Received: 21 February 2022 | Revised: 28 October 2022 | Accepted: 18 November 2022 | Published on: 12 December 2022

DOI: 10.1002/joc.7946

RESEARCH ARTICLE

International Journal of Climatology RMetS

Relating drought indices to impacts reported in newspaper articles

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Funding information
Irish Research Council, Grant/Award Numbers: GOIPG/2017/421, COALESCE/2019/43; Irish Research Council (IRC); Irish Environmental Protection Agency, Grant/Award Number: 2019-CCRP-MS.60

Abstract

Relating drought indicators and real-world impacts is fundamental for understanding and addressing drought vulnerability. We link drought indices and impacts from newspapers compiled in the Irish Drought Impacts Database (IDID) for the period 1900–2016. For three catchment clusters across the island of Ireland we link the Standardized Precipitation Index (SPI) with land-based impacts and the Standardized Streamflow Index (SSI) with water-based impacts by matching total reported articles per month with concurrent drought indices. Using logistic regression we find SPI-3 links best with land-based impact reports, whereas SSI-2 links best with water-based impact reports. Catchments in the east/southeast display the highest sensitivity to land- and water-based impacts; however, in summer months at low deficits northwestern catchments show a higher likelihood of impact reports. In winter months the likelihood of water-based impacts is considerably greater than the land-based equivalent, particularly in east/southeastern catchments. Moreover, the likelihood of news-worthy drought impacts has changed over the 117 year period. More severe deficits are required to induce a high likelihood (0.6) of land- and water-based impacts in east/southeastern and southwestern catchments during 1961–2016 compared with 1900–1960. Largest changes emerge in the southwest with SPI-3 values of −2.51 (<−3.00) required to reach the high impact likelihood threshold in the pre (post) 1961 period. Even greater reductions are found for water-based impacts in the southwest with SSI-2 values associated with high impact likelihoods changing from −2.04 to −2.58. Conversely, for catchments in the northwest more moderate drought deficits result in high impact likelihoods for both land-based (from <−3.00 to −2.32 SPI-3) and water-based impacts (from <−3.00 to −2.29 SSI-2) for the 1961–2016 period. These findings show the value of newspaper archives for understanding regional sensitivities to drought plus their potential for underpinning a near real-time, drought monitoring and warning system in Ireland.

KEYWORDS
drought impacts, hydrological drought, Ireland, meteorological drought, newspaper records, SPI, SSI

1 | INTRODUCTION

Drought is one of the most damaging natural hazards, arising from extended periods of reduced precipitation, often covering large areas for periods of months to years, or even decades (Mishra and Singh, 2010; Van Loon and Laaha, 2015). Impacts may be experienced at local to continental scales (Wilhite *et al.*, 2007), including reduced agricultural output, freshwater shortages, ecosystem degradation, reduced energy and industrial productivity (Gil *et al.*, 2013; Mosley, 2015; Van Vliet *et al.*, 2016; García-León *et al.*, 2021). Given their effects, understanding drought events and associated impacts is crucial to successful management (Wilhite *et al.*, 2007). Typically, drought assessments involve analysing the features of historic drought in terms of their occurrence, duration, intensity and accumulated moisture deficits, expressed through drought indicators. Studies linking indicators to impacts, however, have been relatively rare, primarily due to the limited availability and spatial coverage of historical impact data (Bachmair *et al.*, 2015). Studies undertaken typically relate to agricultural drought and linking indices to historical crop yield data, with multisectoral impact assessments much sparser (Wang *et al.*, 2020). As such studies are of fundamental importance in gaining a better understanding of drought impacts, further research is warranted in this area (Bachmair *et al.*, 2016).

Indices are widely employed to quantify historic and future drought (Steinemann *et al.*, 2015; Ekström *et al.*, 2018). For meteorological drought, indices such as the Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI), Effective Drought Index (EDI), Reconnaissance Drought Index (RDI) and Palmer Drought Severity Index (PDSI) are often used (e.g., Lloyd-Hughes and Saunders, 2002; Tsakiris *et al.*, 2007; Deo *et al.*, 2017; Erfurt *et al.*, 2019; Erfurt *et al.*, 2020). For hydrological drought, indices such as the Standardized Streamflow Index (SSI), Total Storage Deficit Index (TSDI) and Palmer Hydrological Drought Index (PHDI) can be applied (e.g., Karl, 1986; Vicente-Serrano *et al.*, 2012; Nie *et al.*, 2018). Although indicators provide means of quantifying and comparing droughts (Vicente-Serrano *et al.*, 2011), their utility and representativeness of extreme events can be limited when derived from short series (Wu *et al.*, 2005). Furthermore, drought indices may not always reflect actual impacts on society and/or the environment (Bachmair *et al.*, 2016), particularly where there is modulation and propagation of hydrological droughts by catchment properties (Barker *et al.*, 2016; Rust *et al.*, 2021).

Good quality, long-term precipitation and river flow records are essential for drought analysis (Brigode *et al.*, 2016). However, most precipitation datasets are short, with observations typically commencing in the second half of the 20th century in many regions (Brunet and Jones, 2011). For river flows, available records are often even shorter (Mediero *et al.*, 2015). Data rescue efforts are continually extending the availability of observed meteorological variables including precipitation (e.g., Ashcroft *et al.*, 2018; Hawkins *et al.*, 2019; Ryan *et al.*, 2021); however, historical records for river flow are not as readily available. One means of addressing this gap is by reconstructing historic river flows using rainfall-runoff models forced with long-term temperature and precipitation series (e.g., Jones, 1984; Crooks and Kay, 2015; Spraggs *et al.*, 2015; Rudd *et al.*, 2017; Hanel *et al.*, 2018; Smith *et al.*, 2019; Noone and Murphy, 2020; O'Connor *et al.*, 2021).

Drought indicators have been extracted from reconstructed flows to assess historical droughts in a number of studies (e.g., Caillouet *et al.*, 2017; Rudd *et al.*, 2017; Hanel *et al.*, 2018; Moravec *et al.*, 2019; Erfurt *et al.*, 2020; O'Connor *et al.*, 2022). However, knowledge of drought characteristics alone does not necessarily translate into socio-economic impacts. Establishing robust links between indicators and impacts is important for evaluating and communicating drought risks. Methods have been developed to do this by associating meteorological drought indices with historic records (e.g., Vicente-Serrano *et al.*, 2012; Gudmundsson *et al.*, 2014; Bachmair *et al.*, 2015; Blauhut *et al.*, 2015; Stagge *et al.*, 2015; Bachmair *et al.*, 2018; Parsons *et al.*, 2019; Salmoral *et al.*, 2020). Others have related hydrological drought to impact metrics (e.g., Bachmair *et al.*, 2016; Sutanto and Van Lanen, 2020) by drawing on centralized databases (e.g., the European Drought Impact Report Inventory: Stahl *et al.*, 2012). National-level databases also exist, such as the UK Drought Inventory (UKCEH, 2021) and US Drought Impact Reporter (Wilhite *et al.*, 2007). In Ireland, historic monastic writings, including the Irish annals, have been used to evaluate extreme weather events and their impacts over the last two millennia (e.g., Ludlow, 2006; Hickey, 2011). More recently, Murphy *et al.* (2017) demonstrated the value of newspaper archives in an analysis of drought impacts over the past 250 years. Noone *et al.* (2017) also used newspaper collections to verify the occurrence and duration of historical droughts. The utility of newspaper articles as a source of information on drought impacts has also been demonstrated in the UK (e.g., Dayrell *et al.*, 2022) and elsewhere (e.g., Llasat *et al.*, 2009; Linés *et al.*, 2017; Brázdil *et al.*, 2019).

The SPI has been shown to be effective in generating strong links between drought occurrence and agricultural impacts (Vicente-Serrano *et al.*, 2012). Similarly, the SSI has demonstrable utility for linking hydrological drought with groundwater levels, vegetation growth, and agricultural yields (Vicente-Serrano *et al.*, 2021). Most studies explore such associations using correlation analysis, but other methods have been trialled. For example, Bachmair *et al.* (2017) found that random forest and logistic regression models predicted text-based reports of a range of drought impacts well. Similarly, Blauhut *et al.* (2015), Parsons *et al.* (2019), Stagge *et al.* (2015) and Sutanto *et al.* (2019) concluded that logistic regression could generate valuable information on localized impacts.

Although many studies have demonstrated the utility of indices in drought assessments (Kchouk *et al.*, 2021), impacts are often evaluated within a static framework under assumed stationarity. However, population change, demographic profiles, technological developments, water and land management policies, environmental conditions, water demand and social behaviour are all dynamic factors affecting drought vulnerability (Wilhite *et al.*, 2014). Recent studies have begun to address this knowledge gap. For example, Parsons *et al.* (2019) found an increasing likelihood of agriculture-related drought impact reports in the UK, which they equate to increases in actual or perceived vulnerability as a result of changing farming and reporting practices. Stagge *et al.* (2015) attributed interannual variations in agricultural drought impacts across Europe to sampling and reporting bias, changes in impact awareness, coping capacity, economic stressors and political effects. Erfurt *et al.* (2019) found that, despite meteorological drought propagation and types of impacts remaining consistent over time in southwest Germany, impacts and vulnerability have fallen.

In this paper, we relate monthly drought indicators and reported impacts for 51 catchments in Ireland. We use reconstructed catchment precipitation and river flows, alongside drought impacts derived from newspaper archives covering the period 1900–2016. Section 2 provides an overview of the datasets and methods employed, section 3 presents the results of our analysis, then section 4 provides a discussion of key results and insights. Finally, conclusions are drawn and suggestions for further research are offered in section 5.

2 | DATA AND METHODS

2.1 | Meteorological and hydrological data

Meteorological and hydrological data consist of monthly precipitation and river flow reconstructions (1767–2016), produced by O'Connor *et al.* (2021) for 51 catchments across Ireland (https://doi.org/10.1594/PANGAEA.914306). Catchment specific monthly precipitation reconstructions were extracted from the gridded ($0.5^\circ \times 0.5^\circ$) precipitation dataset developed by Casty *et al.* (2007) and bias-corrected to observed catchment data. O'Connor *et al.* (2021) also produced uncertainty estimates for flow reconstructions by applying different model structures and parameter sets; here we use the available ensemble median flow reconstruction for each catchment. Previous hierarchical cluster analysis of the SSI-1, 3, 6 and 12 during 1767–2016 identified three dominant catchment clusters for Ireland from the same 51 test catchments (O'Connor *et al.*, 2022). To allow for a comparison of results between the studies, we conduct our analysis using the same cluster groupings (see Figure 1a). Cluster 1 catchments, located in the wetter northwest of the island, have relatively small areas, low groundwater influences, and most frequent hydrological droughts. Cluster 3 catchments, located in the drier east/southeast, have relatively large groundwater contributions, large areas and the lowest frequency of hydrological droughts that, once established, result in the longest durations and greatest accumulated deficits. Cluster 2 catchments, located in the southwest, have a drought frequency intermediate between Cluster 1 and 3, with short durations and relatively low accumulated deficits. Median monthly flow and precipitation were extracted for catchments comprising each identified cluster. As per O'Connor *et al.* (2022), standardized drought indices for 1767–2016 were applied to median monthly precipitation and flow data in each cluster. These were the Standardized Precipitation Index (SPI; McKee *et al.*, 1993) and Standardized Streamflow Index (SSI; Vicente-Serrano *et al.*, 2012) over accumulations of 1, 2, 3, 4, 5, 6, 9, 12 and 18 months. These were generated using the "SCI" package in R (Gudmundsson and Stagge, 2016). The 70-year reference period (1930–1999) and the Tweedie distribution, both found by O'Connor *et al.* (2022) to perform best at fitting SPI and SSI in Irish catchments, were employed to generate indices. Extracted monthly SPI and SSI series for 1767–2016 were subsequently truncated to 1900–2016, concurrent with the derived drought impact data discussed next.

