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Participatory data collation and standardized hydrometeorological indicators improve understanding of the extent and drivers of flood and drought impacts at the catchment scale

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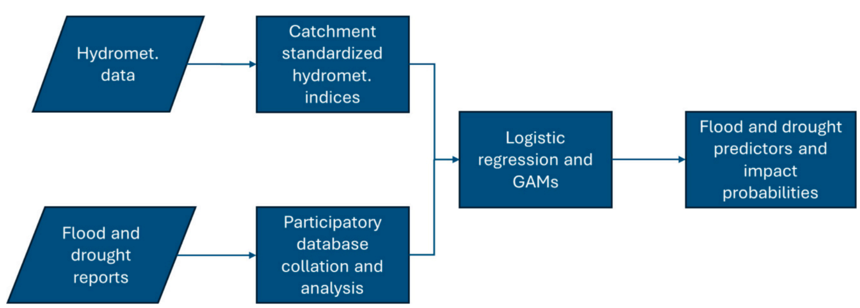
HIGHLIGHTS

- Participatory method for understanding flood and drought impacts.
- SPI-12 is the strongest predictor of reported flood and drought impacts.
- No clear thresholds for drought and flood impacts associated with SPI-12.
- Indicator-impact relationships must be developed at the catchment scale.

GRAPHICAL ABSTRACT



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ABSTRACT

Long-term (>150 years) records of the impacts of droughts and floods at the catchment scale are rare. Here we present a novel approach to improve understanding of historical flood and drought impacts and their hydrometeorological drivers using bottom-up participatory data collation and logistic regression with generalized additive models. Applied to a groundwater-dominated catchment in Southeast England (UK), a database of historical flood and drought impacts was collated based on detailed searches by stakeholders of digital and paper literature covering 1800 to 2023. The spatiotemporal distribution of flood and drought impact reports was evaluated, and drivers of impacts assessed by development of generalized additive models using standardized hydrometeorological indices. The spatiotemporal extent of reported impacts varies between droughts and floods, and between impact classes (e.g. surface water, agriculture). When combined with month and year as co-variates, the standardized precipitation index with a 12 month accumulation period (SPI-12) is the strongest predictor (lowest Akaike Information Criterion and highest deviance explained) of reported flood and drought impacts. The performance of the generalized additive models is better (higher deviance explained, adjusted R^2 and area under curve) than previous studies. There are no clear threshold values of SPI-12 associated with reported flood and drought impacts. For months where SPI-12 $= -2/+2$, the modelled weighted probability of a reported drought/flood impact is 0.46/0.26. We demonstrate the strengths and limitations of participatory approaches to

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understanding floods and droughts. Application of the developed protocol can improve understanding of relationships between indicators and impacts in catchments worldwide.

1. Introduction

Hydrological extremes (droughts and floods) are costly hazards, with global losses of over $2 trillion between 2000 and 2019 alone (Newman and Noy, 2023). Understanding the spatial and temporal extent of flood and drought impacts, and their associated drivers, is therefore critical. Quantitative indicators of hydrological state such as the standardized precipitation (McKee et al., 1993), precipitation-evapotranspiration (Vicente-Serrano et al., 2010), streamflow (Svensson et al., 2017) and groundwater level (Bloomfield and Marchant, 2013) indices are often used for drought and flood impact studies, and are increasingly used for drought monitoring (United States Drought Monitor, 2020). When derived using multidecadal reference periods (e.g. from long term hydro-climatological data or reconstructed streamflow (Chuphal and Mishra, 2023; Miao et al., 2022) and groundwater level time series (Chidepudi et al., 2024; Forstner et al., 2025), these indicators are useful tools to contextualize current hydrological state against previous historical variability. However, relationships between these quantitative indicators with observed drought and flood impacts are often poorly constrained. This is often due to a scarcity of long-term records of floods and drought impacts (Bachmair et al., 2016).

Recently, the development by the hydrological research community of large scale databases of flood and drought impacts at the global (Adhikari et al., 2010), continental (Europe (Blauhut et al., 2015; Stahl et al., 2016)) and country (USA (Wilhite et al., 2007), UK (Dayrell et al., 2022; Parsons et al., 2019), Ireland (Jobbová et al., 2024)) scale have begun to address this problem. Working across five European countries, Stagge et al. (2015) showed that the likelihood of drought impacts across different sectors could be predicted as a function of Standardized Precipitation Index (SPI) and Standardized Precipitation-Evapotranspiration Index (SPEI) for different accumulation periods. Similar approaches were taken at the national scale focussing on drought impacts on agriculture in the UK (Parsons et al., 2019), flood impacts in Chile (Fustos et al., 2017), and on drought impacts across sectors in the UK (Dayrell et al., 2022), Germany (Bachmair et al., 2015) and Ireland (O'Connor et al., 2023). However, the relationships between standardized hydrometeorological indicators and drought and flood impacts are likely to be location-specific associated with variation in climate and catchment characteristics. Consequently many workers have called for indicator-impact relationships to be developed at smaller spatial scales (Bachmair et al., 2015; Dayrell et al., 2022; Parsons et al., 2019; Stagge et al., 2015). Such approaches bring about both challenges and opportunities. Large amounts of local impact data may be available (Dayrell et al., 2022), however collation and interpretation of this information may be laborious, particularly if detailed local knowledge is required for access to records in paper format.

In many countries there is an increased awareness of water-related issues amongst the general public (Consumer Council for Water, 2022). This has supported the development of participatory approaches to understanding the water environment, where members of the public collect environmental data. This has included, for example, citizen science assessments of the water quality (San Llorente Capdevila et al., 2020) and ecological status (Krabbenhoft and Kashian, 2020) of rivers. Combining participatory approaches to historical impact data collection with analysis of drivers using standardized hydrometeorological indicators offers much potential to improve our understanding of floods and droughts. However, to the authors knowledge this approach is untested to date.

In this paper we test this proposed approach through collation of flood and drought impact reports at the catchment scale. Using a novel bottom-up participatory digital and paper literature search, we develop and analyse a detailed catchment-scale flood and drought impact database covering over 200 years. We relate standardized hydrometeorological indicators to impacts for both floods and droughts using logistic regression with generalized additive models (GAM). Our approach reveals the strengths and limitations of participatory data collation in the analysis of historic flood and drought impacts. The method is generic and can be applied in catchments worldwide to advance our understanding of the flood and drought impacts and their drivers.

