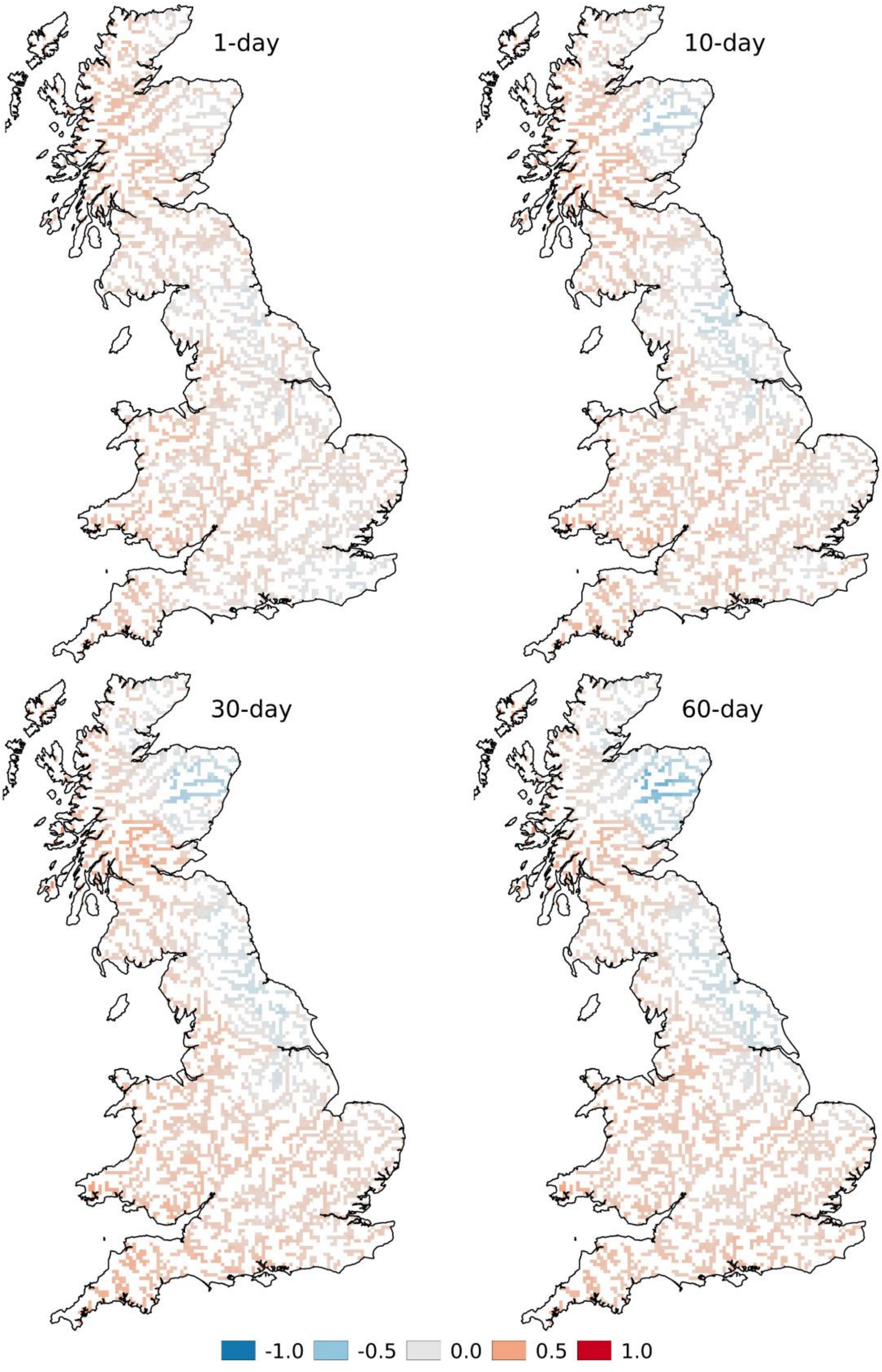

Figure 4 As Figure 2 but simulated without the snow module.