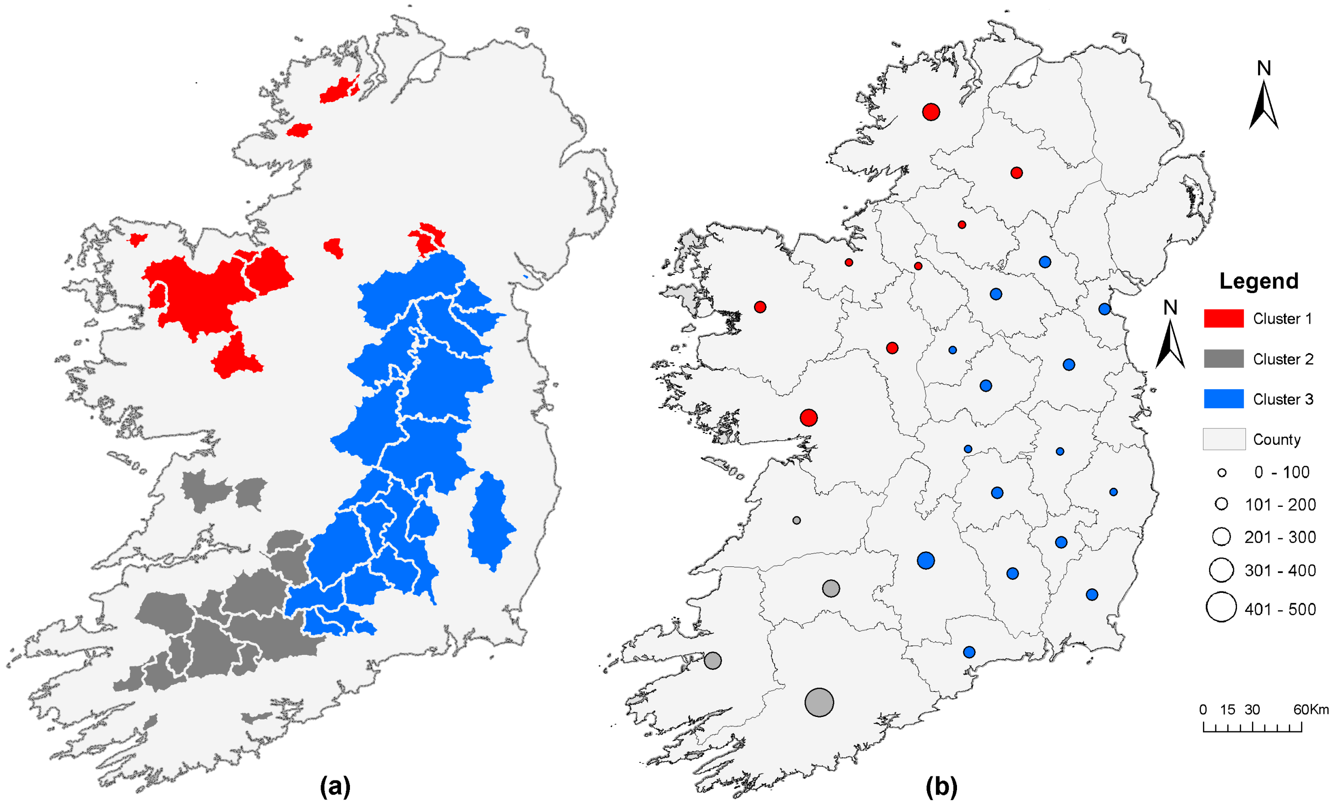

FIGURE 1 Distribution of (a) clusters of catchments used in the analysis, (b) counties and corresponding drought impact article numbers (combined land-based and water-based) over the period 1900–2016 [Colour figure can be viewed at wileyonlinelibrary.com]

2.2 | Drought impact data

Jobbová *et al.* (2022a) developed an Irish Drought Impacts Database (IDID; Jobbová *et al.*, 2022b) from the Irish Newspaper Archive (INA) spanning the period 1737–2019. The INA is an online newspaper database consisting of over 6 million pages of searchable content from 100 titles for the island of Ireland. A number of search terms were trialled (e.g., "dryness," "dry spell," etc.) with the terms "drought" and "droughts" finally chosen to identify relevant newspaper articles. All search results were assessed so as to remove articles that used the term for descriptive or other purposes resulting in a total of 6,319 drought related articles. Using a modification of European Drought Impact report Inventory (EDII; Stahl *et al.*, 2012) adapted to cater for the nature of the Irish newspaper data, returned articles were assigned to 15 drought impact categories (i.e., agriculture and livestock farming; forestry; freshwater aquaculture and fisheries; energy and industry; waterborne transportation; tourism and recreation; public water supply; water quality; freshwater ecosystem: habitats, plants and wildlife; terrestrial ecosystem: habitats, plants and wildlife; soil systems; wildfires; air quality; human health and public safety; conflicts), with the possibility of each article being assigned to one or more categories depending on impacts described. Where the described impact could be classified under multiple categories the final decision on the associated grouping(s) was determined by the authors to ensure consistency in classifications across the entire dataset. For each drought impact, that is, the occurrence of an article that references a specific impact related to a drought event and fitting to one of the pre-defined impact types, information including the date of publication, date of impact, location, newspaper title and a quote from the article were all included in the database.

In total, more than 11,000 individual drought impact reports are included in the IDID dataset. The number of titles contributing to the INA remains relatively stable for the period post-1900, while having good spatial coverage across Irish counties. Therefore, we employ output from the IDID for the period 1900–2016, concurrent with the last year of available meteorological and hydrological data. Of the 15 drought impact categories 13 were further grouped into two simple categories signified as land-based impact reports (related to agriculture and livestock farming, terrestrial ecosystems, soil systems, wildfires, air quality and forestry) and water-based impact reports (related to aquaculture and fisheries, waterborne transport, energy and industry, tourism and recreation, public water supply, water quality and freshwater ecosystems). Human Health and Public Safety, and Conflicts were not retained due to a lack of articles in those categories for the chosen study regions and difficulties associating related articles consistently with land- or water-based impacts. We matched the associated year and month of each reported impact in the IDID to the drought indices on that date. Impact reports which did not include a year and month of impact were excluded from the analysis. Impact reports in the IDID are not systematically compiled for catchments, therefore, we tallied reports for each county, the boundaries of which have remained largely unchanged over the period of assessment, and assigned them to one of our three clusters of catchments (see Figure 1b). Impact reports that did not provide a specific location or from which the relevant county could not be derived were also omitted. When a county straddles two clusters of catchments, impact reports are associated with the cluster overlapping the largest area of that county. Counties with no study catchment(s) contained within their boundaries (five in total) were excluded from the assessment. An inventory of article numbers, by county, allocated cluster, and drought impact subcategory is given in Table S1, Supporting Information. For each cluster, the cumulative number of drought impact reports were then calculated for each month from 1900 to 2016.

2.3 | Model generation and analysis

Logistic regression and Generalized Additive Models (GAMS) have been previously used to link drought indices to impacts (Stagge *et al.*, 2015; Bachmair *et al.*, 2017; Parsons *et al.*, 2019). We take a similar approach by applying binomial logistic regression models to establish relationships between SPI and SSI indices with drought impact occurrence (based on article counts). First, we transform the dependent variable (impact articles) into a binary series by noting the occurrence/nonoccurrence of articles. Logistic regression was then used to determine the odds of event occurrence (impact article), by relating the conditional expectation of the response variable to a combination of linear predictor variables (drought indices). This link was obtained using a logit, or log odds function (Equation (1)) typically applied to derive the probability or likelihood of occurrence of a sample observation, $P(X)$, from regression models (see Peng *et al.*, 2002),

$$\mathrm{logit}(P(X)) = \ln\left(\frac{P(X)}{1-P(X)}\right). \tag{1}$$

Logistic regressions were fit using the Generalized Additive Model (GAM) framework which enables logistic regressions to be applied with a smoothing function for selected predictor variables (month values) to account for nonlinear components in series (e.g., the seasonal components of monthly SPI/SSI values). To convert the log-odds predicted output to a simple likelihood output (i.e., to generate impact likelihood values in the range from 0 to 1) the inverse logit of the predicted values were found. Values could then be easily categorized by their likelihood of impact and assessed for each model.

Model fitting and subsequent predictions were carried out in the R environment using the "mgcv" package (Wood, 2012). Individual models were generated for each cluster linking SPI values to land- and SSI values to water-based articles. Model predictor variables included standardized drought indices, smoothed month values and year values. Month values account for seasonal variations in drought impact reporting likelihoods, while year values allow for any trends in the data (cf., Parsons *et al.*, 2019).

Weights were derived and then applied to each model to account for cases where more than one drought impact article occurred in a given month. For each model we determined the weights by reciprocally ranking the total monthly number of articles. The procedure was as follows: Step 1, the date (month/year) with the highest number of articles was ranked as one (rank1 = 1), the second highest as two (rank2 = 2) and so forth, until all dates were assigned a rank. Dates with the same number of articles were given the same rank, including dates with zero articles which were assigned the lowest rank. Step 2, the Reciprocal Rank was found for this series of ranked values, as shown in Equation (2), with i representing the rank number, Q representing the total number of distinct article values. Step 3, the resultant series of values was then applied as the weighting factor in the final model, in the order of the original time-series,

$$\text{Reciprocal rank} = \sum\nolimits_{i=1}^{Q} \frac{1}{\mathrm{rank}_i}. \tag{2}$$

Reciprocal ranked weights were determined separately for each model. Dependent variable values for each model were represented by the binary occurrence/nonoccurrence of monthly drought impact articles (land- or water-based) for each cluster, with final model output returning the likelihood of occurrence of articles for given SI values.

Following Parsons *et al.* (2019), we test the model by initially generating logistic regression models with a single predictor consisting of either SPI or SSI at accumulations of 1, 2, 3, 4, 5, 6, 9, 12 or 18 months. Only one drought index accumulation period was considered in each model as indices for overlapping periods tend to be highly correlated. Model performances were assessed using the different accumulation periods, with best performing accumulation periods for each cluster identified for the 1900–2016 period and retained. Model performance was assessed by evaluating the amount of explained variance, adjusted for sample size (R2adj). Subsequently, models were regenerated with the inclusion of smoothed monthly values (to account for seasonality of reported impacts) as well as year (to account for any trend). Smoothing was carried out using the Restricted Maximum Likelihood (REML) approach to estimate components of variance resulting from the unbalancing caused by the nonlinear, seasonal impacts of the monthly data. Models were then re-evaluated to examine improvement in skill.