2. Materials and methods

2.1. Study area

This research was focussed on the river Chess catchment in Southeast England (UK), see Fig. 1. The river Chess is a groundwater dominated stream with baseflow derived from the underlying Chalk aquifer (Baseflow Index = 0.95). The Chalk is the principal aquifer in Southeast England (Fig. 1(b)) and discharge from the Chalk provides baseflow in over 250 rivers across the Southeast England, France and Denmark (Rangeley-Wilson, 2021). The Chess catchment is 105 km^2 and is 266 m above ordnance datum (mAOD) at its highest elevation and 47.7 mAOD at its lowest at Rickmansworth (Fig. 1). Typically for Chalk catchments (Rangeley-Wilson, 2021), the Chess has rural land cover in the upper and lower reaches (grassland, woodland and arable land), with some urban areas (12 % of the land use in the catchment) in the central area around the town of Chesham. The river has a length of c. 13 km and is channelised through the urban sections. Chalk catchments in the region and the Chess specifically have been subject to notable recent high (2013/14, Ascott et al. (2017)) and low (2011/12, Marsh et al. (2013)) groundwater level events. These have caused groundwater flooding in the town of Chesham and drying out of the river channel and associated ecological impacts respectively. There is a high degree of local public interest in the river Chess, which has led to the formation of citizen science initiatives coordinated by the River Chess Association (RCA) to help understand river water quality (Schäfer et al., 2022) and flow accretion downstream. The river Chess was chosen for our research as, to the authors knowledge, the Chess is the only river where reported flood and drought impacts over 200 years have been collated into a single database through participatory initiatives (see Section 2.2 below). Further, on the basis of the high baseflow index and urban influence, the Chess is also one of three catchments being instrumented as a part of a long-term study of floods and droughts in the UK (Blackburn and Ascott, 2024). In this context, our research is also motivated by the need to provide analyses of historical flood and drought impact reports to support the development of research infrastructure. The overall workflow used in this research is shown in Fig. 2 and the methodology in detail is discussed herein.

2.2. Flood and drought impact database: collation, processing and analysis

A database of reported flood and drought impacts in the Chess catchment was developed by members of the RCA (K.A. Graves in particular). It is important to note that, in line with the objectives of this research, the development of this database was a bottom-up endeavour by the RCA members without a background in hydrology, and not for the formal objective of quantifying flood/drought indicator-impact relationships. This is as opposed to a top-down research initiative to formally document flood and drought impacts at the continental/national scale (as was previously undertaken by Stahl et al. (2016) and Jobbová et al. (2024)). The strengths and limitations of this bottom-up, participatory approach are discussed in Section 4.3.

The database was developed from a range of digital and paper sources. Online searches of the British Newspaper Archive (2024), using combinations of keywords "River Chess", "Chesham", "Flood" and "Drought" were undertaken. Online searches on the keyword "Chess" were also undertaken within specific local titles (the Bucks Herald and the Bucks Examiner) in the archive. This was supplemented with a review of online historic copies of The Fishing Gazette (including reports from the Gresham Angling Club), local social media reports of flooding and drought impacts in the Chess, and reports of flood and drought impacts made by RCA members and the local water utility. Paper sources consisted of: minutes of the Chesham town council for 1974–2017, minutes of the Chesham Urban District 1890–1928 in the Buckinghamshire County Archive, books on "Water mills of the river chess", "Chesham in old picture postcards" and copies of the Chess Valley Archaeological Society Journal.

For each of the sources above where a flood and drought impact was reported, the following was recorded in the database: the date of impact, a brief summary of the article, keywords summarizing the type of impact (whether a flood or a drought, information relating to which sectors were affected, placenames of locations affected). Online articles were then saved individually and the location of impact information within paper documents recorded.

A number of data processing steps were then undertaken to enable further analysis. The raw database contained 105 unique keywords, many of which were very similar (e.g. "agriculture", "agricultural", "farming"). We therefore rationalized these keywords by mapping them to 8 high-level impact classes: Meteorological, Surface Water, Groundwater, Agriculture, Socioeconomic, Water Supply and Ecology. These classes were defined based on the types of observed impacts in the database, which is likely to be specific to the Chess catchment. However, the classes also broadly map on to the impact classes defined by Stahl et al. (2016). Some reports covered impacts across multiple classes. The database keywords and mapping to impact classes is shown in Table S1 (Supplementary information). We also geocoded the placenames given to give latitude and longitudes using the google geocoding API (Google, 2024). These were subsequently manually checked for accuracy and corrected where necessary.

An initial analysis of the processed database revealed that there were a number of records where newspapers were reporting droughts in previous years ($n = 4$, e.g. "last summer's drought"), or recoveries from low flows ($n = 7$). These records were excluded from further analysis. We then visually assessed how drought and flood impact reports vary temporally and by sector and how this relates to driving hydrometeorology (SPI). We also assessed the spatial distribution of flood and drought impacts across the catchment.

2.3. Logistic regression and GAMs

The reported flood and drought impacts collated in the database

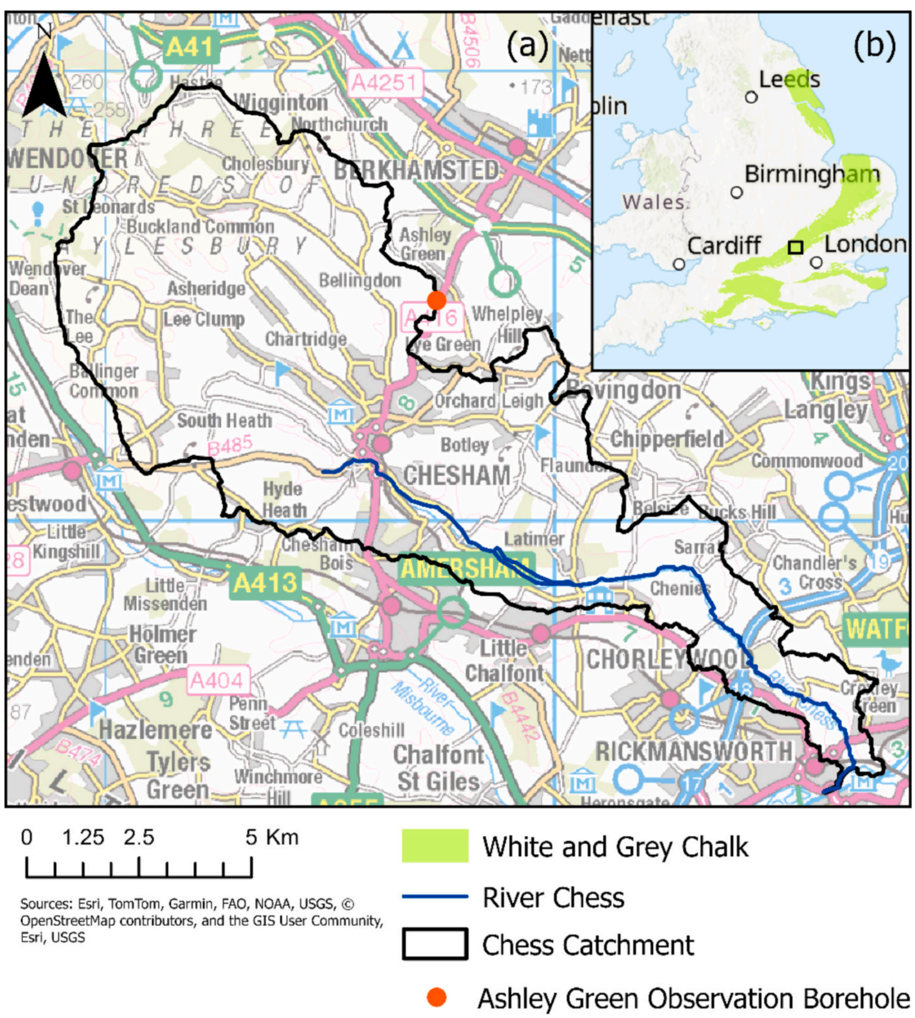

Fig. 1. (a) Location of the river Chess and the Ashley Green observation borehole in the Chess catchment, and (b) location of the study area (black box) in the UK and the outcrop of the White and Grey Chalk subgroups. Contains data held by the UK National River Flow Archive. Contains Ordnance Survey data licensed under the Open Government Licence v3.0. Contains British Geological Survey materials © UKRI 2025.

