Historical Droughts in Irish Catchments: Flow Reconstructions, Drought Characteristics and Impact Analysis

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Abstract

Long-term hydrometric records are required to identify and categorise drought events, their characteristics and impacts. In Ireland, a lack of long-term flow data combined with the paucity of extreme droughts in recent decades has impeded understanding of drought and its impacts. To address this, 250 years of monthly flow reconstructions were generated for 51 river catchments across the island of Ireland for the 1766-2016 period, by employing gridded precipitation and temperature data and an ensemble of hydrological models. Catchment-based standardised precipitation and streamflow indices (SPI; SSI) were derived from reconstructions and analysed to identify the most extreme drought events, spatial and temporal differences in drought characteristics (severity, duration, accumulated and mean deficits) and drought propagation dynamics. Subsequently, a novel database of land-based and hydrological-based drought impact articles (1900-2016) was linked to the derived indices using logistic regression models, finding distinctive regional drought impact likelihoods. Overall results show that Ireland is prone to drought, confirming that recent decades, in which positive North Atlantic Oscillation conditions and related wetter weather have been more prevalent, are unrepresentative of the long-term record. Three regionally distinct catchment groupings were identified with hydrological drought more frequent in the wetter northwest as opposed to the drier east/southeast, a consequence of the flashier features of catchments in that region. Once established however, drought in the south-east tends to last longer and results in greater accumulated deficits due to the larger areas and greater groundwater storage of catchments in the region. Southwestern catchments showed characteristics intermediate of the other two regions. The most extreme island-wide droughts occurred in 1803-1806, 1854-1859, 1933-1935, 1944-1945, 1953-1954 and 1975-1977. Trend assessment found a tendency towards shorter more intense droughts over time. Finally, linking drought impacts (via newspaper articles) and indices found that SPI-3 and SSI-2 perform best for drought impact analyses and that northwestern catchments are more vulnerable to drought impacts, particularly hydrological-based impacts, with increases in the likelihood of reported impacts having occurred in the region post-1961, in contrast to reductions elsewhere. The study findings considerably advance understanding of drought, its dynamics and impacts at the catchment level in Ireland and, together with the flow reconstructions, will be of interest to hydrologists and water managers in Ireland and further afield.

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Chapter 1 | Introduction

1.1 Chapter overview

This chapter introduces the research topic and outlines the background and rationale for the research presented in the remainder of the thesis. Following a brief overview of drought, drought vulnerability, its measurement and international approaches to its assessment, the impacts of recent drought events in Ireland are discussed. Ways of assessing drought are then evaluated with a focus on international approaches. Historical drought research in Ireland is then appraised with the most prominent knowledge gaps identified. The lack of long-term flow records on the island is noted as a hindrance to effective drought analysis so flow reconstruction techniques are then examined. As an important element of the study relates to linking drought indicators to reported impacts, international approaches to achieving this are discussed, followed by a review of historical documentary data available in Ireland that could potentially facilitate such an assessment. In concluding the review an outline of the main hydrological characteristics relating to drought in Ireland are provided including detail on prevailing precipitation patterns, their atmospheric drivers and common trends in hydrometric values. Information relating to the differing catchment characteristics across the country, their influence on flows and the hydrometric stations in place to make measurements is also provided. Finally, the most prominent knowledge gaps, identified through this assessment, are listed along with the means by which each will be addressed; noted as five key research objectives. The chapter ends with a summary of the content of each of the remaining chapters of the thesis.

1.2 Defining Drought

Drought is a common recurrent feature of climate that occurs in virtually all climatic zones and is primarily caused by prolonged deficits of precipitation relative to normal conditions (Wilhite, 2000; MWD, 2007). It is one of the most extreme natural hazards resulting in large monetary and societal impacts around the planet (Wilhite *et al.*, 2007). The reduced availability of water that occurs as a result of changes in the volume, intensity and timing of precipitation and/or anomalously high temperatures can have extreme human impacts, particularly where suitable infrastructure together with adaptive water management policies have not been put in place (Shiferaw *et al.,* 2014). As well as water access issues, some of the main negative consequences of drought include a loss of or a reduction in food production, energy generation and industrial output (MacAllister *et al.*, 2020; Gil *et al.,* 2013; Van Vliet *et al.*, 2016). Drought impacts can also be severe for ecosystems with plant species damaged due to greater wildfires (Gudmundsson *et al.*, 2014), aquatic systems affected by reductions in waterbody volumes and flows and increases in water temperature (Lake, 2003) and increased mortality in both wildlife and livestock as a result of reductions in the availability of food and water (Nkedianye *et al.*, 2011). Drought events are expected to become longer, more severe and more frequent this century (IPCC, 2018), with expected extreme impacts across most of the Americas, southern Europe, southern and central Africa, Australia and southeast Asia (Dai, 2013), highlighting the growing risk of more extreme impacts from the phenomenon.

There are four principal categories of drought: meteorological, which relates to deficits in precipitation; hydrological, which relates to deficits in surface and subsurface water; agricultural, which relates to declining soil moisture and; socio-economic, which relates to water access and a failure to meet water demands (Mishra and Singh, 2010). Meteorological drought commonly precedes all the aforementioned drought types (Chen *et al.,* 2009) and can occur as a result of changes in seasonal precipitation patterns, multi-decadal variations in atmospheric circulation patterns and long-term shifts in localised climatic conditions (Kingston *et al.*, 2015). Hydrological drought is a product of prolonged reductions in the volume of river flows, groundwater storage and lake levels (Van Loon, 2015), brought on by accumulated deficits in precipitation due to meteorological drought. Hydrological drought characteristics are dependent on underlying catchment features, with large variations in drought deficits identifiable dependent on average catchment wetness and elevation (Van Loon and Laaha, 2015). Agricultural drought reflects deficits in moisture content of soil and occurs as a result of decreases in precipitation amounts over extended periods, resulting in limited or reduced crop yields (Sepulcre-Canto *et al.*, 2012). It is directly associated with meteorological drought, through its links to reduced rainfall volumes, and hydrological drought by way of reduced access to surface and/or groundwater from rivers, lakes or aquifers. Socio-economic drought, which is representative of drought impacts to society as a result of a failure to supply water to meet demands and results in adverse impacts on the economy, environment and society as a whole, is one of the least investigated drought types (Huang *et al.*, 2016).

Drought assessments are typically carried out at a global, continental or regional scale (e.g. Spinoni *et al.*, 2019; Kingston *et al.*, 2015; Sousa *et al.*, 2011) with local catchment scale assessments having received less attention (Gibson *et al.*, 2020). This is particularly the case for research on the influence of climate and catchment properties on drought characteristics and propagation (Barker *et al.*, 2016) with the linking of meteorological and hydrological drought in catchments with differing features only becoming of notable interest recently. At the catchment scale, annual and seasonal precipitation volumes, catchment storage/release properties and, catchment characteristics such as mean latitude and longitude, elevation, slope, area, soil hydraulic conductivity, underlying geology and land use classes such as vegetative cover and urban extent all impact drought event onset/recovery, duration and deficits (Van Loon and Laaha, 2015; Yang *et al.*, 2017) and need consideration when assessing a catchment's susceptibility to drought. Catchments are complex adaptive systems with transient features that are always evolving and changing (Tetzlaff *et al.*, 2008), therefore identifying how water moves through a study catchment, together with the inability to precisely identify where, when and how much rainfall will occur in that catchment makes it impossible to exactly predict how drought will develop over extended periods of months to years. Such uncertainties and gaps in knowledge regarding the hydrological process and the links between meteorological and hydrological drought at the catchment level highlight a need for greater analysis due to their crucial link to drought vulnerability and related impacts (Van Loon, 2015).

1.3 Drought vulnerability

Drought vulnerability can be defined as the degree to which a region is susceptible to drought and is determined by factors including sensitivity, exposure and adaptive capacity (Sahana *et al.*, 2021). Whilst measuring drought vulnerability is difficult, drought impacts offer a means to appraise vulnerability by demonstrating the adverse consequences of a given drought event (Blauhut *et al.*, 2015; Wang *et al.*, 2020b). Assessments of drought vulnerability have largely focused on the most drought prone, but least resilient, parts of the planet where impacts are often more severe, leading to significant loss of life, damaging economies and environments and are compounded by governments not having the necessary capacity and resources to provide short term relief and long-term drought mitigation measures (Masih *et al.*, 2014). Drought vulnerability is non-stationary however with the probability of impacts from drought events with similar characteristics changing markedly as societies change (Wilhite *et al.*, 2014). For example, some of the worst drought impacts are in the Horn of Africa where drought is becoming more severe and frequent (Thomas *et al.*, 2020). The vulnerability of communities in these regions is increasing due to poverty and limited technical capacity to deal with drought impacts and is exacerbated by regional conflicts (Nyong and Fifi, 2005). Furthermore, vulnerability changes as populations grow, demand for water increases and land use changes and environmental resources degrade (Masih *et al.*, 2014). The development of long-term drought management strategies with specific plans oriented towards drought risk reduction and management is one of the most important steps in the process of mitigating such drought impacts and reducing drought vulnerability (Rossi *et al.*, 2007).

1.3.1 Drought vulnerability in the context of Ireland

The recent droughts of summer 2018 and spring 2020 induced renewed interest around drought vulnerability in Ireland and the potential impacts the phenomenon can have on people and the environment. The 2018 event in particular resulted in many drought related impacts including restrictions on water access for most of the country, wildfires, crop reductions with noted reductions in harvest volumes in the east but with increases in biomass in the uplands in the west of the island and the bogs of the midlands (Falzoi *et al.*, 2019). Water stress was most notable in the east where anomalous high temperatures and lack of precipitation led to more than three weeks of absolute drought (15 or more consecutive days, on none of which 0.2 mm or more of rain fell - Rohan, 1986) in many locations over the months of June and July (Government of Ireland, 2020). Furthermore, the large concentration of people in the east of the island combined with higher drought deficits in that region resulted in a large increase in water consumption at the time with water restrictions being introduced (Government of Ireland, 2020). The impacts from the relatively short 2018 drought event highlight vulnerabilities in Irish society to drought, particularly in the water sector, agriculture and the natural environment as a whole and raise questions on whether Ireland is prepared for future drought extremes.

Irish Water (2021), recently published their 25 year national water resources plan for Ireland in which they identify vulnerabilities in the water supply system to potential future drought extremes. They highlight that a lack of long-term observed records impedes the evaluation of plausible future impacts and is a notable risk, particularly as the current infrastructure does not deliver the desired level of service at present. As approximately 83% of the country's drinking water is derived from surface water sources (Irish water, 2021) and with water infrastructure currently under considerable strain, the potential risk for negative impacts is substantial (Wilby *et al.*, 2015). Furthermore, the risk of impacts is not just confined to populated regions with pre-perceived water stress issues but could potentially impact other areas of the island (Hall *et al.*, 2010). In order to address these vulnerabilities and reduce the risks associated with future drought it is important to examine the characteristics and impacts of historic events. By finding key information on historical droughts in Irish catchments it will be possible to employ methodologies to "stress-test" the robustness of water supply systems and in the process reduce potential impacts from future extremes (Mens *et al.*, 2015; Spraggs *et al.*, 2015; Wilby *et al.*, 2015).

1.4 Assessment of historical drought

Past weather events offer analogues for possible future extremes (Hazeleger *et al.*, 2015). By examining the characteristics and impacts of historic extremes it is possible to determine plausible risks associated with future events before their occurrence. This is also the case for drought whereby analysis of the dynamics of drought and its causes in a historical context helps improve understanding of drought and its potential impacts (Ault, 2020). Droughts develop differently dependent on climatic conditions, seasonal change and prevailing weather patterns (Van Loon, 2015), and in the case of hydrological drought, the hydrologic conditions of the catchment and catchment properties, including anthropogenic activities, all impact how deficits develop during drought events (Saft *et al.*, 2015; Sabater *et al.*, 2018). Due to drought's slow development, the exact time of onset and termination of events are often difficult to determine and are usually found by operational definitions based on precise characteristics and thresholds that allow for the statistical analysis of drought and the determination of drought characteristic values (Wilhite, 2000; Parry *et al.*, 2016a). Drought metrics are typically employed to analyse drought, with a wide range available, allowing characteristics of particular events to be quantified and compared to other events as well as values from other metrics (Burke *et al.*, 2011). In the case of meteorological drought, indicators including precipitation and temperature can be used to identify and rank historical extreme events (Spinoni *et al.*, 2019) and can help to determine what conditions brought about such extremes. For catchment based drought, multiple meteorological and hydrometric variables are employed in assessments including precipitation, runoff, soil moisture, streamflow and groundwater (Van Loon, 2015).

In order to accurately assess historical drought extremes and, in particular, to identify trends it is important to have long-term data (Vicente-Serrano *et al.*, 2021a). Series length is often dependent on the length of time observations have been acquired and in the case of weather variables relies upon the work of both amateur and professional meteorologists as well as work by data rescuers to retrieve paper based observations. There are large regional variations in the time span of meteorological and hydrometric variables across the world. European records are amongst the longest and most spatially dense instrumental records (Brönnimann *et al.*, 2019), with the Central England Temperature data series, for example, commencing in 1659 (Wang *et al.*, 2017), continuous precipitation series in the British-Irish isles, dating back to 1711 (Murphy *et al.*, 2018), and river flow, which date back to the late 1800s in many locations including 1877 at York in the UK (Macdonald and Sangster, 2017). Whilst the density of historical meteorological observations has been comprehensive across Europe since the 1950s (Klok and Tank, 2009), the northwest of the continent, including the UK and Ireland, has had notably greater spatial coverage, particularly for precipitation observations, which for a relatively large number of stations, date back to the mid-19th century (Vicente-Serrano *et al.*, 2021a). Worldwide the length of river flow records varies considerably with many locations having limited observed measurements (Fekete and Vörösmarty, 2007). Europe is one of the best monitored regions with a high number of flow gauges (in excess of 3737 based on Blöschl *et al.* (2019)'s recent study) with good spatial coverage since the 1960s (Blöschl *et al.*, 2017). European flow record lengths are variable however, with Mediero *et al.* (2015) estimating the average as being 49.7 years based upon data from the Global Runoff Data Centre. In comparison to other meteorological indicators however, such observational record lengths are relatively short (Laaha and Blöschl, 2005) with the risk that extreme historical hydrological drought events may not be accounted for in records.

1.4.1 Assessing drought using indicators and indices

Drought indicators, representative of each component of the water cycle include: temperature, precipitation, groundwater/reservoir levels, soil moisture, snowpack and streamflow (Svoboda *et al.*, 2016). Table 1.1 provides a list of drought indicators and indices recommended by the World Meteorological Organisation for meteorological and hydrological drought analysis. The choice of index is primarily based upon the drought type and availability of required indicator data. For example, whilst popular, the Palmer Drought Severity Index requires precipitation, temperature and available water content values, the latter of which may not always be readily available. For this reason, more simple indices such as the standardised precipitation index, which only relies upon precipitation series as input, are more commonly used for meteorological drought assessment. This is particularly the case in regions lacking other variables such as evapotranspiration data (Halwatura *et al.,* 2015). For hydrological drought, stream flow is most commonly used for analysis, due to the availability of observations, its ease of simulation and its utility to water managers (Van

Loon, 2015). As the standardised streamflow index also only relies upon one input (i.e. flow) and has a very similar fitting procedure to the standardised precipitation index, it allows meteorological and hydrological drought to be assessed in tandem (e.g. Purnamasari *et al.*, 2017), which is useful in terms of assessing drought propagation (Barker *et al.*, 2016).

When applying a drought index a calibration step is required, where the historical data is transferred to the probability space by fitting it to a chosen probability distribution function, which is subsequently used to estimate drought indices (Um *et al.*, 2017). The best probability distribution function to choose is dependent on the distribution of the underlying data (parametric or non-parametric). Whilst it is common to use the full length of the data series in indices calibration (Um *et al.*, 2017), it is possible to use a select (reference) period. Standardised drought indices can be derived for different accumulation periods to evaluate the development of drought over varying timescales. Resultant outputs can then be easily assessed to find common underlying drought characteristics for the chosen accumulation period. Characteristics typically include event timing, duration, spatial extent and severity (or intensity) with such information useful in helping to understand drought processes and impacts (Van Loon, 2015).

Standardised indices provide a useful means of evaluating drought event characteristics, to compare historic events, to assess for trends and to identify links between different drought types (e.g. Jain *et al.*, 2015; Buras *et al.*, 2020; Nagy and Zeleňáková, 2020; Apurv *et al.*, 2017). When carrying out a drought analysis using standardised indices, suitable thresholds in the indices values need to be identified so as to define the point of drought onset and termination. Commonly employed thresholds include those derived by McKee *et al.* (1993) where moderate drought is represented by index values of -1 to -1.49, severe drought for values of -1.5 to -1.99 and extreme drought for values <= -2. Index values relating to these thresholds can be used to determine drought characteristics at the various intensities (see Lennard *et al.*, 2016; Noone *et al.*, 2017; O'Connor *et al.*, 2022a). Once the monthly index value falls below the moderate threshold value of -1 drought commences. As the index value falls below subsequent thresholds the intensity of the drought becomes progressively more severe. This continues until such a time as it reduces in severity and eventually reaches an index value of zero, by which time the drought has terminated. Derived monthly standardised indices values for a given event can then be assessed to find the event's characteristics. Figure 1.1 displays an example plot of deficits associated with a drought event for which this drought classification procedure has been applied.

Table 1.1 List of indicators and indices available for (a) meteorological and (b) hydrological drought (adapted from Svoboda and Fuchs, 2016). Indicator variables: AWC = available water content; CD = crop data; ET = evapotranspiration; GW = groundwater; Mod = modelled; P = precipitation; PET = potential evapotranspiration; Rad = solar radiation; RD = reservoir; S = snowpack; SF = streamflow; T = temperature; Td = dew point temperature; W = wind data.

Meteorological	*Page*	*Ease of use*	*Input parameters*	*Additional information*
Aridity Anomaly Index (AAI)	11	Green	P, T, PET, ET	Operationally available for India
Deciles	11	Green	P	Easy to calculate; examples from Australia are useful
Keetch–Byram Drought Index (KBDI)	12	Green	P, T	Calculations are based upon the climate of the area of interest
Percent of Normal Precipitation	12	Green	P	Simple calculations
Standardized Precipitation Index (SPI)	13	Green	P	Highlighted by the World Meteorological Organization as a starting point for meteorological drought monitoring
Weighted Anomaly Standardized Precipitation (WASP)	15	Green	P, T	Uses gridded data for monitoring drought in tropical regions
Aridity Index (AI)	15	Yellow	P, T	Can also be used in climate classifications
China Z Index (CZI)	16	Yellow	P	Intended to improve upon SPI data
Crop Moisture Index (CMI)	16	Yellow	P, T	Weekly values are required
Drought Area Index (DAI)	17	Yellow	P	Gives an indication of monsoon season performance
Drought Reconnaissance Index (DRI)	17	Yellow	P, T	Monthly temperature and precipitation are required
Effective Drought Index (EDI)	18	Yellow	P	Program available through direct contact with originator
Hydro-thermal Coefficient of Selyaninov (HTC)	19	Yellow	P, T	Easy calculations and several examples in the Russian Federation
NOAA Drought Index (NDI)	19	Yellow	P	Best used in agricultural applications
Palmer Drought Severity Index (PDSI)	20	Yellow	P, T, AWC	Not green due to complexity of calculations and the need for serially complete data
Palmer Z Index	20	Yellow	P, T, AWC	One of the many outputs of PDSI calculations
Rainfall Anomaly Index (RAI)	21	Yellow	P	Serially complete data required
Self-Calibrated Palmer Drought Severity Index (sc-PDSI)	22	Yellow	P, T, AWC	Not green due to complexity of calculations and serially complete data required
Standardized Anomaly Index (SAI)	22	Yellow	P	Point data used to describe regional conditions
Standardized Precipitation Evapotranspiration Index (SPEI)	23	Yellow	P, T	Serially complete data required; output similar to SPI but with a temperature component
Agricultural Reference Index for Drought (ARID)	23	Red	P, T, Mod	Produced in south-eastern United States of America and not tested widely outside the region
Crop-specific Drought Index (CSDI)	24	Red	P, T, Td, W, Rad, AWC, Mod, CD	Quality data of many variables needed, making it challenging to use
Reclamation Drought Index (RDI)	25	Red	P, T, S, RD, SF	Similar to the Surface Water Supply Index, but contains a temperature component

(a)

Hydrological	Page	Ease of use	Input parameters	Additional information
Palmer Hydrological Drought Severity Index (PHDI)	27	Yellow	P, T, AWC	Serially complete data required
Standardized Reservoir Supply Index (SRSI)	28	Yellow	RD	Similar calculations to SPI using reservoir data
Standardized Streamflow Index (SSFI)	29	Yellow	SF	Uses the SPI program along with streamflow data
Standardized Water-level Index (SWI)	29	Yellow	GW	Similar calculations to SPI, but using groundwater or well-level data instead of precipitation
Streamflow Drought Index (SDI)	30	Yellow	SF	Similar calculations to SPI, but using streamflow data instead of precipitation
Surface Water Supply Index (SWSI)	30	Yellow	P, RD, SF, S	Many methodologies and derivative products are available, but comparisons between basins are subject to the method chosen
Aggregate Dryness Index (ADI)	31	Red	P, ET, SF, RD, AWC, S	No code, but mathematics explained in the literature
Standardized Snowmelt and Rain Index (SMRI)	32	Red	P, T, SF, Mod	Can be used with or without snowpack information

(b)

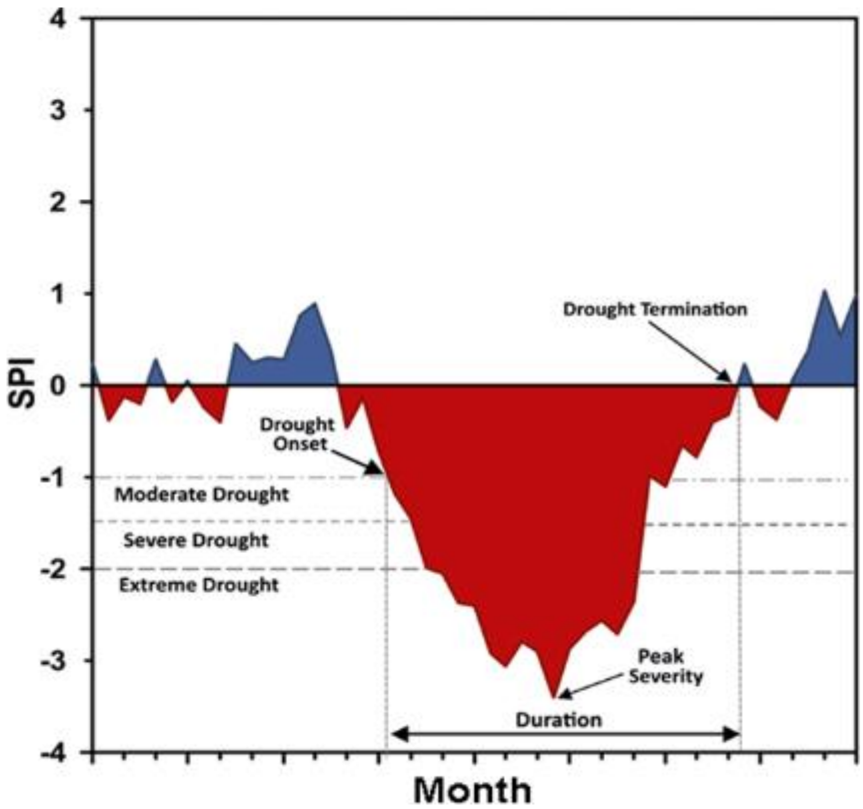


Figure 1.1 Sample drought event assessed using the Standardised Precipitation Index (adapted from Lennard *et al.*, 2016). Drought classification thresholds (moderate -1 to -1.49; severe -1.5 to -1.99; extreme <= -2) and characteristics (drought onset, duration, peak severity and termination values) are displayed with the accumulated deficit equalling the sum of monthly SPI values and mean deficit equal the accumulated deficit divided by the drought duration.

1.4.2 International approaches to drought assessment

The use of indices to generate catalogues of the most significant historical drought events has been extensively demonstrated in international studies of meteorological drought derived from historic precipitation series (e.g. Lloyd-Hughes and Saunders, 2002; Spinoni *et al.*, 2015; Noone *et al.*, 2017; Oikonomou *et al.*, 2020) and for hydrological drought derived from historical flows (e.g. Stahl, 2001; Hannaford *et al.*, 2011; Sutanto *et al.*, 2020). Using such techniques it is possible to calculate drought characteristics for all events in a series with the most extreme being easily identified. These extreme droughts can then be compared and contrasted with other events in the generated series, with the ability to rank droughts based on duration, severity and intensity for varying accumulations (e.g. Wu *et al.*, 2011; Deo *et al.*, 2017; Tian *et al.*, 2019). Regional differences in extreme event characteristics including differences in timing of drought onset to termination, the duration of events, the severity and maximum intensity, the return period of events and in the processes revealing location specific characteristics in regions of differing climatic conditions can also be found (Dayal *et al.*, 2018). Drought indices assessments also provide the ability to measure and compare drought characteristics and impacts over different time periods (e.g. Masud *et al.*, 2020). By employing such techniques to improve understanding of drought characteristics as well as spatiotemporal drought patterns, it is possible to enhance future drought resilience (Lennard *et al.,* 2014; Tian *et al.*, 2019) and in the case of hydrological drought can help identify which catchments are most susceptible to multiyear events (Brunner and Tallaksen, 2019).

Identifying trends in drought event occurrence has also been the subject of considerable international interest in recent years as researchers try to determine changes in drought risk across the world. The recent release of the Intergovernmental Panel on Climate Change's AR6 Working Group I findings (IPCC, 2021) have brought together the most up-to-date understanding of such change. Their findings suggest that human influences have likely increased the chances of concurrent heatwaves and droughts across the globe with more intense and frequent meteorological droughts identifiable (medium confidence; IPCC, 2021). For hydrological drought in Europe there is high confidence of past and future increases in drought occurrence and intensity across the Mediterranean basin whilst for the rest of the continent the direction of change is less clear (IPCC, 2021). Limited trends in hydrological drought in Northern, Western and Central Europe are identifiable with future increases in precipitation offsetting the effect increased evapotranspiration has on streamflow droughts (IPCC, 2021). Historically, relatively few studies have investigated long-term trends in drought characteristics such as drought frequency, duration and severity (Chiang *et al.*, 2021). Such trends are typically detected using non-parametric monotonic statistical tests (e.g. Mann Kendall test) (Wang *et al.*, 2020a). In order to derive meaningful trends from such assessments a relatively long series of observations is required as the direction and magnitude of trends in short term records are strongly influenced by inter-decadal variability (Hannaford *et al.*, 2013; Harrigan *et al.*, 2014). Such deviations manifest themselves in drought assessments too, where trends have been found to vary temporally (dependent on start and end year) for meteorological drought (e.g. Bordi *et al.*, 2009; Vicente-Serrano *et al.*, 2021a) and hydrological drought (e.g. Hisdal *et al.*, 2001). One means to address this is by extending the observed record using flow reconstruction techniques.