For each cluster, models were used to relate SPI and SSI to predicted impact report likelihoods, that is, the probability of a drought related newspaper article for a given SPI or SSI value. To aid interpretation, we classify reported impact likelihood scores as follows: "very low" (0–0.19), "low" (0.20–0.39), "medium" (0.40–0.59), "high" (0.60–0.79) and "very high" (0.80–1.00). We primarily focus on the high threshold (≥0.60) as it represents an above average likelihood of impact report occurrence. We identify temporal and spatial variations in drought impact reports for each catchment cluster over the full 117 years using SPI and SSI values at that threshold and at the lower limit of −3 SI, matching that used by Parsons *et al.*, 2019. We also investigate the variation in reported impact likelihoods at annual and monthly timescales with the latter allowing for assessment of how reported impacts change within clusters over the course of a year. Annual values were derived by finding the mean of monthly likelihoods for each year across the 1900–2016 period. Finally, we assess homogeneity in reported drought impact likelihoods by identifying any significant change points in the drought impact report series for each cluster, using the nonparametric Pettitt (1979) test. Theil–Sen slope estimates (Sen, 1968) were also calculated to identify significant trends in the series. We subsequently investigate how impact report likelihoods (for SPI and SSI values of −3) and SPI and SSI values required to exceed the high likelihood (0.6) threshold have changed in each cluster, pre/post identified break point.

3 | RESULTS

3.1 | Indices and impact data

SPI and SSI were derived for each cluster for the period 1900–2016 for accumulations of 1, 2, 3, 4, 5, 6, 9, 12 and 18 months (sample plots are shown in Figures S1 and S2). Across the period several extreme events emerge in both the SPI and SSI series, and over multiple accumulation periods. These include the 1933–1935, 1953–1954, 1971–1972 and 1975–1977 droughts. Other prominent events in the SPI series are less notable in the SSI equivalent, such as the 1911–1912 and 1983–1984 droughts, while events such as the 2003–2004 drought show greater prominence in the SSI series. Figure 2 plots the annual number of articles by cluster over the period 1900–2016. Notable are the high counts of articles for Cluster 3 and the large decrease in land-based drought reports in both Clusters 1 and 2 during recent decades. Some of the largest meteorological and hydrological drought article numbers occur in 1921, 1938, 1940, 1949, 1959, 1975 and 1984. Differences in article numbers for certain events are identifiable between clusters and article types. Although most droughts coincide with article occurrence (e.g., the 1911–1912 and 1975 droughts) others show fewer impact reports, despite being classified as severe or extreme droughts by the standardized indices (e.g., the 1933–1934 and 1972–1973 droughts). Conversely, events such as the 1921 and 1949 droughts do not rank as significant droughts in SPI- and SSI-12 series despite producing some of the highest number of drought impact reports. It should be noted, however, that the level of agreement between drought impact reports and indices depends on the accumulation period applied.

3.2 | Model performance analysis

Logistic regression and GAMs show the relationship between SPI/SSI and land-/water-based impact reports in each cluster. Figure 3 displays results of this assessment with R2adj values for different SPI/SSI accumulation periods plotted for land- and water-based impact reports (lighter coloured bars). For water-based impact reports SSI-2 performed best across all three clusters (R2adj values of 0.14 ($p < .05$; Cluster 1), 0.18 ($p < .05$; Cluster 2) and 0.25 ($p < .05$; Cluster 3)). For land-based impact reports SPI-3 performed best having the highest R2adj score for Cluster 1 (0.10; $p < .05$) and 3 (0.17; $p < .05$). For Cluster 2, SPI-2 performed marginally better than SPI-3 (0.11; $p < .05$) vs. (0.10; $p < .05$). For simplicity, SPI-3 was adopted as the best predictor of land-based drought impact reports in all clusters.

Following Parsons *et al.* (2019), both month and year predictor variables were added to each of the best performing single variable models (i.e., SPI-3 and SSI-2), with monthly smoothing implemented using the REML method (see section 2.3). Model performance was again assessed using R2adj, with results presented in Figure 3 (darker coloured bars). Across all clusters, inclusion of month led to significant model improvements. Final model structures for land- and water-based drought impact reports are given in Equations (3) and (4), where $P(X)$ represents the likelihood of occurrence of a land-based

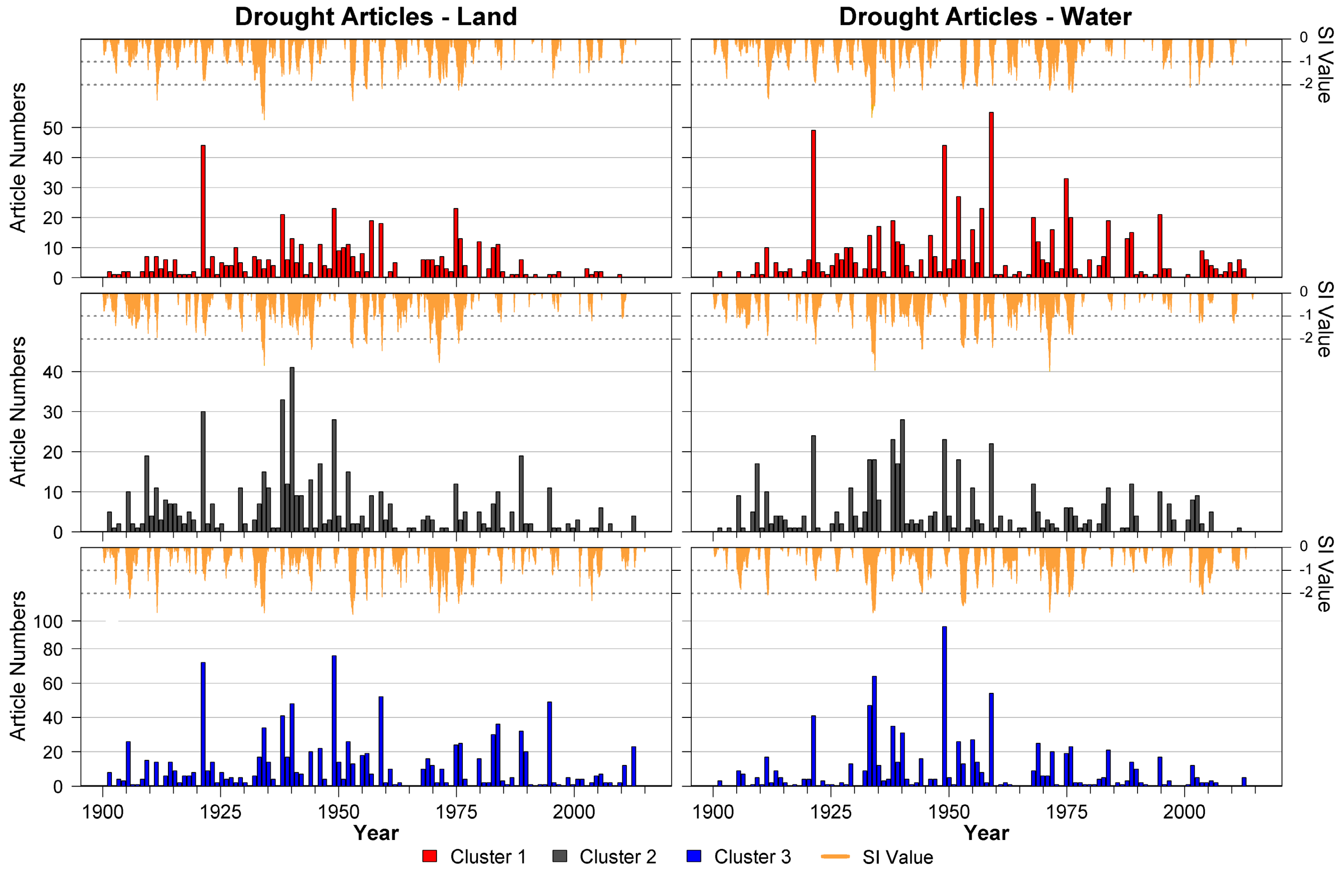

FIGURE 2 Distribution of land-based (left) and water-based (right) drought impact reports (annual totals) for each cluster (bottom of each panel) are displayed for the period 1900–2016. Also displayed are related SI values (top of each panel; SPI-12 on the left and SSI-12 on the right) [Colour figure can be viewed at wileyonlinelibrary.com]

(X_{land}) or water-based (X_{water}) drought impact report, β_0 is the intercept value, β_1 and β_2 are the indices and year coefficient values, $s()$ is the smoothing function applied to the month value and ε is the standard error. Additional performance metrics are provided in Table 1. For reported land-based impacts (Equation (3)) model performance is best for Cluster 3 (R2adj = 0.49; $p < .05$), with Cluster 1 and 2 having R2adj values of 0.34 ($p < .05$). For reported water-based impacts (Equation (4)) model performance is greater than the land-based equivalent for Cluster 1, 2 while for Cluster 3 it is lower, with R2adj values of 0.38, 0.35 and 0.42, respectively (all with p-values of <.05),

$$\operatorname{logit}(P(X_{\text{land}})) = \beta_0 + \beta_1(\text{SPI-3}) + s(\text{month}) + \beta_2(\text{year}) + \varepsilon, \tag{3}$$

$$\operatorname{logit}(P(X_{\text{water}})) = \beta_0 + \beta_1(\text{SSI-2}) + s(\text{month}) + \beta_2(\text{year}) + \varepsilon. \tag{4}$$

Receiver operator characteristic (ROC) curves, which demonstrate the ability of models to correctly predict the occurrence or nonoccurrence of an event, are shown in Figure 4 (see Stagge *et al*., 2015 for a similar application). Values are assessed for increasing thresholds across the [0–1] range. For a perfect model the proportion of correctly identified impact articles is equal to 1 across all threshold values and will have an area under the curve (AUC) value of 1. A model with zero skill produces an AUC of 0.5 and will lie on the diagonal (0:1) line. Here, both land- and water-based models show good skill at correctly classifying drought impact reports, with the former performing marginally better overall. For land-based impact reports AUC scores are highest for Cluster 3 (0.90) and lowest for Cluster 2 (0.85). For water-based impact reports AUC scores are highest for Cluster 1 and 3 (0.87) and lowest for Cluster 2 (0.85).