(Section 2.2) were related to the driving hydrometeorology using logistic regression with GAMs, similar to the approach of previous studies (O'Connor et al., 2023; Parsons et al., 2019; Stagge et al., 2015). Logistic regression models the relationship between the probability of occurrence of a binary dependent variable (in this case, a flood or drought impact report) and a linear function of a continuous predictor variable (e.g. SPI) using the logit transform:

$$\text{logit}(p(t)) = ln\left(\frac{p(t)}{1-p(t)}\right) = \beta_0 + \beta_1 \text{SPI}$$

where $p(t)$ is the probability of occurrence in time interval t and the β_i are regression coefficients that are fitted to the available data. This can be extended to a GAM by including other terms (e.g. smooth functions of month or year) on the right hand side of the logistic regression equation.

We first extracted time series of hydrometeorological variables as potential predictor variables of reported flood and drought impacts. A time series of mean monthly precipitation (P) for 1836–2023 for the Chess catchment was extracted from HadUK-Grid (Hollis et al., 2023). Time series of monthly catchment potential evapotranspiration (PET) for 1890–2015 calculated using the McGuinness-Bordne method (calibrated period: 1961–1990) were extracted from Tanguy et al. (2017). Precipitation and PET time series were then used to calculate SPI and SPEI time series for 1, 3, 6, 12, 18 and 24 month accumulation periods. SPI and SPEI were calculated by fitting a gamma distribution to the P and P-PET time series. The observed P and P-PET are then transformed to normal distribution, allowing the SPI and SPEI to express deviations from the mean in terms of standard deviations, with positive values indicating wet periods and negative values indicating dry periods. Monthly raw reconstructed groundwater level (GWL) and standardized reconstructed groundwater level (SGI) time series for a borehole at Ashley Green (Fig. 1) for 1891–2015 were downloaded from Bloomfield et al. (2018). Groundwater levels have been measured at Ashley Green at approximately monthly frequency from 1987 to 1992, and on a daily frequency using automatic water level pressure transducers from 1992 onwards (Environment Agency, 2025). The method for GWL reconstruction used by Bloomfield et al. (2018) is briefly described as follows.

Reconstructed GWL time series at Ashley Green were derived using the lumped conceptual model AquiMod (Ascott et al., 2020; Jackson et al., 2016; Mackay et al., 2014). The model was calibrated over the full GWL time series (1987–2015) using monthly GWL observations. The model was then run using historical precipitation and temperature time series and the calibrated model parameter sets to generate reconstructed monthly GWL time series for 1891–2015. Calculation of the SGI is similar to that of SPI and SPEI, but a non-parametric normal scores transform is applied to GWL data for each month. For both GWL and SGI the full monthly reconstructed time series was used as a predictor. For each predictor time series (P, P-PET, SPI for accumulation periods above, SPEI for accumulation periods above, GWL, SGI) we also calculated lagged version of these time series for 1 to 6 months.

For each month over 1836–2023, we recorded as 0 or 1 for absence and presence of flood or drought impact reports separately in the database. If there was a report, the number of flood or drought impact reports in that month was also recorded. To test whether predictors perform differently between floods and droughts separate models for flood and drought impacts were developed. Predictor time series are likely to be highly correlated with each other, so only one was included in each model.

Previous approaches (O'Connor et al., 2023; Parsons et al., 2019; Stagge et al., 2015) have shown that inclusion of smoothed month and year terms can significantly improve model performance. This has been attributed to the predominance of drought impacts in summer months and changing drought reporting and vulnerability over time. To test whether these terms are significant drivers of flood and drought impact reporting in our study, we first calculated an initial null model with no covariates. We then compared the Akaike Information Criterion (AIC) of this model to models including (1) smoothed month, (2) smoothed year, (3) smoothed month and smoothed year. Smoothing was estimated using a GAM with the Restricted maximum likelihood (REML) method. For month terms a cyclic cubic regression spline was used with $k = 12$ to avoid a discontinuity between December and January. This showed models using smoothed month and smoothed year as covariates performed significantly better (ΔAIC > 10) than other models.

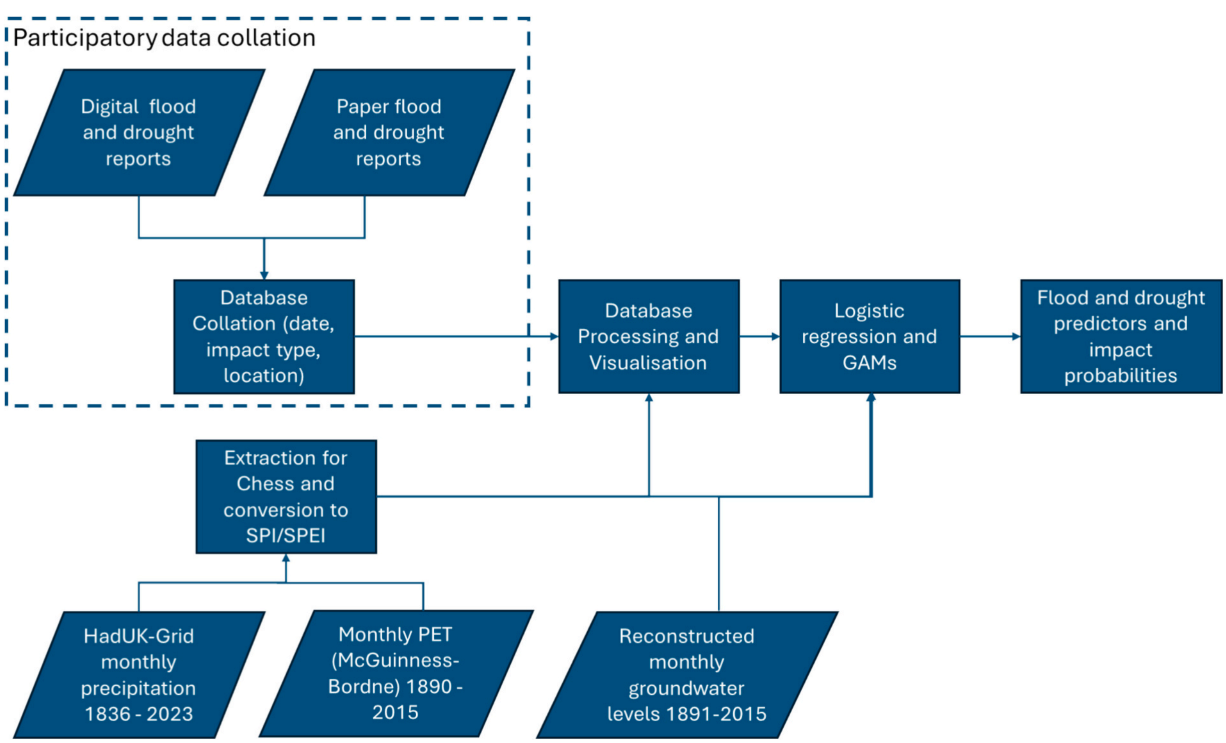

Fig. 2. Workflow developed in this research to collate, analyse and model flood and drought impacts in the Chess catchment.