1.4.3 Previous Irish drought research

Relatively few studies have investigated drought in Ireland, with most historic analysis relying upon assessments of precipitation, temperature and flow (Barrington, 1888; Ó Laoghóg, 1979; Mac Cárthaigh, 1996; Wilby *et al.*, 2016; Noone *et al.*, 2016; Murphy *et al.*, 2018)) and written records (Dooge, 1985; Murphy *et al.*, 2017). More recently research has focused on determining in more detail the characteristics of past drought events using standardised drought indices (Noone *et al.,* 2017; Murphy *et al.,* 2020a). These studies have focused on meteorological drought due to the availability of long-term precipitation records. Work on understanding the characteristics of other drought types including hydrological drought has been limited, a common finding for other locations across the world (Xu *et al.*, 2019). For example only one study investigating the characteristics of multiple historical hydrological droughts has been undertaken on the island (Noone and Murphy 2020), and is limited to a total of twelve catchments covering the 1850-2015 period. Mac Cárthaigh (1996) also carried out an assessment of hydrological drought in Ireland but only focused on a single event (the drought of 1995), comparing flow values to impacts from the historic 1976 event. Common drought characteristics are identifiable in all three studies with clear similarities in meteorological and hydrological drought event occurrence and severity identifiable, however questions remain over how other catchments across the island respond to hydrological drought, what regional differences are identifiable, what are the predominant trends in drought characteristics and how meteorological and hydrological drought relate at the catchment scale.

1.5 The importance of a catchment based approach

At the catchment scale, drought is defined by deficits in some components of the hydrological cycle (e.g. precipitation, soil moisture, water levels and flows) covering the whole area of the catchment and are representative of reductions in the chosen metrics values from the normal with drought onset and termination differing depending on the drought type and chosen threshold. Spatial aspects, including the area of the catchment in drought and related total deficits, are important when characterising catchment scale drought events as the size of the affected area provides a measure of the severity of the event (Tallaksen *et al.*, 2009). In order to be in the position to study drought impacts at the catchment scale a clear understanding of the link between meteorological and hydrological drought is required. For meteorological drought, deficits come about primarily as a result of reductions in overall catchment precipitation levels (rainfall, snowfall and other sources of moisture) but are also strongly influenced by other factors including evapotranspiration, whose magnitude is dependent the characteristics of the land surface, the season, weather and wind conditions (Hanson, 1991). For hydrological drought, deficits are measured by calculating reductions in hydrometric variables, with river flows most employed due to the availability of observations, the ease with which it can be simulated and its use to water resource managers (Van Loon, 2015). Climatic conditions, the hydrologic characteristics of the catchment and catchment properties, all impact how deficits develop during drought events (Saft *et al.*, 2015). External anthropogenic activities can also impact deficits such as water abstraction and groundwater exploitation as well as the construction of physical infrastructure such as weirs, dams and channelization (Sabater *et al.*, 2018).

By carrying out drought assessments at the catchment level it is possible to calculate how meteorological drought events impact streamflow and in the process develop understanding on how drought propagates through the catchment system. This is of importance when attempting to understand the internal characteristics of the catchment, to measure its vulnerability to drought impacts and to assist in the development of means to reduce drought impact vulnerability (Haslinger *et al.*, 2014; Wang *et al.*, 2016). Propagation is often dependent on regional hydrometric features and the interplay between precipitation, temperature and characteristics of the catchment (Van Loon *et al.*, 2012). By deriving indices values for both meteorological and hydrological drought for a sample catchment at varying accumulation periods it is possible to evaluate how both drought types relate and is often carried out by a simple correlation analysis of indices values (e.g. Xu *et al.*, 2019; Jehanzaib *et al.*, 2020; Ho *et al.*, 2021). This process can reveal underlying catchment characteristics, with high groundwater content resulting in a delayed response to drought onset (Schreiner-McGraw and Ajami, 2021) and a lower risk of immediate drought impacts. The slow response of such catchments means that drought occurrence is low, however, when it does occur drought can last for long durations (Van Lanen *et al.*, 2013). In contrast, when catchments have low groundwater storage and "flashy" hydrographs they respond much quicker to changes in precipitation intensity which can result in a high number of short duration drought events (Van Lanen *et al.*, 2013). Analysis of drought indices values derived for such catchments reveals high correlations between meteorological and hydrological indices at shorter accumulation periods as drought transfers quickly, in contrast to catchments with high groundwater content, where correlations are higher at longer monthly accumulations (Barker *et al.*, 2016). Such information is invaluable when determining the vulnerability of catchments to drought impacts and facilitates prompt action to mitigate potential negative impacts in these locations.

1.6 Reconstructing river flows

As well as hindering research on historical hydrological drought, short flow records impact understanding of other processes that affect hydrology (Dixon *et al.*, 2006) including catchment characteristics (Chiverton *et al.*, 2015) and limit the ability to account for a range of extremes under varying climate conditions (Smith *et al.*, 2019). In order to address this, longer flow records are required, which entails the use of a suitable methodology to extend flows. The appropriate technique to deploy is dependent on a number of factors including the length of the desired reconstruction, the catchment location and the availability of long-term hydrometric observations, required to accurately train and validate models. Various methodologies have been trialled successfully to estimate flows including the use of proxy data such as tree rings (Meko *et al.*, 2007), coral luminescence lines (Lough, 2007), stalagmite isotopes (Xu, 2015). Historically the paired catchment approach has been widely employed, which uses relationships between observed flows from neighbouring rivers to generate reconstructions (Andréassian *et al.*, 2012). One of the most popular techniques involves hydrological models that use observations of precipitation and temperature (either from observed historical records or derived reanalysis data), flow and catchment characteristics to generate flow values. Hydrological model types include conceptual rainfall runoff models, physically-based, mechanistic flow models and empirical black box models (including neural network models) (e.g. Ho *et al.*, 2019; Noone and Murphy, 2020; Kwak *et al.*, 2020). An overview of hydrological model structures and their principle characteristics is provided in Table 1.2. Flows generated from such model types are principally catchment specific but have also been applied to reconstruct flow over large temporal and spatial domains (Nasreen *et al.*, 2021).

Potential-evapotranspiration (PET) is an important variable used in the generation of flows. Numerous models have been developed to derive PET from meteorological observations using aerodynamic-based methods (e.g. Albrecht, 1950), temperature-based methods (e.g. Oudin *et al.*, 2005), radiation-based methods, (e.g. Priestly and Taylor, 1972) and combination-based methods (e.g. Penman, 1948), with the choice of method typically dependent on available observations and temporal/spatial aspects of the study (Yang *et al.*, 2021). The performance of the different PET generation techniques has been widely assessed (e.g. Tanguy *et al.*, 2018; Yadeta *et al.*, 2020; Goh *et al.*, 2021) with results showing that PET generation techniques' performance is dependent on many factors including location, relative temperatures and the local conditions of the site of interest including plant cover and soil type. Considering its influential role in hydrological modelling, the performance of PET generation techniques have often been linked directly to the skill of the model at generating flows at the catchment scale (e.g. Bai *et al.*, 2016; Dakhlaoui *et al.*, 2020). In their assessment of 27 PET generation techniques Oudin *et al.* (2005) measured PET hydrological performance at flow generation for 308 catchments in France using PET outputs. Their findings suggested that temperature and radiation based methods perform just as well as more complicated techniques.

Table 1.2 Three main model structures and their competencies (taken from Devia *et al.*, 2015).

Empirical model	Conceptual model	Physically based model
Data based or metric or black box model	Parametric or grey box model	Mechanistic or white box model
Involve mathematical equations , derive value from available time series	Based on modeling of reservoirs and Include semi empirical equations with a physical basis.	Based on spatial distribution, Evaluation of parameters describing physical characteristics
Little consideration of features and processes of system	Parameters are derived from field data and calibration.	Require data about initial state of model and morphology of catchment
High predictive power, low explanatory depth	Simple and can be easily implemented in computer code.	Complex model. Require human expertise and computation capability.
Cannot be generated to other catchments	Require large hydrological and meteorological data	Suffer from scale related problems
ANN, unit hydrograph	HBV model, TOPMODEL	SHE or MIKESHE model, SWAT
Valid within the boundary of given domain	Calibration involves curve fitting make difficult physical interpretation	Valid for wide range of situations.

Hydrological models can have multiple parameter values, which are representative of some of the major internal processes describing watershed characteristics (Devia *et al.*, 2015), with the best model producing output that is as close to reality as possible with the least amount of parameters and complexity (Sorooshian *et al.*, 2008). All models are calibrated on a portion of the observed flow record in order to train the model and then validated against an independent period in the observed record to measure their performance. Model parameters can be calibrated to perform better for high or low flow modelling using objective functions (Garcia *et al.*, 2017) such as the Nash Sutcliffe and Kling Gupta, which perform well in model parameter selection for peak (Price *et al.*, 2012) and low (Garcia *et al.*, 2017) flows, respectively. Model output can be at daily, monthly or annual timescales however for drought analyses, monthly intervals are typically employed with drought indices used to identify drought occurrence in the reconstructed flow values. Model output will only be as long as the length of the input variables employed in their development. For lengths extending beyond the observed record, reanalysis datasets can be used to extend meteorological variable records, which in turn can drive hydrological models (e.g. Bastola and François, 2012). Resultant flows can then be examined to identify temporal and spatial patterns of hydrological drought together with characteristics of events for individual or grouped catchments, offering insight into historic drought occurrence.

1.7 Linking drought metrics and historical impacts

Understanding the relationship between drought metrics and impacts and how that relationship changes over time allows potential vulnerability associated with future drought extremes to be identified and addressed. Drought indices provide insight into the nature and severity of drought hazards and when linked to historical records can be used to characterise the impacts that specific events have on society, the economy and the environment (Wang *et al.*, 2020b). Historical impacts can be determined by linking hydrometeorological indicators such as precipitation and river flow to specific categories of impacts including water supply and access, power generation, and agricultural impacts (e.g. Vicente-Serrano *et al.*, 2012a; Bachmair *et al.*, 2016; Blauhut *et al.*, 2016). A small number of international studies have linked drought metrics to impacts for historical drought indices across extended periods (e.g., Stagge *et al.*, 2015a; Bachmair *et al.*, 2016; Wang *et al.*, 2020b). These studies show that, despite differing drought event characteristics, it is possible to measure drought impacts, both spatially and temporally, using proxy data. Historical records of impacts can be sourced from academic work, governmental and other organisation reports, news publications, web articles and other sources including databases, maps and press releases (Stahl *et al.*, 2016). Such data is not always readily available over extended periods however and can contain inconsistent temporal and spatial record densities, particularly for records outside of the agricultural sector (Bachmair *et al.*, 2017).

Commonly used databases of historical drought impact records include the US Drought Impacts Reporter (Svoboda and Hayes, 2011), European Drought Impact Report Inventory (Stahl *et al.*, 2016) and the Chinese State Flood Control and Drought Relief information collection system (Wang *et al.*, 2020b). Such impact data can be linked to drought indices using different model structures. Databases of historical records pertaining to impacts on agricultural and livestock farming, public water supply and water quality are often dominant in such assessments (Stahl *et al.*, 2016). The relationships between indices and impacts can also be examined to identify temporal and spatial changes (Parsons *et al.*, 2019) which allows for trends in drought impacts along with regional vulnerability to be identified (O'Connor *et al.*, 2022b). Having access to such information greatly increases understanding of drought and allows for the measurement of changes in drought impacts over time, which is essential in the process of planning for future drought through risk analysis and can aid in the commissioning of early warning systems and contingency planning for drought extremes (Zargar *et al.*, 2011).

In Ireland the availability of historic monastic writings on extreme weather events and their impacts, such as the Irish annals, allows for evaluation of historical extremes over extended periods. For example, Hickey (2011) used these writings to assess the occurrence of cold spells on the island over the last two millennia whilst Ludlow (2006) focused on extreme weather events and natural hazards in Ireland in the 12th to 15th centuries. Murphy *et al.* (2020a) availed of the long historic record of newspaper publications in Ireland to validate extreme drought events they identified from drought indices applied to precipitation reconstructions for England and Wales, Scotland and Ireland for the period 1748-2000. Noone *et al.* (2017) reconstructed precipitation from 1765 to 2015 and employed 250 years of drought related newspaper articles to assess the impacts of meteorological drought across the island, connecting documented events with derived SPI-12 statistics for the most extreme events. The authors found strong correlations between the most extreme droughts and written recordings at the time with agricultural and health related impacts being prominent in the early part of the series. However, the analysis was limited in scope with temporal and spatial differences of the relationship between article occurrence and drought metrics not being subject to review and therefore presents opportunities for further research.

Recently a new database of historical newspaper articles relating to drought impacts has been made available in Ireland (Jobbová *et al.*, 2022). The database provides details on drought impact articles for over 100 publications covering the 1737-2019 period and for each impact, of which there are in excess of 11,000 entries, details about the related publication, location, date and type of impact and a brief excerpt from the article describing its occurrence are given. Using drought indices and recorded historical impacts noted in this database it is possible to link drought indices values to real world events, offering a means to evaluate the performance of indices and to garner new insight on temporal and spatial impacts of extreme events over time. This new data also provides a way to assess catchment based meteorological and hydrological drought impacts and trends across the island, in turn allowing for the knowledge gap in that area to be filled.

1.8 Hydroclimatology of Ireland

The occurrence and characteristics of meteorological and hydrological drought in catchments across the island of Ireland is the primary focus of this research. Ireland is located on the Atlantic margin of northwestern Europe and has a total area of approximately 84,421 km^2 (Coll *et al.*, 2020). The majority of the island has elevations of 150 m or less above sea-level and is primarily comprised of undulating inland lowlands, with mountainous regions located near the coasts (Mockler *et al.*, 2016), reaching a maximum height of 1,038 m above sea level (at Carrauntoohil in the southwest of the island; Coll *et al.*, 2020). Ireland has more than 13,200 km of rivers, 12,000 lakes and 3,171 km of coastline (Daly *et al.*, 2017). Rivers have a channel length ranging from as short as 6 kms for the Corrib in the west (Reddington *et al.*, 2020) to 360 kms for the river Shannon catchment in the midwest (West *et al.*, 2021), with the latter identifiable as the longest river in the British and Irish Isles (Soulsby, 2009).

Despite having individually unique characteristics, regional similarities are identifiable in Irish catchments. In the west, catchments are subject to greater orographic enhancement of precipitation compared to the rest of the island due to their higher elevations and exposure to Atlantic weather systems (Broderick *et al.*, 2016). As a result, annual rainfall in the region, specifically the mountainous southwest, is in excess of 3000 mm compared to 800 mm along the east coast (Mockler *et al.*, 2016). In general, catchments on the western seaboard and upland regions are smaller, having thin peaty soils and impermeable geology resulting in "flashier" flow regimes due to more linear rainfall runoff responses (Broderick *et al.*, 2016). Catchments in the midlands, east and southeast of the country are generally low lying and drier with greater storage (Broderick *et al.*, 2016), being of relatively larger size having less steep inclines (in general) and contain bedrock that is more accommodating to groundwater storage. The commonly found anthropogenic influences in European rivers, such as water extraction, damming for power generation, land use changes for agricultural production, reforestation and dredging to facilitate transportation, flood alleviation infrastructure and growing urban extent (Stahl *et al.*, 2010) are also found in Irish catchments with arterial drainage and peat extraction activities having a notable impact on their flow regimes (Murphy *et al.*, 2013) and need consideration in any comparative assessment between two or more drought events.

1.8.1 Precipitation in Ireland and the influence of the NAO

Across the British and Irish isles the most common source of precipitation are polar fronts, which form over the Atlantic as cool polar air meets warm tropical air (Douglas, 1939). Typically drought occurs when the movement of these fronts is restricted for prolonged periods of time due to dominating high pressure systems (Government of Ireland, 2020). The North Atlantic Oscillation (NAO) is the most important mode of atmospheric variability determining long-term weather patterns in Ireland, accounting for circa 40% of monthly variance in sea level pressure in the North Atlantic (Blessing *et al.*, 2005). Due to the impact it has on the positioning of the jet stream (see Figure 1.2) it indirectly influences precipitation patterns and can result in extended periods of above or below normal rainfall (West *et al.*, 2019). During the negative phase of the NAO the pressure gradient between the Azores high and Icelandic low pressure anomalies is weak resulting in calmer, drier conditions in northwest Europe, that can be up to several months long (Ulbrich and Christoph, 1999; Woollings *et al.*, 2015), and has been shown to directly influence meteorological and hydrological drought occurrence and characteristics (e.g. Wedgbrow *et al.*, 2002; Hannaford *et al.*, 2011; Rahiz and New, 2012; Kingston *et al.*, 2015). In Ireland studies have shown its large influence on precipitation (Murphy and Washington, 2001; McElwain and Sweeney, 2003; Leahy and Kiely, 2011) and river flows (Kiely, 1999; Murphy *et al.*, 2013; Brady *et al.*, 2018; Donegan *et al.*, 2021), with obvious implications for catchment scale drought on the island.

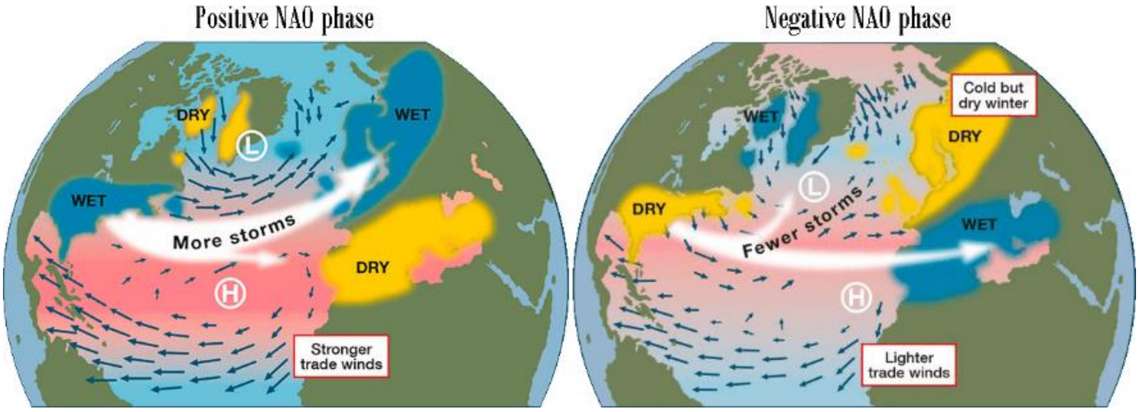


Figure 1.2 Effect of the positive (left) and negative (right) NAO phases on weather patterns across the north Atlantic (adapted from Mäll *et al.*, 2018).

1.8.2 Irish hydrometric data

By international standards Ireland has a relatively dense hydrometric network of over 900 stations actively monitoring river flows (Quinlan *et al.*, 2018) with record lengths averaging 36 years (www.epa.ie/publications/monitoring--assessment/freshwater--marine/register-of-hydrometric -stations-in-ireland-2021.php [accessed 2/12/2021]). Whilst the longest flow series dates back to August 1929 on the manmade headrace canal at Ardnacrusha (ID: 25055), the first and longest operating river flow station gauge is on the river Boyne at Slane Castle (ID: 07012), dating back to June 1940. Hydrological monitoring of this and many other catchments commenced in tandem with the roll out of large scale arterial drainage schemes across Ireland at the time (O'Kelly, 1955), which facilitated an increase in productivity of agricultural land by alleviating overland flooding in many catchments (Bhattaraia and O'Connor, 2004, King *et al.*, 2008). A subsequent increase in hydrological monitoring, which brought about the sizeable majority of gauges in operation today, occurred in the early to mid-1970s in response to extreme drought at that time, which affected flows across the island (Murphy *et al.*, 2013).

Anthropogenic activities, such as arterial and field drainage, can considerably impact catchment flow characteristics over time (Harrigan *et al.*, 2014), therefore reconstructed flows derived from rivers which contain such influences may not accurately reflect historic values. Choosing rivers with minimal human impacts is thus an important element in flow reconstruction work and any potential catchment based drought analysis. In Ireland, Murphy *et al.* (2013) developed the Irish Reference Network (IRN) database, which consists of 43 Irish rivers that have minimal human influences, have long-term hydrologic records and which are suitable for such analyses. The criteria required to include a catchment in the database were as follows:

- High quality, consistent hydrometric data (particularly at extremes) with accurate rating curves.
- Near natural flow regimes with abstractions limited (impacting less than 10% of flow at or in excess of the low flow parameter Q95, i.e. the 5th percentile of flows) or stable.
- Flow records of at least 25 years.
- Limited land-use influences with the exclusion of stations subject to arterial drainage or the use of post drainage observations in such circumstances that allow.
- Stations having good spatial coverage across the island and being representative of Irish hydrological conditions and climate regions (Murphy *et al.*, 2013).

By applying international Reference Hydrometric Network (RHN) standards when deciding upon what sample catchments to include, Murphy *et al.* (2013) have generated a database of high quality, near natural flows, with the identification process acting as a standard by which further catchments can be added. Unfortunately, the relatively short record length of IRN catchments poses problems for historical hydrological drought analysis. As a result of the identified drought poor period since the mid-1980s in Ireland (Noone *et al.*, 2017), observed flows may not contain values representative of plausible drought extremes. By applying flow reconstruction techniques it would be possible to extend these series thereby incorporating more severe events in the record and allowing for a more accurate analysis of catchment based drought on the island.

1.8.3 Historical changes in hydrometric records

Regional variations in total annual rainfall volumes across the island of Ireland directly impacts the occurrence and the characteristics of drought in Irish catchments. Taking into consideration the central role precipitation plays in drought occurrence in mid-latitude temperate climate regions such as Ireland, it is important to understand to what degree precipitation volume, intensity and spatial distribution have altered in the past. Noone *et al.* (2016) found decreasing trends in summer and increasing trends in winter rainfall totals for 25 stations across Ireland over the 1850-2010 period, with trends being highly dependent on the chosen period for assessment and having high inter-decadal variability. Ryan *et al.* (2021b)'s analysis of the persistence of trends in long-term (118 years on average) historical daily precipitation data for 30 stations across Ireland found predominantly increasing trends in total annual wet-day rainfall totals for trend tests commencing prior to the 1970s.The authors link this increase to more prevalent positive NAO conditions since that time. These results match those from studies for the UK and northern Europe which, in general, show increasing trends in precipitation, specifically in winter months (Fleig *et al.,* 2015; Caloiero *et al.*, 2018; Simpson and Jones 2014). Trends in meteorological drought occurrence have been extensively investigated in Europe with magnitudes and directions generally replicating the inverse of patterns identified in precipitation, with overall decreasing annual trends identifiable in Northern Europe (Gudmundsson, L. and Seneviratne, 2015; Spinoni *et al.*, 2015; Stagge *et al.*, 2017). Analysis of trends in meteorological drought in Ireland have been limited to work by Vicente-Serrano *et al.* (2021a) who found increasing meteorological drought severity at a three month accumulation in summer. Reductions in droughts at longer accumulations coincide with statistically significant positive trends in SPI values (wetter conditions) across the island, likely related to increased rainfall in winter months.

In northern and northwestern Europe as well as the UK overall increasing trends in annual flows are identifiable (Masseroni *et al.*, 2021; Hannaford and Marsh, 2006), with the greatest changes in the UK evident in autumn and winter (Hannaford and Buys, 2012). In Ireland, Murphy *et al.* (2013) assessed seasonal changes in mean and high flows at the 43 IRN stations finding that the record length, which averaged 40 years (ending in 2009), impacted the direction and magnitude of trends. For example winter mean flows showed decreasing trends for stations with shorter record lengths but increasing trends for longer series. Also trends in summer flows are at odds with those expected, with values increasing. The author's findings of large temporal variability in trends in flows highlights the limitations of relying upon short records. Of the limited assessments conducted on hydrological drought across Europe consistent trends have been difficult to identify with largely non-significant change found across the continent (Hisdal *et al.*, 2001), including in the UK (Hannaford, 2015), with temporal and spatial variations in trends very much dependent on chosen period and region. In Ireland no assessments of trends in hydrological drought have been carried out to date.

1.9 Key research gaps

Research gap 1: Ireland has a relatively short observational record of river flows, which for many catchments fails to contain data relating to historic drought events of importance. Not having long-term flow values hinders progress in identifying hydrological drought vulnerability. Using historic weather records and rainfall runoff models, the opportunity exists to extend these records.

Research gap 2: Whilst meteorological drought has been comprehensively investigated in Ireland, with characteristics of the most prominent historic events identified and classified, limited work on hydrological drought has been carried out, with previous research only focusing on drought occurrence in less than 13 catchments. Having broader knowledge of past historic drought events and how their characteristics differ at the catchment scale would provide better insight into drought vulnerability on the island.

Research gap 3: To date, no research linking meteorological and hydrological drought at the catchment scale in Ireland has taken place. Furthermore, assessment of regional characteristics of drought has been limited. By analysing the characteristics of meteorological and hydrological drought across multiple catchments it will be possible to determine how drought develops and propagates over time and offers a means to identify regional differences in drought vulnerability of catchments.

Research gap 4: Assessing changes in drought characteristics over time allows for trends to be identified, which can be used to prepare for the future. For accurate trend assessments long-term records are essential, however in Ireland short observed flow records hinder such analysis. Using derived long-term flow reconstructions, it would be possible to assess how drought characteristics including, occurrence, duration, mean and accumulated deficits have changed both spatially and temporally across the island in the last 250 years.