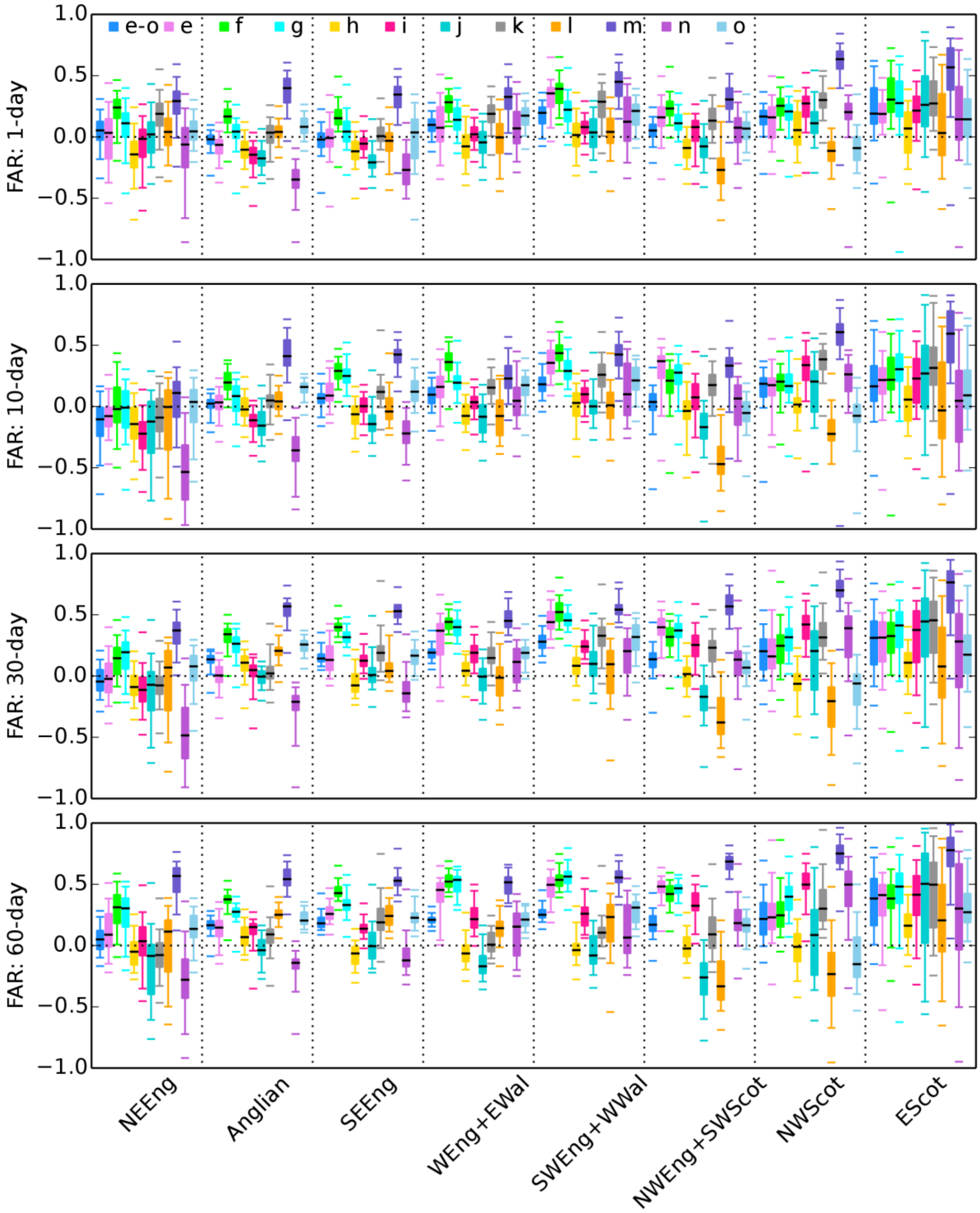

Figure 5 Boxplots summarising the range of FAR values for eight regions across GB (Figure 3b) for 1-, 10-, 30- and 60-day mean flows, for the pooled Natural ensemble ('e-o') and each Natural ensemble ('e' to 'o') separately (see key). The boxes are defined as in Figure 3a.