For each predictor time series in turn, we then estimated a model for the period 1893–2015 using smoothed month and smoothed year as additional covariates (e.g. SPI-12 + s(month) + s(year)). This period was used as this is when all predictors had data (note that whilst the PET time series start in 1890, to calculate SPEI-24 with a 6 month lag requires starting in 1893). Presence/absence of drought and flood impacts was weighted based on the number of impact reports in each month following the approach of Parsons et al. (2019). This ensures that the model estimation procedure places extra emphasis on correctly classifying months with multiple impacts. The weighting approach used here (and also used by Parsons et al. (2019) and O'Connor et al. (2023)) effectively leads to the months with impacts being over-sampled and therefore the weighted probability p(t) is an over-estimate of the probability of an impact occurring in time interval. Cyclic cubic regression splines for month and the REML method was used. For each model we calculated the following performance metrics: deviance explained (DE), adjusted R^2, AIC, Bayesian Information Criterion (BIC), and the Receiver-Operating Characteristic (ROC) Area Under Curve (AUC). A review of these metrics showed that the model driven by SPI-12 had the lowest AIC for both flood and drought impacts. We therefore regenerated these models using data for the period 1836–2023.

We then plotted ROC curves for these models and evaluated the shape of the smoothed month and year covariates. We then plotted the modelled weighted probability of reported drought and flood impact as a function of SPI-12 for the whole time period 1836–2023 and for each month separately. All analysis was undertaken using R (R Core Team, 2022) and the packages "SPEI" (Beguería et al., 2014) and "mgcv" (Wood, 2017).

3. Results

3.1. Distribution of reported flood and drought impacts

In the processed database there were 498 impact reports (331 drought, 167 flood). The first report was recorded in 1803, and the latest in 2021. Fig. 3 shows the breakdown of reported impacts by impact class. For droughts, c. 63 % of impact reports were related to surface water, c. 11 % were related to water supply, and the remaining 26 % related to other impact classes. For floods, c. 49 % of impact reports were related to surface water, c. 14 % were related to water supply and socioeconomic impacts and the remaining 23 % related to other impact classes.

Fig. 4 shows drought and flood impact reports over time as a function of SPI-12 by impact class. As also illustrated by Fig. 3, there are substantial differences between classes in the number of flood and drought impact reports. In general, drought and flood impact reports occur when SPI-12 is negative and positive respectively. There are a small minority of impact reports where the reverse is true. 11 % of drought impact reports occur when SPI-12 > 0, and 1.7 % of drought impact reports

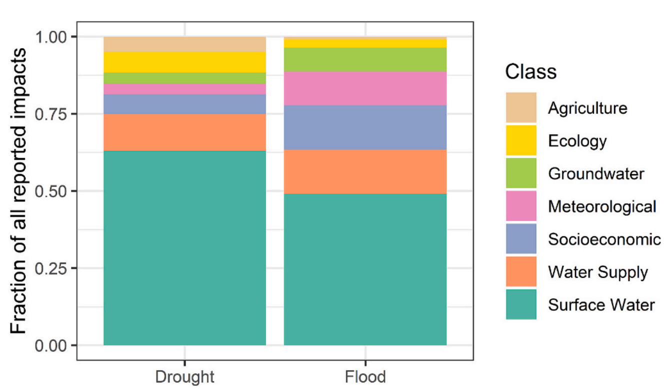

Fig. 3. Fraction of reported drought and flood impacts by impact class.

occur when SPI-12 > 1. 13 % flood impacts reports occur when SPI-12 < 0, and 2.4 % flood impact reports occur when SPI-12 < −1. Potential reasons for these discrepancies are discussed in Section 4.1.

Fig. 5 shows the spatial distribution of flood and drought impacts by sector. Visually, reported drought impacts have a slightly larger spatial distribution than flood impacts. Flood impacts are principally located with the town of Chesham and river valleys immediately up and downstream of the town. Whilst drought impacts occur in and around Chesham, impacts are also reported away from the river valley. There does not appear to be any systematic variability in the location of different impact classes. This is unsurprising given the dominance of surface water impact reports for both floods and droughts.

3.2. GAM performance

Table 1 shows performance metrics for GAMs for reported drought and flood impacts over the period 1893–2015 including smoothed month and year terms. All models show improvement (based on ΔAIC > 2) over the null models (s(month) + s(year)) for both drought and flood impacts. For all drought models the hydrometeorological predictors were significant ($p < 0.05$) and their coefficients negative (lower SPI results in a higher probability of drought). For all flood models the hydrometeorological predictors were significant ($p < 0.05$) and positive (higher SPI results in a higher probability of flood). For both flood and drought impacts, SPI-12 has the lowest AIC, highest DE, lowest BIC, and highest AUC. However for droughts the differences between the best performing models are small (ΔAIC < 2 for SPI-12 vs. SPEI-12). Models incorporating lagged predictors did not improve model performance (see Table S2 in Supplementary information).

In comparison to the same models for 1893–2015 (Table 1), the models fitted to data for 1836–2023 using SPI-12 + s(month) + s(year) resulted in a slightly better performance for drought (DE = 0.41, $AdjR^2$ = 0.41, AUC = 0.88) and a similar performance for flood (DE = 0.26, $AdjR^2$ = 0.19, AUC = 0.83). SPI-12 was a significant predictor for flood and drought impacts ($p < 0.01$) with a negative and positive coefficients for drought and flood respectively. The trade-off between model sensitivity (true positive rate) and specificity (1- false positive rate) is shown by the Receiver-Operating Characteristic Curves for the drought and flood models shown in Fig. 6. Both flood and drought models have discriminative ability, with curves approaching the top left corner. Based on the AUC values in Fig. 6 and Table 1, the drought model has a slightly higher ability to discriminate reported impacts than the flood model.

Fig. 7 shows the smoothed GAM response of the drought and flood models to the month and year terms. There is an increased probability of reporting of drought impacts in summer months, with the highest probability in August and the lowest in April. There is an increased probability of reporting of flood impacts in spring, with the highest probability in April and the lowest in October. The magnitude of seasonal variability in the GAM smoothing is substantially greater for drought than for flood. There is substantial variability in the response to year terms for both flood and drought models. The probability of reported drought impacts increases over time, with a large increase over 1850–1900, a relatively stable period for 1900–2000 and another increase for 2000–2015. The probability of reported flood impacts is more variable over time, with increases over 1850–1900, and then subsequent increases and decreases over 1900–2015.

Fig. 8 shows the modelled weighted probability of reported flood and drought impacts as a function of SPI-12. There is no clear threshold value of SPI-12 associated with flood or drought impact reports. The mean weighted probabilities of a reported drought or flood impacts at any time are 0.18 and 0.11 respectively. When SPI-12 = −1 and −2, the mean weighted probabilities of a reported drought impacts are 0.2 and 0.46 respectively. When SPI-12 = 1 and 2, the mean weighted probabilities of a reported flood impacts are 0.13 and 0.27 respectively.