3.3 | Linking indices to reported impacts

Derived models were used to determine the likelihood of impact reporting at annual and monthly timescales. Initially, an examination of outputs from models generated using annualized SPI and SSI at 1, 2, 3, 4, 5, 6, 9, 12 and 18 month accumulations was carried out revealing that

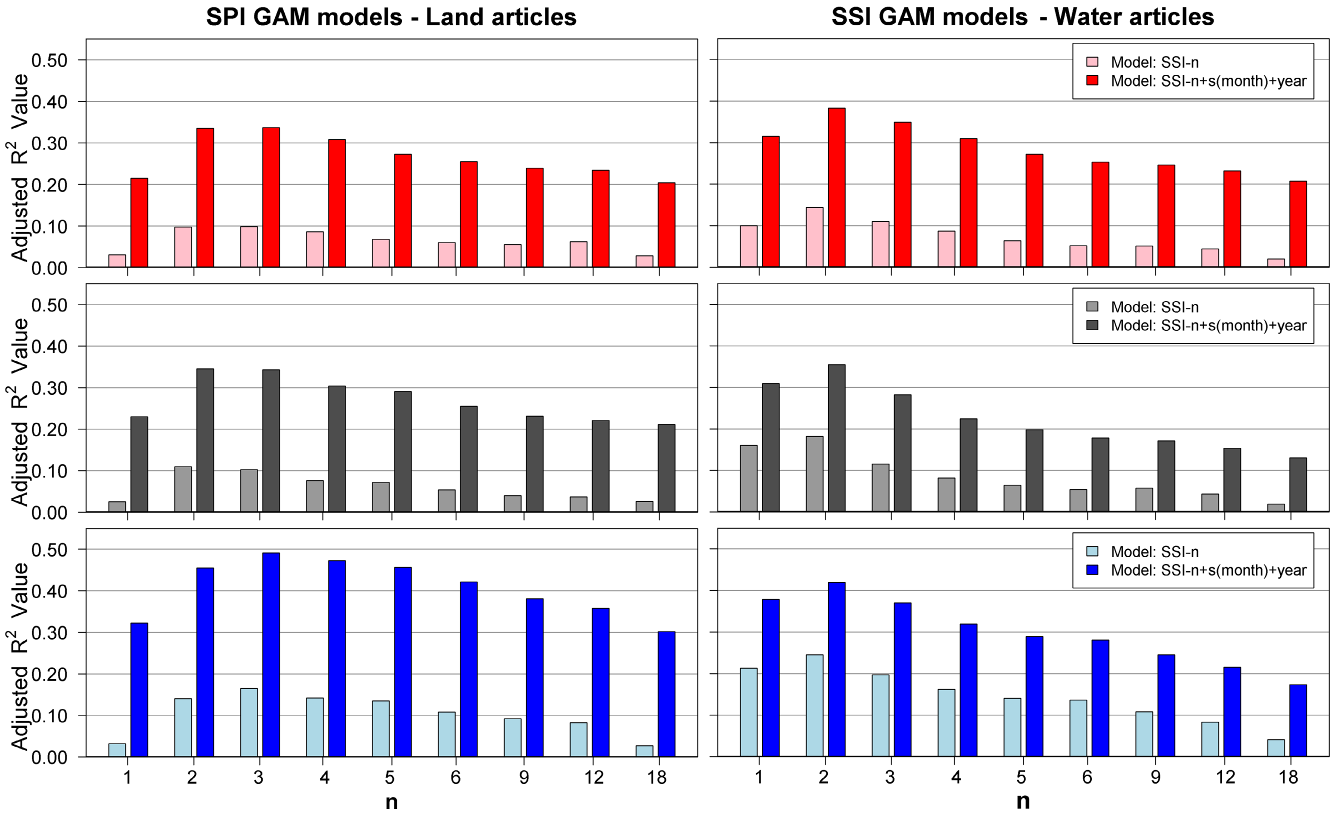

FIGURE 3 Adjusted R^2 values of the logistic regression models for selected SPI/SSI accumulation periods (n) when simulating monthly land-based (left) and water-based (right) impact articles for each cluster during 1900–2016. Results are also shown for models including month and year (darker colours) [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 1 Performance indicators for land-based impact article models ($\beta_0 + \beta_1$(SPI-3) + s(month) + β_2(year) + ε) and water-based impact article models ($\beta_0 + \beta_1$(SSI-2) + s(month) + β_2(year) + ε) generated for each cluster over the 1900–2016 period

Model	Cluster no.	Intercept coeff. (β_0)	Indices coeff. (β_1)	Year coeff. (β_2)	Adjusted R^2	p-value	% deviance	AUC	AIC	BIC
SPI-3 + s(month) + year	1	17.30	−1.11	−0.01	0.34	0.001	35.07	0.87	13.61	46.49
	2	25.11	−1.04	−0.01	0.34	0.001	33.55	0.85	13.27	46.24
	3	21.34	−1.43	−0.01	0.49	0.002	45.94	0.90	12.90	46.00
SSI-2 + s(month) + year	1	2.64	−1.28	0.00	0.38	0.001	37.90	0.87	13.42	46.39
	2	19.30	−1.37	−0.01	0.35	0.001	34.36	0.85	12.71	44.68
	3	20.22	−1.58	−0.01	0.42	0.002	38.21	0.86	12.35	43.83

SPI-3 and SSI-2 generated the highest likelihoods of drought impacts across clusters, specifically at low deficits. Impact likelihood values reduced markedly for accumulations above and below 3 and 2 months, respectively. Notably, the patterns of change in values across clusters remained similar for all accumulations. As SPI-3 and SSI-2 produced the highest impact likelihoods and best model performances for land-based and water-based impact reports they were retained for further analysis. Figure 5 shows the predicted likelihood of reported impacts on an annual basis over the period 1900–2016. Cluster 3 has the highest reported impact likelihoods for both SPI and SSI values. Clusters 1 shows the lowest reported impact likelihoods for any given SPI value. For SSI-2, Cluster 1 shows a higher likelihood of impact reports than Cluster 2 for modest deficits, while the opposite is the case for more extreme SSI-2 deficits. Figure 5 also identifies SPI/SSI thresholds resulting in at least a high likelihood of impact reports (0.60). For land-based impacts SPI-3 ≤ −2.68 for Cluster 1, ≤ −2.35 for Cluster 2 and ≤−1.98 for Cluster 3 result in at least a high impact likelihood on an annual scale. For water-based impacts

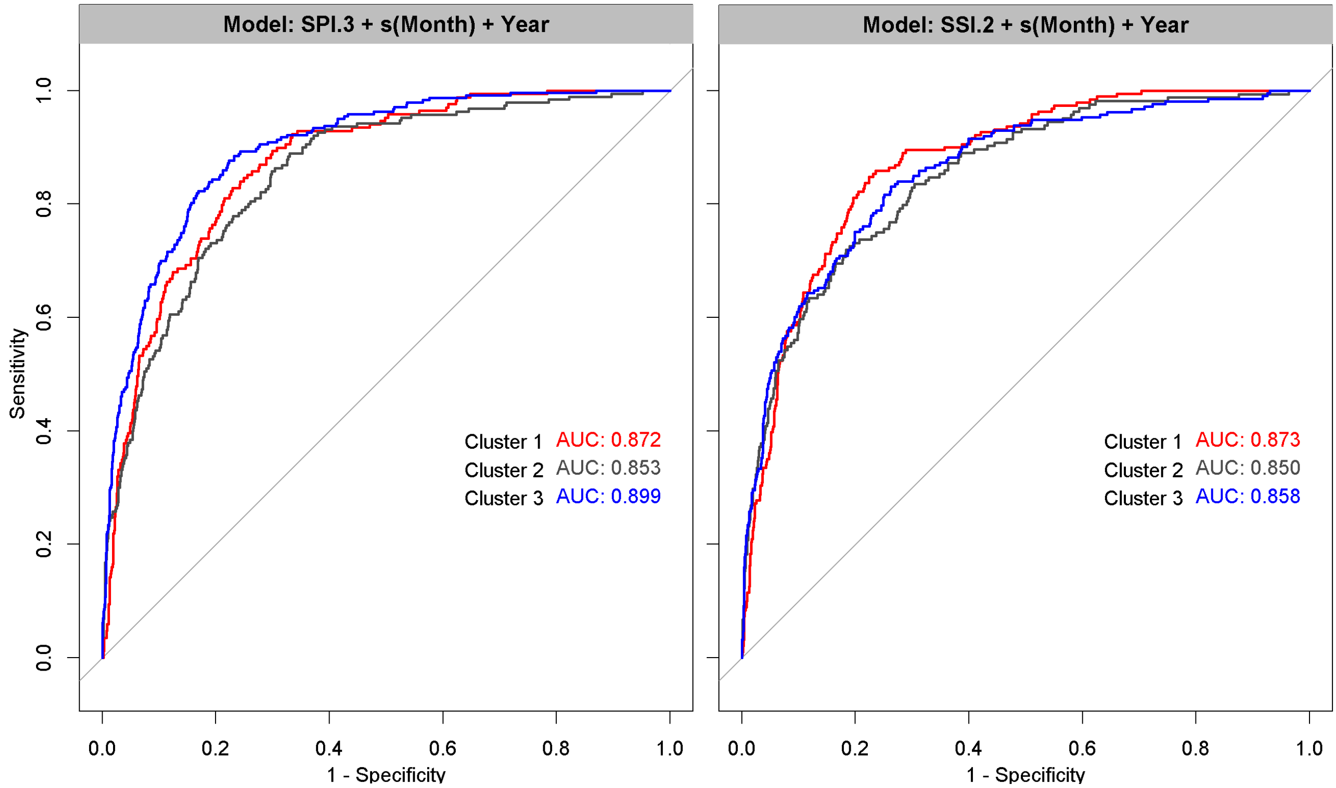

FIGURE 4 Receiver operating characteristic (ROC) curves displaying performance of the logistic regression models generated using land-based newspaper articles and SPI-3 indices (left) and for models generated using water-based newspaper articles and SSI-2 indices (right) for each cluster [Colour figure can be viewed at wileyonlinelibrary.com]

the equivalent values are SSI-2 ≤ -2.48 for Cluster 1, ≤ -2.02 for Cluster 2 and ≤ -1.60 for Cluster 3. Cluster 3 is identified as most likely to experience both land- and water-based drought impact reports, whereas Cluster 1 is least likely. Indices values required to reach each land- and water-based drought impact report threshold are given in Table 4.

Figure 6 displays results of the monthly land-based drought impact report analysis. There are large variations in the propensity for reported impacts across months and clusters. December and January show very low to low impact report likelihoods, even for extreme deficits in SPI-3. February is the winter month with highest land-based values, reaching a moderate likelihood for deficits of -3 SPI-3 in Cluster 2 and a high likelihood in Cluster 3. Excluding December, Cluster 3 consistently shows the highest propensity for impact reporting in all months. The 0.6 threshold (dashed black horizontal lines) helps identify SPI-3 deficit values resulting in a high likelihood of impact reports. Notably, in summer (JJA) months only very modest SPI-3 deficits (not less than -1.2 SI) are required to reach this threshold for land-based impact reports in Cluster 3. July (closely followed by June) is the month most prone to reported impacts, with the most modest SPI-3 deficits resulting in high impact report likelihoods (-0.90 for Cluster 1, -0.73 for Cluster 2 and -0.28 for Cluster 3). In autumn (SON), the SPI-3 deficits required to reach the high impact threshold become more extreme, with Cluster 3 remaining the most vulnerable. Throughout most months (excluding winter) there is little difference in land-based drought impact likelihoods between Clusters 1 and 2.