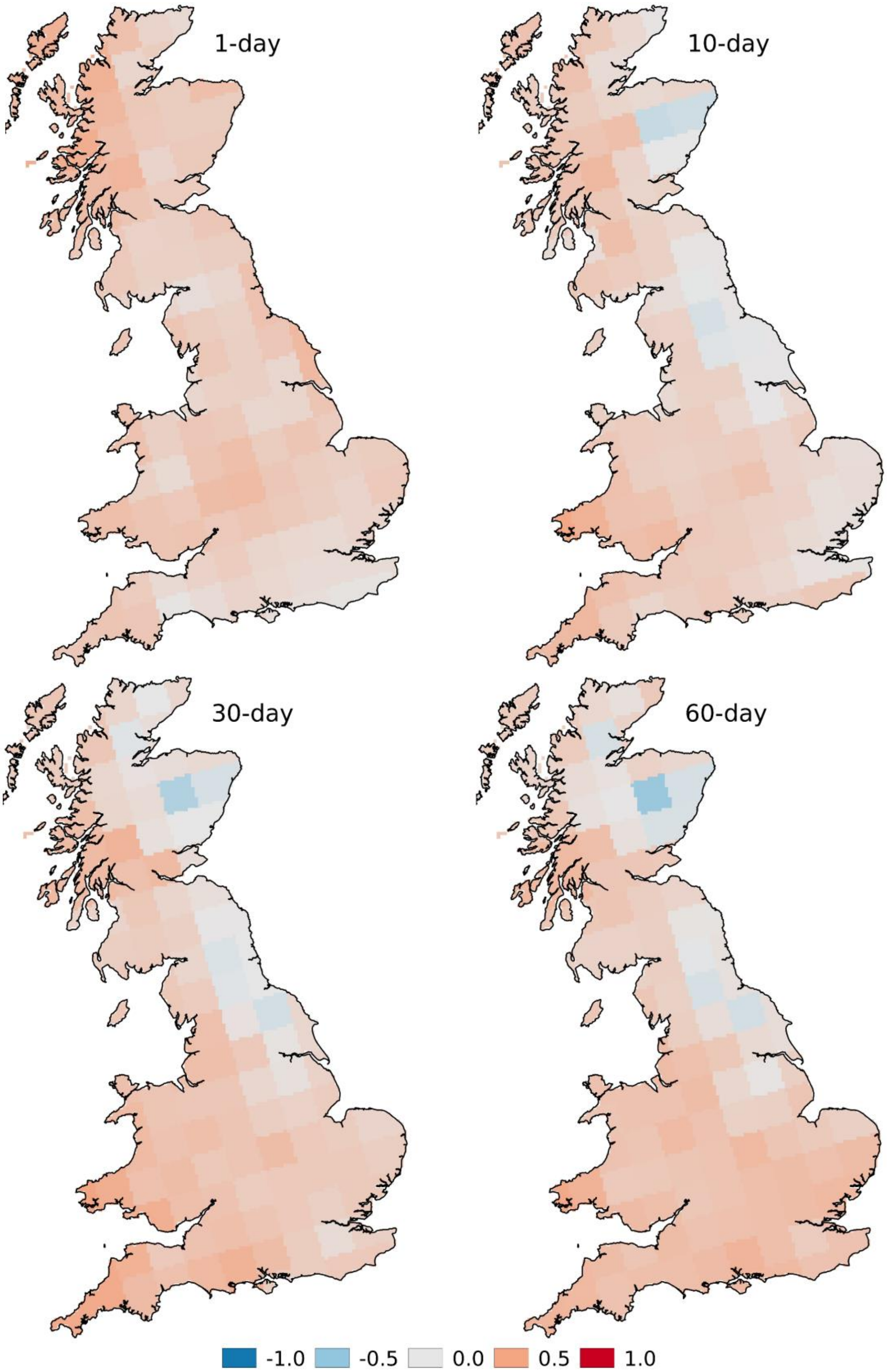

Figure 6 Maps of precipitation FAR values (using the pooled Natural ensemble), for 1-, 10-, 30- and 60-day accumulation periods.