Research gap 5: Whilst drought indices are a useful tool for quantifying drought characteristics and detecting trends they are often limited to numerical assessments with limited applications in real-world scenarios. Linking drought indices and impacts has only recently garnered greater attention and shows great potential for identifying catchment based impacts for varying indices values over the course of the year. Using the newly developed database of historic newspaper articles on drought impacts (Jobbová *et al.*, 2022), it would be possible to link derived meteorological and hydrological indices to historically reported impacts on the ground. This assessment would also provide a means to identify temporal and spatial differences and trends in drought impact likelihoods across the island.

1.10 Research aim and objectives

The principal aim of this research is to address each of the five knowledge gaps identified in Section 1.9 and in the process present the most comprehensive assessment to date of catchment-based drought in Ireland. This will result in a greater understanding of drought, its characteristics and how it relates to historical socio-economic impacts and will generate valuable information and insights into catchment-based drought for water managers, engineers and hydrologists in Ireland and further afield. In order to address each of the research gaps the following objectives were set:

Objective 1: Using historic gridded precipitation and temperature data and an ensemble of river flow models, generate a database of historic river flow reconstructions for a set of diverse catchments across Ireland.

Objective 2: Using the reconstructed flow series and hydrological drought indices, identify extreme hydrological droughts in the record and classify them based on their duration, maximum intensities and accumulated (total) deficits to produce a catalogue of the most highly ranked extreme events.

Objective 3: Using the reconstructed flow series and hydrological drought indices, examine historical hydrological drought characteristics for catchments across the island, specifically focusing on drought occurrence, duration, mean deficits and accumulated (total) deficits. In the process, examine how catchment characteristics influence the experience of hydrological droughts and the propagation of meteorological to hydrological events.

Objective 4: Evaluate trends in meteorological and hydrological droughts and their characteristics including occurrence, duration, mean deficits and accumulated deficits for both individual and clustered catchments to better understand variability and change.

Objective 5: Using derived drought indices, historical impact data and modelling techniques, examine if a relationship exists between meteorological and hydrological drought and recorded impacts at the catchment scale and identify regional differences and changes in the likelihood of reported drought impacts over time.

1.11 Thesis structure

In line with the format of a PhD by publication, three manuscripts were prepared and submitted to reputable journals for peer-review. Paper one has been published in the Geoscience Data Journal whilst paper two has been published in the International Journal of Climatology. Paper three has been submitted to the International Journal of Climatology and is currently under review. The journals were chosen based on their relevance to the research topic, their highly regarded reputation, their good impact factors and their ability to provide open-access at a reasonable rate to allow for the greatest possible dissemination of the research to an audience that would most benefit from the study's findings. Each of the three manuscripts is presented as an individual chapter within the thesis, i.e. Chapters 2, 3 and 4, with the structure and information contained within each, meeting all requirements for a typical thesis chapter. Together, the chapters extensively address the five objectives of the research and in each case present a detailed background to the particular topic under review, the methodology employed to achieve the given research objective(s), the results obtained and a detailed discussion of those results. The final chapter of the thesis summarises the main findings presented in Chapters 2 to 4 and provides more detail on the limitations and possible future directions for the research. Further information on chapter contents and the relevant publication to which each relates (where applicable) follows:

Chapter 2 provides information on how the 250 years (1766-2016) of monthly river flow reconstructions for 51 catchments across Ireland was developed. Details on gridded precipitation and temperature data extraction, hydrological model generation, uncertainty assessment and reconstruction evaluations are all provided along with an analysis of the most notable annual, seasonal and monthly extremes in the developed series. Information on how to access the resulting dataset is also provided.

Relevant publication: O'Connor, P., Murphy, C., Matthews, T. and Wilby, R.L., 2021b. Reconstructed monthly river flows for Irish catchments 1766–2016. *Geoscience Data Journal*, 8(1), pp.34-54. https://doi.org/10.1002/gdj3.107

Relevant dataset: O'Connor, P., Murphy, C., Matthews, T. and Wilby, R.L., 2021a. Monthly river flows reconstructions for Ireland 1766–2016. *PANGAEA*. https://doi.org/10.1594/PANGAEA.914306

Chapter 3 provides an analysis of hydrological drought occurrence in Ireland over the last 250 years, derived from the flow reconstructions described in Chapter 2. Following the provision of a summary on the relevant literature, a detailed description of how the monthly drought indices were derived for individual and grouped catchment flows, along with related precipitation values, is given. An analysis of the occurrence, duration, mean and accumulated deficits of historical events is then provided. The most extreme events in the series are then identified, categorised and analysed to extract prominent temporal and spatial features and assess how meteorological drought propagates to hydrological drought in catchments and cluster groupings. Finally, the derived indices are examined for trends in drought characteristics across the length of the full series and in a moving window assessment. Results are then compared to other similar international studies to identify commonalities between findings.

Relevant publication: O'Connor, P., Murphy, C., Matthews, T. and Wilby, R.L., 2022a. Historical droughts in Irish catchments 1767-2016. *International Journal of Climatology*. Early view. https://doi.org/10.1002/joc.7542

Chapter 4 outlines the process by which a relationship between meteorological and hydrological drought indicators and documented real-world impacts can be developed. Following an initial assessment of the underlying indices data (derived in the same manner as those described in Chapter 3) and a novel database of historical documentary records of drought impacts, relationships between both series are developed using regression models. Spatial and temporal deviations in impact likelihoods are then identified for meteorological and hydrological drought across Ireland for the 1900-2016 period, with regional characteristics of drought impact likelihoods identified in the process. Findings are then discussed to, amongst other things, ascertain the reasons for varying regional drought impact likelihoods and related trends.

Relevant publication: O'Connor, P., Murphy, C., Matthews, T. and Wilby, R.L., 2022b. Relating drought indices to impacts reported in newspaper articles. *International Journal of Climatology*. Submitted for review (31st January 2022).

Chapter 5 provides an overall summary of the research presented in this thesis, drawing together the key findings from the three publications in Chapters 2, 3 and 4. An assessment of whether or not each of the five research objectives was achieved is given with the main results from each identified, summarised and discussed in detail. A discussion of the study's limitations is then presented, identifying areas that need particular consideration when using the developed dataset and research findings. Finally, possible future work is noted.

Chapter 2 | Reconstructed monthly river flows for Irish catchments 1766-2016

2.1. Introduction

Continuous, long-term river flow records are needed for evaluations of hydro-climatic variability and change, historical extremes and catchment processes (Machiwal and Jha, 2006). They also underpin water management and provide a means of stress-testing existing and planned systems to a range of variability and past droughts (Wilby and Murphy, 2019). Unfortunately, there are few continuous and homogeneous river flow records spanning a century or more (Mediero *et al.,* 2015). Instead, available records are often impacted by confounding factors or large amounts of missing data (Wilby *et al.*, 2017).

Various techniques exist for extending observations by reconstructing river flows. This typically involves forcing statistical or conceptual hydrological models with long-term precipitation and temperature/evapotranspiration data provided by reanalysis (e.g. Brigode *et al.,* 2016; Kuentz *et al.,* 2013) or long-term historical datasets (e.g. Jones 1984; Spraggs *et al.,* 2015; Hanel *et al.,* 2018, Rudd *et al.,* 2017; Crooks and Kay 2015; Smith *et al.*, 2019; Noone and Murphy, 2020). Others have leveraged international data rescue initiatives to generate gridded historical weather variables (Casty *et al.*, 2007). While these kinds of information have been used to reconstruct river flows in parts of Europe (e.g. Moravec *et al.*, 2019), they have yet to be deployed in the British-Irish Isles.

Here, we develop a dataset of reconstructed monthly river flows for 51 catchments across the island of Ireland back to 1766. This was achieved using gridded historical meteorological data, bias corrected to contemporary observations in each catchment. These data provided the input to a conceptual hydrological model and an artificial neural network (ANN), both of which were trained and verified using river flow observations. In addition, we use recently rescued precipitation data to evaluate model reconstructions for selected catchments during the period 1850-2010. The following sections describe the catchments, datasets and modelling approaches, before we present the derived reconstructions.

2.2 Data production methods

2.2.1 Catchments and data

Reconstructions were generated for 51 catchments (Table 2.1 and Figure 2.1) that are relatively free from artificial influences (following criteria applied by Murphy *et al.* (2013):

they have at least 25 years of record and acceptable quality rating curves). The catchments are broadly representative of hydro-climatological conditions across the island, with a recognised under-representation of upland catchments along coastal margins (Broderick *et al.*, 2019). Urban extent averages <2% of the combined area of all catchments, which individually vary in size between 10 and 2418 km^2. However, given the extent of arterial drainage works undertaken in Ireland, it is unavoidable that some catchments have been impacted by such activities. We note which catchments are known to be affected by arterial drainage in Table 2.1.

Daily flow series were obtained from the Office of Public Works (OPW; http://waterlevel.ie/) and the Environmental Protection Agency (http://www.epa.ie/hydronet/) then aggregated to total monthly mean flows. Flows were subsequently converted from cumecs to mm per catchment area to allow for a direct comparison with catchment area precipitation values. The average amount of missing flow data was <6% across the 51 catchments, with a notable outlier of 31% being the Blackwater at Duarrigle (ID: 18050). Of the total missing days (11% overall) the majority have been previously infilled using rainfall-runoff modelling techniques (Murphy *et al.*, 2013). As the remaining missing data only represented 1% of the total, they were not repopulated.

We use gridded (1 × 1 km) monthly precipitation and temperature series (Walsh, 2012) area-averaged for each catchment, alongside concurrent river flow records, to calibrate the hydrological models (see below). Monthly potential evapotranspiration (PET) was estimated from air temperature and radiation following the method of Oudin *et al.* (2005). We favoured this over more physically-based methods (e.g. Penman-Monteith), because the latter have greater data requirements (e.g. wind speed, humidity) that cannot be met over the full duration of the reconstruction period. Instead, the sensitivity of monthly river flow simulations to PET estimation methods was tested for periods with complete variable sets. Six PET estimation methods (Penman-Monteith (Penman, 1948; Monteith, 1965), Blaney and Criddle (1950), Hamon (1961), Oudin *et al.* (2005), Thornthwaite (1948) and Kharrufa (1985)) were evaluated using the hydrological model GR2M (Mouelhi *et al.*, 2006). This revealed that the Oudin method performed similarly to the Penman-Monteith method, with an average RMSE of 3.6 mm between flows generated from the two methodologies for five catchments for the period 1974-2000 (equating to 0.38% of mean annual total flows).

Table 2.1 Details of the 51 catchments for which flow reconstructions were generated. Included are calibration and validation periods for each catchment, together with logNSE, KGE and PBIAS scores for the validation period for all ANN, GR2M and Ensemble median simulations.

River Flow Station		Waterbody	Area	Calibration	Validation	GR2M Validation Score			ANN Validation Score			Ensemble Validation Score		
(ID)	(Name)	(Name)	(km^2)	(Years)	(Years)	(NSE)	(KGE)	(PBIAS%)	(NSE)	(KGE)	(PBIAS%)	(NSE)	(KGE)	(PBIAS%)
3051	Faulkland	Blackwater	143	1976 - 2000	2001 - 2016	0.79	0.69	-16.40	0.78	0.67	-14.80	0.80	0.69	-16.00
6013	Charleville	Dee	309	1976 - 2000	2001 - 2016	0.78	0.75	-12.50	0.82	0.70	-9.10	0.83	0.72	-11.20
6014	Tallanstown	Glyde	270	1976 - 2000	2001 - 2016	0.77	0.75	-8.00	0.82	0.73	-4.50	0.81	0.73	-7.70
6030	Ballygoly	Big	10	1975 - 2000	2001 - 2016	0.86	0.86	-2.10	0.83	0.78	-1.00	0.86	0.83	-1.80
7009	Navan Weir	Boyne	1658	1977 - 2000	2001 - 2016	0.77	0.73	-9.90	0.81	0.73	-6.40	0.81	0.71	-9.60
7012	Slane Castle	Boyne	2408	1961 - 2000	2001 - 2016	0.79	0.74	-11.90	0.83	0.71	-8.60	0.84	0.72	-10.90
9011	Frankfort	Slang	5.5	1983 - 2000	2001 - 2016	0.84	0.88	1.70	0.77	0.86	4.20	0.85	0.87	2.40
12001	Scarrawalsh	Slaney	1031	1961 - 2000	2001 - 2016	0.76	0.73	-15.10	0.80	0.81	-11.90	0.78	0.74	-14.50
14007	Derrybrock	Stradbally	115	1980 - 2000	2001 - 2016	0.83	0.77	-10.10	0.88	0.79	-8.80	0.86	0.75	-10.30
14019	Levitstown	Barrow	1697	1961 - 2000	2001 - 2016	0.81	0.74	-12.40	0.86	0.79	-8.00	0.84	0.74	-11.60
15001	Annamult	Kings	445	1972 - 2000	2001 - 2016	0.87	0.90	-1.00	0.88	0.82	1.10	0.89	0.87	-0.30
15003	Dinin Bridge	Dinin	140	1972 - 2000	2001 - 2016	0.87	0.86	-7.40	0.84	0.75	-8.90	0.88	0.82	-7.80
15005	Durrow Ft. Br.	Erkina	379	1972 - 2000	2001 - 2016	0.78	0.68	-11.90	0.83	0.72	-8.50	0.82	0.68	-10.60
15006	Brownsbarn	Nore	2418	1972 - 2000	2001 - 2016	0.87	0.88	-3.90	0.90	0.87	0.30	0.91	0.87	-2.10
15007	Kilbricken	Nore	340	1982 - 2000	2001 - 2016	0.82	0.71	-11.30	0.81	0.68	-8.60	0.82	0.70	-10.70
16008	New Bridge	Suir	1090	1961 - 2000	2001 - 2016	0.85	0.84	-6.90	0.86	0.87	-2.40	0.88	0.84	-5.40
16009	Caher Park	Suir	1583	1962 - 2000	2001 - 2016	0.86	0.87	-7.50	0.90	0.93	-3.20	0.89	0.89	-6.20
16010	Anner	Anner	437	1973 - 2000	2001 - 2016	0.80	0.89	-1.20	0.84	0.92	2.90	0.85	0.91	0.60
16011	Clonmel	Suir	2144	1962 - 2000	2001 - 2016	0.88	0.89	-0.10	0.89	0.94	3.20	0.90	0.90	1.10
16012	Tar Bridge	Tar	230	1969 - 2000	2001 - 2016	0.83	0.83	0.80	0.83	0.89	2.00	0.85	0.85	1.30
16013	Fourmilewater	Nire	94	1973 - 2000	2001 - 2016	0.69	0.85	-0.80	0.82	0.84	-1.20	0.80	0.86	-1.50
18002	Ballyduff	Blackwater	2334	1972 - 2000	2001 - 2016	0.90	0.91	6.00	0.87	0.86	10.30	0.91	0.92	7.40
18003	Killavullen	Blackwater	1257	1972 - 2000	2001 - 2016	0.91	0.88	0.80	0.92	0.95	3.80	0.93	0.91	1.60
18006	Cset Mallow	Blackwater	1052	1978 - 2000	2001 - 2016	0.88	0.83	-0.20	0.89	0.88	3.80	0.90	0.85	1.10
18050	Duarrigle	Blackwater	250	1982 - 2000	2001 - 2016	0.89	0.86	-5.50	0.89	0.84	-5.00	0.90	0.85	-5.30
19001	Ballea	Owenboy	103	1973 - 2000	2001 - 2016	0.85	0.76	-16.30	0.82	0.74	-12.60	0.85	0.75	-14.50
21002	Coomhola	Coomhola	65	1976 - 2000	2001 - 2016	0.90	0.83	-6.40	0.92	0.89	-4.70	0.93	0.87	-5.30
22006	Flesk	Flesk (Laune)	329	1990 - 2000	2001 - 2016	0.84	0.75	-7.20	0.91	0.84	-6.40	0.89	0.80	-6.60
22035	Laune Bridge	Laune	560	1992 - 2000	2001 - 2016	0.81	0.73	-6.10	0.87	0.84	-6.30	0.86	0.78	-6.40
23002	Listowel	Feale	647	1975 - 2000	2001 - 2016	0.93	0.90	2.80	0.92	0.87	3.40	0.94	0.89	3.40
24008	Castleroberts	Maigue	806	1977 - 2000	2001 - 2016	0.89	0.83	-0.40	0.88	0.83	3.30	0.90	0.82	0.90
24030	Danganbeg	Deel	259	1981 - 2000	2001 - 2016	0.92	0.90	1.70	0.91	0.90	4.20	0.93	0.90	2.80
25001	Annacotty	Mulkear	648	1973 - 2000	2001 - 2016	0.88	0.82	-1.50	0.88	0.82	0.00	0.89	0.82	-1.00
25002	Barrington Br.	Newport (Mun.)	230	1961 - 2000	2001 - 2016	0.91	0.92	-0.90	0.91	0.94	0.70	0.92	0.93	-0.20
25006	Ferbane	Brosna	1163	1961 - 2000	2001 - 2016	0.83	0.79	-10.40	0.86	0.80	-6.80	0.87	0.78	-9.50
25030	Scarriff	Graney	279	1973 - 2000	2001 - 2016	0.86	0.81	-6.80	0.86	0.83	-4.10	0.87	0.82	-5.50
25034	Rochfort	L. Ennell Trib	11	1976 - 2000	2001 - 2016	0.81	0.84	-7.90	0.85	0.81	-7.60	0.86	0.82	-8.30
26021	Ballymahon	Inny	1099	1973 - 2000	2001 - 2016	0.83	0.86	-4.10	0.84	0.88	-0.60	0.88	0.85	-3.40
26029	Dowra	Shannon	117	1976 - 2000	2001 - 2016	0.86	0.85	-8.80	0.83	0.81	-8.00	0.86	0.84	-8.20
26058	Ballyrink Br.	Inny Upper	60	1982 - 2000	2001 - 2016	0.75	0.82	4.50	0.85	0.82	4.40	0.85	0.82	2.60
27002	Ballycorey	Fergus	511	1961 - 2000	2001 - 2016	0.83	0.74	-8.70	0.84	0.81	-6.90	0.85	0.75	-8.50
30007	Ballygaddy	Clare	470	1975 - 2000	2001 - 2016	0.89	0.85	-7.50	0.91	0.90	-4.30	0.91	0.86	-6.40
32012	Newport Weir	Newport	146	1982 - 2000	2001 - 2016	0.90	0.85	-6.00	0.90	0.89	-3.80	0.91	0.87	-4.80
33001	Glenamoy	Glenamoy	76	1978 - 2000	2001 - 2016	0.93	0.95	-0.50	0.87	0.94	0.00	0.93	0.96	0.30
34001	Rahans	Moy	1975	1970 - 2000	2001 - 2016	0.90	0.92	-4.60	0.89	0.94	-1.90	0.92	0.92	-4.00
35002	Billa Bridge	Owenbeg	81	1972 - 2000	2001 - 2016	0.86	0.88	4.70	0.87	0.92	5.60	0.88	0.90	5.30
35005	Ballysadare	Ballysadare	640	1961 - 2000	2001 - 2016	0.89	0.90	-2.30	0.90	0.90	-2.10	0.91	0.90	-2.40
36015	Anlore	Finn	153	1973 - 2000	2001 - 2016	0.84	0.76	-9.50	0.79	0.65	-10.40	0.84	0.73	-9.80
36019	Belturbet	Erne	1492	1961 - 2000	2001 - 2016	0.83	0.85	-5.60	0.79	0.77	-7.60	0.86	0.80	-6.90
38001	Clonconwal	Ownea	111	1973 - 2000	2001 - 2016	0.93	0.87	-4.00	0.93	0.88	-4.50	0.94	0.88	-3.60
39006	Lennan	Claragh	245	1977 - 2000	2001 - 2016	0.85	0.88	8.00	0.85	0.87	7.90	0.86	0.88	8.00
39009	Aghawoney	Fern O/L	207	1973 - 2000	2001 - 2016	0.91	0.90	-1.00	0.91	0.88	-2.20	0.92	0.90	-1.20

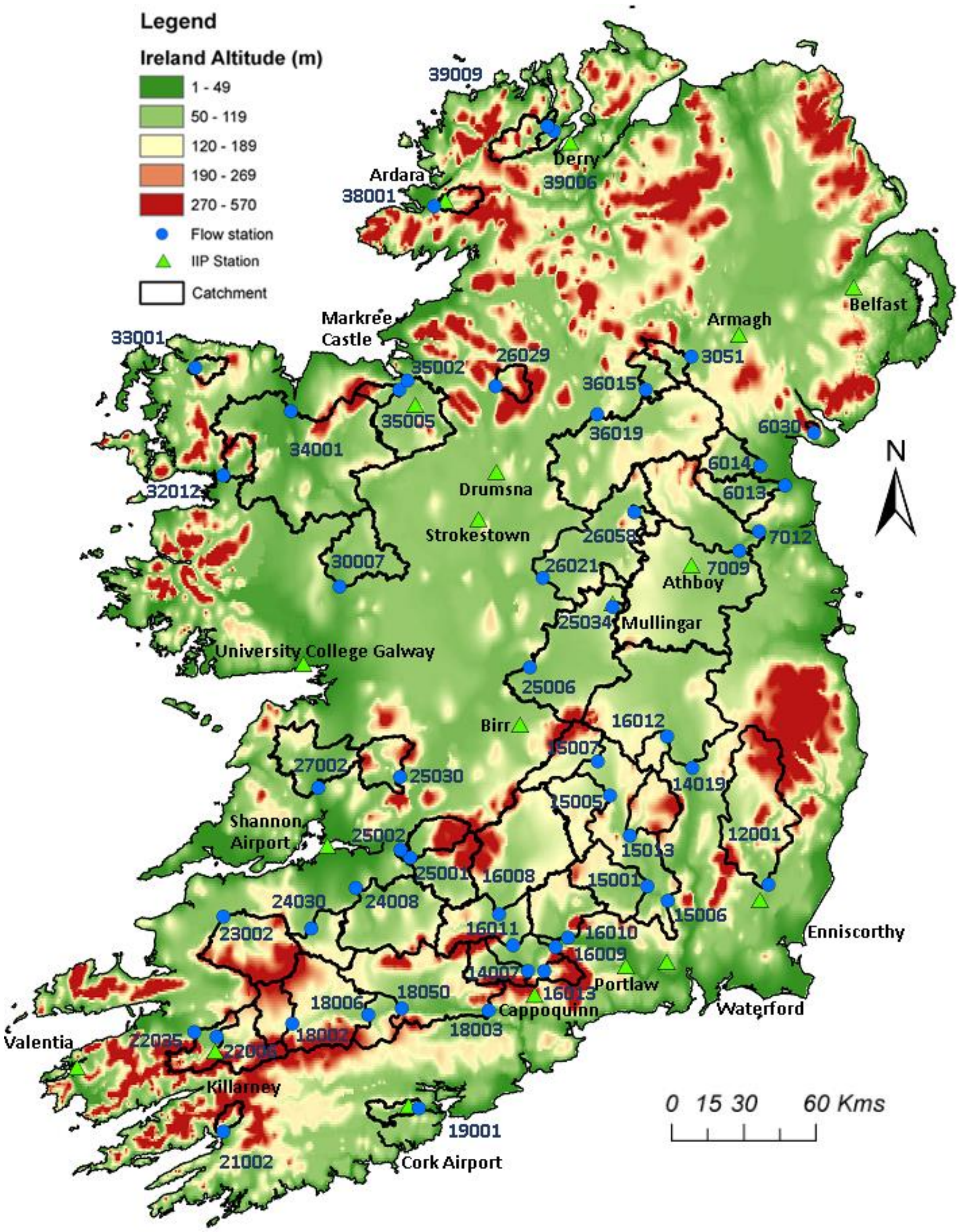


Figure 2.1 The 51 study catchments along with the locations of corresponding flow stations and island of Ireland precipitation (IIP) series synoptic stations.

2.2.2 Historical gridded precipitation and temperature data

Casty *et al.* (2007) (henceforth Casty data) produced gridded (0.5° x 0.5°) monthly temperature and precipitation series for Europe covering the period 1766-2000 using nonlinear principal component regression of a spatial network of available station data against reanalysis data, with independent predictors used for different variables (Casty *et* *al.*, 2007). Monthly mean temperature and total precipitation were extracted and averaged for grids overlying each catchment for the years 1766-2000. Quantile mapping (Maraun, 2016) was used to bias correct Casty data to catchment averages using the aforementioned gridded (1 × 1 km) monthly precipitation and temperature series. We perform quantile mapping by interpolating the empirical quantiles using local linear least square regression to robustly estimate the values of the quantile-quantile relationship between the Casty and observed data for each catchment. For values outside the historical range a constant correction – equivalent to the highest quantile in that series – was applied (Boé *et al.,* 2007). Bias correction was carried out on a monthly basis using the 'qmap' R package (Gudmundsson, 2016). Sample bias correction plots for nine catchments are shown in Figure 2.2 (temperature) and Figure 2.3 (precipitation). Across the 51 catchments, the bias adjustment produced minimal change in mean annual temperature values (-0.15°C). Precipitation corrections were more substantial, with a mean increase of 94.2mm/year (7.7% of mean annual precipitation). Once bias corrected, observed temperature and precipitation were appended to each catchment series to bring values up to 2016. The Oudin method was then used to derive PET estimates from the Casty temperature data for each catchment.

2.2.3 Hydrological models and calibration procedures

To ascertain the contribution to uncertainty generated by model structure two model types were implemented - a conceptual hydrological model (GR2M) and an empirical based Artificial Neural Network (ANN). These models are explained below.

2.2.3.1 The GR2M conceptual model

GR2M is a simple water balance model (Mouelhi *et al.*, 2006), originally developed for French catchments, now available via the airGR R hydrological modelling package (Coron *et al.*, 2017). The monthly flow model contains two reservoirs representing a soil store and routing reservoir (Figure 2.4) governed by two parameters: the production store capacity and groundwater exchange coefficient. GR2M has been widely deployed across diverse catchment types and applications (e.g. Louvet *et al.*, 2016), including for flow reconstructions (Dieppois *et al.*, 2016).