Figure 7 displays monthly likelihoods for water-based impact reports. Cluster 3 shows the highest propensity for reported impacts across all months, particularly in autumn (SON), winter (DJF) and early spring. However, differences with Cluster 1 and 2 during late spring and summer, especially from May to August, are minimal, with Cluster 1 showing higher likelihood of impacts at low deficits during these months. From June through to August Cluster 2 is least sensitive to water-based impact reports. Late autumn and winter months show the greatest differences between clusters with the possibility of water-based impacts in Cluster 3 markedly greater than that for Cluster 1 and marginally greater than Cluster 2 from October till March. Cluster 3 consistently reaches the 0.6 high likelihood of reported impacts threshold across the year, but only for extreme SSI-2 deficits in winter months. During summer months, deficits of close to -1 SSI-2 are required to reach that same threshold in most clusters. July is the

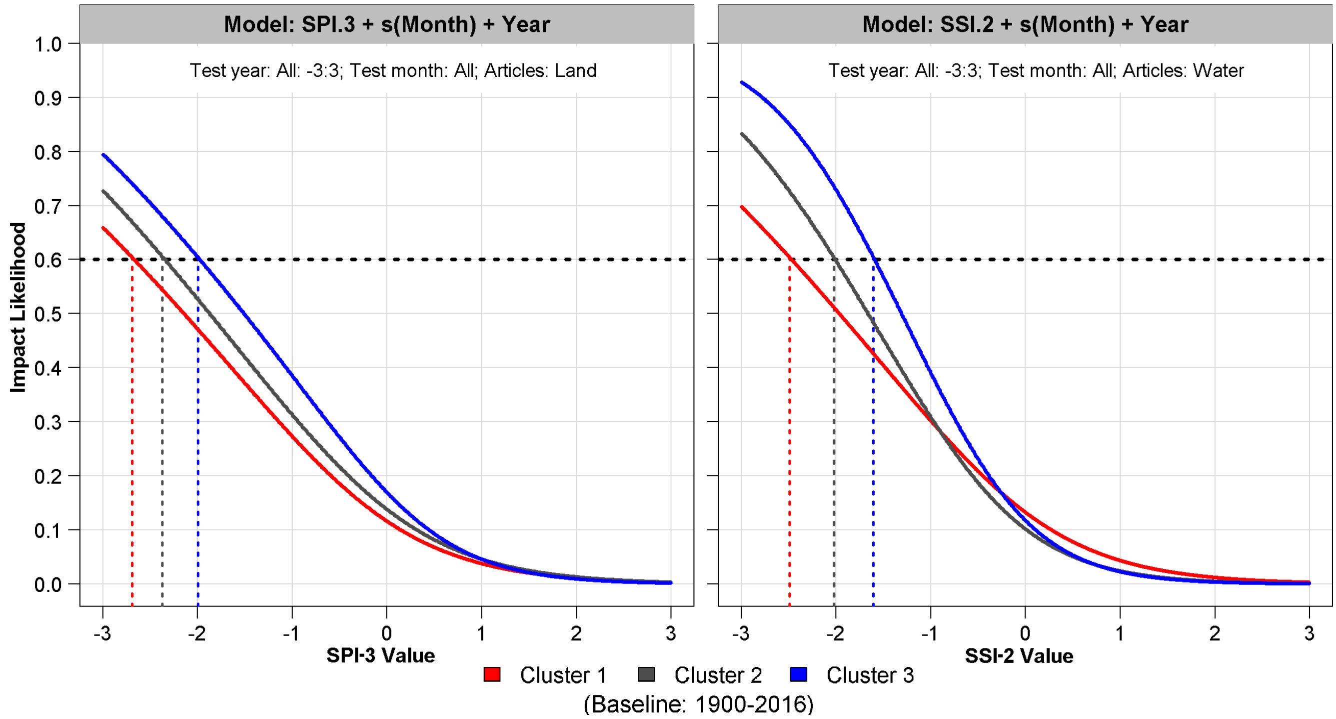

FIGURE 5 Predicted likelihood of reported impacts (annual) from models generated using land-based impact articles and SPI-3 indices (left) and from models using water-based impact articles and SSI-2 indices (right). Impact likelihoods for each cluster over the period 1900–2016 are shown for indices values ranging from −3 to 3. Indices values resulting in high reported impact likelihoods (0.60) are denoted by the dashed horizontal line [Colour figure can be viewed at wileyonlinelibrary.com]

month most prone to water-based impact reporting, with the most modest SSI-2 deficits resulting in high impact report likelihoods (−0.72 for Cluster 1, −0.98 for Cluster 2 and −0.80 for Cluster 3). The lowest reported impact likelihoods are in December for Cluster 1 (very low likelihood) and January for Clusters 2 and 3 (moderate and high likelihoods) for SSI-2 values of −3.

3.4 | Sensitivity of results to impacts baseline

All clusters display a negative year coefficient (β_2) for land- and water-based impact reports, with the exception of Cluster 1 for water-based reported impacts (Table 1). Significant negative trends across all clusters were confirmed using Theil–Sens slope testing, again with the exception of water-based reported impacts for Cluster 1. This suggests that during the 1900–2016 period there was an overall decline in reported drought impacts. According to the Pettitt test, there are notable step changes in the number of impact articles for each cluster and impact type, with statistically significant changes ($p < .05$) identifiable in the land-based articles (see Table 2).

In Cluster 1 a significant downward step change in land-based drought impact articles was identified in 1985. In Cluster 2 and 3 significant downward changes were identified in 1961. For reported water-based drought impacts, no significant changes (0.05 level) were found. Given the prominence of 1961 as a step change in drought impacts series, we evaluate the changing likelihood of reported impacts pre and post-1961. Table 3 shows model results and coefficients for the pre/post-1961 periods. Modest reductions in skill between the 1900–1960 and 1961–2016 periods are evident with greatest reductions in R2adj for land-based impact report models occurring in Cluster 2 (from 0.36 to 0.25; both $p < .05$). The largest reduction in R2adj for water-based impact models occurs for Cluster 3 (from 0.46 to 0.31; both have $p < .05$). The smallest change in R2adj between periods occurs for Cluster 1, land-based impact models. AUC scores show little change relative to the earlier period. Reductions in model performance post-1961 can be partially attributed to reduced occurrence of drought in the latter period as identified by Noone *et al.* (2017), while article numbers also fall by 59% (Cluster 1), 69% (Cluster 2) and 46% (Cluster 3) for land- and 40% (Cluster 1), 58% (Cluster 2) and 63% (Cluster 3) for water-based impact reports.

Figure 8 shows annual results for reported impact likelihoods for land- and water-based drought, with groupings A and B representing results derived from the 1900–1960 and 1961–2016 baseline periods, respectively,

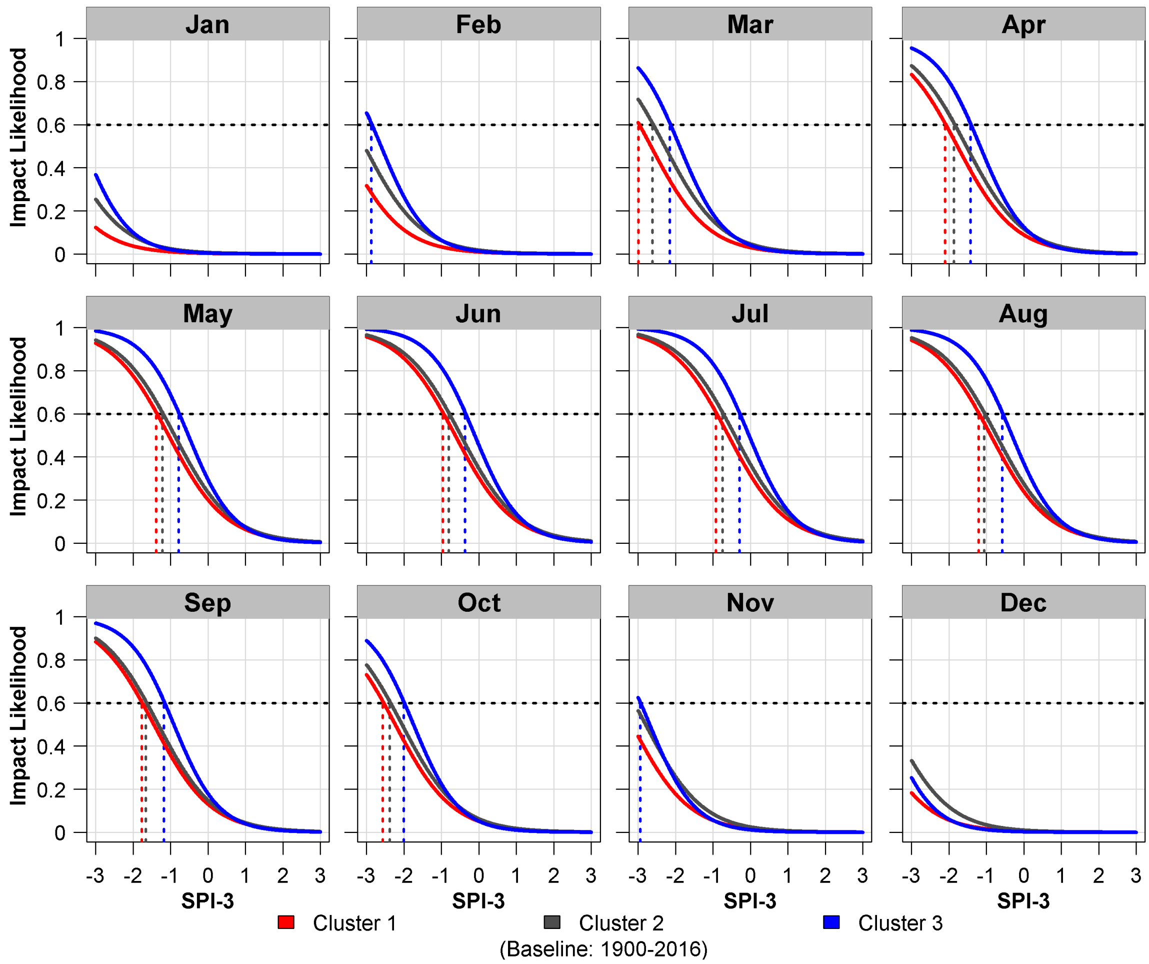

FIGURE 6 Predicted likelihood of reported impacts (monthly) from models generated using land-based impact articles and SPI-3 indices. Impact likelihoods for each cluster over the period 1900–2016 are shown for indices values ranging from −3 to 3. Indices values for each cluster resulting in a high reported impact likelihood (0.60) are also identified (dashed horizontal line) [Colour figure can be viewed at wileyonlinelibrary.com]

for Clusters 1, 2 and 3. Differences between reported impact likelihood curves are apparent for all three clusters and both impact categories, but are greater for land-based impact reports where agricultural and livestock farming dominate (91 and 79% of land-based reports across all clusters for the 1900–1960 and 1961–2016 periods, respectively). For both Clusters 2 and 3 the 1961–2016 period returns lower likelihoods of drought impact reports. For Cluster 1, however, larger SPI-3 deficits produce a greater likelihood of impact reporting for the 1961–2016 period, while for values closer to zero the risk is higher for the 1900–1960 period, indicating that the possibility of reported impacts has increased for extreme droughts and decreased for more moderate droughts. For SSI-2 both Cluster 2 and 3 show lower likelihoods of reported water-based drought impacts for the 1961–2016 period, however the reduction is not as large as seen for land-based impacts. Cluster 1 also shows a higher likelihood of water-based impact reports for the 1961–2016 period but only at larger SSI-2 deficits.