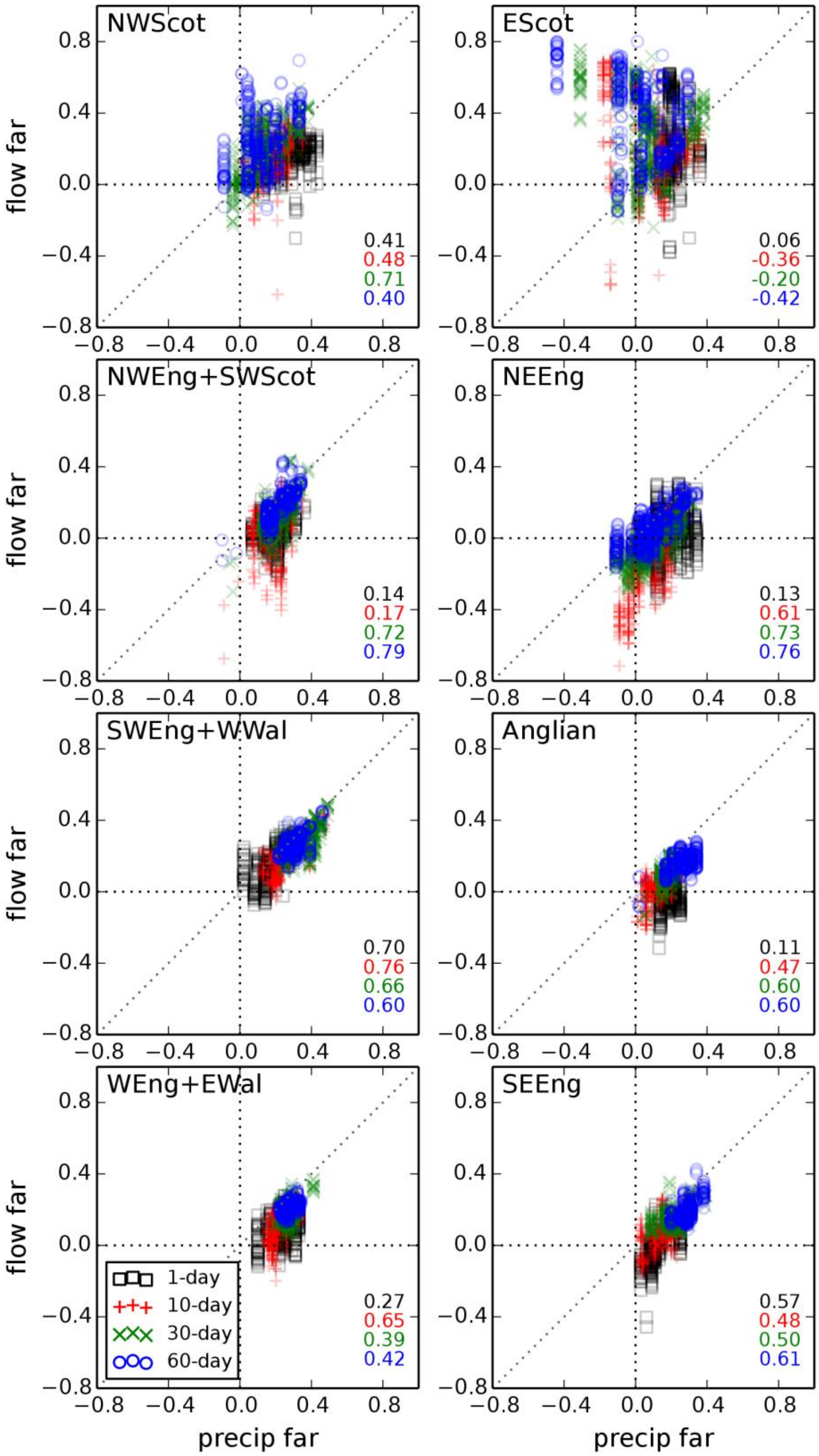

Figure 7 Scatter plots of flow FAR versus precipitation FAR (using the pooled Natural ensemble), for river points in eight regions across GB (Figure 3b), for 1-, 10-, 30- and 60-day durations. The Pearson r correlation for each duration is shown in the bottom-right of each plot.