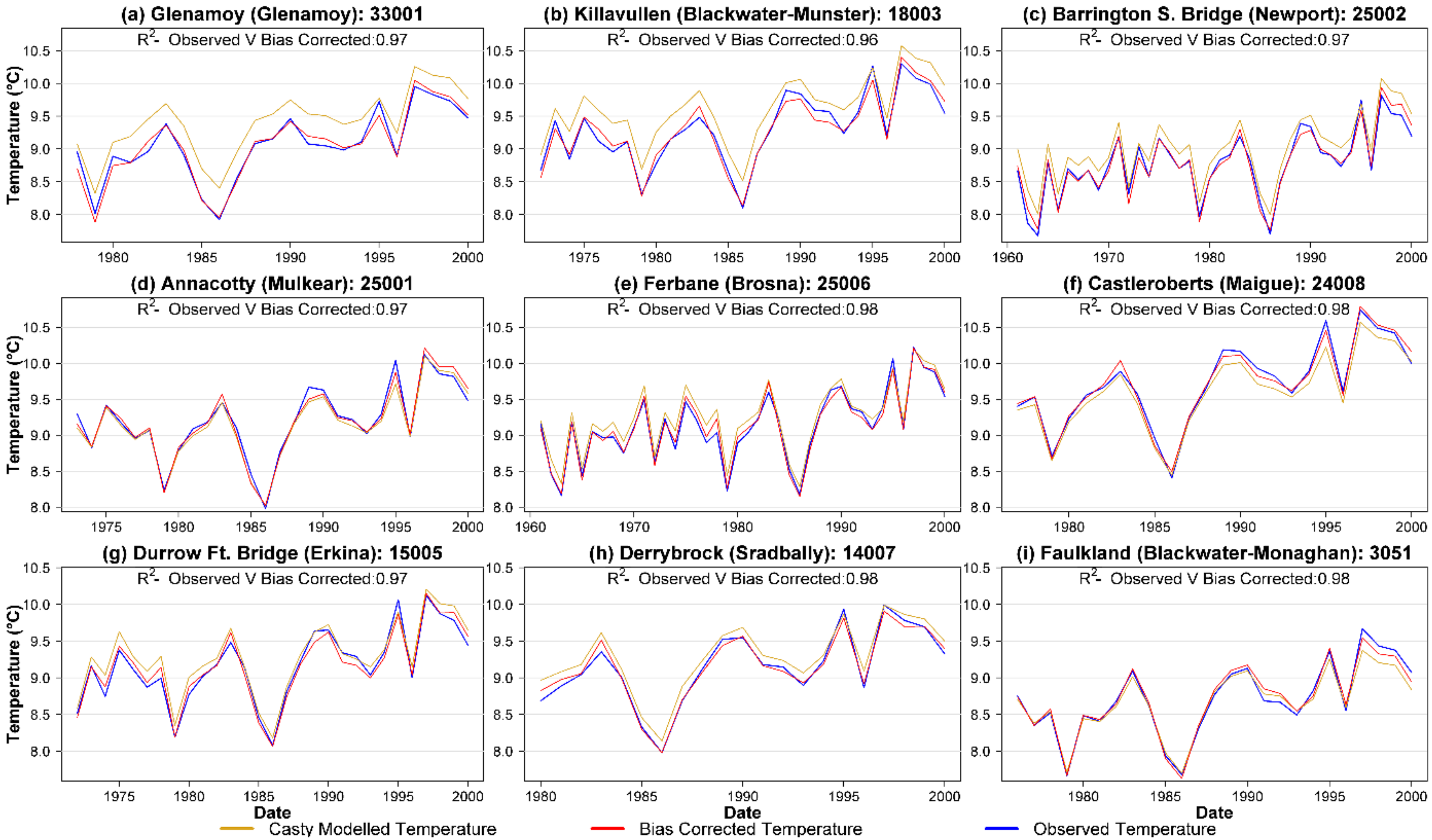


Figure 2.2 Annual bias corrected Casty temperature for nine catchments from the start of the respective observations up until the year 2000. R^2 scores between bias corrected and observed temperature values are also provided.

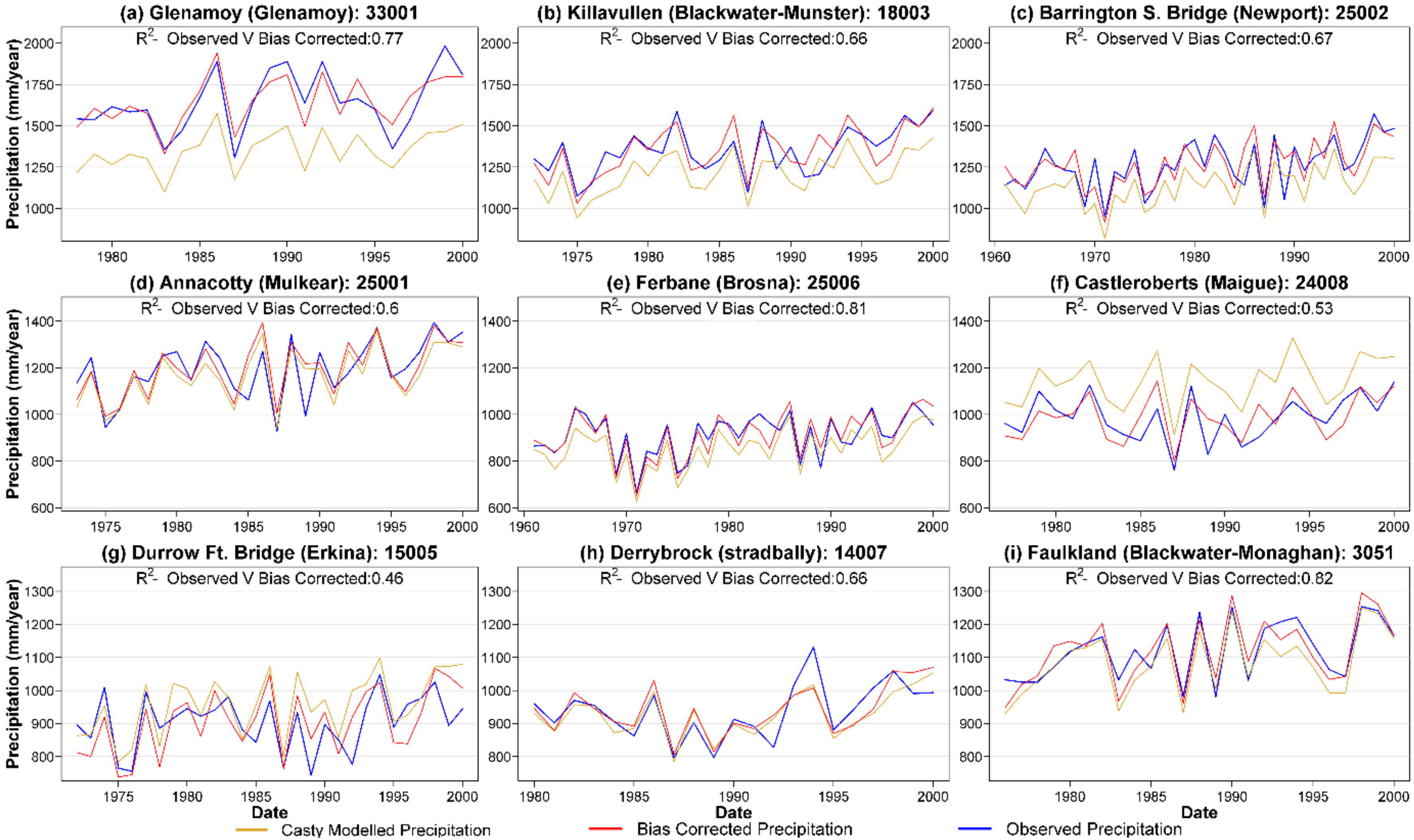
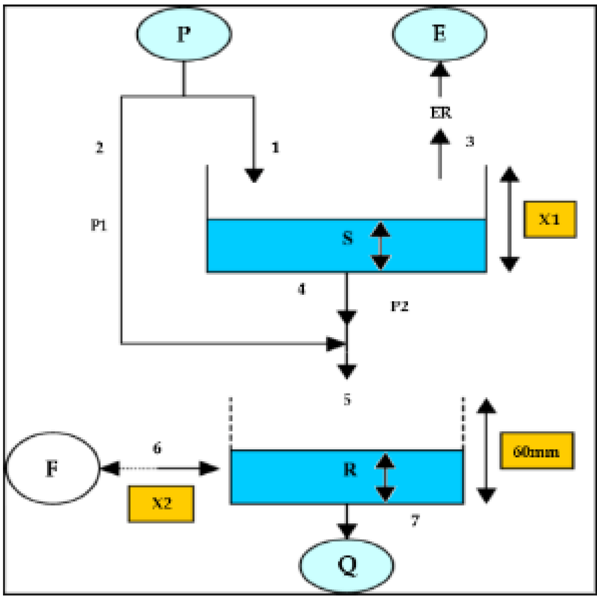


Figure 2.3 Annual bias corrected Casty precipitation values for nine catchments from the start of the respective observations up until the year 2000. R^2 scores between bias corrected and observed precipitation values are also provided.

For each catchment, GR2M was calibrated and validated on observed data before using the bias corrected Casty data to reconstruct flows. A split record for calibration/validation was applied as this allows direct comparison between GR2M and ANN model outputs on a catchment-by-catchment basis. Calibration for all catchments (including a one year warm-up period), was undertaken from the start of the flow record up to December 2000. This time-interval captures periods of large flow variability ranging from the drought rich 1970s to the flood rich 1980s. Validation was undertaken using the 15 years post calibration (2001-2016) for all catchments (see Table 2.1).



(1) $S_1 = \frac{S+X_1\varphi}{1+\varphi\frac{S}{X_1}}$ with $\varphi = tanh\frac{P}{X_1}$

(2) $S_2 = \frac{S_1(1-\Psi)}{1+\Psi\left(1-\frac{S_1}{X_1}\right)}$ with $\Psi = tanh\frac{E}{X_1}$

(3) $S = \frac{S_2}{\left[1+\left(\frac{S_2}{X_1}\right)^3\right]^{1/3}}$; $P_2 = S_2 - S$

(4) $P_1 = P + S - S_1$

(5) $R_1 = R + P_1 + P_2$

(6) $R_2 = X_2 . R_1$

(7) $Q = \frac{R_2{}^2}{R_2+60}$; $R = R^2 - Q$

Figure 2.4 Outline of the structure of the GR2M model together with relevant equations defining the model structure. (Adapted from Mouelhi (2013) and Lespinas *et al.*, 2014).

Uncertainty in GR2M model parameters was sampled using Monte Carlo methods. For each parameter, 20,000 values were randomly drawn from a uniform distribution of [0-2500 mm] for the production store capacity and [0-2] for the groundwater exchange coefficient. Each parameter set was used to simulate flows for the calibration period (yielding a 20,000-member ensemble). The performance of parameter sets was evaluated using two objective functions to ensure robust performance across the flow regime: the Nash Sutcliffe Efficiency (NSE) (Nash and Sutcliffe, 1970) derived from log transformed flows (logNSE) and the modified Kling Gupta Efficiency (KGE) derived from raw flows (Gupta *et al.,* 2009; Kling *et al.,* 2012). Two steps were then undertaken to determine which parameter sets to retain. First, objective function scores were ranked by their performance, with the top 400 sets from each being retained. Second, retained simulations were evaluated by their absolute percent bias (PBIAS) relative to observed flows, with the 200 best performing parameter sets for both logNSE and KGE retained. The median (henceforth GR2M median) and 95th percentile confidence intervals of GR2M simulated flows, retained from this process, were then determined.

2.2.3.2 The ANN Model

ANNs have been widely used for rainfall-runoff modelling (Dawson and Wilby, 1998; Dastorani *et al.*, 2010). A backpropagation ANN was developed here using the neuralnet R package (Fritsch *et al.,* 2019), with different combinations of inputs and neurons tested with two hidden layers. The same calibration and validation periods for individual catchments were employed as those for the GR2M, again using observed data to generate the model. When determining the ANN structure, input data were limited to observed variables that were also available for the full reconstruction period (temperature, precipitation and PET). Lagged variables (e.g. precipitation from previous months) were also included. Whilst the performance of models varied based on chosen input data and their relationship to catchment characteristics, overall the best performing inputs were found to be temperature and precipitation from the current month, plus precipitation lagged by one, two and three months. These inputs were applied consistently across all ANN models to allow for a like-for-like comparison between model performances. An example ANN structure which generated the best efficiency scores for one catchment is shown in Figure 2.5.

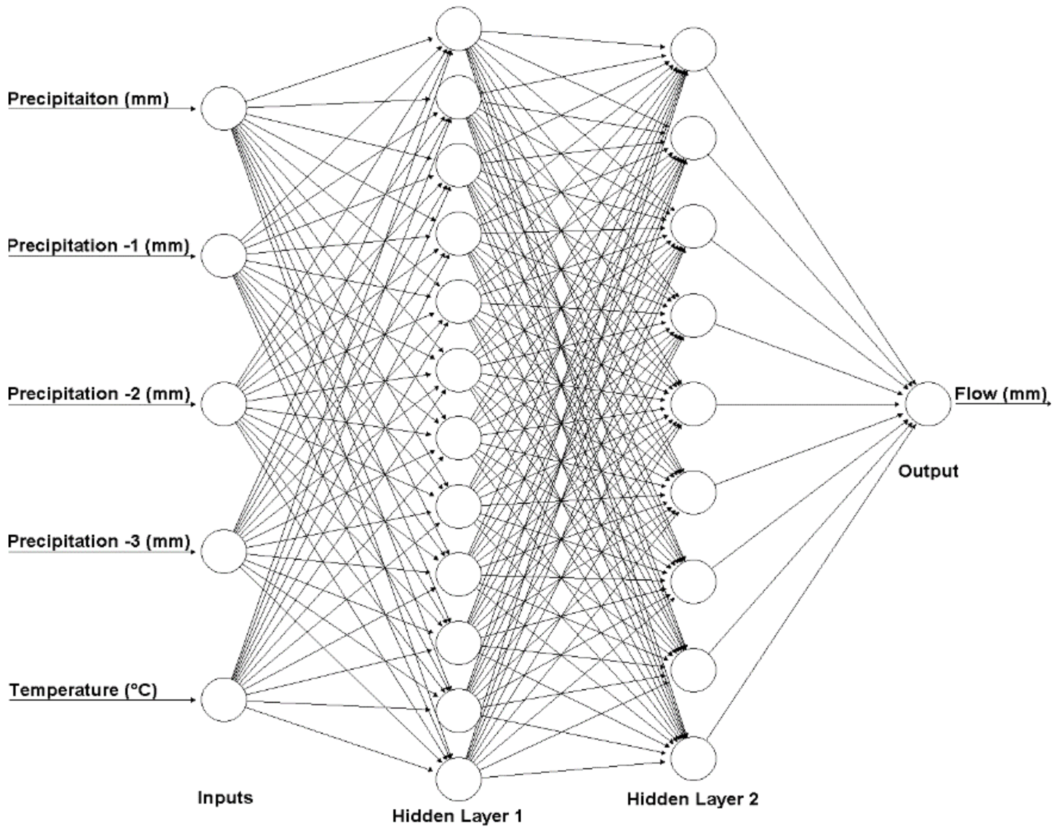


Figure 2.5 Schematic of a typical ANN model structure employed with five inputs, two hidden layers (with 12 and 9 neurons respectively) and monthly flow output. Negative one, two and three values represent the number of lagged months for precipitation.

Uncertainty in ANN model structure was explored by varying combinations of neurons in one or two hidden layers. Neuron permutations, varying from one to twenty for each hidden layer (giving 420 independent model structures in total), were used to simulate flows for the given calibration period. Each model structure was then independently evaluated using logNSE and KGE and ranked in order of performance. As per the GR2M model, the top 400 ANN model structures according to each objective function were identified and those which subsequently produced the 200 lowest PBIAS scores were retained. The median (henceforth ANN median) and 95th percentile confidence intervals of simulated flows were then obtained.

Finally, a mixed ensemble was derived from both GR2M and ANN model structures and parameters by combining the 200 retained simulations from each. The median (henceforth Ensemble median) and 95th percentile confidence intervals of simulated flows were obtained and used to evaluate model reconstructions.

2.2.3.3 Validation results

Figure 2.6 displays the performance of the GR2M, ANN and Ensemble median simulations for all 51 catchments for the 2001-2016 validation period according to logNSE, KGE and PBIAS scores. The ANN and GR2M simulations perform equally well with average logNSE, KGE and PBIAS scores across all 51 catchments of 0.86, 0.83 and -3.04 % for GR2M median and 0.85, 0.83 and -4.97% for ANN median. The combined Ensemble median returned scores of 0.87, 0.83 and -4.38%. Individual catchment results also show similar performance for both model types.

Skill scores for GR2M, ANN and Ensemble median simulations during validation for each catchment are provided in Table 2.1. Poorest performances are evident for the Nire at Fourmilewater (ID: 16013) which has a logNSE score of 0.69 (ANN median) and the Finn at Anlore (ID: 36015) with a KGE score of 0.65 (GR2M median). PBIAS scores vary between catchments with the largest bias evident for the Blackwater at Faulkland (ID: 3051) (-16.4%; ANN median) and a minimum of 0% for the Glenamoy at Glenamoy (ID: 33001) (GR2M median). PBIAS values are generally higher for the ANN median.

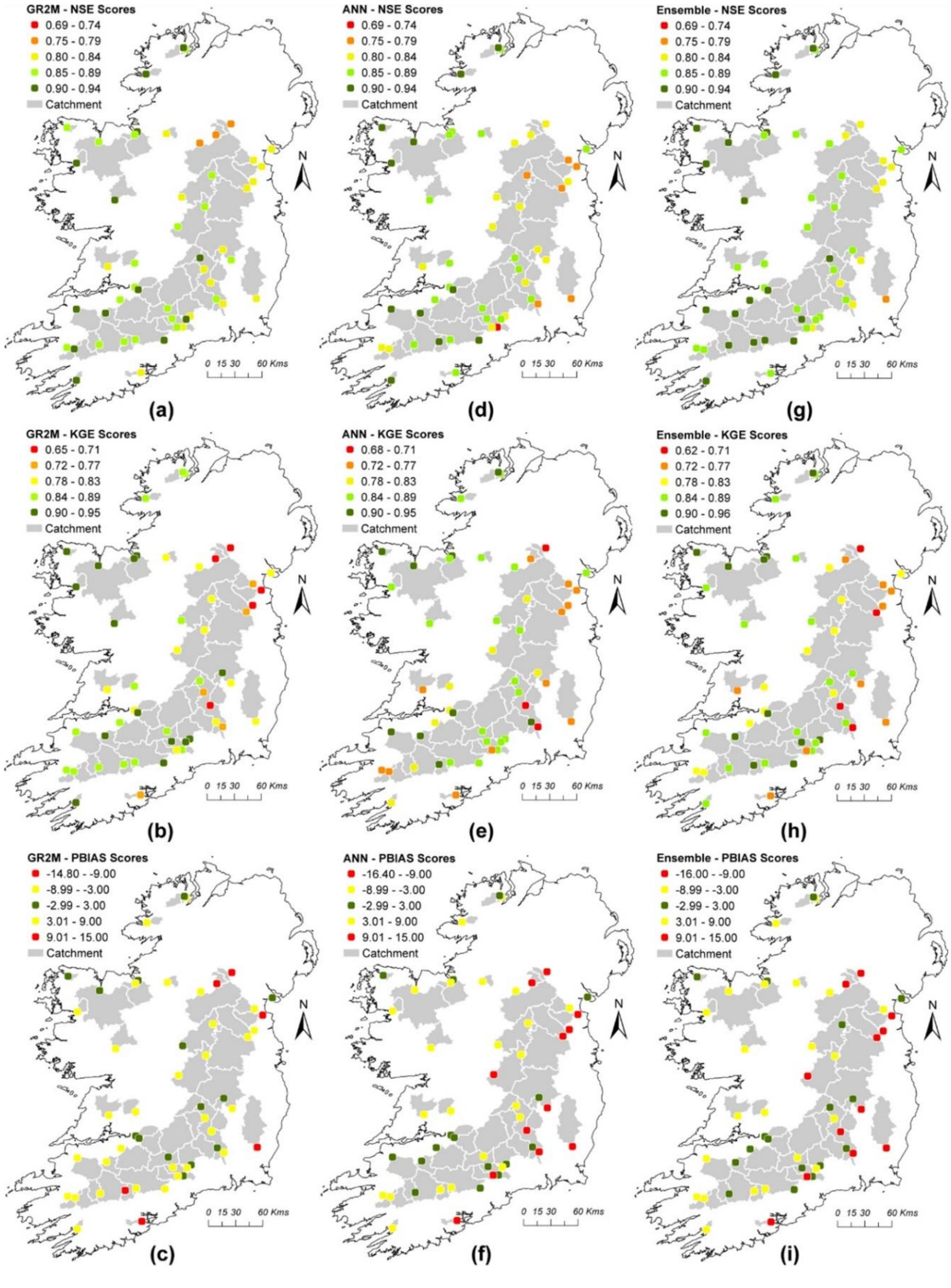


Figure 2.6 Maps of logNSE, KGE and PBIAS scores for GR2M, ANN and Ensemble median simulations for all 51 catchments. Scores are derived from the observed versus modelled flows for the independent validation period (2001 to 2016) for each catchment.

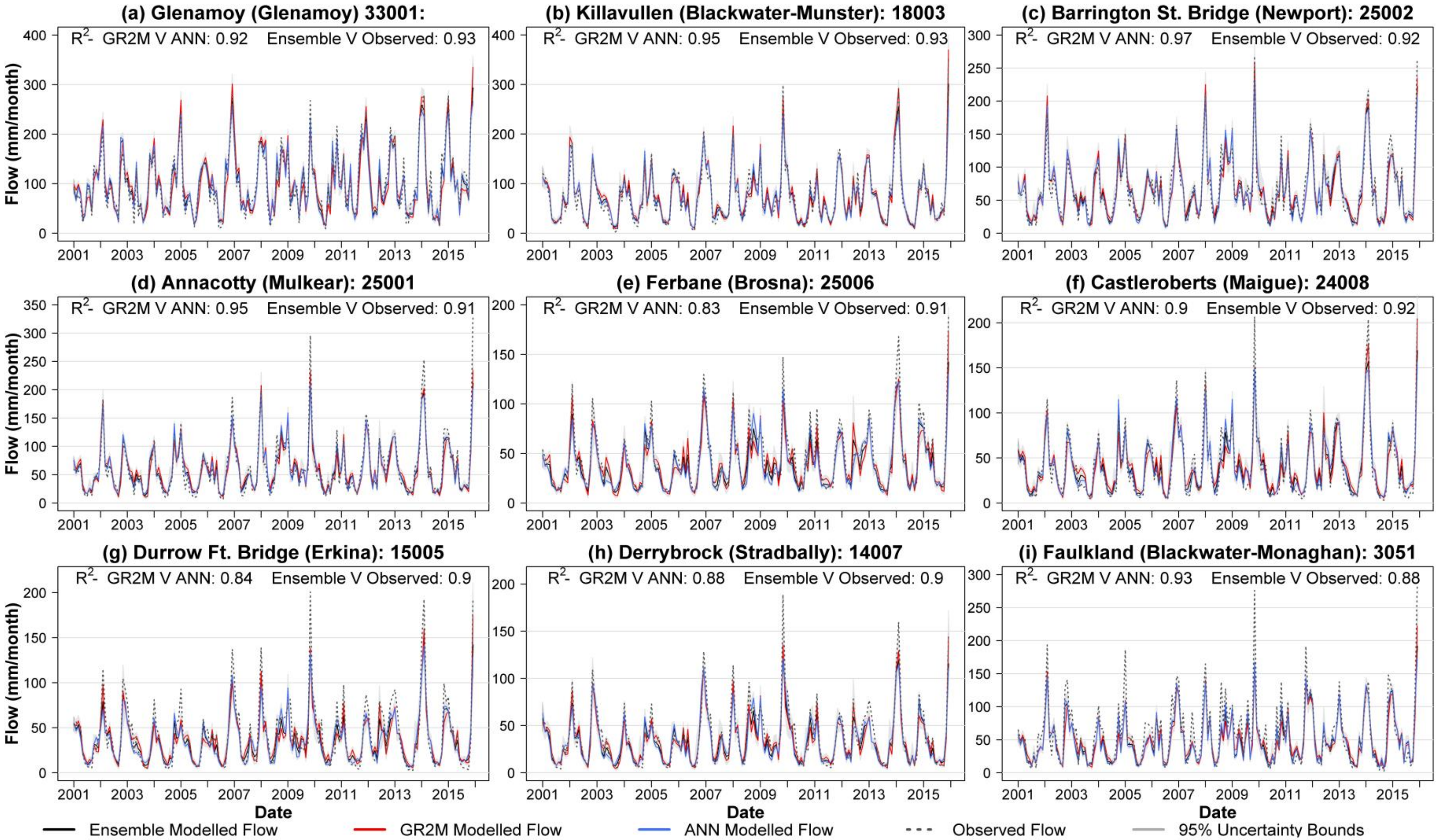


Figure 2.7 Observed and simulated mean annual flows for nine sample catchments representing best (top row), average (middle row) and worst (bottom row) performing models. Plotted are the GR2M (red), ANN (blue) and Ensemble median (black) simulations, together with observed flows (dashed dark-grey). 95% uncertainty range (grey) is derived from the Ensemble median simulations.

Observed and simulated monthly flows for the validation period for nine catchments are shown in Figure 2.7. This sub-set represents a spread of the best (top row), average (middle row) and worst (bottom row) performing catchments. The proportion of observed variance (R^2) captured by the Ensemble median simulation for each catchment is also provided – varying between 0.88 and 0.93 for the nine sample catchments. The average Ensemble median R^2 value across all 51 catchments for the same validation period is 0.90. ANN and GR2M median simulations show good agreement for the majority of catchments. Whilst observed flows are largely contained within the uncertainty bounds for each of the catchment reconstructions, some discrepancies are apparent in peak values. Arterial drainage works have been identified as a probable cause of this, with previous work showing the tendency for elevated peak flows following drainage (Harrigan *et al.,* 2014). Peak flows also tend to be underestimated for smaller catchments where gridded precipitation data may not adequately capture flood generating convective rainfall events that can produce large rainfall amounts at localised scales over short periods.

2.3 Reconstructed flows

2.3.1 Assessment of reconstructed flows

Following calibration and validation with observed data, bias corrected Casty data (precipitation/temperature and Oudin PET) were input to the hydrological models to reconstruct monthly river flows back to 1766. The following subsections present the resulting annual, seasonal and monthly flow reconstructions across all 51 catchments.