The reduction in impact report likelihoods for the 1961–2016 period is reflected in an increase in deficits required to reach the high likelihood of impact threshold (0.6), with differences greatest in Cluster 1 catchments. For Cluster 3 land-based impact reports, the SPI-3 value associated with a high likelihood of impact reporting changes from −2.08 SPI-3 for 1900–1960 to −2.63 SPI-3 for 1961–2016. For water-based drought in the same cluster, values change from −1.65 to −2.06 SSI-2. For Cluster 2 catchments, high impact likelihoods for land-based articles occur at −2.51 SPI-3 for the 1900–1960 period and <−3.00 SPI-3 for the 1961–2016 period. Water-based impact reports change from −2.04 to −2.58 SSI-2. The largest change in deficit thresholds returning high likelihoods of reported impacts is in Cluster 1 for both land- and water-based droughts (<−3.00 to −2.32 SPI-3 and <−3.00 to −2.29 SSI-2). Table 4 provides a cluster specific

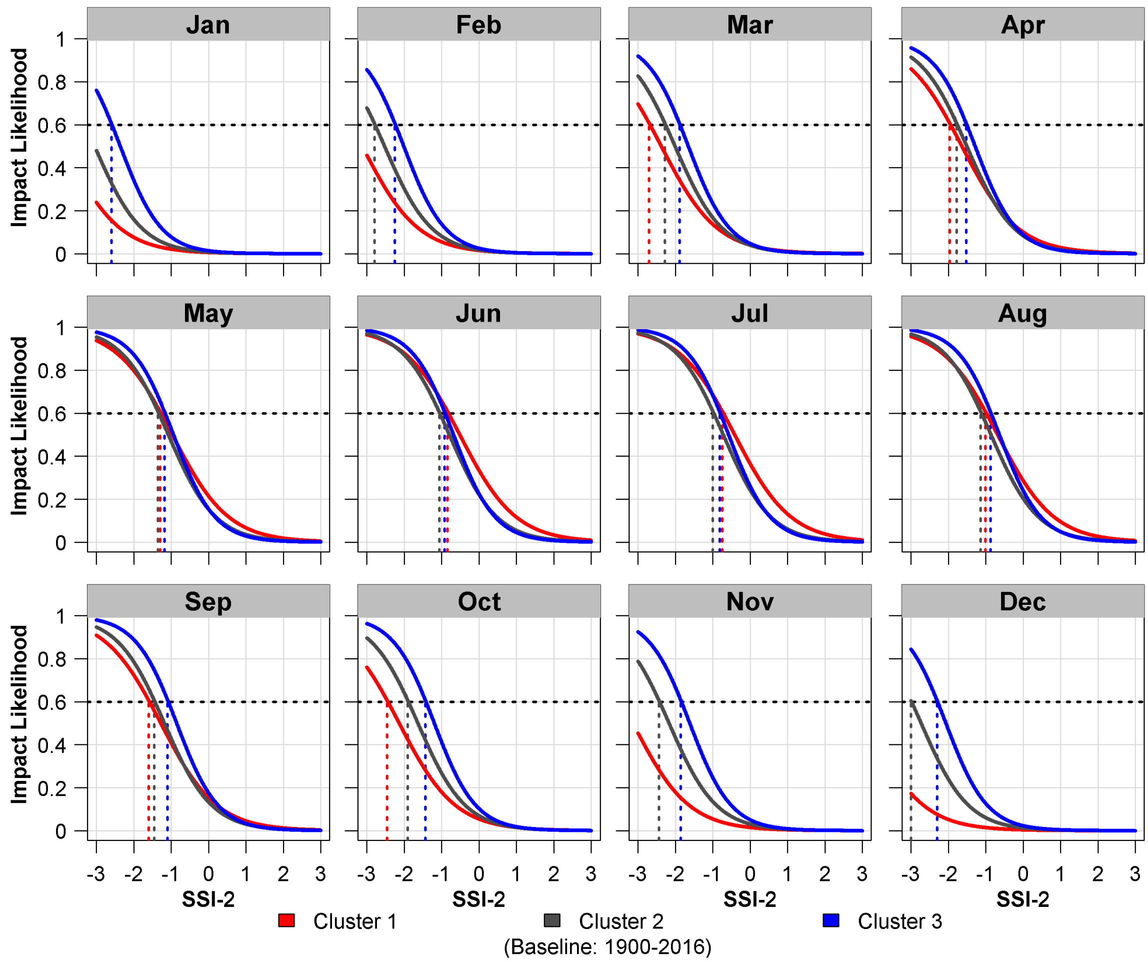

FIGURE 7 As in Figure 6 but for water-based impact articles and SSI-2 indices [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 2 Step change month and year identified for land- and water-based impact articles grouped by each cluster over the 1900–2016 period

Article type	Cluster	Month	Year	*p*-value	Direction
Land-based	1	6	1985	.03	Downward
	2	7	1961	.01	Downward
	3	9	1961	.02	Downward
Water-based	1	8	1977	.47	Downward
	2	6	1961	.18	Downward
	3	10	1959	.08	Downward

breakdown of SSI-2 and SPI-3 values required to reach each impact threshold.

Figures 9 and 10 repeat the analysis on a monthly basis for land- and water-based reported impacts, respectively. The likelihood of land-based impacts being reported in Clusters 2 and 3 is consistently lower for all months for the 1961–2016 period, with the exception of January for Cluster 3. The opposite is the case for Cluster 1 where at larger deficits the latter period displays greater likelihoods of reported drought impacts while at more modest deficits the earlier period dominates from April to October. For the 1961–2016 period, high likelihoods of impact reporting are most easily attained in June for Cluster 1 and July for Cluster 2 and 3 with corresponding SPI-3 values of −1.38, −1.56 and −0.93, compared to −0.75, −0.51, 0.01 (all in July) for equivalent values derived from the 1900–1960 period. The lowest likelihood of reported impacts is in January for all Clusters, with the exception for Cluster 3 (1961–2016) which occurs in December. All clusters have low to very low impact report likelihoods at −3 SPI-3. Between baseline periods, impact reporting also differs markedly for water-based

TABLE 3 Performance indicators for land-based impact article models ($\beta_0 + \beta_1$(SPI-3) + s(month) + β_2(year) + ε) and water-based impact article models ($\beta_0 + \beta_1$(SSI-2) + s(month) + β_2(year) + ε) generated for each cluster over the 1900–1960 and 1961–2016 periods

Model (period)	Cluster no.	Intercept coeff. (β_0)	Indices coeff. (β_1)	Year coeff. (β_2)	Adjusted R^2	p-value	% deviance	AUC	AIC	BIC
SPI-3 + s(month) + year (1900–1960)	1	−42.10	−1.01	0.02	0.37	.028	36.46	0.87	13.52	42.02
	2	−0.51	−1.01	0.00	0.36	.007	31.98	0.83	12.87	41.14
	3	−15.39	−1.48	0.01	0.52	.007	48.66	0.90	12.54	40.98
SSI-2 + s(month) + year (1900–1960)	1	−65.10	−1.34	0.03	0.47	.025	45.23	0.90	13.28	41.91
	2	−2.82	−1.36	0.00	0.37	.003	34.27	0.83	12.36	39.75
	3	−25.41	−1.66	0.01	0.46	.001	41.69	0.86	11.97	38.98
SPI-3 + s(month) + year (1961–2016)	1	50.52	−1.37	−0.03	0.36	.053	38.54	0.89	11.80	38.41
	2	6.27	−1.02	−0.01	0.25	.007	30.63	0.87	11.87	38.64
	3	−0.91	−1.28	0.00	0.41	.007	40.85	0.89	11.92	38.81
SSI-2 + s(month) + year (1961–2016)	1	11.63	−1.28	−0.01	0.34	.027	34.58	0.86	11.76	38.27
	2	19.80	−1.22	−0.01	0.28	.000	29.91	0.86	11.66	37.94
	3	38.78	−1.30	−0.02	0.31	.001	30.33	0.85	11.16	36.31

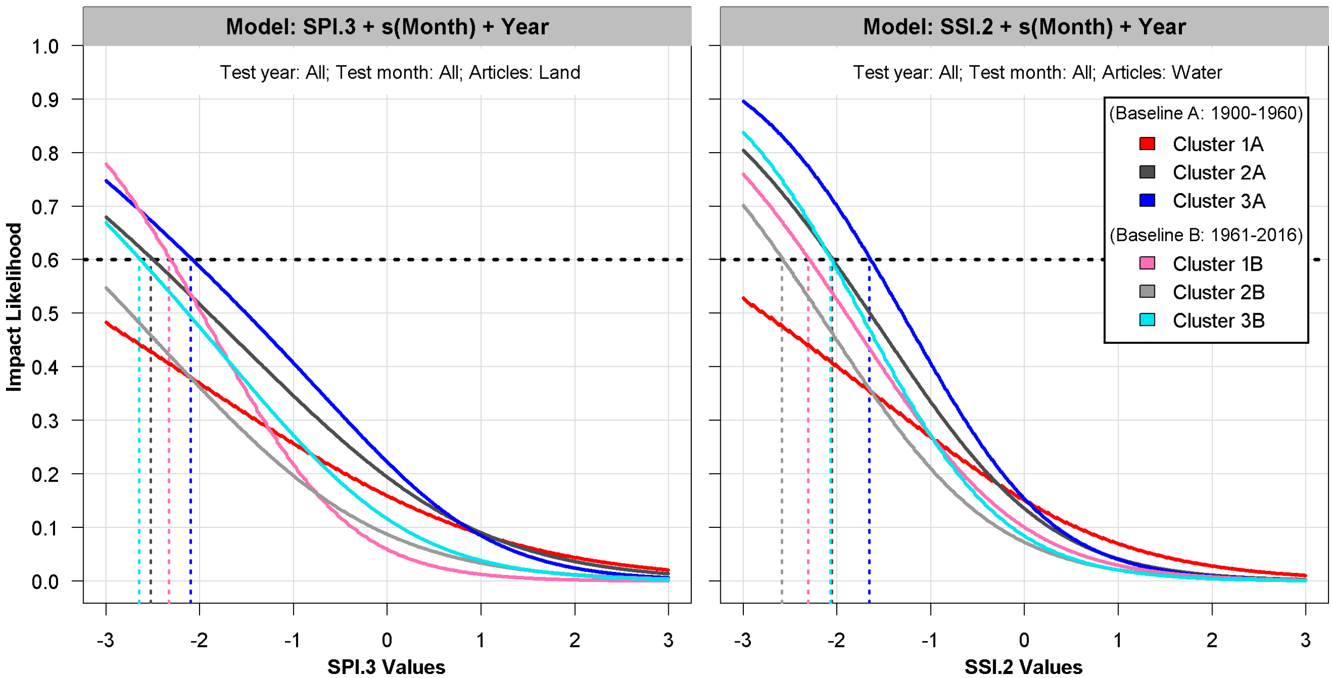

FIGURE 8 Predicted likelihood of reported impacts (annual) from models generated using land-based impact articles and SPI-3 indices (left panel) and from water-based impact articles and SSI-2 indices (right panel). Impact likelihoods for each cluster over the baseline period A: 1900–1960 (i.e., Clusters 1A, 2A and 3A) and baseline period B: 1961–2016 (i.e., Clusters 1B, 2B and 3B) are shown in each panel for indices values ranging from −3 to 3. Indices values for each cluster resulting in a high reported impact likelihood (0.60) are also identified (dashed horizontal line) [Colour figure can be viewed at wileyonlinelibrary.com]

articles (Figure 10). For the 1961–2016 period, Cluster 3 shows the greatest sensitivity to drought impacts in each month. Also, across the year Cluster 1 consistently has a greater propensity for producing impact reports at more extreme deficits in the later period compared to 1900–1960. As with land-based impact reports (excluding January in Cluster 3), the likelihood of water-based impact reports in Cluster 2 and Cluster 3 is consistently lower for all months for the 1961–2016 period. The month with the greatest likelihood of reported water-