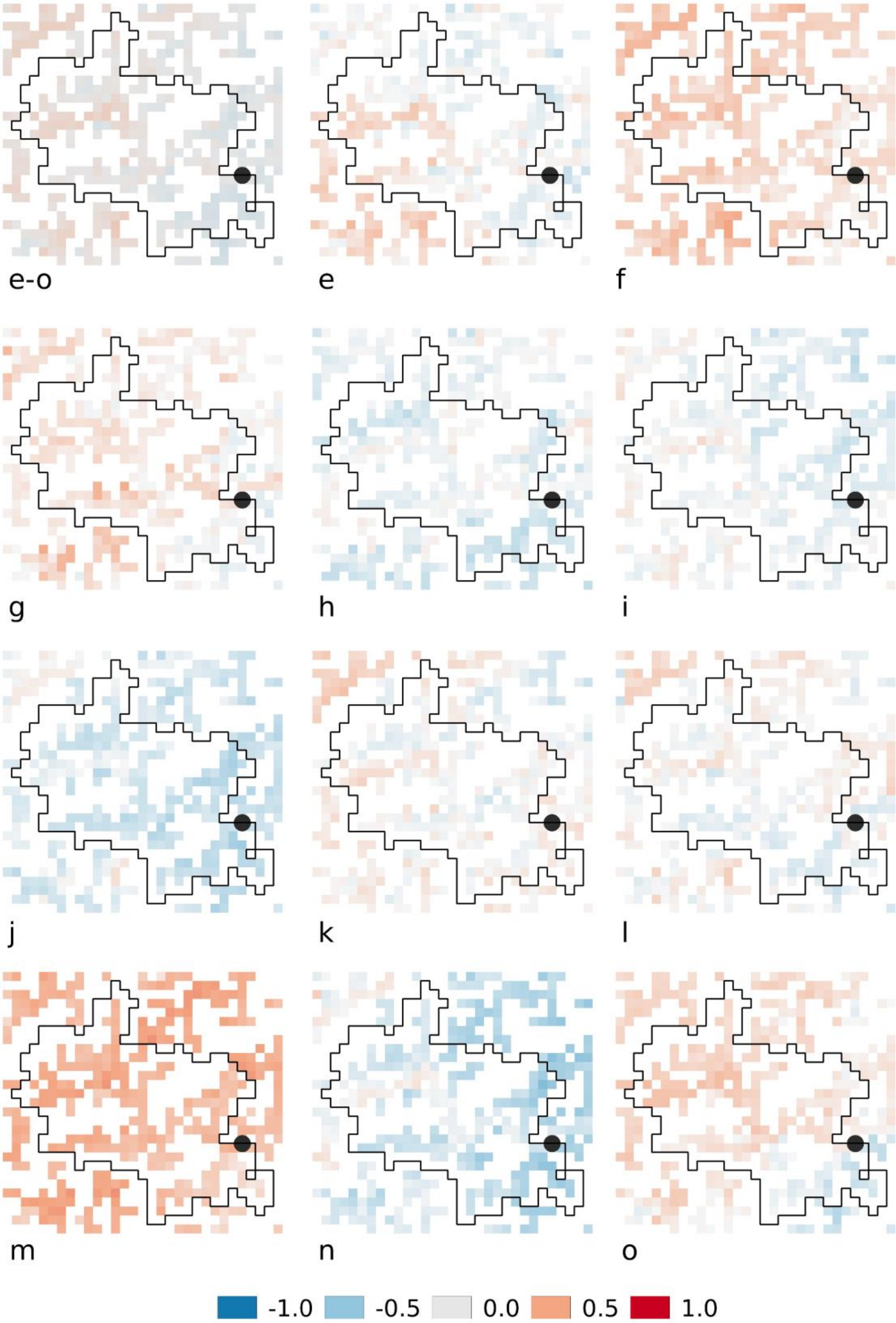

Figure 8 Maps of FAR values for 1-day mean flows in the Thames@Kingston catchment (black outline and dot), using the pooled Natural ensemble ('e-o') and each Natural ensemble ('e' to 'o') separately. See the Thames@Kingston catchment outline in the GB map of Figure 3b.