2.3.1.1 Annual flow reconstructions

The median of annual reconstructed flows for all 51 catchments from 1766 is shown in Figure 2.8. GR2M and ANN median reconstructions show close agreement (R^2 = 0.97). In Figure 2.8 and subsequent plots, observed flows from 1980 onward are displayed as, by this year, observed values are available for over 84% of catchments. Overall, the percentage of median annual observed flow values across all 51 catchments contained within the uncertainty ranges of the median ensemble (henceforth the containment value), is 97%. Observed and Ensemble median simulated series across all catchments show close agreement (R^2 = 0.81). Some divergence is evident between modelled and observed flows around 1989 due to differences between Casty and observed precipitation at that time.

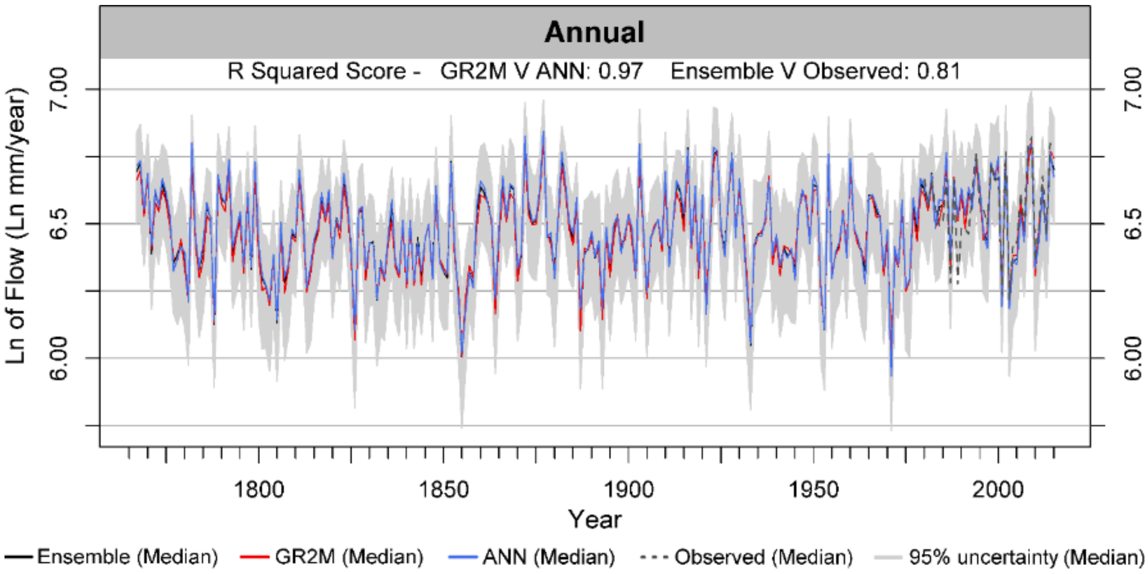


Figure 2.8 Median annual flow values across all 51 catchments for the period 1766-2016 for GR2M (red), ANN (blue) and Ensemble median (black) reconstructions. The median of observed flows across the catchment sample for years 1980-2016 are in dark-grey, while 95% uncertainty ranges (grey) are derived from the ensemble simulations.

2.3.1.2 Seasonal and monthly flow reconstructions

Seasonal and monthly flow reconstructions for all 51 catchments are displayed in Figures 2.9 and 2.10, respectively, with reconstructions showing strong agreement with observations for 1980-2016 in all seasons. There is some evidence that summer flows are overestimated in 1989, consistent with annual flows. For all other periods and seasons, observed flows lie within uncertainty estimates (minimum containment value, i.e. the minimum percentage of observed values contained within the uncertainty bounds in any given year, is 89%) and show good agreement with reconstructions (R^2 between Ensemble median values and observations range from a high of 0.9 in summer [JJA] to a low of 0.76 in autumn [SON]). Close agreement is also evident between GR2M and ANN median reconstructions (R^2 > 0.91) in all seasons. It is notable from Figure 2.9, that GR2M reconstructions for spring and summer are slightly higher and autumn values lower than ANN reconstructions. This likely occurs as a result of differences in model structures/assumptions along with the differing inputs in both model types (e.g. the inclusion of PET in the GR2M as opposed to temperature in the ANN).

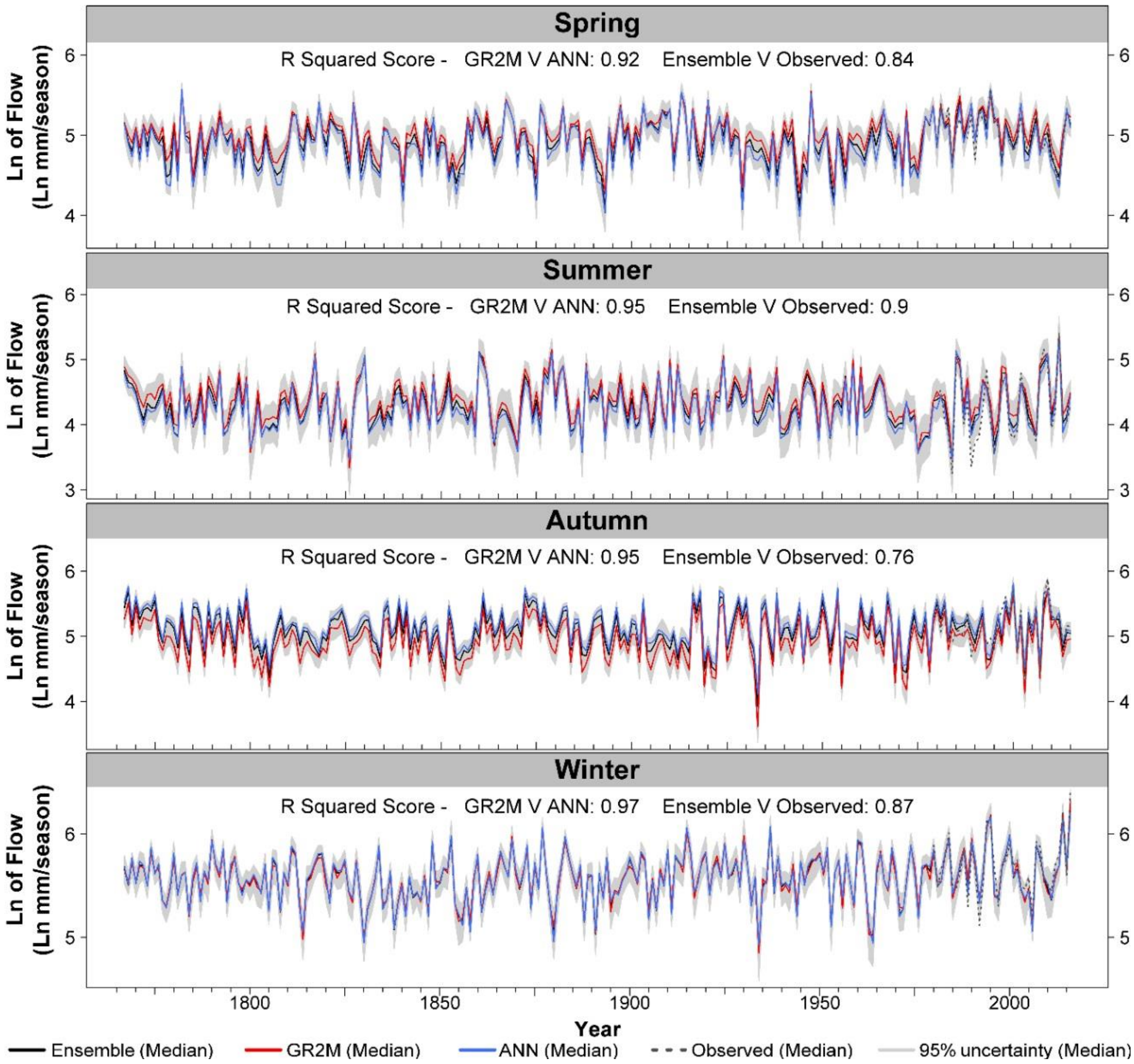


Figure 2.9 As in Figure 2.8 but for seasonal median flows: Winter [DJF], spring [MAM], summer [JJA], autumn [SON].

Monthly reconstructions are displayed in Figure 2.10 for all 51 catchments. Good agreement is evident between GR2M and ANN median reconstructions ($R^2 > 0.84$ in all months). GR2M median reconstructions are slightly higher than the ANN in April, May, June and July, while GR2M output in September, October and November is lower than the ANN equivalent, concurrent with summer and autumn differences between GR2M and ANN values identified above. As expected, performance of monthly simulations are poorer than for seasonal and annual time steps. Monthly observed flows generally lie within uncertainty estimates (mean containment value across all months is 68%) and show satisfactory agreement with observations (R^2 for Ensemble median values versus observations range between 0.56 in April to 0.91 in July).

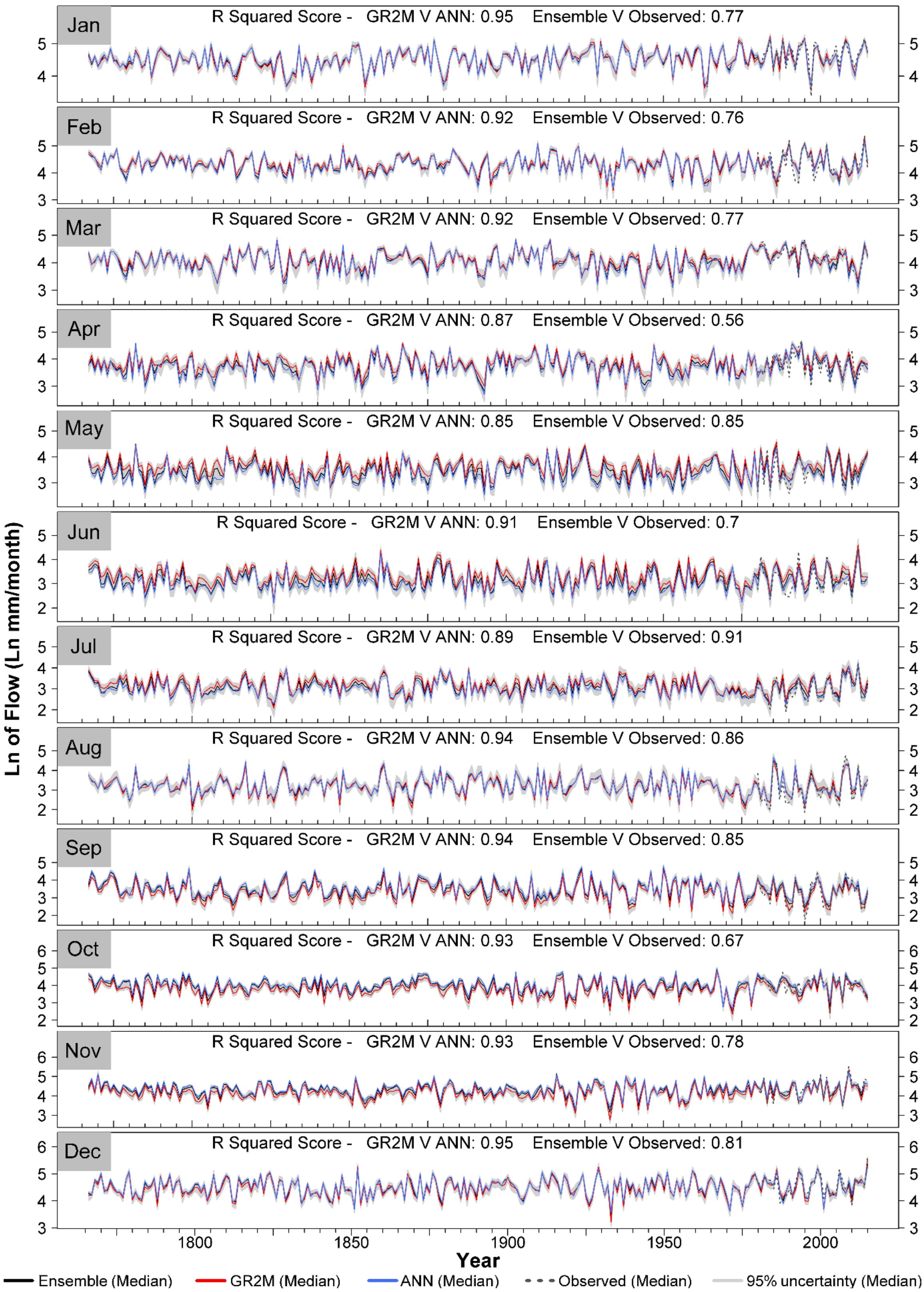


Figure 2.10 As in Figure 2.8 but for monthly median flows.

2.3.2 Comparison with reconstructions from long-term precipitation series

Monthly river flow reconstructions generated with the bias corrected Casty data were evaluated against reconstructions based on monthly precipitation data for stations within the Island of Ireland Precipitation (IIP) network 1850-2010 (Noone *et al.*, 2016). For each catchment, we identified the nearest IIP station (see Figure 2.1) and then bias corrected data to catchment average precipitation, as per the Casty data. Bias corrected precipitation, together with bias corrected monthly temperature/PET derived from the Casty data, was used to reconstruct flows back to 1850, using the same methods as described above. Although some of the IIP data are likely contained within the Casty gridded precipitation (so there is a degree of circularity) it was deemed important to compare both data sources, given the different methods used in their construction.

Figure 2.11 shows the Ensemble median annual mean flow reconstructions from 1850-2016 for four exemplar catchments, using Casty precipitation or IIP as input. Strong agreement between the reconstructions is evident despite the different input data with IIP reconstructions largely contained within the uncertainty ranges of the Casty reconstructions. Across the four case study catchments, the R^2 between IIP and Casty reconstructed annual mean flows varies between 0.70 and 0.77. Differences between flows generated from the two data sources are not unexpected given that IIP data are station based and often located outside catchment boundaries, whereas Casty data are gridded.

2.3.3 High- and low-flow assessment

The most notable extreme flow years for seasonal and annual Casty reconstructions were identified (Table 2.2), with the top five highest and lowest flow years across all catchments displayed for calendar years (1767-2016) as well as winter and summer seasons (1767-2016). The percentage anomaly relative to the mean of the full record is also provided. The most exceptional high-flow years across the sample include 1877, 1872 and 1916, whilst the most notable winter seasons include 2015/16, 1994/95 and 2013/14. In terms of exceptional low-flow years, 1855, 1933 and 1971 standout across the catchments, whereas 1826, 1975 and 1887 dominate the most notable low-flow years for summer. Annual flow anomalies across all 51 catchments range from 150% to 58% of the long-term mean for all catchments, whilst seasonally, winter and summer extreme anomalies range from 173% to 37% of the respective long-term seasonal mean values. Our extreme years and seasons show considerable agreement with a similar evaluation of reconstructed river flows (1865-2002) in the UK (Jones *et al.*, 2006), with the previously identified exceptional high and low flow seasons and years (1865-2002) all found at least once in the top five equivalent events for multiple catchments in that series.

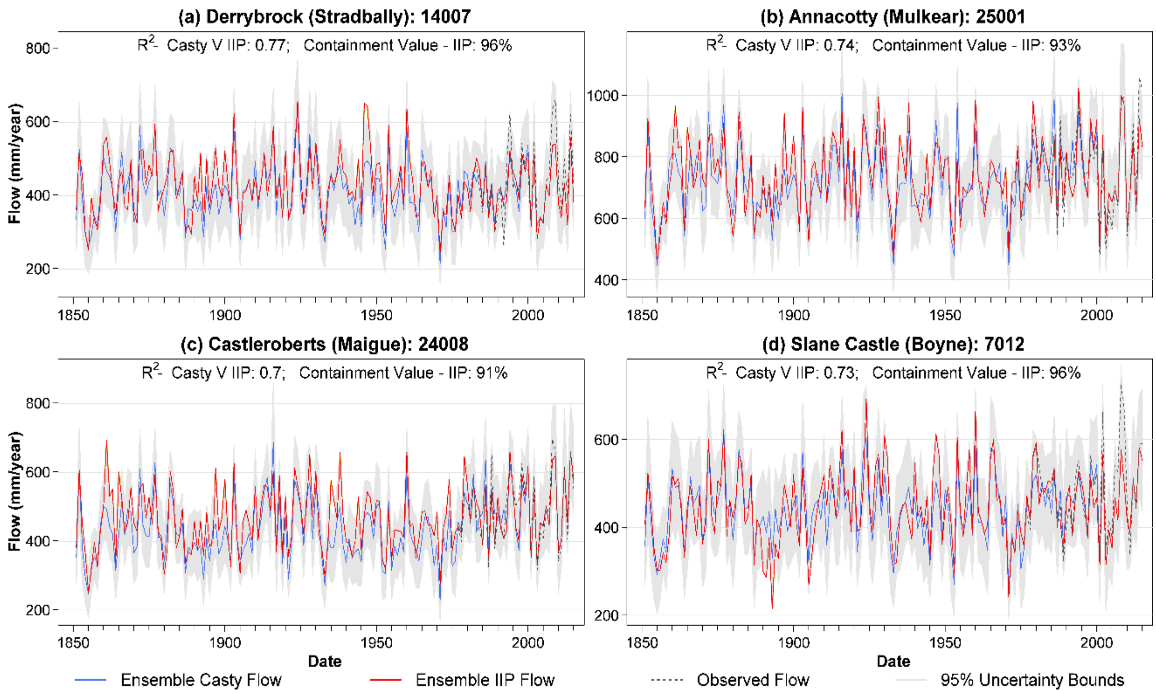


Figure 2.11 Reconstructed annual mean flow values for four sample catchments. Ensemble median simulations generated using Casty precipitation data (blue), and Island of Ireland Precipitation (IIP) data (red), together with observed flows (dashed dark-grey) are displayed for each catchment.

2.4 Dataset access, uses and limitations

The derived monthly flow reconstructions are freely available from the PANGAEA data centre (doi.org/10.1594/PANGAEA.914306). Data are presented as five individual tab-delimited text files, representing reconstructions for each catchment from the GR2M, ANN and Ensemble median simulations, along with 2.5% and 97.5% quantiles derived from the Ensemble simulation.

Table 2.2 **Years with the five highest and lowest annual (calendar), winter [DJF] (year given for January) and summer [JJA] flows for the period of reconstructions 1767-2016 across all 51 catchments. The percentage anomaly relative to the long-term annual/winter/summer mean flows (1767-2016) are provided. Values highlighted in progressively darker blue represent the top three occurring high flow events whilst those in red represent the top three occurring low flow events.**

Station	Top 5 High Flow Years										Top 5 Low Flow Years									
	Annual					Winter (December - February)					Annual					Summer (June to August)				
(ID)	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
3051	2015	2002	1877	1954	2009	2016	1995	1994	2014	1937	1933	1826	1855	1953	1971	1826	1975	1983	1800	1870
	150%	145%	144%	138%	137%	193%	172%	166%	161%	159%	59%	62%	62%	65%	65%	33%	33%	35%	37%	39%
6013	1877	1966	2002	1782	1872	2016	1877	1994	1883	1915	1953	1971	1933	1975	1855	1975	1826	1887	1995	1870
	154%	150%	146%	141%	138%	170%	158%	154%	151%	151%	53%	57%	62%	63%	64%	30%	32%	38%	39%	42%
6014	2002	1877	1966	1782	1872	2016	1877	1883	1994	1915	1953	1971	1855	1933	1826	1975	1826	1995	1887	1870
	160%	152%	146%	138%	136%	174%	153%	151%	151%	148%	55%	57%	63%	63%	64%	35%	36%	43%	44%	47%
6030	2002	1877	2015	1782	1872	2016	2013	1994	1877	1990	1933	1826	1953	1887	1911	1995	1800	1826	1949	1983
	173%	142%	141%	137%	137%	201%	173%	163%	161%	158%	61%	64%	65%	67%	69%	24%	28%	28%	31%	31%
7009	1877	1924	1782	1872	1960	2016	2014	1877	1995	1994	1971	1953	1855	1933	1826	1975	1826	1995	1887	1870
	142%	137%	135%	135%	133%	173%	151%	147%	146%	145%	57%	61%	66%	67%	68%	36%	38%	42%	44%	45%
7012	1877	1924	1782	1872	1965	2016	1877	2014	1937	1995	1971	1953	1855	1933	1826	1975	1826	1887	1995	1870
	152%	141%	140%	138%	138%	180%	164%	163%	161%	158%	56%	60%	64%	64%	65%	32%	34%	41%	41%	43%
12001	1960	1930	1872	1924	2009	2016	1877	1995	1994	1930	1971	1953	1905	1788	1855	1975	1826	1995	1887	1984
	158%	150%	148%	146%	145%	192%	177%	177%	170%	169%	55%	62%	64%	66%	66%	37%	38%	42%	44%	44%
14007	1924	1877	1872	1960	1903	1915	2014	1995	2016	1883	1971	1953	1855	1788	1933	1975	1826	1995	1887	1870
	155%	145%	144%	143%	141%	171%	169%	168%	165%	160%	53%	62%	64%	66%	67%	38%	40%	43%	45%	47%
14019	1924	1960	2008	1877	1872	2014	2016	1995	1915	1994	1971	1953	1855	1905	1933	1975	1826	1995	1887	1870
	149%	144%	142%	141%	140%	175%	173%	170%	165%	162%	57%	65%	67%	69%	70%	43%	46%	47%	52%	53%