Fig. 9 shows the weighted probability of reported flood and drought

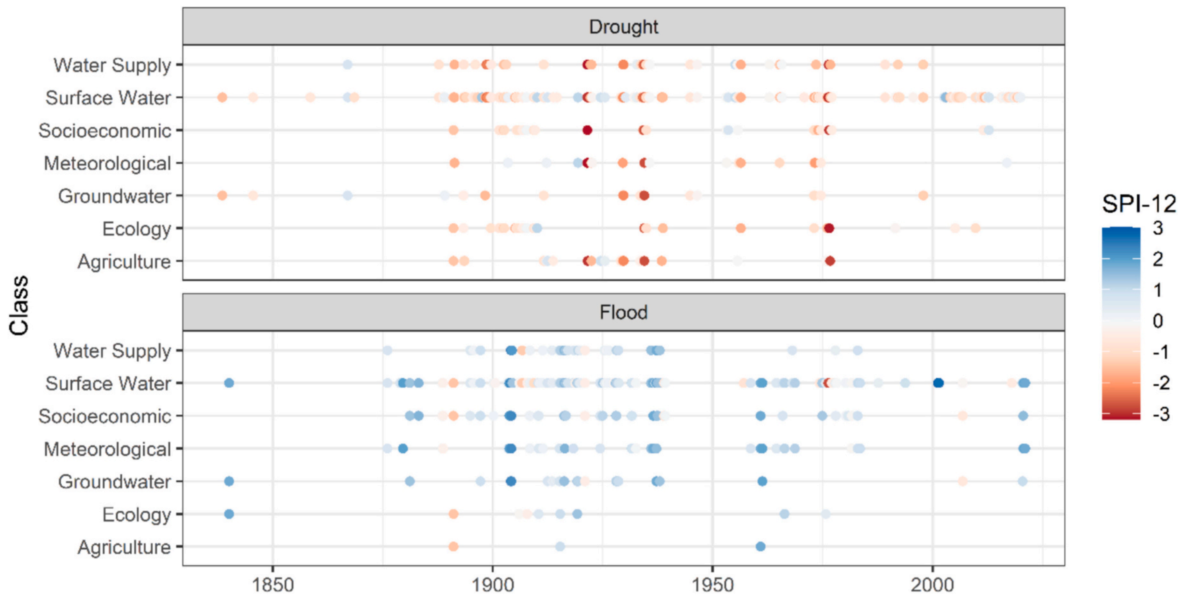

Fig. 4. Reported drought (top) and flood (bottom) impacts over time by impact class as a function of SPI-12.

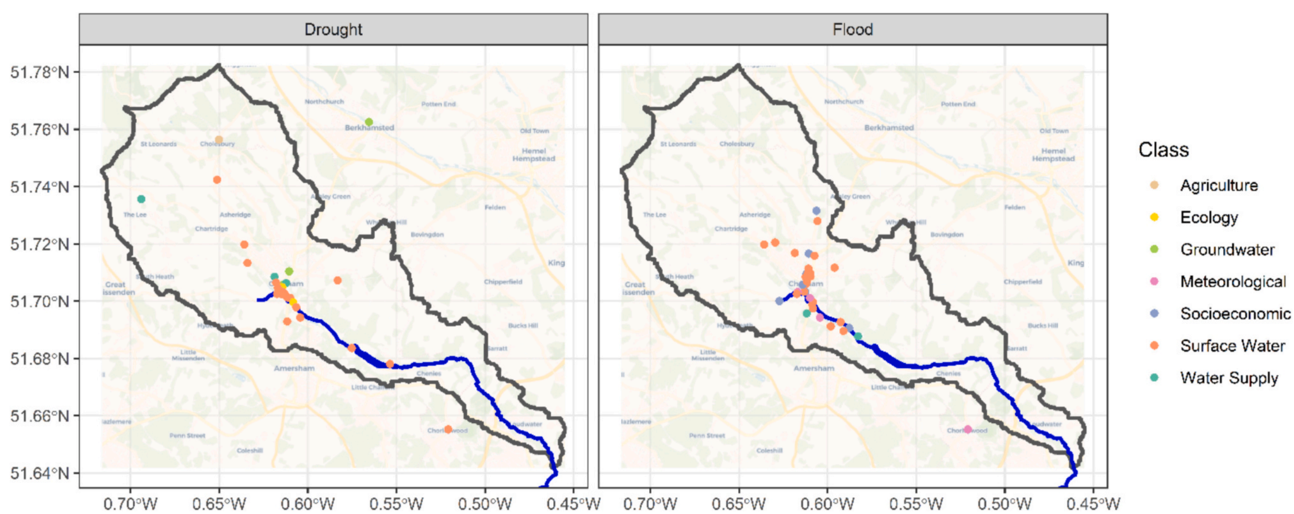

Fig. 5. Spatial distribution of reported drought (left) and flood (right) impacts by impact class. Contains data held by the UK National River Flow Archive. Contains Ordnance Survey data licensed under the Open Government Licence v3.0.

impacts as a function of SPI-12 split by month. The greatest probability of reported drought impact associated with SPI-12 occurs in August (weighted probability when SPI-12 = −2 is 0.64) and the lowest is in April (weighted probability when SPI-12 = −2 is 0.35). The variation in probability between months by SPI-12 for reported flood impacts is more subdued. The weighted probability of a reported flood impact when SPI-12 = 2 in April is 0.3, and the weighted probability of a reported flood impact when SPI-12 = 2 in October is 0.25.

4. Discussion

4.1. Spatio-temporal patterns of reported flood and drought impacts

The distribution of flood and drought impacts across impact classes, time and space generally agrees with previous conceptual models of hydrological extremes in the Chess catchment (Blackburn and Ascott, 2024) and more broadly across the Chalk aquifer of Southeast England (Ascott et al., 2017; Marchant and Bloomfield, 2018). The largest class of both flood and drought impacts is surface water, with socio-economic the second largest class for flooding (Fig. 3). These impacts are associated with groundwater emergence and stream drying in the river Chess valley (Fig. 5). It is notable that water supply impacts are a substantial minority of the total number of reports for both droughts and floods. Water supply impact reports for floods and droughts are associated with groundwater infiltration into the sewer network and groundwater abstraction from boreholes, wells and springs, respectively.

The high degree of variability in reporting of impacts (Fig. 4) between classes over time is likely to reflect changes in awareness and media interest in floods and droughts and also vulnerability to hydrological extremes. Several well-known extreme events (e.g. the locked pump drought of 1933–35, the standpipe drought of 1975/6 (UK Centre for Ecology and Hydrology, 2024), the 2000/2001 winter floods (Marsh and Sanderson, 2014)) are evident. Before 1933, two of the spatially extensive drought events (1887, 1911) reported in the Chronology of British Hydrological Events (Black and Law, 2004) are also reported in the Chess database. Interestingly, however, neither the spatially extensive drought event in 1826 nor the spatially extensive flood events in 1852, 1875 or 1929 are reported in the Chess database. A detailed

Table 1
Performance metrics for drought and flood impact models using data over period 1893–2015. DE = Deviance Explained, AdjR^2 = Adjusted R^2, AIC = Akaike Information Criterion, BIC = Bayesian Information Criterion, AUC = Area Under Curve. Models are ordered by lowest to highest AIC.