TABLE 4 SPI-3 and SSI-2 values producing incremental increasing impact likelihoods from very low to very high, for land- and water-based models for the full period 1900–2016 and sub-periods 1900–1960 and 1961–2016

Index (period)	Cluster number	Very low (0.00–1.99)	Low (0.20–0.39)	Moderate (0.40–0.59)	High (0.60–0.79)	Very high (0.80–1.00)
SPI-3 (1900–2016)	1	>3.00	−0.60	−1.65	−2.68	<−3.00
	2	>3.00	−0.42	−1.41	−2.35	<−3.00
	3	>3.00	−0.17	−1.07	−1.98	<−3.00
SSI-2 (1900–2016)	1	>3.00	−0.46	−1.49	−2.48	<−3.00
	2	>3.00	−0.57	−1.33	−2.02	−2.83
	3	>3.00	−0.39	−1.03	−1.60	−2.27
SPI-3 (1900–1960)	1	>3.00	−0.47	−2.27	<−3.00	<−3.00
	2	>3.00	−0.06	−1.33	−2.51	<−3.00
	3	>3.00	0.12	−0.97	−2.08	<−3.00
SSI-2 (1900–1960)	1	>3.00	−0.47	−2.00	<−3.00	<−3.00
	2	>3.00	−0.39	−1.26	−2.04	<−2.98
	3	>3.00	−0.23	−0.99	−1.65	<−2.43
SPI-3 (1961–2016)	1	>3.00	−0.93	−1.66	−2.32	<−3.00
	2	>3.00	−1.03	−2.21	<−3.00	<−3.00
	3	>3.00	−0.60	−1.65	−2.63	<−3.00
SSI-2 (1961–2016)	1	>3.00	−0.66	−1.52	−2.29	<−3.00
	2	>3.00	−0.95	−1.82	−2.58	<−3.00
	3	>3.00	−0.71	−1.47	−2.06	<−2.81

based impacts for 1961–2016 is July with SSI-2 values required to reach the (0.6) threshold having values of −1.23, −1.54 and −1.36 SSI-2 in Clusters 1 to 3 compared to −0.57, −0.92 and −0.76 SSI-2 for the 1900–1960 period.

4 | DISCUSSION

Employing drought indices derived from historic river flow and precipitation reconstructions, together with a database of newspaper articles on historical drought impacts, we have shown that it is possible to relate counts of newspaper articles to drought indicators using GLMs at the regional scale. The process of model development closely followed Parsons *et al.* (2019) and Stagge *et al.* (2015) who both showed the effectiveness of logistic regression models in linking drought indices and reported impacts. Our model evaluation highlighted the strong relationship between short accumulation SPI/SSI periods and drought impact reports in Ireland. An analysis of model performance scores at accumulations of 1, 2, 3, 4, 5, 6, 9, 12 and 18 months together with an examination of model outputs showed that SPI-3 was best at modelling land-based drought impact reports across each catchment cluster. This is consistent with Bachmair *et al.* (2018), Haro-Monteagudo *et al.* (2018) and Naumann *et al.* (2015), each of whom found SPI-3 correlated well with reported agricultural impacts. For water-based drought impacts, SSI-2 generated the best model performance scores and the highest impact likelihood values of all accumulations.

Model performance varied by region, but overall Cluster 3 in the east/southeast produced the best performing land- and water-based models. The weakest land-based model was Cluster 1 in the northwest whereas the weakest water-based model was Cluster 2 in the southwest. Drought impact article counts have a notable influence on model performance with Cluster 3 catchments, containing the greatest number of land- and water-based articles, producing better results than those for Cluster 1 and 2. Overall, we find that Cluster 1 and 2 models derived from land-based articles and SPI indices perform better than the water-based equivalent, while the opposite is the case for Cluster 3 models. Catchment characteristics likely influence model performance with Cluster 3 catchments, which tend to have greater groundwater storage (O'Connor *et al.*, 2022) and are influenced more by the nonlinear propagation of drought through such catchment systems, producing lower model performances than the faster responding catchments in Cluster 1 and 2. The addition of smoothing to monthly values considerably improved model performance (by a factor of

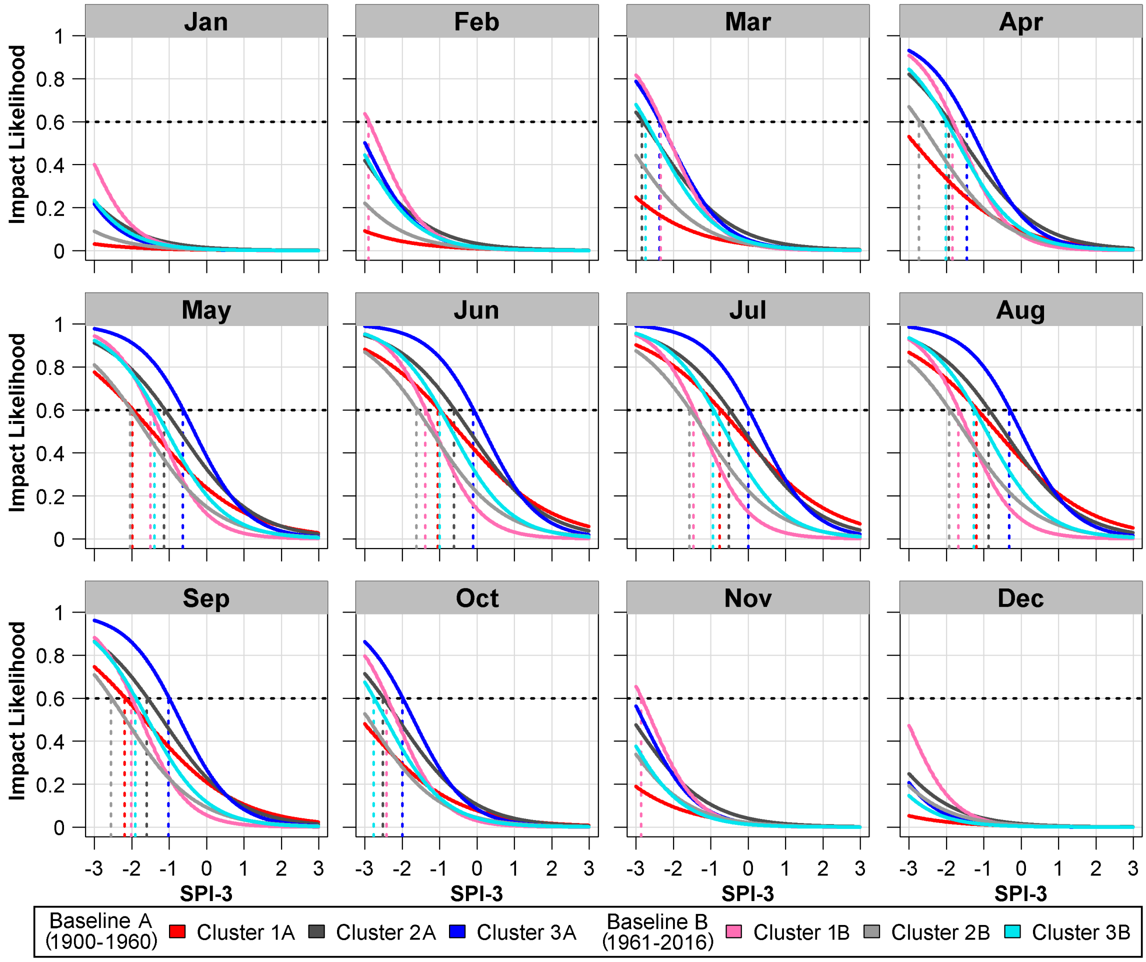

FIGURE 9 Predicted likelihood of reported impacts (monthly) from models generated using land-based impact articles and SPI-3 indices. Impact likelihoods for each cluster over the baseline period A: 1900–1960 (i.e., Clusters 1A, 2A and 3A) and baseline period B: 1961–2016 (i.e., Clusters 1B, 2B and 3B) are shown in each panel for indices values ranging from −3 to 3. Indices values for each cluster resulting in a high reported impact likelihood (0.60) are also identified (dashed horizontal line) [Colour figure can be viewed at wileyonlinelibrary.com]

3.1 on average), as was found by Parsons *et al.* (2019). Weighting of predictors by reciprocal rank of drought article occurrence further improved model performance (by a factor of 1.4 on average). Performance scores for our models (R2adj and AUC) compare favourably with similar studies (Stagge *et al.*, 2015; Parsons *et al.*, 2019).

Our results show that the likelihood of drought impacts being reported is influenced by location, drought type, and time-of-year. On an annual basis Cluster 3 catchments consistently showed the greatest propensity for land- and water-based impact reports, whereas Cluster 1 showed the least for land- and water-based impact reports at more extreme deficits. For moderate deficits, Cluster 2 showed the least propensity for water-based impact reports. On a monthly basis, our results indicate large intra-annual variations in the likelihoods of reported drought impacts across clusters. In all clusters and for both impact categories, summer shows the highest reported impact likelihoods, which is unsurprising as agricultural activities (crop and livestock production) and water use (consumption) increase markedly in these warmer months. For land-based impacts, all clusters display a high likelihood of impact reports in July, associated with very modest SPI-3 deficits (none less than −1), indicating a very high vulnerability to drought in that month. Conversely, winter months show lower likelihoods of drought impacts being reported, with deficits as extreme as <−3 SPI-3 in January resulting in low likelihoods across clusters. Previous studies on drought characterization in Ireland (e.g., Noone *et al.*, 2017; O'Connor *et al.*, 2022) have employed a common year-round threshold of −1 SPI to identify the onset of drought events. These findings suggest that the use of such fixed thresholds for drought analysis in Ireland, which has a strong seasonal cycle in both the mean and variability of precipitation and flows, poorly reflects *experienced* drought