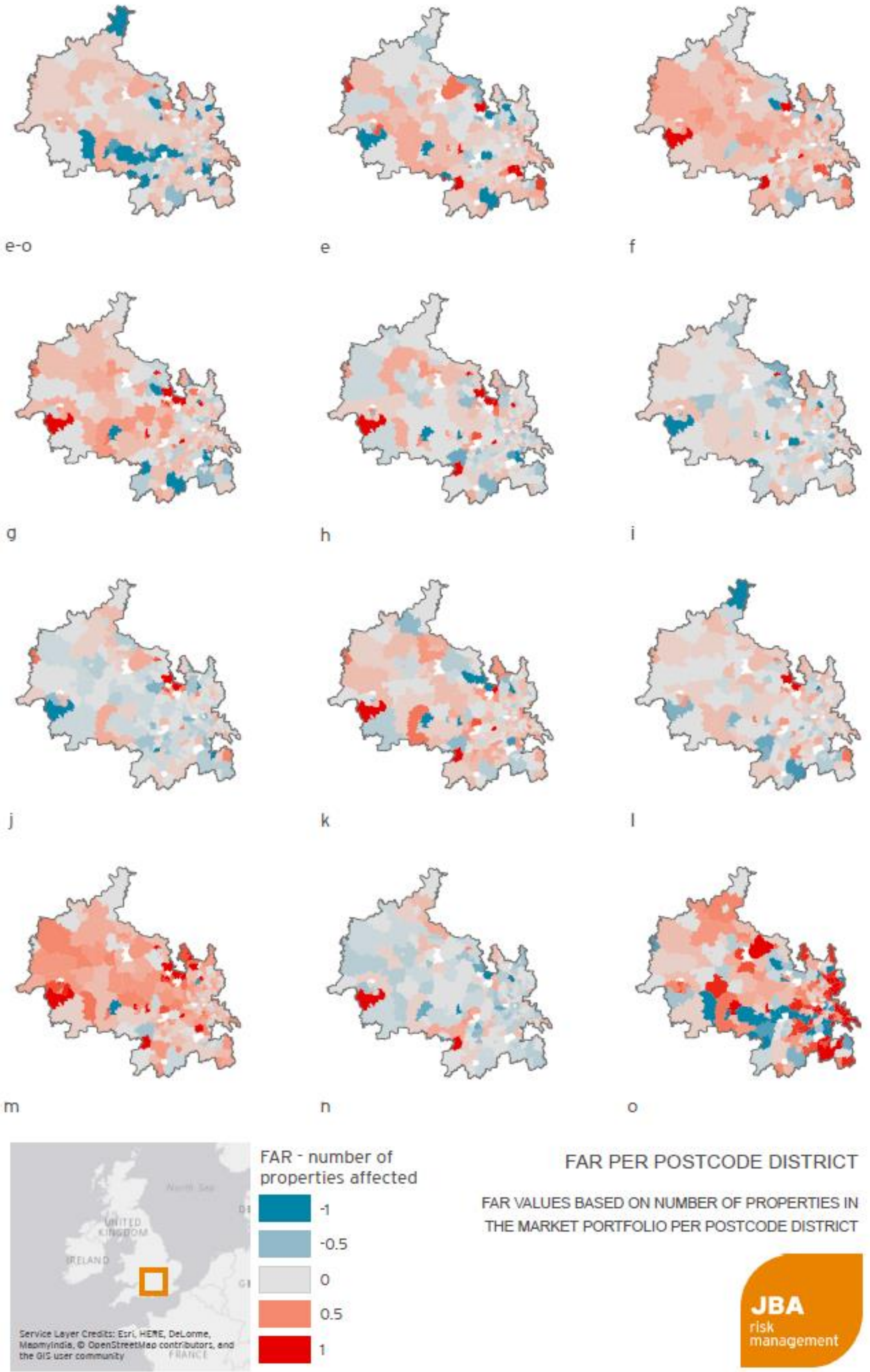

Figure 9 As Figure 8 but for flooded properties in each postcode district of the Thames@Kingston catchment.

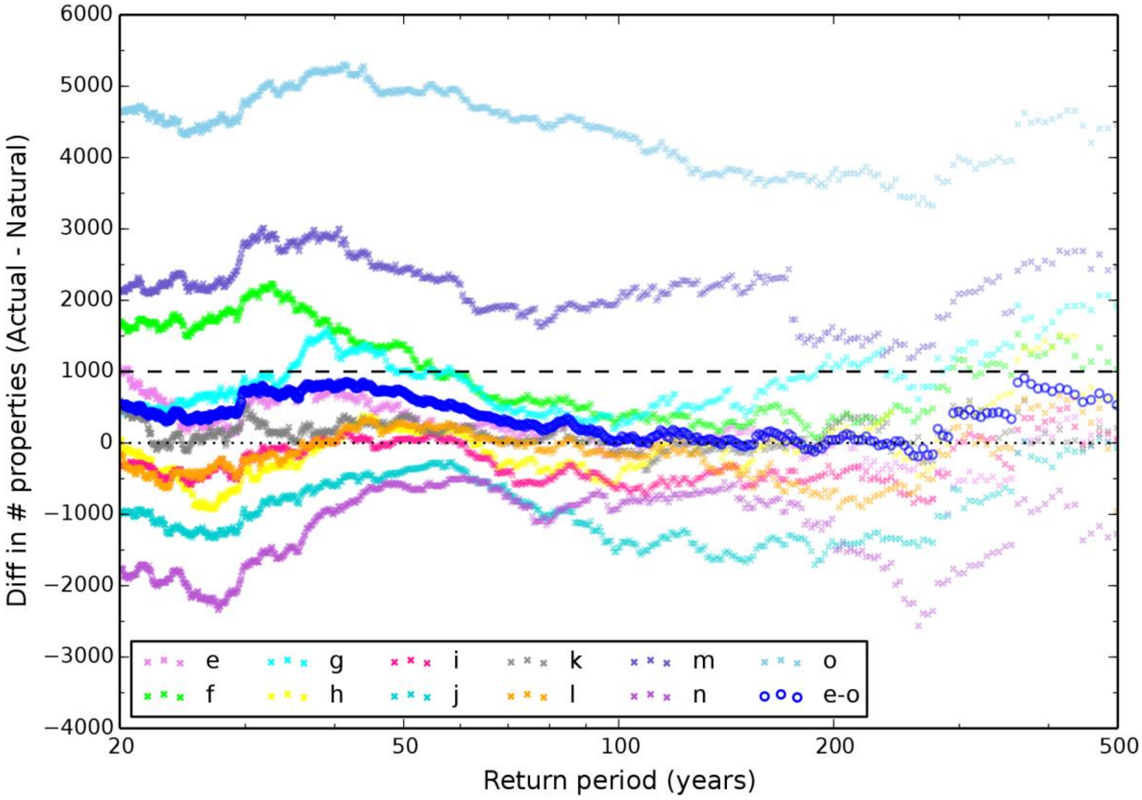

Figure 10 Difference between number of properties flooded in the Actual ensemble relative to the pooled Natural ensemble ('e-o') and each Natural ensemble ('e' to 'o') separately. Data are plotted as a function of relative level of extremeness within the ensemble (interpreted as a return period in years). The dashed line shows the estimate made by Schaller et al. (2016) under spatial uniformity assumptions.