Predictor	Drought impact models (predictor + s(month) + s(year))					Predictor	Flood impact models (predictor + s(month) + s(year))				
	DE	AdjR2	AIC	BIC	AUC		DE	AdjR2	AIC	BIC	AUC
SPI-12	0.377	0.394	933	1014	0.841	SPI-12	0.257	0.219	732	798	0.802
SPEI-12	0.376	0.396	934	1016	0.841	SPEI-12	0.254	0.214	735	801	0.800
SPEI-18	0.370	0.394	942	1024	0.828	SPI-18	0.243	0.200	745	811	0.802
SPI-18	0.369	0.388	943	1025	0.828	SPEI-18	0.239	0.194	750	816	0.800
SPEI-24	0.328	0.351	1003	1085	0.807	SPI-6	0.230	0.184	757	821	0.788
SPI-24	0.326	0.346	1006	1087	0.806	SPEI-6	0.226	0.180	762	827	0.787
GWL	0.302	0.331	1041	1126	0.807	SPI-24	0.205	0.167	782	849	0.776
SGI	0.294	0.322	1053	1136	0.799	SPEI-24	0.201	0.162	786	854	0.775
SPI-6	0.269	0.275	1089	1171	0.789	SPI-3	0.191	0.140	794	859	0.758
SPEI-6	0.267	0.274	1092	1174	0.790	SPEI-3	0.187	0.135	799	864	0.757
SPI-3	0.218	0.213	1164	1250	0.766	GWL	0.179	0.144	802	856	0.744
SPEI-3	0.218	0.214	1164	1249	0.765	SGI	0.183	0.141	802	866	0.760
SPI-1	0.184	0.178	1212	1297	0.742	SPEI-1	0.137	0.080	847	912	0.732
SPEI-1	0.184	0.179	1213	1298	0.740	SPI-1	0.136	0.080	847	912	0.730
P-PET	0.179	0.172	1219	1300	0.736	P	0.137	0.079	847	914	0.731
P	0.179	0.171	1220	1303	0.736	P-PET	0.136	0.079	848	917	0.730
Null Model	0.174	0.162	1230	1320	0.737	Null Model	0.125	0.076	855	912	0.715

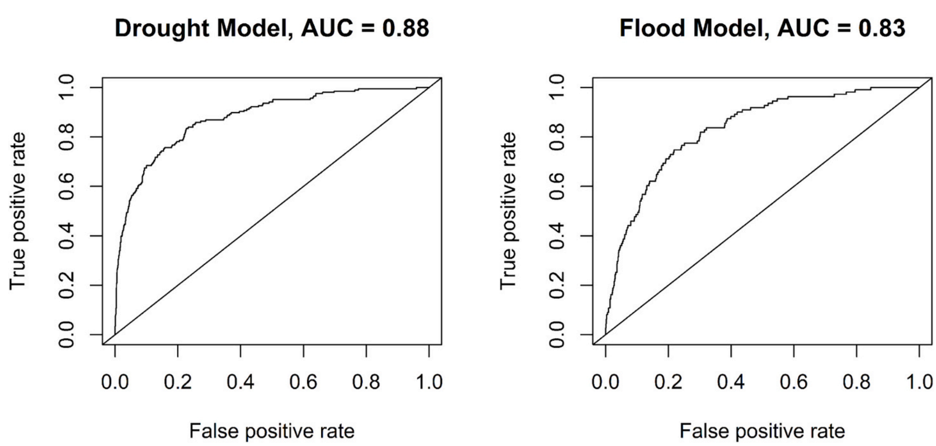

Fig. 6. Receiver-Operating Characteristic Curves for best drought (left, SPI-12 + s(month) + s(year)) and flood (right, SPI-12 + s(month) + s(year)) impact models.

comparison of presence/absence of reports within the Chess database and within national scale databases of each individual historical flood or drought event is beyond the scope of this research.

The larger spatial footprint of drought impacts than flood impacts (Fig. 5) is likely to be associated with a combination of differences in driving drought/flood meteorology and vulnerability. The driving meteorology of drought events has been shown to have a larger spatial coverage than flood events globally (He et al., 2020), and in the Southeast England in particular (Ascott et al., 2017). Vulnerability to flood impacts is highly localized towards urban areas around the river Chess such as the town of Chesham. Areas vulnerable to drought are likely to have a wider spatial extent, particularly when considering drought impacts that are not in the "surface water" class (e.g. agricultural drought impacts on rainfed crops, groundwater drought affecting boreholes and wells).

The overall consensus between reported flood and drought impacts and the sign of SPI-12 (Fig. 4) is expected, however the presence of a minority drought/flood impacts when SPI-12 is positive/negative is somewhat surprising. Inspection of the text within the original impact reports reveals the causes of this. Where SPI-12 is positive but a drought is reported, this is associated with a very short duration period of zero or negligible rainfall. For example, the following agricultural drought report from the Bucks Examiner, 26 June 1925: "Prolonged drought threatening crops. Over 20 days without rain. An 'absolute drought' is 14 days without rain and a 'partial drought' is 28 days without reasonable rain.". In this month SPI-12 = 0.33, but SPI-1 = −4.4, and it is possible that this period may be considered a "flash drought" (Noguera et al., 2025). Where SPI-12 is negative but a flood is reported, this is associated with either local drainage and water management issues (e.g. from Bucks Herald 15 September 1888 when SPI-12 = −0.35, "Bad drainage of the road between the old Blacksmith's shop and the Town's End-Road to be dealt with by installing pipes. Over the last month part of the town had been flooded.") or short duration flash flood events (e.g. from Bucks Herald 21 July 1900 when SPI-12 = −0.23 "Storm in Chesham led to streets being flooded and shops and houses flooded in the ground floors."). These examples show that short duration extreme events and specific local water management issues provide some limitations to the use of SPI-12 to predict flood and drought impacts in this catchment.

4.2. GAM performance and relationships between indices and indicators

Based on the largest DE and lowest AIC, SPI-12 is the best predictor of both flood and drought impacts when combined with smoothed month and year terms. It should also be noted, however, that in our study there is little difference in model performance metrics between the top 4 models, with models driven by SPI-12, SPEI-12, SPEI-18 and SPI-18 having a range of DE of 0.377–0.369. Differences in study area scale, catchment characteristics, research focus and heterogeneity in impact reporting make direct comparisons with previous research challenging,