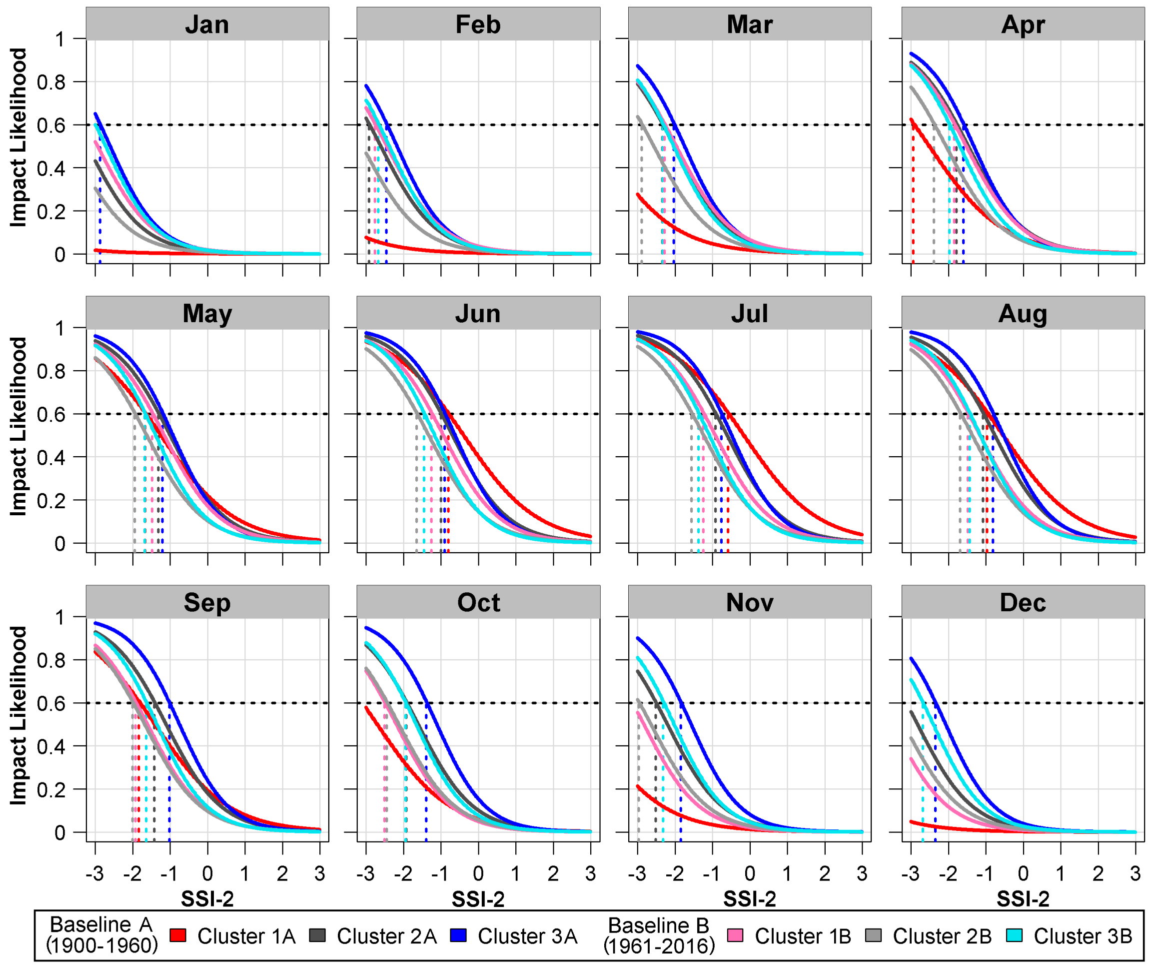

FIGURE 10 As in Figure 9 but for water-based impact articles and SSI-2 indices [Colour figure can be viewed at wileyonlinelibrary.com]

conditions. Our work suggests that nonstationary, location dependent threshold values would more accurately capture the changing impacts of drought across seasons on the island.

We find a close relationship between hydrological drought impact reporting and catchment characteristics. Despite revealing the lowest likelihood of reported land-based impacts, Cluster 1 catchments show the highest likelihood of water-based impacts at low deficits in summer months. These findings are consistent with O'Connor *et al.* (2022) who identify Cluster 1 catchments as being the most susceptible to hydrological drought in summer due to the lack of groundwater storage. Cluster 3 catchments show the highest likelihoods of impact reporting from September through April where even in December at more extreme deficits there exists a very high chance of drought related impact reports occurring. These catchments tend to have higher groundwater storage and more delayed hydrological drought onset, consistent with higher impact report likelihoods from September through April. As per many aspects of the analysis, Cluster 2 catchments show impact likelihood patterns intermediate between Cluster 1 and 3.

Inclusion of the "year" predictor variable in our model revealed a decreasing trend in reported drought impacts across all three clusters for both land- and water-based models during the 1900–2016 period, a result confirmed by Theil–Sens slope testing. We also identify step changes towards fewer drought impact reports for recent decades in each cluster, especially for land-based impact reports. As drought reports in this category are dominated by impacts on agricultural and livestock farming this may be indicative of autonomous adaptation in that sector. These results differ to the UK where Parsons *et al.* (2019) found a marked increase in the likelihood of reported drought impacts in the agricultural sector. Similarly, Stagge *et al.* (2015) found notable differences in trends in agricultural drought impacts between five European countries. Both studies linked possible biases in reporting of impacts, resulting from a change in the actual or perceived drought vulnerability of farms and/or changes in reporting practices, as a cause of such deviations, something that may well affect results obtained here. Furthermore, it should be noted that the period since the 1980 s in Ireland has been relatively drought poor (Wilby *et al*., 2015; Noone *et al*., 2017), as reflected by the relative lack of articles on the subject. For the 1961–2016 period the risk of reported land-based impacts is lower for Clusters 2 and 3. Changes in the reporting of water-based drought impacts are less extreme but nevertheless notable and coincide with findings by O'Connor *et al*. (2022) showing reduced hydrological drought occurrence in recent years. However, Cluster 1 catchments contradict this trend, whereby an increased likelihood of drought impact reports for extreme deficits in the 1961–2016 period was found. One plausible explanation for the difference is that the economic growth and industrial development that occurred in Ireland from the 1960s (Daly, 2016), which likely resulted in reduced vulnerability to drought impacts, was not universally felt across the island with the northwest the latest to benefit from these changes, as suggested by Martin and Townroe (2013). However drought impacts are not a direct measure of, but a symptom of drought vulnerability (Wang *et al*., 2020). Furthermore, drought vulnerability is also a function of exposure, sensitivity and adaptive capacity (Smit and Wandel, 2006) so accurately apportioning attribution for such changes is not possible without a more in-depth analysis.

Linking drought metrics and reported impacts at the regional scale opens the possibility of more grounded drought monitoring and warning systems (Bachmair *et al*., 2016). This work identifies the accumulation periods for SSI and SPI that are most closely associated with drought impact reporting and identifies thresholds for impact likelihoods associated with different values of each drought metric for various catchment types. Although we detect a decrease in the likelihood of drought impact reports for some catchment clusters in recent decades, this may be an artefact of reduced drought occurrence in that period given the widespread and significant impacts of the 2018 drought in Ireland (Dillon *et al*., 2018; Falzoi *et al*., 2019; Government of Ireland, 2020). Moreover, we show the value of newspaper archives as a source of information on drought impacts. The IDID (Jobbová *et al*., 2022b) provides an unprecedented resource for investigating drought impacts in Ireland, as well as new opportunities for evaluating societal effects and responses to drought events.

There are several methodological limitations to note. Historic precipitation reconstructions from which SPI indices have been generated are subject to varying uncertainties across seasons (Casty *et al*., 2007). Flow values from which SSI values have been derived also have uncertainties, linked to the underlying precipitation data and rainfall runoff models used in their generation. Considerable efforts were made to address these concerns using different model structures and datasets to evaluate the quality of the reconstructions (see O'Connor *et al*., 2021). While drought impact reports have been meticulously assessed and grouped, uncertainty arises from differences in the duration, frequency, spatial extent and regional density of the newspaper publications (see Jobbová *et al*., 2022a). For example, some publications were only in print in the early half of the 20th century while others commenced in the latter half of the century. The frequency of publication also differed between some newspapers while smaller regional publications had a greater local emphasis in reports. Furthermore, drought reporting competes with other local/national events which may have more pressing news content, thereby impacting the number of and space provided for drought articles, particularly over extended drought periods. The count of drought impact articles is, therefore, an imperfect proxy for the significance of reported impacts. As the models applied weights based on reciprocal ranking of total monthly article counts, the aforementioned sources of bias would all impact model performance which might account for the superior performance of models with relatively short accumulation periods. While aggregation of data by catchment clusters helps to constrain some of these biases, a more substantive assessment of the text of the articles together with a sectoral based approach of model generation would help reduce this source of uncertainty further.

Possibilities for future work include the application of other drought metrics such as SPEI and/or low flow indicators. Alternative modelling approaches could also be considered. For instance, Bachmair *et al*. (2017) demonstrate the utility of machine learning for linking drought impacts and metrics which could potentially better handle the complex, multithreshold relationships found here, including accounting for nonbinary impact series. Other impact datasets could be explored to supplement use of newspaper articles including historical inventories, such as harvest volumes, and/or records of impacts on online social media platforms such as Twitter, which facilitates a near real-time analysis of impacts as has been demonstrated for flooding events (Basnyat *et al*., 2017; Thompson *et al*., 2021). Our analysis has shown that drought indices and article counts do not always coincide (as was the case for the 1945 and 1921 droughts). Examining the relationships between the frequencies of drought impact reporting and evolving drought indices for such events would be beneficial. Finally, real-time drought monitoring is an essential component of drought risk management (Senay *et al*., 2015), with the success of drought mitigation measures largely dependent upon the gathering of information on drought onset, progress and areal extent (Morid *et al.*, 2006). The identification of regional vulnerability to drought impacts here offers an additional element to drought monitoring that could potentially yield societal benefits. The development of such a system for Ireland, using these research findings, should be explored further.

5 | CONCLUSIONS

This paper applied logistic regression and GAMs to link reconstructed SPI and SSI metrics to reported land- and water-based drought impacts as inferred from newspaper reports covering the period 1900–2016 in 51 catchments in Ireland. We find that, based on model performance metrics and impact likelihood scores, SPI-3 and SSI-2 are most closely related to reported land- and water-based impacts, respectively. Catchments in the east/southeast show the highest likelihood of land- and water-based impact report occurrence on an annual timescale, displaying notably higher impact reporting likelihoods during winter months, which might be attributed to the greater influence of groundwater sources in these catchments. During summer months, catchments in the northwest display the highest water-based impact reporting likelihoods at low SSI-2 deficits, despite having the lowest equivalent land-based values. Our findings show that maximum drought impacts across the 1900–2016 period occur in July for SPI-3 and SSI-2 with even modest deficits resulting in a high likelihood of impacts. Overall, the lowest impacts occur in January for SPI-3 and SSI-2 were indices values of <−3 for the former only generate very low to low likelihoods of impact reports, while for the latter they generate differences from low impacts (Cluster 1) to high impacts (Cluster 3). These findings suggest that the use of fixed thresholds for identifying drought impacts is not suitable. Our analysis of impact reports over the last 117 years reveal a decreasing likelihood of drought impact reports for catchments in the east/southeast and southwest. Northwestern catchments show an increasing likelihood of reported impacts for more extreme drought deficits in recent decades, particularly in respect of agricultural and livestock farming. The results reported here have the potential to inform the development of a near real-time, drought monitoring and warning system both regionally and at the catchment scale across Ireland.

AUTHOR CONTRIBUTIONS

Paul O'Connor: Conceptualization; data curation; formal analysis; investigation; methodology; project administration; resources; software; validation; visualization; writing – original draft. **Conor Murphy:** Conceptualization; funding acquisition; project administration; resources; supervision; validation; writing – review and editing. **Tom Matthews:** Conceptualization; supervision; validation; writing – review and editing. **Robert L. Wilby:** Conceptualization; validation; writing – review and editing.

ACKNOWLEDGEMENTS

Paul O'Connor acknowledges funding from the Irish Research Council (IRC). Conor Murphy acknowledges funding from the Irish Environmental Protection Agency through the JPI/AXIS project CROSSDRO (2019-CCRP-MS.60) and IRC Coalesce Project COALESCE/2019/43. We thank the OPW, EPA and Met Éireann for their data. Open access funding provided by IReL.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: O'Connor, P., Murphy, C., Matthews, T., & Wilby, R. L. (2023). Relating drought indices to impacts reported in newspaper articles. *International Journal of Climatology*, *43*(4), 1796–1816. https://doi.org/10.1002/joc.7946