15001	1877	1872	1924	1928	1903	1930	1995	1877	1915	1937	1971	1953	1855	1788	1826	1826	1975	1984	1870	1887
	160%	155%	153%	152%	151%	193%	192%	190%	190%	184%	51%	54%	59%	60%	64%	32%	33%	35%	36%	36%
15003	1924	2009	1872	1877	1916	2014	1995	1915	2016	1937	1971	1953	1788	1855	1933	1826	1975	1870	1887	1995
	150%	148%	147%	147%	147%	179%	177%	173%	164%	162%	50%	57%	61%	64%	64%	24%	24%	27%	28%	28%
15005	1877	1872	1903	1916	1924	1930	1915	1937	2016	1877	1953	1971	1855	1788	1933	1826	1984	1887	1975	1870
	152%	145%	142%	142%	141%	180%	175%	174%	174%	171%	57%	61%	62%	67%	67%	39%	40%	43%	43%	46%
15006	1877	1872	1924	1928	1903	1915	1995	2016	1930	1877	1971	1953	1855	1788	1933	1826	1975	1984	1887	1870
	152%	146%	145%	144%	143%	178%	178%	176%	174%	172%	57%	60%	65%	66%	68%	39%	41%	42%	44%	45%
15007	1872	1877	1954	1903	1924	2016	1995	1937	2014	1915	1971	1953	1855	1933	1826	1826	1984	1800	1870	1975
	142%	142%	141%	140%	140%	177%	173%	172%	172%	168%	57%	58%	59%	61%	65%	37%	39%	43%	43%	44%
16008	1877	1872	1903	1923	1954	2016	1937	1995	1877	2014	1953	1855	1971	1933	1826	1984	1826	1870	1887	1975
	144%	143%	140%	139%	139%	180%	168%	167%	161%	161%	58%	59%	60%	65%	67%	38%	40%	44%	47%	48%
16009	1877	2009	1872	1903	1916	2016	1995	1937	1915	2014	1855	1971	1953	1933	1826	1826	1984	1870	1975	1887
	147%	144%	143%	143%	142%	189%	184%	175%	172%	170%	60%	61%	62%	66%	68%	45%	45%	51%	51%	52%
16010	2009	1877	1928	1903	1916	1930	2016	1915	1995	1994	1855	1971	1788	1953	1893	1826	1984	1870	1975	1887
	153%	152%	152%	148%	145%	189%	189%	187%	181%	179%	61%	64%	66%	67%	68%	44%	47%	50%	50%	51%
16011	1877	1903	2009	1928	1872	2016	1995	1915	1994	1937	1971	1855	1953	1933	1788	1826	1984	1975	1870	1887
	143%	141%	141%	140%	139%	185%	181%	172%	168%	167%	64%	65%	67%	69%	71%	51%	52%	56%	57%	57%
16012	1928	2009	1877	1903	1960	1995	2016	1915	1930	1925	1855	1971	1826	1933	1887	1826	1984	1887	1975	1870
	143%	141%	140%	138%	138%	188%	187%	170%	169%	168%	65%	66%	70%	71%	72%	47%	50%	53%	53%	56%
16013	1928	2009	1938	1903	1960	1930	1995	2016	1915	1994	1971	1933	1855	1788	1887	1826	1984	1870	1800	1887
	152%	148%	147%	145%	145%	196%	185%	185%	184%	182%	63%	66%	67%	68%	69%	38%	40%	43%	45%	46%
18002	1916	2009	1877	2000	1872	2016	2014	1995	1915	1994	1971	1855	1933	1788	1826	1826	1984	1887	1975	1870
	151%	142%	140%	139%	135%	209%	188%	184%	163%	162%	56%	61%	69%	70%	71%	44%	45%	50%	50%	51%
18003	1916	2009	2000	1877	1994	2016	2014	1995	1915	1994	1971	1855	1788	1826	1921	1984	1826	1887	1975	1870
	150%	143%	141%	138%	138%	215%	199%	189%	170%	167%	54%	61%	67%	69%	69%	38%	39%	45%	45%	47%
18006	1916	2009	2000	1994	2002	2016	2014	1995	1915	1994	1971	1855	1826	1933	1788	1984	1826	1887	1975	1800
	145%	144%	141%	140%	139%	217%	205%	191%	177%	173%	58%	62%	68%	69%	70%	42%	43%	47%	47%	48%
18050	2009	2002	2008	2000	1872	2016	2014	1995	1915	1994	1971	1855	1788	1826	1921	1826	1984	1800	1975	1944
	142%	139%	139%	138%	137%	203%	200%	185%	179%	172%	58%	62%	69%	69%	70%	40%	41%	42%	43%	44%
19001	2009	1982	1928	2000	1872	2016	1995	2014	1915	1994	1971	1855	1788	1933	1854	1984	1826	1887	1870	1975
	159%	153%	151%	150%	149%	233%	211%	203%	188%	187%	48%	57%	63%	63%	65%	37%	38%	40%	41%	42%
21002	2009	1982	1872	1914	1916	2016	1995	1915	2014	1994	1971	1855	1955	1788	1887	1800	1976	1955	1975	1864
	142%	136%	134%	134%	134%	203%	178%	168%	167%	164%	60%	70%	71%	72%	72%	33%	39%	42%	42%	46%
22006	1916	1872	1982	2000	2002	2016	2014	1995	1915	1994	1971	1855	1933	1788	1921	1800	1976	1975	1984	2006
	137%	135%	135%	135%	135%	199%	187%	183%	175%	169%	62%	66%	69%	71%	72%	45%	47%	51%	54%	54%
22035	2000	1872	1916	1982	1994	2016	2014	1995	1915	1994	1971	1855	1933	1788	1921	1800	1975	1984	1826	1976
	137%	136%	135%	135%	131%	202%	182%	176%	168%	163%	62%	67%	72%	73%	73%	51%	53%	56%	57%	58%
23002	2008	2015	1986	1916	1872	2014	2016	1995	1915	1994	1971	1855	1788	1826	1921	1800	1984	1826	1975	1976
	157%	145%	141%	140%	138%	215%	205%	195%	187%	177%	56%	61%	68%	68%	68%	35%	38%	39%	39%	39%
24008	1916	2014	2009	1986	2008	2016	2014	1995	1994	1915	1971	1855	1933	1788	1826	1984	1826	1975	1887	1870
	160%	154%	151%	148%	148%	228%	224%	212%	180%	176%	53%	58%	63%	66%	66%	37%	38%	42%	43%	45%
24030	1916	1986	1994	2000	2008	2014	2016	1995	1994	1915	1971	1855	1826	1933	1921	1984	1826	1887	1870	1975
	156%	153%	151%	151%	150%	228%	226%	213%	189%	188%	51%	56%	64%	64%	65%	35%	36%	42%	44%	44%
25001	1916	2008	1986	1954	1877	1995	2016	2014	1937	1994	1855	1933	1971	1953	1826	1984	1826	1800	1870	2006
	141%	140%	138%	137%	136%	185%	180%	177%	163%	161%	63%	63%	63%	67%	69%	42%	44%	47%	48%	50%
25002	2008	1872	1877	1994	1916	1995	2016	2014	1994	1937	1971	1933	1855	1953	1826	1984	1826	1800	1870	2006
	141%	138%	137%	135%	134%	186%	167%	164%	163%	162%	62%	64%	65%	67%	68%	30%	34%	38%	39%	41%
25006	2014	1877	1872	1924	1954	2016	2014	1937	1995	1877	1971	1855	1933	1953	1826	1826	1975	1984	1995	1887
	144%	143%	140%	140%	138%	194%	181%	179%	168%	163%	59%	66%	66%	67%	68%	44%	46%	47%	50%	51%
25030	2015	1986	2014	2009	1994	2016	2014	1995	1994	1937	1855	1933	1971	2003	1826	1984	1826	1800	2006	1870
	157%	145%	144%	140%	139%	219%	210%	201%	177%	162%	59%	63%	63%	63%	66%	39%	40%	41%	42%	46%
25034	2014	1872	1924	1960	1877	2016	2014	1995	1915	1937	1971	1855	2003	1826	1933	1975	1826	1995	1887	1870
	145%	140%	140%	140%	139%	190%	165%	158%	154%	152%	54%	66%	67%	68%	68%	30%	33%	35%	40%	41%
26021	2015	1924	2014	1877	2002	2016	2014	1937	2007	1995	1971	1855	1933	1826	1805	1975	1826	1984	1887	1995
	141%	139%	139%	138%	135%	196%	163%	159%	153%	148%	58%	65%	65%	67%	70%	35%	37%	42%	44%	45%
26029	2015	1986	2002	1992	1877	2016	2014	1995	1937	1994	1933	1855	2001	1826	1805	1800	1826	1984	1821	1983
	144%	138%	134%	133%	131%	183%	173%	164%	154%	152%	64%	65%	65%	69%	73%	30%	34%	34%	35%	37%
26058	2002	1877	1924	2015	2014	2016	2014	1937	2007	1995	1971	1855	1933	1826	1805	1975	1826	1887	1995	1984
	143%	140%	139%	138%	136%	195%	166%	153%	144%	143%	58%	62%	62%	65%	68%	33%	34%	42%	43%	44%
27002	2009	2015	2008	1872	1986	2016	2014	1995	1994	1915	1855	1971	1933	1921	1826	1984	1826	1975	1800	1887
	160%	150%	148%	139%	139%	221%	199%	192%	168%	165%	57%	58%	63%	64%	66%	33%	34%	39%	40%	41%
30007	2015	1986	1950	1954	2002	2016	2014	1995	1937	1994	1855	1933	1826	1805	1921	1826	1984	1887	1870	1978
	154%	148%	140%	140%	138%	197%	169%	165%	164%	153%	58%	62%	65%	68%	68%	38%	39%	46%	49%	49%
32012	2015	1986	2008	1949	2011	2016	2014	1995	1994	1937	1855	1933	1826	1805	1971	1800	1826	1984	1983	1976
	147%	142%	137%	130%	130%	180%	178%	165%	154%	151%	64%	65%	71%	73%	73%	42%	46%	48%	50%	52%
33001	2015	1986	2008	1992	1949	2014	2016	1995	1994	2000	1855	1933	1826	1805	1971	1800	1983	1995	1984	1968
	149%	141%	131%	128%	127%	185%	177%	166%	151%	147%	65%	66%	74%	76%	76%	34%	35%	44%	45%	46%
34001	2015	1986	1950	2008	1877	2016	2014	1995	1937	1950	1855	1933	1805	1826	2003	1826	1984	1975	1800	1887
	143%	141%	138%	138%	136%	185%	175%	159%	156%	149%	60%	63%	68%	69%	70%	41%	45%	49%	51%	51%
35002	2015	2008	2002	1986	1949	2016	2014	1995	2015	1994	1855	1933	1805	1826	1921	1800	1826	1995	1983	1984
	150%	146%	145%	136%	132%	187%	181%	167%	156%	154%	63%	64%	70%	70%	75%	40%	43%	43%	47%	47%
35005	2015	2002	2008	1986	1950	2016	2014	1937	1995	2015	1855	1933	1805	1826	1921	1826	1984	1800	1995	1975
	149%	144%	143%	140%	137%	190%	186%	164%	163%	153%	62%	63%	66%	66%	69%	38%	42%	46%	46%	47%
36015	1877	1954	1998	2002	1782	1995	2016	1937	1994	1877	1933	1826	1855	1971	1921	1975	1826	1983	1800	1870
	146%	145%	142%	141%	138%	169%	164%	158%	157%	153%	57%	60%	60%	63%	65%	27%	28%	31%	32%	33%
36019	2002	1877	2015	1954	1998	2016	2014	1937	1995	2007	1971	1933	1826	1855	1953	1826	1975	1984	1870	1887
	155%	146%	141%	139%	138%	179%	166%	158%	154%	153%	58%	59%	61%	61%	65%	24%	24%	31%	33%	31%
38001	2015	1949	2011	1992	1986	1995	2014	2016	1994	2015	1933	1855	1805	1826	1864	1800	1821	1995	1983	1984
	145%	139%	136%	132%	131%	183%	180%	165%	162%	160%	63%	64%	69%	70%	75%	29%	37%	37%	40%	40%
39006	2015	1990	1949	1992	1999	2016	1995	2015	2014	1994	1855	1933	1826	1805	1911	1800	1995	1983	1824	1984
	167%	141%	138%	138%	137%	189%	185%	179%	176%	173%	60%	63%	66%	67%	70%	34%	34%	36%	37%	38%
39009	2015	1949	1990	1992	1999	2016	1995	2015	2014	1994	1855	1933	1805	1826	1911	1800	1983	1995	1984	1824
	165%	140%	140%	138%	138%	186%	184%	177%	175%	173%	60%	62%	67%	67%	71%	32%	34%	34%	35%	36%

2.4.1 Potential uses

The reconstructed flow series provide a resource for assessing the impacts of extreme meteorological events, such as drought, on river flows across Ireland, extending the work of Noone *et al.* (2017) and Noone and Murphy (2020). Our reconstructions could also inform spatio-temporal assessments of variability plus support detection of multi-centennial changes in river flows (e.g. Wilby, 2006). Furthermore, the multi-centennial time scale of our reconstructions offers the potential to examine how modes of ocean and climate variability influence river flows over extended periods. For example, it is known that Atlantic multidecadal variability exerts an important control on Ireland's climate (McCarthy *et al.*, 2015), but its impact on river flows is less clear. Our long-term dataset offers the means to explore any potential control, including its stationarity. In turn this could help facilitate improved seasonal forecasting (e.g. Wedgbrow *et al.,* 2002).

This work represents the first reconstruction of monthly flows for a large number of Irish catchments using long-term reanalysis data and observations. Given the uncertainties involved, this dataset should be treated as a benchmark and evaluated and improved by future products. The approach to flow reconstruction adopted here is easily transferable to other catchments in Europe (i.e. the domain of Casty data). By taking advantage of observed runoff data, available from the Global Runoff Data Centre (https://www.bafg.de/GRDC/EN/Home/homepage_node.html), it would be possible to generate similar archives of monthly flow reconstructions for the entire continent.

2.4.2 Limitations

There are several recognised limitations to reconstructed river flows. First, arterial drainage has had a pervasive impact on Irish rivers. Catchments in this dataset that have been drained tend to have higher peak flows during winter months (post-drainage) than those captured by the reconstructions. This is consistent with the findings of Harrigan *et al.* (2014) for the Boyne catchment. Hence, our reconstructions may be useful for quantifying the impact of arterial drainage on flow response. Moreover, we note that there is limited knowledge about how arterial drainage affects low flow and drought responses – again, our reconstructions may provide a useful point of reference.

Changes in land-use can have considerable impacts on flows over time (Yan *et al.*, 2013). Lack of meta-data on historic land-use change hinders the quantification of such impacts. Moreover, Slater *et al.* (2019) highlight that rivers are treated as conduits of fixed conveyance by models even though changes in channel geometry and structure are known to occur in response to periods of hydro-climatic variability. Here, we assume that land-use and channel geomorphology remain static over the period of reconstruction; a common assumption attached to long-term flow reconstructions. Jones (1984) asserts that such assumptions can be justified. Water resource infrastructure designs are based on flows relating to current land-use as opposed to historic conditions, suggesting that catchment responses tuned to present conditions are a useful resource.

Second, potential biases or inaccuracies in precipitation data could propagate into the reconstructed flow series. The gridded Casty dataset employed in this study was generated using both reanalysis and observed precipitation values, with principal component regression to interpolate across space. Interpolation of station data is more uncertain before the 1900s as the number of stations decreases rapidly prior to this time. Casty *et al.* (2005) highlight that European wide precipitation patterns in the early part of their series should be treated with caution, especially before 1800 when station numbers are low. For Ireland, we believe that data prior to 1850 should be treated with caution due to the sparseness of observed precipitation records on the island. A further source of uncertainty relates to the quality of early precipitation observations. Murphy *et al.* (2019) show that pre-1870 winter precipitation observations in the UK were likely affected by under-catch of snowfall due to gauge design and observer practice. It is likely that early Irish precipitation totals are affected by the same biases during winter months (Murphy *et al.*, 2020b).

Third, the sensitivity of hydrological model parameters to prevailing climatic conditions during the calibration period can result in uncertainties when models are used to simulate conditions different to those used for training. Broderick *et al.* (2016) showed that changes in climatic conditions can affect model performance depending on catchment, model type and assessment criteria. A shift from relatively wet to dry conditions resulted in poorer results. Future work should assess the robustness of monthly reconstructions to the wetness or dryness of periods used for training.

2.5 Conclusions

This paper presents a dataset of monthly river flow reconstructions back to 1766 for 51 Irish catchments. Gridded reconstructions of monthly precipitation and temperature, bias corrected to observed catchment datasets, are used with derived PET to force a conceptual hydrological model and an Artificial Neural Network to generate monthly flows spanning more than 250 years. Reconstructed flows are subject to uncertainties associated with hydrological response to arterial drainage and land-use change, together with potential biases in early precipitation observations and non-stationary hydrological model parameters. With these caveats in mind, the dataset is suitable for examining hydrological responses to arterial drainage, tracking hydrological variability and change, or testing the robustness of water plans and/or contextualising modern hydrological droughts.

Chapter 3 | Historical droughts in Irish catchments 1767-2016

3.1 Introduction

Drought is a complex hazard (Van Loon *et al.*, 2016), typically characterised by the component of the hydrological cycle affected (e.g., atmosphere [meteorological], soil moisture [agricultural], or river flows [hydrological] droughts) (Haile *et al.*, 2020). Impacts can unfold slowly, with propagation of meteorological to hydrological drought dependent on controls governing catchment response, including land cover, geology and rainfall-runoff relationships (Lorenzo-Lacruz *et al.*, 2013; Wong *et al.*, 2013; Barker *et al.*, 2016; Huang *et al.*, 2017; Guo *et al.*, 2020). Recently, there has been greater attention to evaluating historical droughts, facilitated by increased information availability from data rescue efforts (Noone *et al.*, 2017; Tanguy *et al.*, 2021); use of extreme droughts for stress testing models of water supply systems (Wilby and Murphy, 2019; Murphy *et al.*, 2020b); interest in placing recent extremes in a long-term context (Lhotka *et al.*, 2020; Moravec *et al.*, 2021); and evaluations of variability and change in drought occurrence and characteristics (Hanel *et al.*, 2018; Vicente-Serrano *et al.*, 2021a).

Although most work has focused on meteorological drought, increasingly researchers are using long-term precipitation and temperature records to study hydrological droughts for periods before systematic river flow measurements. For example, Caillouet *et al.* (2017) reconstructed 140 years (1871-2011) of river flow for 600 French catchments. This information was then screened for hydrological droughts using a threshold level approach, and uncovered well known European droughts of 1921, 1945, 1949, 1954, 1976 and 1989-1990 events, as well as less well-known events in 1878 and 1893. Multi-centennial reconstructions have been produced elsewhere in Europe (Moravec *et al.*, 2019; Hanel *et al.*, 2018; Erfurt *et al.*, 2020) and assessed for drought occurrence using hydrological drought indicators. An overarching theme of these studies is that, despite variations in temporal and spatial extents, extreme hydrological droughts have been a regular feature in long-term reconstructions for mainland Europe.

Trends in meteorological drought across Europe have been extensively investigated (e.g., Gudmundsson and Seneviratne 2015; Stagge *et al.*, 2017; Hänsel *et al.*, 2019; Oikonomou *et al.*, 2020; Vicente-Serrano *et al.*, 2021a). However, research into hydrological drought trends are less common (Sutanto and Van Lanen 2020) because long records are not as readily available for observed river flow as for meteorological variables (Mediero *et al.*, 2015). Across Europe, trends in low flows have been found to vary considerably between regions with a general lack of clear patterns (Stahl *et al.*, 2010; Van Loon, 2015). Such inconsistencies are the result of changing temporal characteristics of precipitation deficits which impact directly on low flows and result in spatio-temporal variability in hydrological drought intensities (Hanel *et al.*, 2018).

Historical droughts in UK catchments have also been the subject of much research (e.g., Jones and Lister, 1998; Jones *et al.*, 2006; Spraggs *et al.*, 2015; Wilby *et al.*, 2015; Parry *et al.*, 2016b). For instance, Rudd *et al.* (2017) assessed hydrological drought over the period 1891-2015 and found that, whilst there was considerable spatial and temporal variability between individual events, few changes in drought characteristics were identifiable. More recently, Barker *et al.* (2019) assessed hydrological drought occurrence in 108 UK catchments for the same period and found regionally distinctive drought characteristics. Significant drought episodes included 1890-1910, 1921-1922, 1933-1934, in the 1940s, and early 1970s prior to the notable 1975-1976 event. Overall, evidence of trends in hydrological drought occurrence and severity in the UK is limited (Hannaford, 2015).

Research in Ireland has focused on historical meteorological drought (e.g., Wilby *et al.*, 2016; Noone *et al.*, 2017; Murphy *et al.*, 2018; Murphy *et al.*, 2020a), with relatively little attention to long-term hydrological drought. One exception is Noone and Murphy (2020) who used rescued and transcribed monthly precipitation data (Noone *et al.*, 2016) to reconstruct river flows in 12 catchments during the period 1850-2015. Drought events were identified using the low flow Q95 threshold, with major episodes in 1887-1888, 1891-1894, 1902-1912, 1933-1934, 1944, 1953, and 1971-1976. Murphy *et al.* (2013) investigated trends in observed river flows for 43 catchments. However, they found that the short records hindered robust assessment, highlighting the value of reconstruction techniques for understanding multi-decadal (or even multi-centennial) variability and change in river flows.

Recently, O'Connor *et al.* (2021b) produced monthly reconstructions of river flow for 51 catchments in Ireland. We employ these reconstructions to assess historical meteorological and hydrological drought by fitting standardised indices to precipitation series and reconstructed river flows spanning the period 1767-2016. As well as identifying major drought events, we evaluate changes in drought characteristics (severity, duration, maximum intensity, accumulated and mean deficits) and investigate regional controls on drought propagation. This is the first assessment of multi-centennial drought properties for Ireland – a place where drought has been popularly overlooked as a recurrent threat to water security and the wider socio-economy.

The remainder of the chapter is structured as follows: Section 3.2 describes the catchments, datasets and methods employed. Section 3.3 presents the results, with details about the characteristics of historical droughts across catchments then an assessment of variability and change. Section 3.4 discusses the detected trends, study caveats, potential applications, and scope for further research. Finally, Section 3.5 concludes with a summary of key findings.

3.2 Data and methods

3.2.1 Catchments and data

We evaluate historical droughts for 51 catchments across Ireland, employing reconstructed monthly precipitation and discharge estimates for each catchment for the period 1767-2016, derived by O'Connor *et al.* (2021b). The choice of end year was determined by the availability of concurrent hydrological and meteorological data. The sample represents diverse hydrological conditions in Ireland, including catchments that have good quality data and limited evidence of disturbance/river regulation during the period of the observational record (Murphy *et al.*, 2013). Table 3.1 lists the catchments considered and Figure 3.1 shows their spatial distribution. Full details of the construction of the long-term precipitation and discharge series are provided by O'Connor *et al.* (2021b). Briefly, monthly gridded (0.5° x 0.5°) reconstructed precipitation and temperature datasets developed by Casty *et al.* (2007) were bias-corrected to observed catchment data, before being used to force a conceptual hydrological model and an Artificial Neural Network to reconstruct monthly river flows. We employ the ensemble median of the reconstructed discharge series for each of the 51 catchments assessed.

To aid interpretation, we employ hierarchical agglomerative clustering to identify a reduced subset of catchments following previous studies (e.g., Clubb *et al.*, 2019; Berhanu *et al.*, 2015; Schmitt *et al.*, 2007). Clustering was undertaken based on the Standardised Streamflow Index (SSI; see Section 3.2.2) with Euclidean distance determining dissimilarities between catchment SSI-1, 3, 6 and 12 values and Ward's (1963) linkage criterion used to identify clusters. The strong geographical coherence of the resultant clusters was not due to methodological design but instead points to the dominance of spatial factors influencing catchment groupings through related SI values. Silhouette information (Rousseeuw, 1987), which interprets the consistency of clustered data, was also derived to confirm the optimum number of clusters. Median SPI and SSI series were extracted for catchments comprising each identified cluster.

Table 3.1 Details of the 51 study catchments. The cluster number, Pearson correlation value between SSI-1 and SPI-1, 3, 6 and 12 month accumulation values, Standard period Average Annual Rainfall (SAAR) value, Base Flow Index (BFIsoil) and Area (km2) are displayed. Rows are ordered by correlation scores between SPI-1 and SSI-1 from highest (blue) to lowest (red) allowing correlation scores at higher SPI accumulations, SAAR, BFI and Area values to be compared. All correlation values are significant (p≤0.05).

River Flow Station ID	Station Name	Waterbody Name	Cluster No.	SPI-1 vs SSI-1	SPI-3 vs SSI-1	SPI-6 vs SSI-1	SPI-12 vs SSI-1	SAAR (mm)	BFIsoil (index)	Area (km^2)
21002	Coomhola	Coomhola	2	0.98	0.65	0.46	0.32	2158	0.37	65
38001	Clonconwal	Ownea	1	0.97	0.68	0.48	0.34	1795	0.28	111
22006	Flesk	Flesk (Laune)	2	0.96	0.71	0.51	0.35	1741	0.39	329
26029	Dowra	Shannon	1	0.96	0.69	0.48	0.34	1546	0.46	117
33001	Glenamoy	Glenamoy	1	0.95	0.68	0.47	0.33	1509	0.29	76
35002	Billa Bridge	Owenbeg	1	0.95	0.73	0.53	0.38	1458	0.42	81
22035	Laune Bridge	Laune	2	0.94	0.75	0.55	0.38	1858	0.64	560
23002	Listowel	Feale	2	0.94	0.74	0.53	0.37	1388	0.31	647
3051	Faulkland	Blackwater (Mon)	1	0.93	0.76	0.57	0.41	1049	0.42	143
18050	Duarrigle	Blackwater	2	0.93	0.75	0.53	0.36	1511	0.41	250
32012	Newport Weir	Newport	1	0.93	0.76	0.55	0.39	1652	0.59	146
6030	Ballygoly	Big	1	0.92	0.75	0.54	0.38	1106	0.45	10
39006	Lennan	Claragh	1	0.92	0.76	0.54	0.38	1435	0.44	245
39009	Aghawoney	Fern O/L	1	0.92	0.76	0.55	0.39	1485	0.4	207
18006	Cset Mallow	Blackwater	2	0.91	0.77	0.56	0.38	1311	0.5	1055
15003	Dinin Bridge	Dinin	3	0.90	0.76	0.56	0.39	992	0.38	299
16013	Fourmilewater	Nire	3	0.90	0.78	0.57	0.39	1303	0.54	94
25002	Barrington S Br.	Newport (Mun)	2	0.90	0.77	0.56	0.38	1229	0.54	222
25030	Scarriff	Graney	2	0.90	0.78	0.57	0.40	1183	0.54	280
36015	Anlore	Finn	1	0.90	0.77	0.58	0.41	1009	0.42	154
25001	Annacotty	Mulkear	2	0.89	0.78	0.58	0.39	1138	0.52	648
15007	Kilbricken	Nore	3	0.88	0.81	0.60	0.42	1078	0.59	340
18003	Killavullen	Blackwater	2	0.87	0.81	0.61	0.42	1287	0.46	1257
24030	Danganbeg	Deel	2	0.87	0.80	0.60	0.41	1013	0.53	259
35005	Ballysadare	Ballysadare	1	0.87	0.81	0.61	0.43	1212	0.61	640
16012	Tar Bridge	Tar	3	0.84	0.85	0.67	0.48	1222	0.63	230
18002	Ballyduff	Blackwater	2	0.84	0.83	0.63	0.44	1213	0.62	2334
30007	Ballygaddy	Clare	1	0.84	0.84	0.65	0.45	1097	0.65	470
16011	Clonmel	Suir	3	0.83	0.84	0.65	0.45	1072	0.67	2144
27002	Ballycorey	Fergus	2	0.83	0.84	0.64	0.44	1262	0.7	511
12001	Scarrawalsh	Slaney	3	0.82	0.86	0.67	0.47	1068	0.72	1031
14007	Derrybrock	Stradbally	3	0.82	0.84	0.67	0.47	869	0.64	95
15001	Annamult	Kings	3	0.82	0.83	0.63	0.43	955	0.51	444
15006	Brownsbarn	Nore	3	0.82	0.83	0.64	0.45	950	0.63	2418
16008	New Bridge	Suir	3	0.82	0.84	0.65	0.44	1002	0.64	1090
16009	Caher Park	Suir	3	0.82	0.85	0.65	0.45	1047	0.63	1583
19001	Ballea	Owenboy	2	0.82	0.84	0.65	0.45	1199	0.68	103
6014	Tallanstown	Glyde	3	0.81	0.85	0.67	0.48	913	0.63	270
14019	Levitstown	Barrow	3	0.81	0.85	0.67	0.47	839	0.62	1697
24008	Castleroberts	Maigue	2	0.81	0.84	0.64	0.45	948	0.54	806
34001	Rahans	Moy	1	0.81	0.86	0.65	0.45	1290	0.78	1975
6013	Charleville	Dee	3	0.80	0.84	0.67	0.48	880	0.62	309
25034	Rochfort	L. Ennell Trib	3	0.80	0.85	0.68	0.47	958	0.76	11
26058	Ballyrink Br.	Inny Upper	3	0.80	0.87	0.68	0.49	971	0.77	60
7012	Slane Castle	Boyne	3	0.79	0.85	0.68	0.48	888	0.68	2408
16010	Anner	Anner	3	0.79	0.86	0.69	0.48	961	0.62	437
25006	Ferbane	Brosna	3	0.78	0.86	0.68	0.47	898	0.71	1163
7009	Navan Weir	Boyne	3	0.77	0.85	0.68	0.48	869	0.71	1684
15005	Durrow Ft. Br.	Erkina	3	0.75	0.86	0.69	0.48	889	0.71	379
36019	Belturbet	Erne	3	0.74	0.86	0.67	0.47	991	0.79	1492
26021	Ballymahon	Inny	3	0.73	0.87	0.71	0.50	942	0.83	1099

Physical Catchment Descriptors (PCDs) , derived by Mills *et al.* (2014), were compiled for each cluster grouping to determine the importance of catchment characteristics in modifying the occurrence and propagation of hydrological droughts. The PCDs were the: standard period average annual rainfall, 1961-1990 (SAAR); baseflow index derived using catchment soil type (BFIsoil); Taylor-Schwartz measurement of mainstream slope (TAYSLO); proportion of area covered by peat (PEAT); proportion of time soils are typically wet (FLATWET); and mainstream length in kilometres (MSL). These six PCDs were previously used by Broderick *et al.* (2019) to classify Irish catchments.