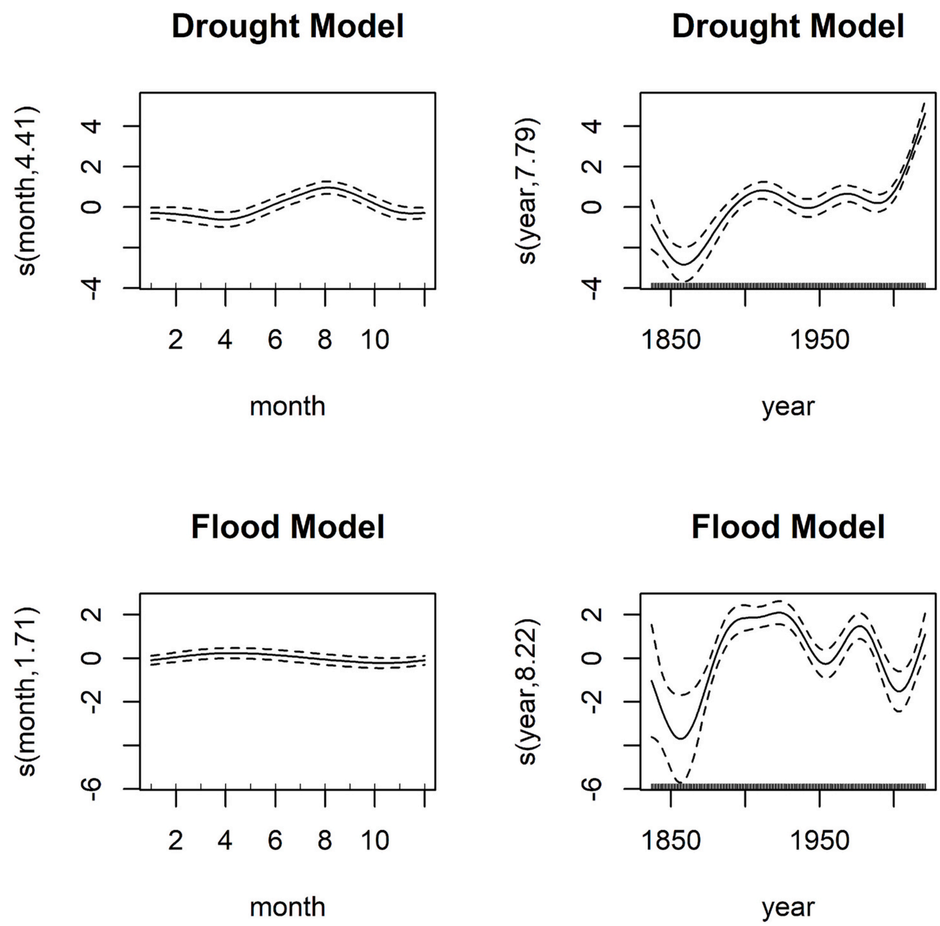

Fig. 7. Response in drought (top) and flood (bottom) impact model to month (left) and year (right) covariates.

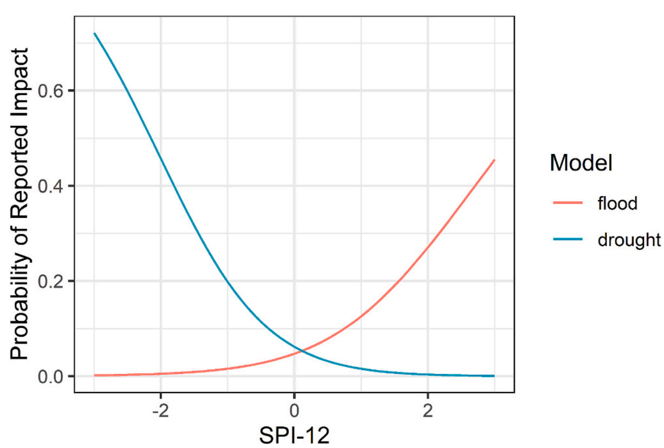

Fig. 8. Weighted probability of reported flood and drought impacts as a function of SPI-12.

and to the authors knowledge there are no logistic regression and GAM flood impact studies to compare with. In this context some general observations can be made. National scale studies in the UK (Parsons et al., 2019) and Ireland (O'Connor et al., 2023) used SPEI-6 and SPI-3/SSI-2 as drivers respectively. Differences in which indicators and accumulation periods perform best are unsurprising given the very high baseflow index of the Chess catchment and that Parsons et al. (2019) focussed on agricultural drought impacts. Stagge et al. (2015) used a range of predictors for UK drought impacts, many of which had 12 month or greater accumulation periods and were associated with groundwater dominated catchments. Our results corroborate this, but the results of Stagge et al. (2015) were also affected by a very small number of drought events for some impact classes. For the period 1893–2015, the model performance metrics are good in the context of previous work, with greater DE, AdjR^2 and AUC than previous national scale work in the UK (Parsons et al., 2019) and Ireland (O'Connor et al., 2023).

The shape of the smoothed GAM response to month agrees with the conceptual model of hydrological extremes in the catchment (Blackburn and Ascott, 2024). The greater likelihood of drought impact reports in the summer is associated with the cumulative impact of (inter)annual rainfall deficits. This was also observed in the UK by Stagge et al. (2015) and Parsons et al. (2019). In the Chess and other groundwater-dominated catchments, recharge is generally low in the summer months. Drought events are controlled by below-average winter rainfall and subsequent lack of winter recharge, with the most extreme drought events (e.g. 1975/76, UK Centre for Ecology and Hydrology (2024)) controlled by multiple successive dry winters. In the Chess this results in a reduced river length, with the source just downstream of Chesham (Fig. 1). Reported flood impacts show less seasonal fluctuation, as flash flood events in particular can occur at any time (Blackburn and Ascott, 2024). The small peak in flood impacts in spring (Fig. 7) is due to the groundwater-dominated flow regime of the Chess resulting in lags between precipitation and flood impacts. For example, flooding in spring 2001 in Chalk catchments of the UK has been attributed to a wet spring in 2000 raising groundwater levels to above average, followed by a very wet autumn/winter 2000/2001 (Finch et al., 2004). In the Chess this has caused an increased length of river with the source upstream of Chesham (Fig. 1), very high discharge and flooding of urban areas in Chesham.

The shape of the smoothed GAM response to year was variable over time. In addition to changing drought and flood vulnerability, this may

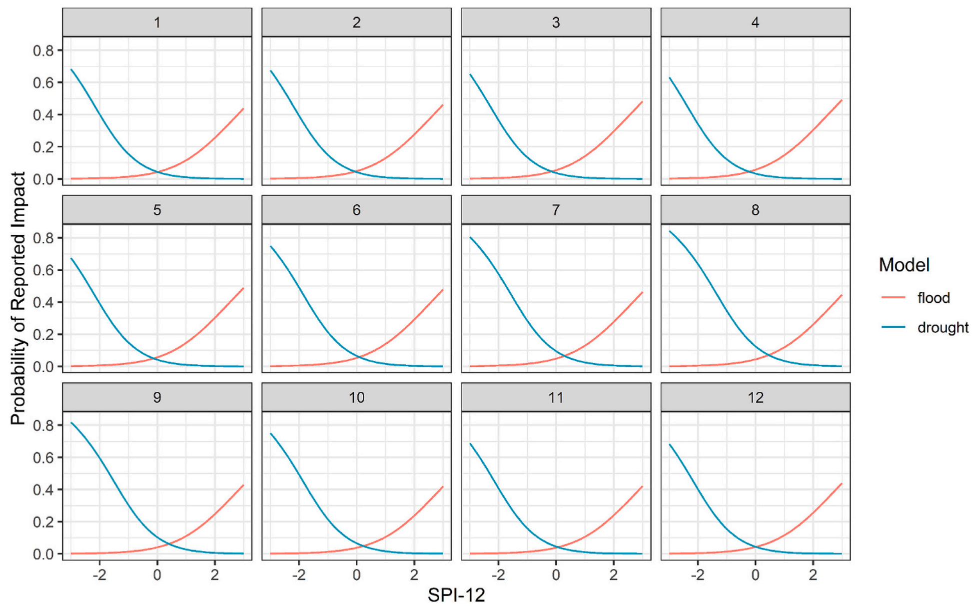

Fig. 9. Weighted probability of reported flood and drought impacts as a function of SPI-12 by month.

be attributed to variability in reporting and media awareness of hydrological extremes. The large increase in the response to year in the drought model from 2000 onwards is associated with an increased public awareness of drought and environmental issues in the UK, and in the Chess in particular (Schäfer et al., 2022), as well as increased reporting via social media.