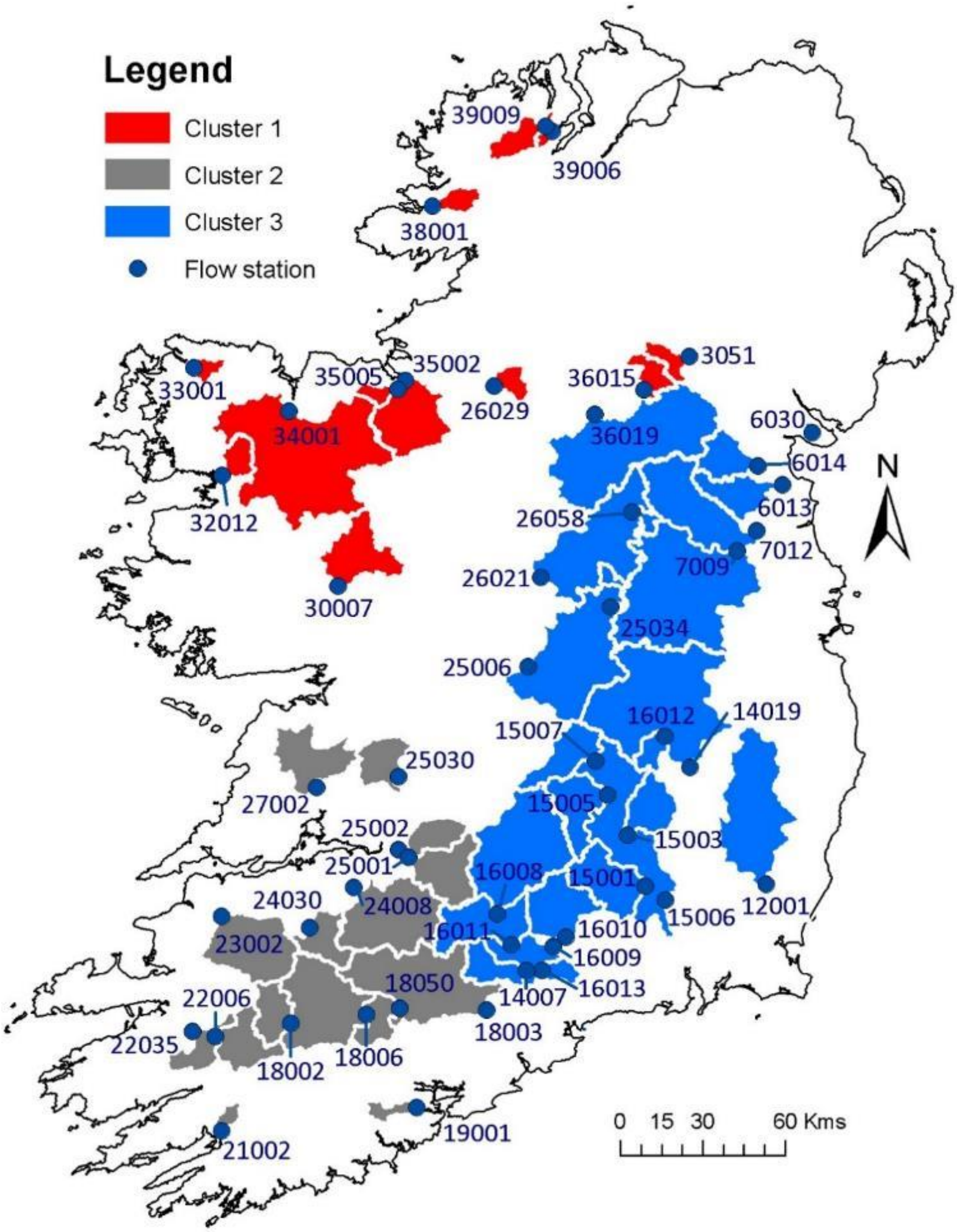


Figure 3.1 Catchment areas with flow station codes and cluster membership.

3.2.2 Standardised drought indices

We derive the Standardised Precipitation Index (SPI; McKee *et al.*, 1993) and Standardised Streamflow Index (SSI; Vicente-Serrano *et al.*, 2012b) for the 51 catchments and clusters for the period 1767-2016 using the "SCI" package in R (Gudmundsson and Stagge, 2016). Both SPI and SSI series were extracted for accumulation periods of 1, 3, 6 and 12 months. Two key decisions when applying standardised indices are (1) the statistical distribution and (2) the reference period for standardising data. The effect of distribution has been previously investigated (Stagge *et al.*, 2015b; Vicente-Serrano *et al.*, 2012b; Soľáková *et al.*, 2014; Bloomfield and Marchant, 2013; Svensson *et al.*, 2017). We evaluate the performance of three distributions when deriving the SPI and SSI, namely: the Gamma distribution, commonly used for long-term precipitation series (Shiau, 2020); the Log-logistic distribution, which has been used in fitting precipitation and streamflow series (e.g. Vicente-Serrano and Beguería (2016); and the Tweedie distribution, which has been found to perform well for SSI (Svensson *et al.*, 2017) due to the ability to constrain the lower bound to zero (Tweedie, 1984).

Others have highlighted the importance of the reference period used to derive SPI for the detection of historical droughts (Um *et al.*, 2017; Paulo *et al.*, 2016; Núñez *et al.*, 2014). The selection of a representative benchmark is particularly important for Ireland given the influence of low frequency ocean-atmosphere variability (Murphy *et al.*, 2013; McCarthy *et al.*, 2015). Here, the optimum reference period, which most closely matched average conditions, was specified by minimising the mean of positive and negative SSI values for 1, 3, 6 and 12 month accumulations for different start years (1767-1990) and reference period durations (30-250 years). We found the reference period 1930-1999 to be optimum, generating a mean SI value of 0.001 (for comparison the 1980-1999 period produced a mean SI value of -0.154). Moreover, a 70-year window is consistent with the 60 to 80 year period typical of the Atlantic Multidecadal Oscillation (AMO), which has been shown to modulate the frequency of drought across northwestern Europe (Wilby *et al.*, 2015; Sutton and Dong, 2012). To test the sensitivity of our results to the reference period, we considered three other periods: 1767-2016 (250 years), 1900-1999 (100 years) and 1981-2010 (30 years), with the latter as recommended by the World Meteorological Organisation (WMO, 2017).

We categorise drought severity for both SPI and SSI following McKee *et al.* (1993) with values of -1.00 to -1.49 representing moderate drought, -1.50 to -1.99 representing severe drought, and values ≤-2.00 representing extreme drought. We examine the occurrence of hydrological droughts across the 51 catchments over the period 1767-2016 by generating heatmaps for SSI accumulations over 3 (SSI-3), 6 (SSI-6) and 12 (SSI-12) months. For each drought category (i.e., moderate, severe and extreme) and accumulation period we extract meteorological (SPI) and hydrological (SSI) drought indices. Individual droughts commence when the respective standardised index falls below the drought category's upper value and terminate when recovered to zero. Events are categorised as moderate, severe, or extreme according to the maximum deficit recorded. For each drought index, accumulation period, and severity category we derive the following statistics:

- *Number of events*: sum of drought event numbers.
- *Duration*: number of months from the start until the end of the drought event.
- *Maximum Intensity*: minimum index value attained during the event.
- *Accumulated deficit*: sum of monthly deficits during the drought event.
- *Mean deficit*: accumulated deficit divided by duration.

For our assessment of *extreme* historical droughts we focus on event duration, accumulated deficit, and maximum intensity; for our analysis of *average* historical drought characteristics we investigate the number of events (total), drought durations (mean), accumulated deficits (mean) and mean deficits (mean) for each catchment cluster.

Trends in the number of events (per year), duration (months) and deficits (accumulated and mean) of moderate and severe droughts for both SSI and SPI at 1, 3, 6 and 12 month accumulations were assessed for all catchments and clusters using a modified version of the Mann-Kendall (MK) test (Yue and Wang, 2004) which employs variance correction to address serial correlation. Trends were evaluated at the 0.05 significance level with a MK Z statistic >1.96 indicating a significant positive trend and a score <-1.96 indicating a significant negative trend. Following Wilby (2006) and Murphy *et al.* (2013) the sensitivity of trends to the period of record was evaluated by considering different start and end dates with a minimum record length of 30 years.

Finally, we examine the propagation of meteorological to hydrological drought using a similar approach to Barker *et al.* (2016). We compute Pearson correlation coefficients between SSI-1 and SPI- 1, 3, 6, 12 for each catchment within each cluster. Stronger correlations between SSI-1 and SPI series over longer accumulation periods indicate a delay in drought propagation from precipitation to discharge, signalling a non-linear drought response due to catchment storage.

3.3 Results

3.3.1 Fitting standardised indices

To select the most appropriate distribution for deriving SPI and SSI, the Gamma, Tweedie and Log-logistic distribution functions were evaluated for 1, 3, 6 and 12 month accumulations using median precipitation and river flow series. Following Svensson *et al.* (2017), function performance was assessed using Anderson-Darling and Shapiro-Wilk scores (see Table 3.2). Although the Gamma and Tweedie functions performed well for standardised precipitation, Tweedie performed markedly better for flow standardisation. Visual assessment of the fitted distributions was also undertaken (see Figures 3.2 and 3.3). All three functions replicate the distribution of precipitation but the Tweedie and Log-Logistic are better for flow. The Tweedie function was best at capturing the lower tails of flow distributions, particularly in summer months, so was selected for use as in Barker *et al.* (2018). Sample plots of SPI and SSI indices for each distribution for the mid-1970s drought (Figure 3.4), indicate that sensitivity to distribution is greatest for maximum drought intensity over shorter accumulation periods.

3.3.2 Cluster analysis

The optimum number of catchment clusters was determined through visual and numerical assessment of the height between nodes in the dendrogram derived from the agglomerative cluster analysis. We determined that a three-cluster grouping best distinguished SSI values (at 1, 3, 6 and 12 month accumulations) across the 51 catchments. K-means clustering, with the use of silhouette information, also confirmed three groups as optimal. Figure 3.1 displays each of the clusters and catchment IDs, with further details of cluster membership given in Table 3.1. Cluster 1 catchments (n= 13) tend to be in the northwest and are relatively small and wet, with low groundwater storage (characterised by BFIsoil), steeper slopes and a higher proportion of peat and wetter soils (see Figure 3.5a). Catchments in Cluster 2 (n=15) tend to be in the southwest and are intermediate between Cluster 1 and 3 in terms of the PCDs evaluated. Cluster 3 catchments (n=23) are in the east and southeast, tend to be larger and drier, have greater groundwater storage, with shallow slopes and a low proportion of peat cover.

Table 3.2 Anderson-Darling and Shapiro-Wilk test statistic scores and p-values derived for SPI and SSI (mean from 1, 3, 6 and 12 month accumulations) using Gamma, Log-logistic and Tweedie distribution functions. Best performing test scores for each index (per month) are highlighted in bold.

Test & Indices	Month	Gamma (Test Stat.)	Gamma (P Value)	Log Logistic (Test Stat.)	Log Logistic (P Value)	Tweedie (Test Stat.)	Tweedie (P Value)
Anderson -Darling							
	Jan	0.658	0.382	0.732	0.396	**0.367**	**0.513**
	Feb	0.872	0.523	1.345	0.514	**0.554**	**0.494**
	Mar	**0.628**	**0.404**	1.067	0.217	0.683	0.448
	Apr	0.819	0.226	1.118	0.169	**0.445**	**0.374**
	May	**0.717**	**0.289**	0.707	0.216	0.766	0.312
SPI	Jun	0.773	0.313	1.378	0.068	**0.556**	**0.195**
	Jul	0.701	0.471	1.172	0.261	**0.408**	**0.518**
	Aug	**0.699**	**0.080**	1.221	0.018	0.788	0.213
	Sep	**0.424**	**0.416**	0.832	0.068	0.566	0.411
	Oct	0.493	0.342	**0.385**	**0.448**	0.444	0.439
	Nov	0.723	0.108	1.006	0.189	**0.629**	**0.253**
	Dec	0.477	0.479	0.634	0.391	**0.345**	**0.649**
	Mean:	0.665	0.336	0.966	0.246	**0.546**	**0.402**
	Jan	0.367	0.524	0.365	0.507	**0.267**	**0.681**
	Feb	**0.287**	**0.650**	0.542	0.361	0.350	0.639
	Mar	0.430	0.424	0.648	0.125	**0.251**	**0.709**
	Apr	0.457	0.447	0.546	0.261	**0.352**	**0.493**
	May	1.494	0.316	1.230	0.203	**0.822**	**0.580**
SSI	Jun	1.104	0.169	1.008	0.076	**0.520**	**0.377**
	Jul	1.170	0.215	0.896	0.111	**0.393**	**0.653**
	Aug	0.846	0.078	0.681	0.136	**0.302**	**0.680**
	Sep	0.623	0.214	0.734	0.102	**0.404**	**0.364**
	Oct	0.627	0.155	0.580	0.205	**0.232**	**0.787**
	Nov	0.516	0.212	0.661	0.173	**0.329**	**0.520**
	Dec	0.400	0.456	0.472	0.308	**0.378**	**0.539**
	Mean:	0.693	0.322	0.697	0.214	**0.383**	**0.585**
Shapiro-Wilk							
	Jan	0.984	0.424	0.982	0.447	**0.994**	**0.458**
	Feb	0.990	0.555	0.983	0.491	**0.993**	**0.504**
	Mar	0.989	0.317	0.984	0.200	**0.991**	**0.480**
	Apr	0.987	0.287	0.983	0.149	**0.994**	**0.446**
	May	**0.991**	**0.310**	0.987	0.162	0.991	0.284
SPI	Jun	0.987	0.418	0.979	0.039	**0.990**	**0.242**
	Jul	0.992	0.558	0.984	0.204	**0.994**	**0.504**
	Aug	**0.989**	**0.128**	0.980	0.010	0.989	0.180
	Sep	**0.991**	**0.259**	0.984	0.020	0.987	0.397
	Oct	0.993	0.361	**0.993**	**0.336**	0.991	0.354
	Nov	**0.991**	**0.147**	0.988	0.149	0.991	0.167
	Dec	0.991	0.426	0.989	0.368	**0.995**	**0.645**
	Mean:	0.990	0.349	0.985	0.215	**0.992**	**0.388**
	Jan	0.991	0.144	0.994	0.410	**0.996**	**0.726**
	Feb	**0.993**	**0.248**	0.987	0.021	0.991	0.109
	Mar	0.989	0.054	0.984	0.008	**0.993**	**0.246**
	Apr	0.980	0.002	0.986	0.015	**0.991**	**0.153**
	May	0.950	0.000	0.966	0.000	**0.976**	**0.000**
SSI	Jun	0.978	0.001	0.986	0.015	**0.996**	**0.780**
	Jul	0.974	0.000	0.989	0.058	**0.998**	**0.997**
	Aug	0.978	0.001	0.985	0.008	**0.994**	**0.460**
	Sep	0.990	0.103	0.991	0.154	**0.994**	**0.499**
	Oct	0.986	0.015	0.992	0.193	**0.996**	**0.708**
	Nov	**0.994**	**0.422**	0.989	0.057	0.991	0.122
	Dec	**0.997**	**0.876**	0.991	0.115	0.991	0.109
	Mean:	0.990	0.320	0.988	0.145	**0.993**	**0.472**

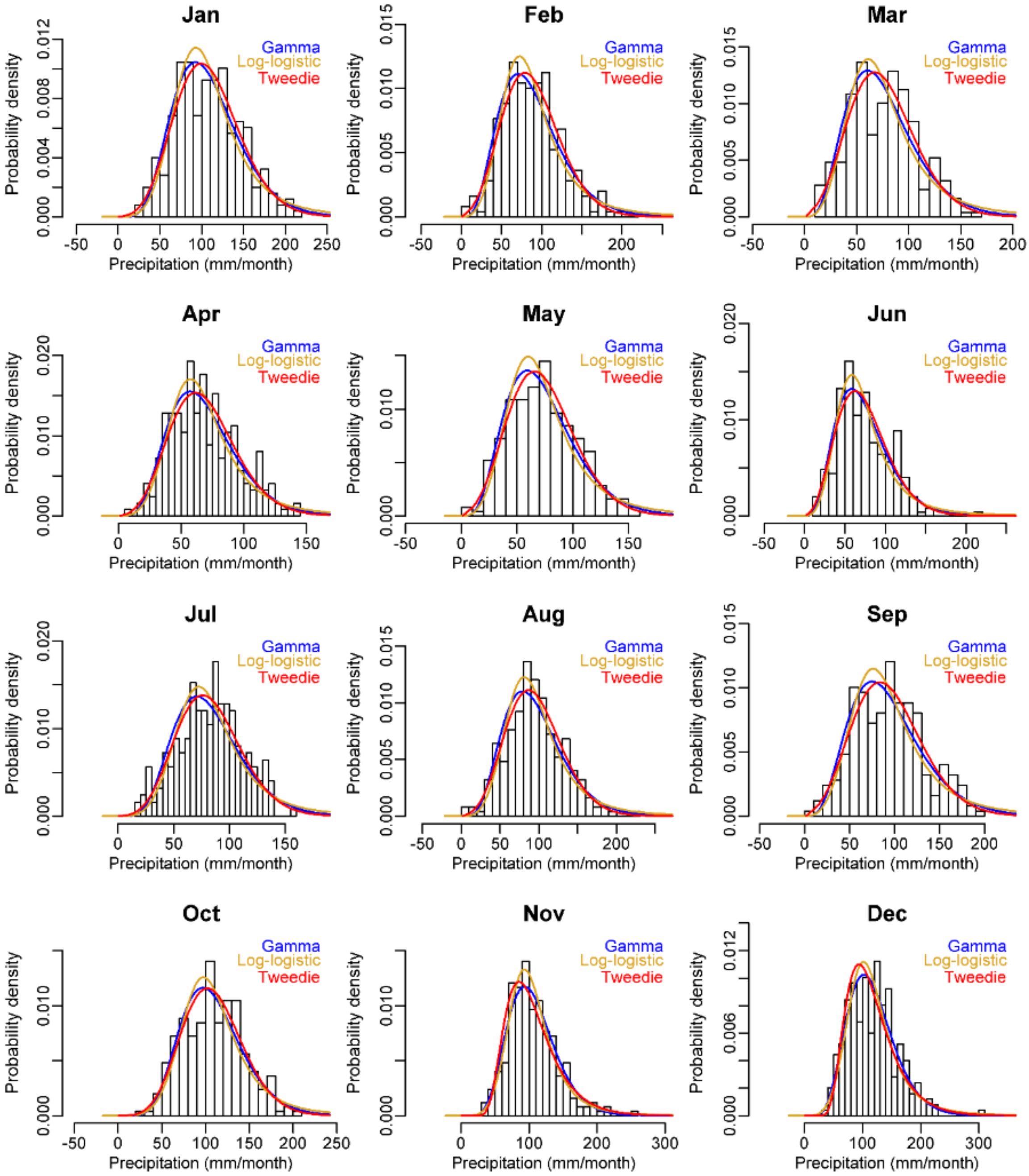


Figure 3.2 Fit of Gamma, Log-Logistic and Tweedie distributions for monthly SPI-1 fitted to median precipitation values from all 51 catchments.

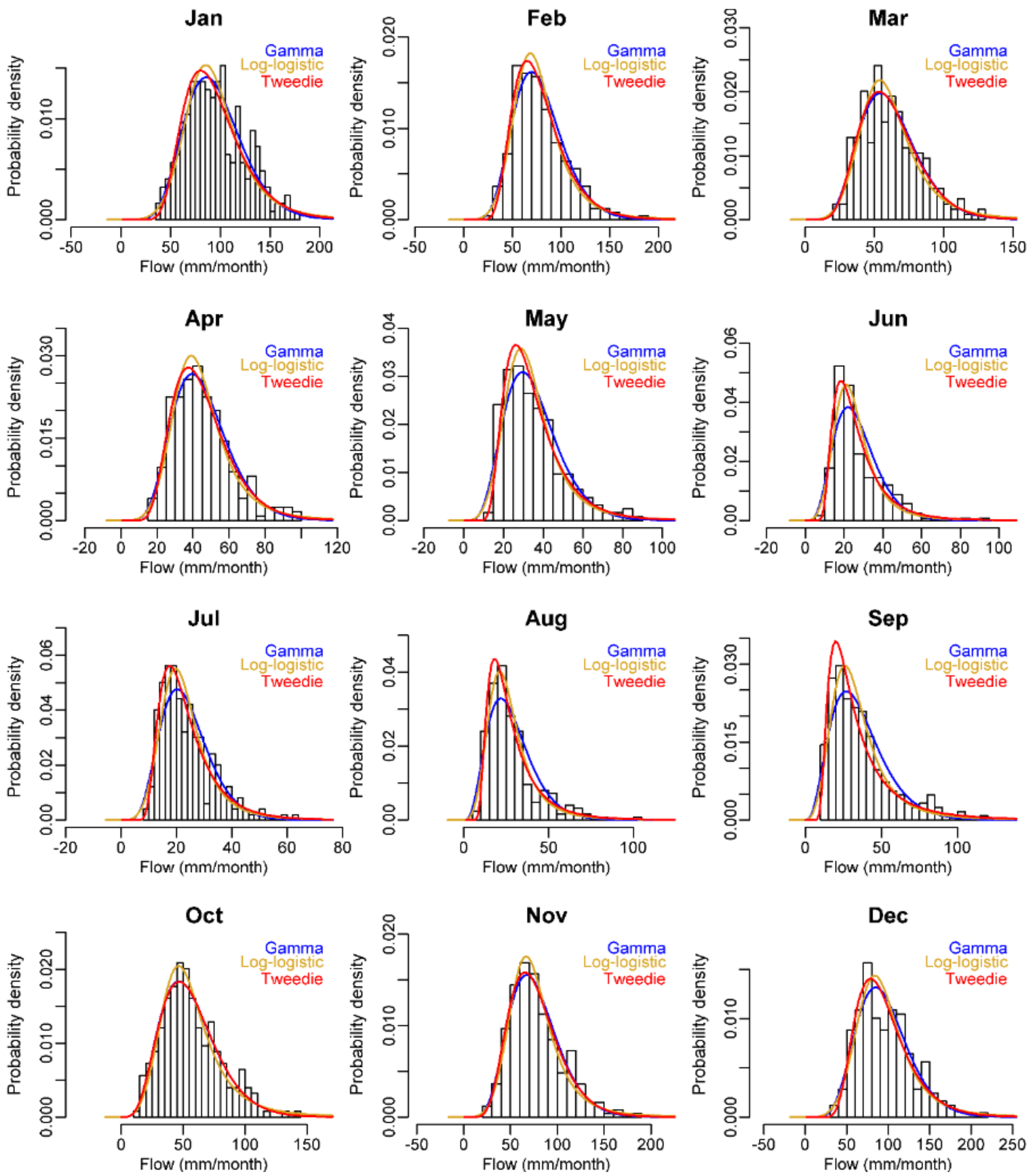


Figure 3.3 As Figure 3.2 but for SSI-1 fitted to median flow reconstructions.

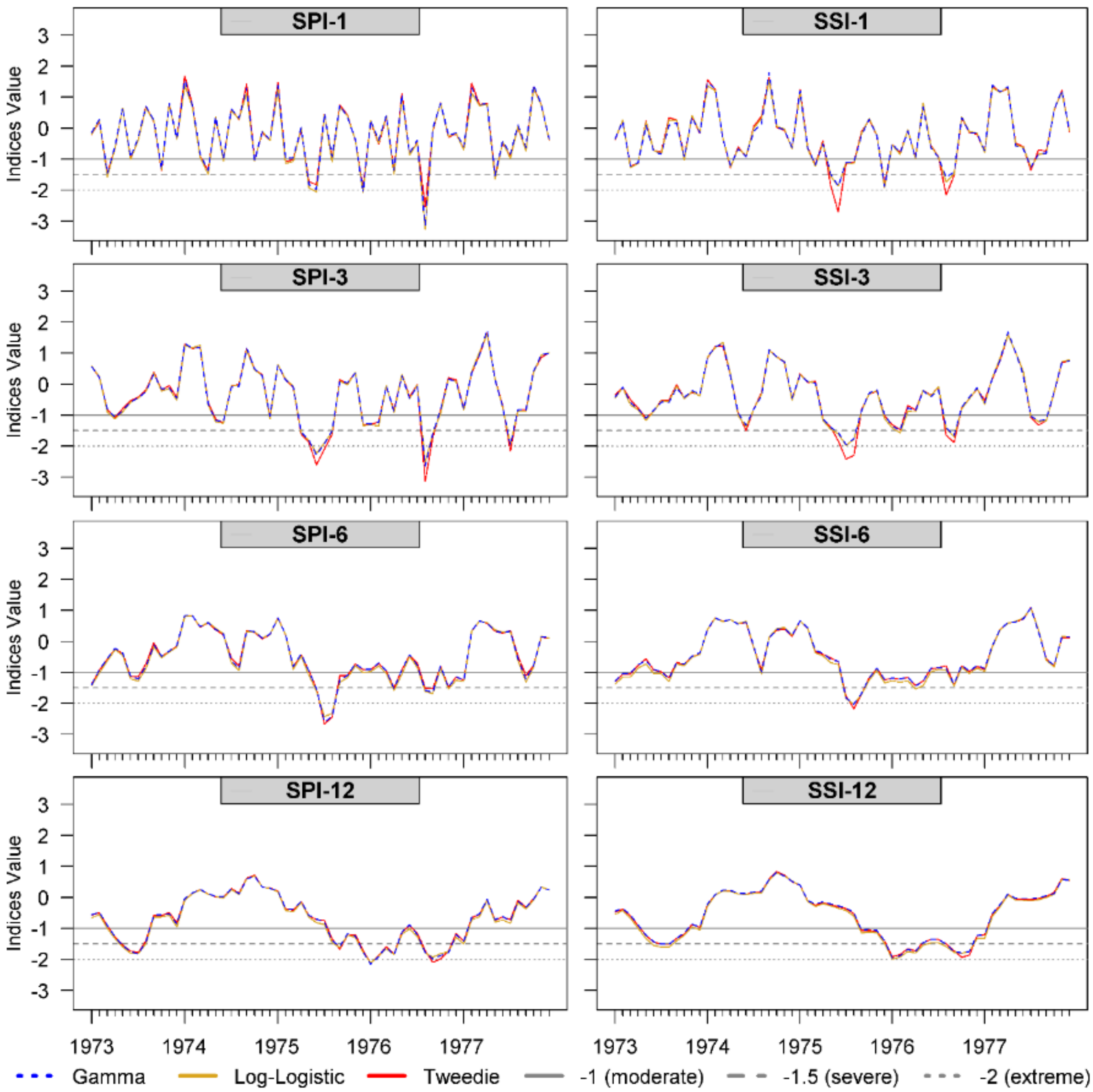


Figure 3.4 SPI and SSI-1, 3, 6, 12 output derived from median precipitation and flow (1973-1977) using Gamma, Log-Logistic and Tweedie distributions and a 1930-1999 reference period.