Figs. 8 and 9 show that there is no clear threshold value of SPI-12 that is associated flood or drought impact reports, similar to the finding of O'Connor et al. (2023). Notwithstanding this, it is interesting to note that in July, August and September (Fig. 9), there is a decrease in the rate of increase of probability of drought impacts below SPI-12 $= -1.5$. The probability of reported impact for a given negative SPI-12 is also greatest in these months. In general, the shape of relationships between SPI-12 and drought and flood impact probability agree with previous work (O'Connor et al., 2023; Parsons et al., 2019), although the probabilities of drought impacts as a function of standardized indicators are slightly lower.

4.3. Participatory data collation for flood and drought impacts: strengths, limitations and an outlook for future work

This study has, for the first time, combined participatory collation of drought and flood impact reports with logistic regression with GAMs to improve our understanding of the impacts of hydroclimatic extremes at the catchment scale. For the Chess catchment, forecasting of SPI-12 in combination with the month of year may provide (albeit imperfect) insights into potential drought and flood impact likelihood in the next year. The total number of drought impact reports for the Chess catchment (331) exceeds the number of impact reports collated in the European Drought Impact Inventory for the UK as a whole and modelled by Stagge et al. (2015) (189). The number of drought impact reports in the Chess catchment is also c. 22 % of the number of impact reports for UK agriculture in the UK drought inventory (1480 reports, Parsons et al. (2019)). This highlights the fundamental importance of reporting where and when flood and drought impacts occur. It also shows the potential strength of our approach to participatory collation of impact reports at the catchment scale by local stakeholders to complement formal drought and flood impacts research.

There are, however, a number of limitations and potential areas of future work, discussed herein. Due to the nature of the bottom-up, participatory approach to collation of impact reports, the developed database may be biased towards Chesham and may not be a fully systematic search of historical reports. There may be additional sources of information which weren't uncovered during the database development. The development of the database was a voluntary initiative with hundreds of person-hours spent collating historical records; this would be challenging to resource if undertaken as part of a formal role as a researcher in the hydrological sciences. Further, it should also be noted that the Chess is a relatively small catchment with a limited number of historical publications included within the collated database (Section 2.2). Larger catchments are likely to have a much greater number of publications that would need reviewing systematically for flood and drought impact reports. Outside of the UK publications may be in multiple languages depending on the location of catchments, and different countries may have differing levels of availability of historical publications and driving hydrometeorological data to use as model predictors.

These limitations could be addressed through coordination of the collation of historic flood and drought impact records through formal citizen science initiatives. This would result in a more structured, systematic and more representative methodology. Citizen science initiatives have already proved successful in the Chess catchment (Schäfer et al., 2022) and the large increase in flood and drought reports since 2000 (Figs. 4 and 7) reflects an increased awareness and interest in hydrological extremes amongst the public and media. Specifically, we suggest that any initiative should (i) ensure that the objectives of the collation of records are well defined, (ii) set clear criteria for inclusion/exclusion of impact records, (iii) ensure there is formal documentation of when and where literature searches were made. Upscaling of the approach using citizen science initiatives could also facilitate collation of flood and drought impacts across many catchments covering different climatological and hydrogeological characteristics. In catchments less dominated by groundwater, it is likely that the best predictors for flood and drought impacts are hydrometeorological indices with shorter accumulation periods than SPI-12. The citizen science approach may also address the resource implications of collating historical records, with these methods having already been shown to be effective in the large scale “rescue” of historical weather data (Brunet and Jones, 2011; Hawkins et al., 2023).

There is clear variability in the extent of reporting of flood and drought impacts over time. Whilst some of this variability will be associated with changes in vulnerability, it should be noted that the impacts are *reported* rather than actual systematic observations. There is likely to have been changes in perceptions over time in what constitutes a drought or flood, and whether an impact is deemed worthy of reporting in the media. Evaluation of a subset of recent flood and drought media reports with on-the-ground systematic observations of impacts may be a helpful approach to evaluating the collated database. Reconstructed SSI time series for the Chess were not available as predictors in the GAM. Further work to reconstruct SSI for the Chess and use this as a potential predictor would be beneficial. Similarly, given the groundwater-dominated nature of the Chess catchment, the standardized groundwater flood index (SGFI, Ascott et al. (2017)) may be a good predictor of floods. The GAM considers floods and droughts as two separate binary outcomes weighted to the number of reports, with the explicit aim of identifying separate predictors for floods and droughts. A multinomial logistic regression model considering droughts and floods together would be an interesting area of further work.

5. Conclusions

In this research we developed a novel approach to improve understanding of historical flood and drought impacts and their hydrometeorological drivers using bottom-up participatory data collation and logistic regression with GAMs. The following conclusions can be drawn:

- Relative to the scale of the study area, the development of databases of drought and flood impacts using participatory approaches can yield substantially more impact records than previous top-down research activities.
- When combined with month and year as co-variates, SPI-12 is the strongest predictor (lowest Akaike Information Criterion and highest deviance explained) of reported flood and drought impacts.
- The models developed in this research perform favourably in comparison to previous studies, and there are no clear thresholds for drought and flood impacts associated with SPI-12.
- In combination with logistic regression with GAMs, participatory collation of impact records coordinated through citizen science initiatives offers potential to improve our understanding of the spatio-temporal distribution of the impacts of floods and droughts and their drivers in catchments worldwide.

CRediT authorship contribution statement

M.J. Ascott: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **K.A. Graves:** Writing – review & editing, Investigation, Data curation. **B. Marchant:** Writing – review & editing, Methodology. **J.P. Bloomfield:** Writing – review & editing, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2025.179608.

Data availability

Precipitation data from HadUK-Grid (Hollis et al., 2023) are available from https://catalogue.ceda.ac.uk/uuid/8a51496be92b4e9488954c7c0199f3f9/. Reconstructed groundwater levels (Bloomfield et al., 2018) are available from https://catalogue.ceh.ac.uk/id/ccfded8f-c8dc-4a24-8338-5af94dbfcc16. Potential evapotranspiration data (Tanguy et al., 2017) are available from https://catalogue.ceh.ac.uk/id/17b9c4f7-1c30-4b6f-b2fe-f7780159939c. The historic flood and drought impact reports for the Chess catchment are available from the literature cited in the text, and the database is available from the authors on request.

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