3.3.3 Drought propagation

The propensity for meteorological drought to propagate to hydrological drought was assessed for catchments in each cluster by deriving Pearson correlation scores between SSI-1 and SPI-1, 3, 6 and 12 over the full period of reconstructions. Boxplots of derived Pearson scores for each of the clusters are displayed in Figure 3.5b. Cluster 1 catchments show strongest correlations between SSI-1 and SPI-1, consistent with their low groundwater storage and more rapid propagation of drought. Cluster 3 catchments have strongest correlations between SSI-1 and SPI-3, but remain strong for SPI accumulations over 6 and 12 months, highlighting the slower propagation of drought in larger catchments with greater groundwater storage. Cluster 2 catchments are intermediate, with correlations between SSI and SPI decreasing for longer accumulation periods. In terms of the influence of PCDs, we find a strong association between SAAR and likelihood of a drought, with total annual rainfall correlating strongly with the risk of drought occurrence at one month accumulation (Table 3.1). Also evident is the link between groundwater storage and delayed drought onset, whereby catchments with greater groundwater storage (higher BFIsoil) show stronger correlations between SSI-1 and SPI over longer accumulations.

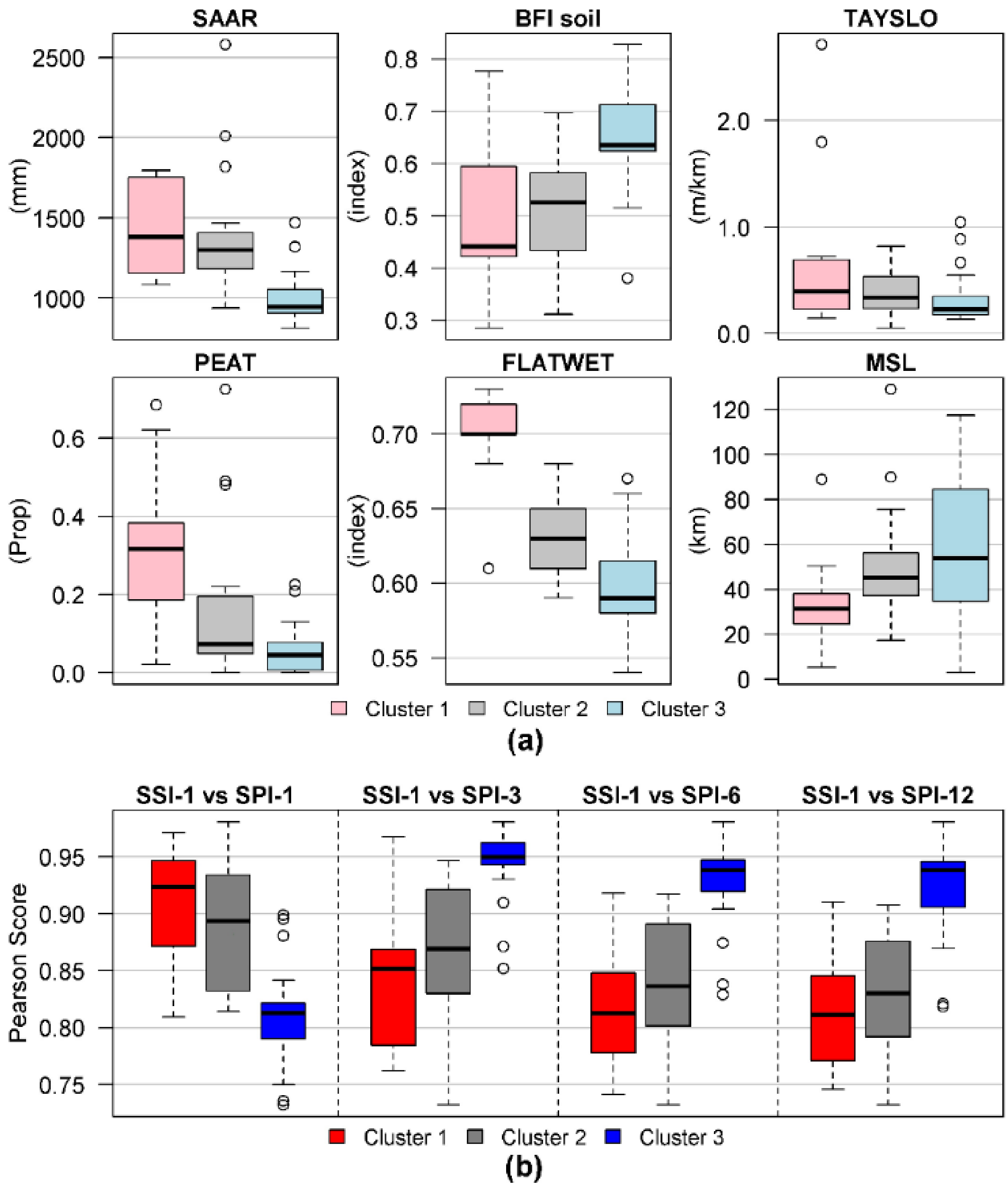


Figure 3.5 (a) Distributions of the six physical catchment descriptors for each cluster and (b) Pearson correlation coefficients scores between SSI-1 and SPI-1, 3, 6, and 12 for each cluster.

3.3.4 Historical hydrological droughts

Figure 3.6 displays SSI-1, 3, 6 and 12 generated from the median flow values of each cluster. The variability of SSI between clusters is apparent with different responses in drought event intensity as a function of accumulation period. High variability in SSI-1 values is a feature of the short accumulation period, resulting in more moderate, severe and extreme events. This is evidenced by SSI values falling below the previously defined McKee *et al.* (1993) thresholds more frequently than for other accumulation periods. Persistent and extreme droughts are more easily detected in the SSI-12 series which produces the lowest number of events across all intensities. Differences in drought intensities between catchment groupings are also visible. For example, whilst Cluster 1 and 2 catchments register an extreme SSI-6 drought in 1984, this event only reaches severe classification in Cluster 3. Furthermore, whilst Cluster 2 catchments experience no SSI-12 drought exceeding moderate intensity in the period 1978-2016, both Cluster 1 and 3 return at least one severe and one extreme event. Cluster 1 generates the most hydrological droughts of all intensities (51 SSI-12 events), followed by Cluster 2 (50 SSI-12 events), and Cluster 3 generating the least (43 SSI-12 events).

Figure 3.7 displays heatmaps of SSI-3, 6 and 12 for the full 250-year period for individual catchments, organised by cluster membership. The most prominent events include the 1803-1806, 1855-1859, 1887-1890, 1933-1935, 1953-1954, 1971-1974 and 1975-1977 droughts. Conversely, the periods 1860-1885 and 1978-2004 were notably drought poor. Catchment specific variations in drought durations and deficits align closely within clusters, particularly in the case of Cluster 1 which differ noticeably from Cluster 2 and 3. For example, in the SSI-6 and 12 reconstructions, the 1921-1923 drought shows much greater intensity in Cluster 1 compared with other clusters. Differences between Cluster 2 and 3 are also evident. For instance, deficits in the 2004 drought (SSI-12) were severe/extreme in most Cluster 3 catchments but less so in Cluster 2 catchments. Although differences in drought numbers, durations, and deficits *between* clusters are considerable, similarities in drought characteristics for catchments *within* clusters are high.

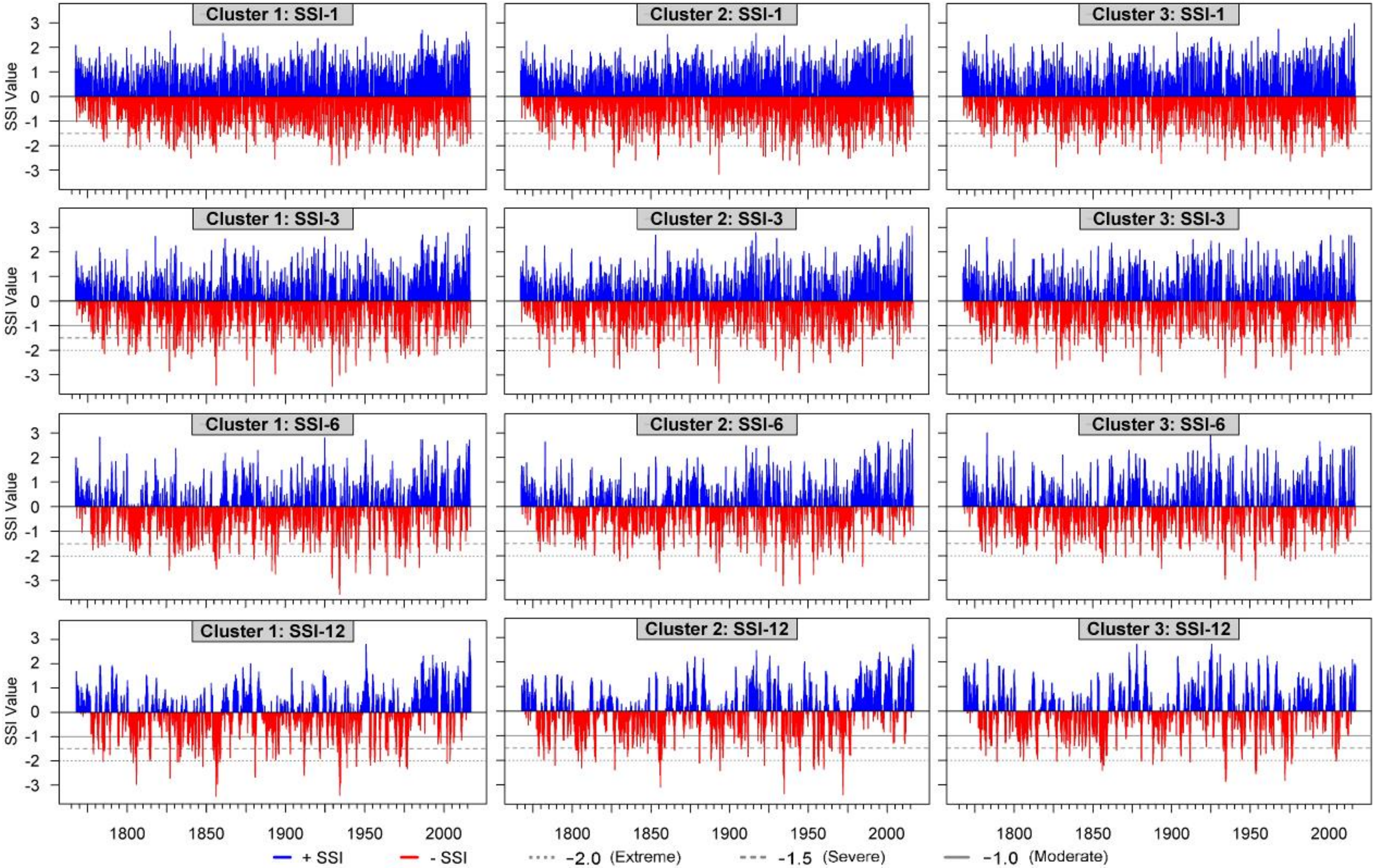


Figure 3.6 Time-series of SSI-1, 3, 6 and 12 derived from median flows for each cluster for the period 1767-2016, using the Tweedie distribution and 1930-1999 reference period. Horizontal lines represent moderate (SSI=-1), severe (SSI=-1.5), and extreme (SSI=-2) drought thresholds.

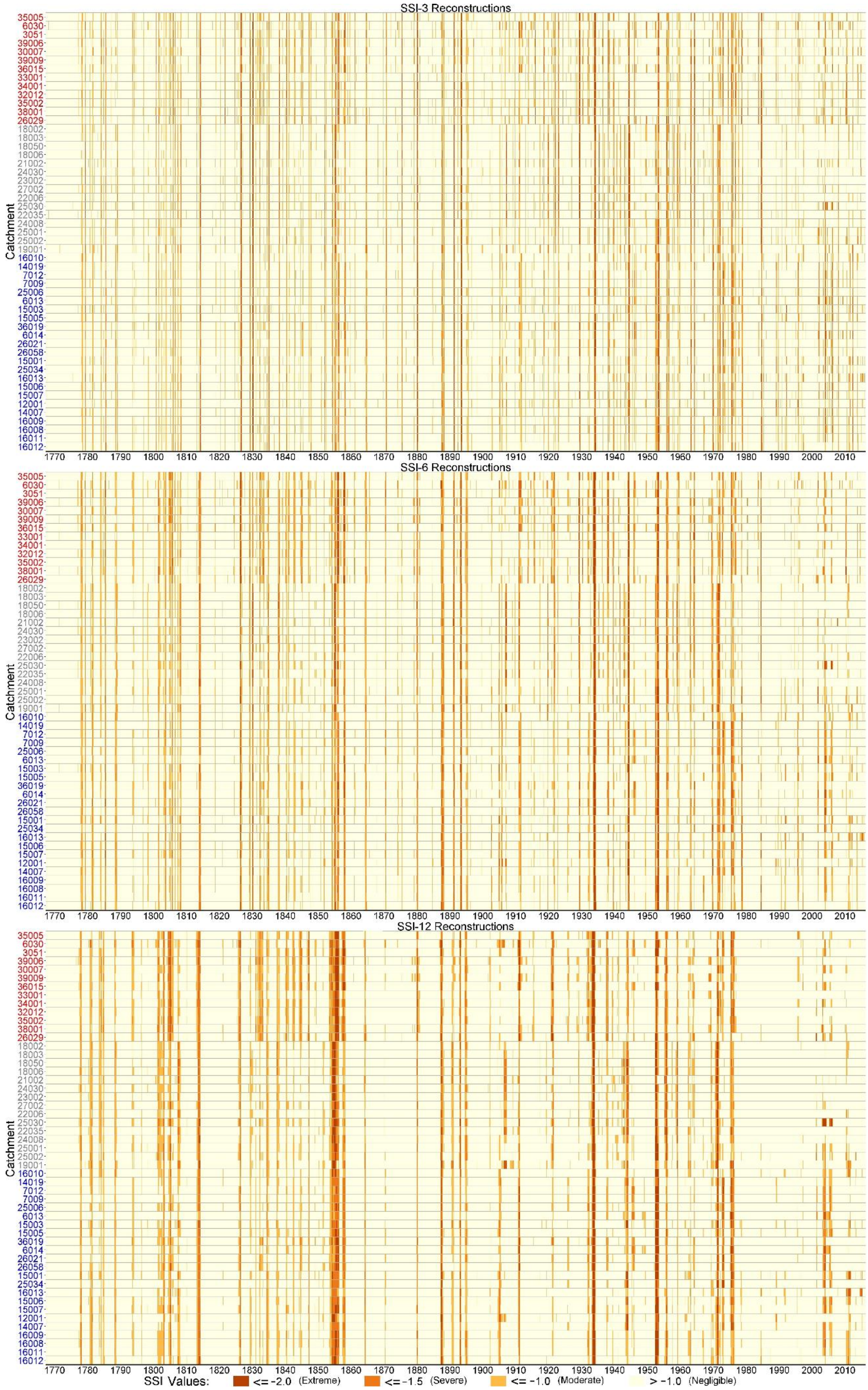


Figure 3.7 Heatmaps of SSI-3, 6 and 12 reconstructions for all 51 catchments grouped by cluster (Cluster 1: red; Cluster 2: dark grey; Cluster 3: blue). Colour coded are the main drought severity categories (moderate: -1.00 to -1.49; severe: -1.50 to -1.99 and extreme: ≤-2.00).

3.3.5 Meteorological and hydrological drought characteristics

A summary of moderate, severe and extreme meteorological (SPI) and hydrological (SSI) historical drought characteristics is presented in Figure 3.8. For equivalent intensities and accumulations, the number of SSI drought events (Figure 3.8a) is almost always lower than for SPI. Although the number of SPI events is often highest in Cluster 3 catchments, SSI event numbers are amongst the lowest, indicating that meteorological droughts in Cluster 3 do not always translate into hydrological drought. Conversely, Cluster 1 catchments have the highest overall number of SSI drought events despite the number of SPI drought events being similar to Cluster 3, suggesting that the former are more vulnerable to hydrological drought onset. Cluster 2 catchments have the lowest total number of meteorological droughts but register more hydrological droughts than Cluster 3. Mean drought duration statistics (Figure 3.8b) show that SSI events tend to persist longer than corresponding SPI events. However, for Cluster 3 catchments SSI drought durations are longest, suggesting this cluster is susceptible to more persistent droughts once deficits become established.

Accumulated deficit statistics (Figure 3.8c) indicate that, on average, SSI events produce greater deficits than SPI events. Drought deficits are typically greatest in Cluster 1 for meteorological drought but rank behind Cluster 3 for hydrological drought, highlighting that whilst more susceptible to drought, Cluster 1 catchments recover quicker than Cluster 3 catchments. Cluster 2 catchments tend to show intermediate accumulated deficits. Cluster 3 catchments consistently show lower accumulated deficit values for SSI-1, 3, 6 and 12 compared to equivalent SPI accumulations which is directly related to longer drought durations in this grouping. Mean drought deficit statistics (Figure 3.8d) indicate that most SPI events produce greater mean deficits than equivalent SSI events. For the majority of SSI accumulation periods, mean drought deficits in Cluster 3 catchments are less than Cluster 1 and 2 despite being equal or greater than the equivalent SPI mean deficits. This results from longer drought durations in these catchments.

Numbers of moderate, severe, and extreme hydrological drought events, their durations, accumulated deficits and mean deficits for SSI-1, 6 and 12 were also derived for each catchment. Results display similar patterns to those found in the cluster analysis above, albeit with catchment specific variations (see Figures 3.9 – 3.11). The Anner at Anner (ID: 16010; Cluster 3) has the least number of moderate, severe and extreme drought events for SSI-1, 6 and 12, whereas the Shannon at Dowra (ID: 26029; Cluster 1) has the most. Catchments in the southwest have on average the shortest drought durations, the greatest mean deficits, and least accumulated deficits (at moderate, severe and extreme intensities), with the Blackwater at Killavullen (ID: 18050; Cluster 2) having the shortest mean drought duration and least accumulated deficits (7.10 months; -7.48 SSI). The Feale at Listowel (ID: 23002) has the greatest mean deficits (-1.18 SSI) and is a Cluster 2 catchment. At the other extreme, the Glyde at Tallanstown (ID: 6014) has the longest durations (10.24 months) and greatest accumulated deficits (-10-60 SSI) whilst the Erkina at Durrow (ID: 15005) has the least mean deficits (-1.07 SSI), with both catchments belonging to Cluster 3. Overall catchments in the northwest display the most variability in numbers of hydrological drought events, durations, and deficits.

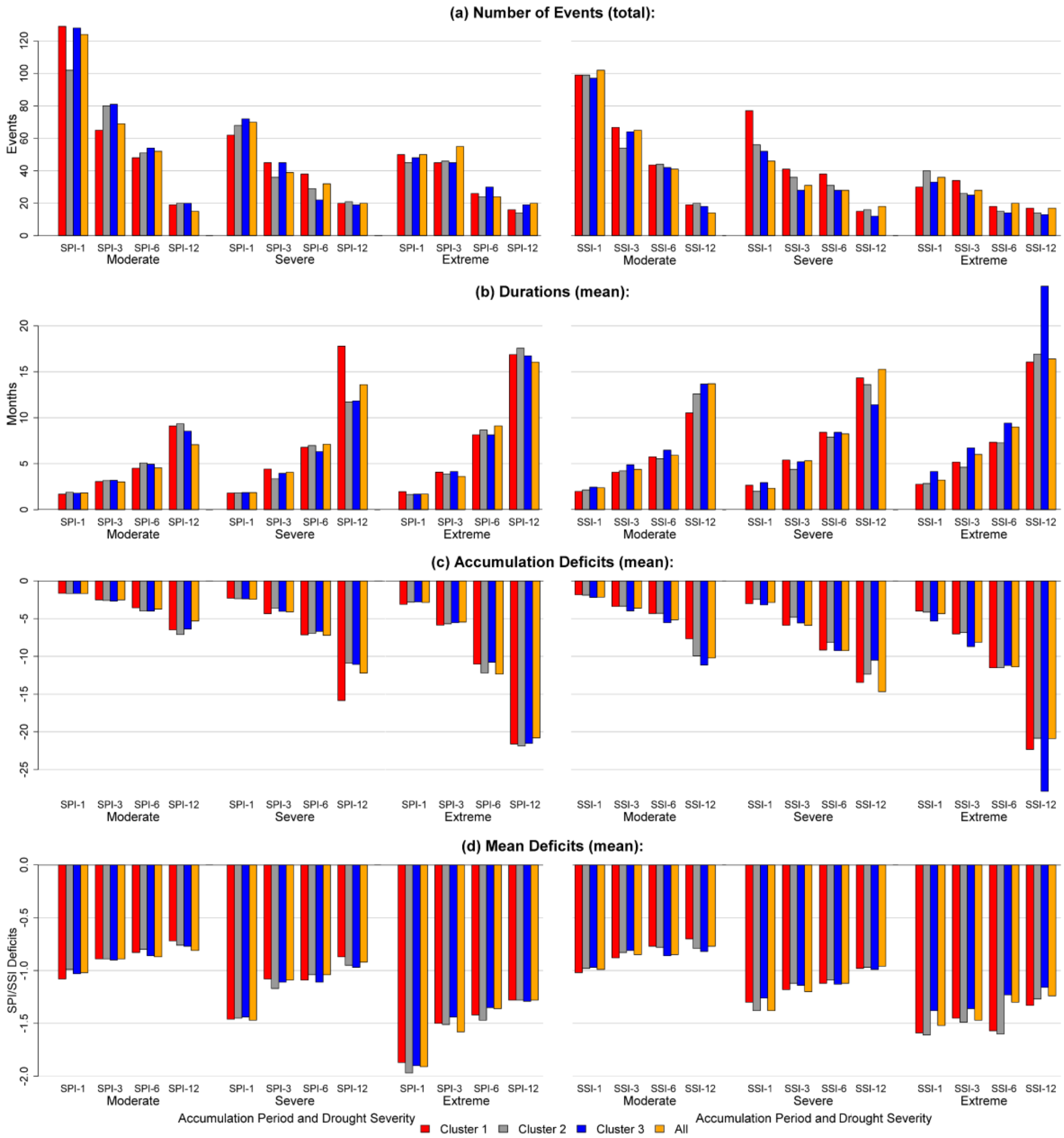


Figure 3.8 Meteorological (SPI) and hydrological (SSI) droughts, (a) total number of events, (b) mean durations, (c) mean accumulated deficits and (d) mean deficits for moderate, severe and extreme droughts derived from median SPI and SSI series for each cluster grouping (Cluster 1: red, Cluster 2: dark grey, Cluster 3: blue, All Clusters: orange). SPI and SSI event characteristics are derived for accumulation periods of 1, 3, 6, and 12 months.

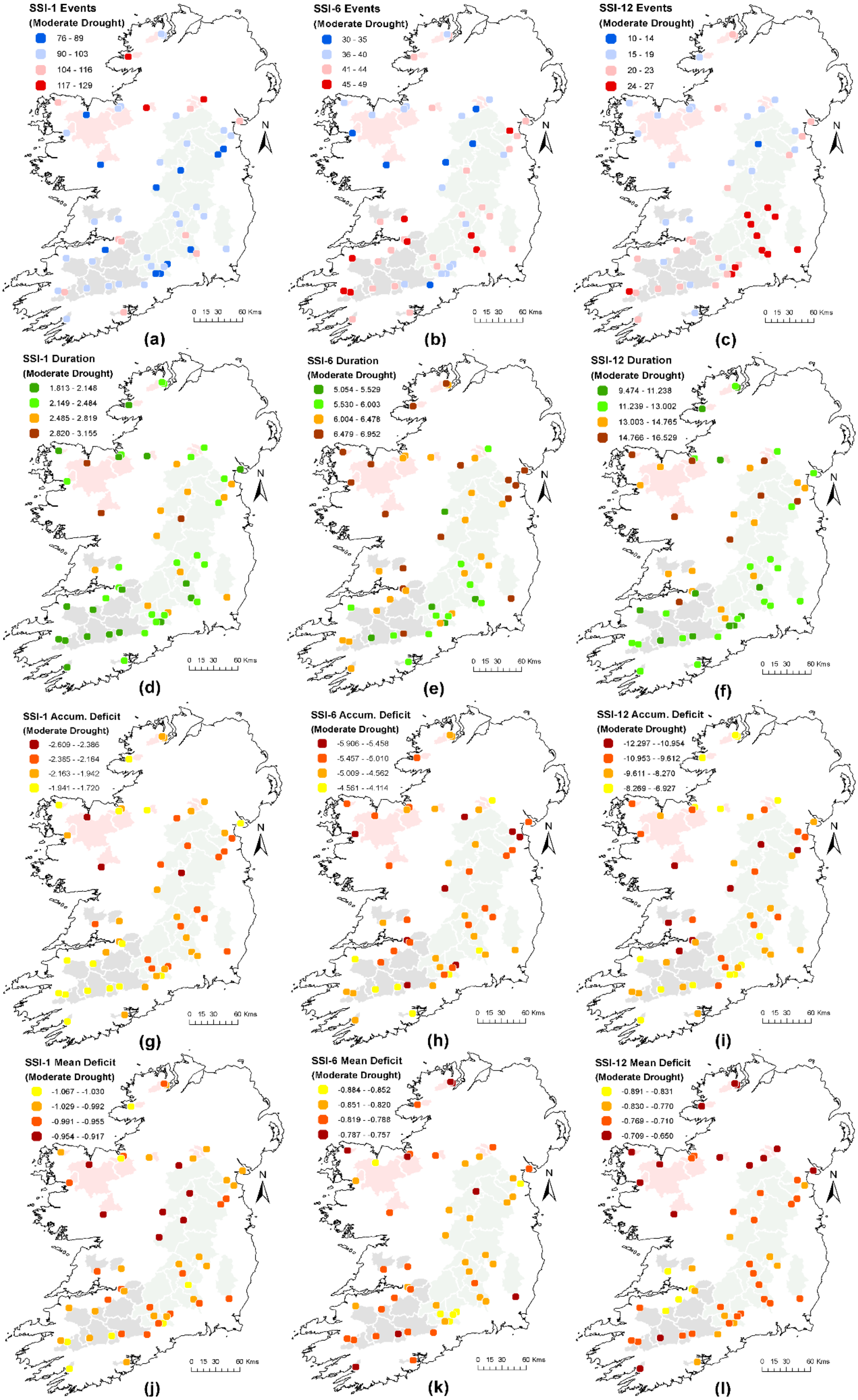


Figure 3.9 Moderate drought characteristics (number of events, duration and accumulated deficits) for all 51 catchments for SSI-1 (left), SSI-6 (middle) and SSI-12 (right), with each superimposed on the cluster membership map shown in Figure 3.1.

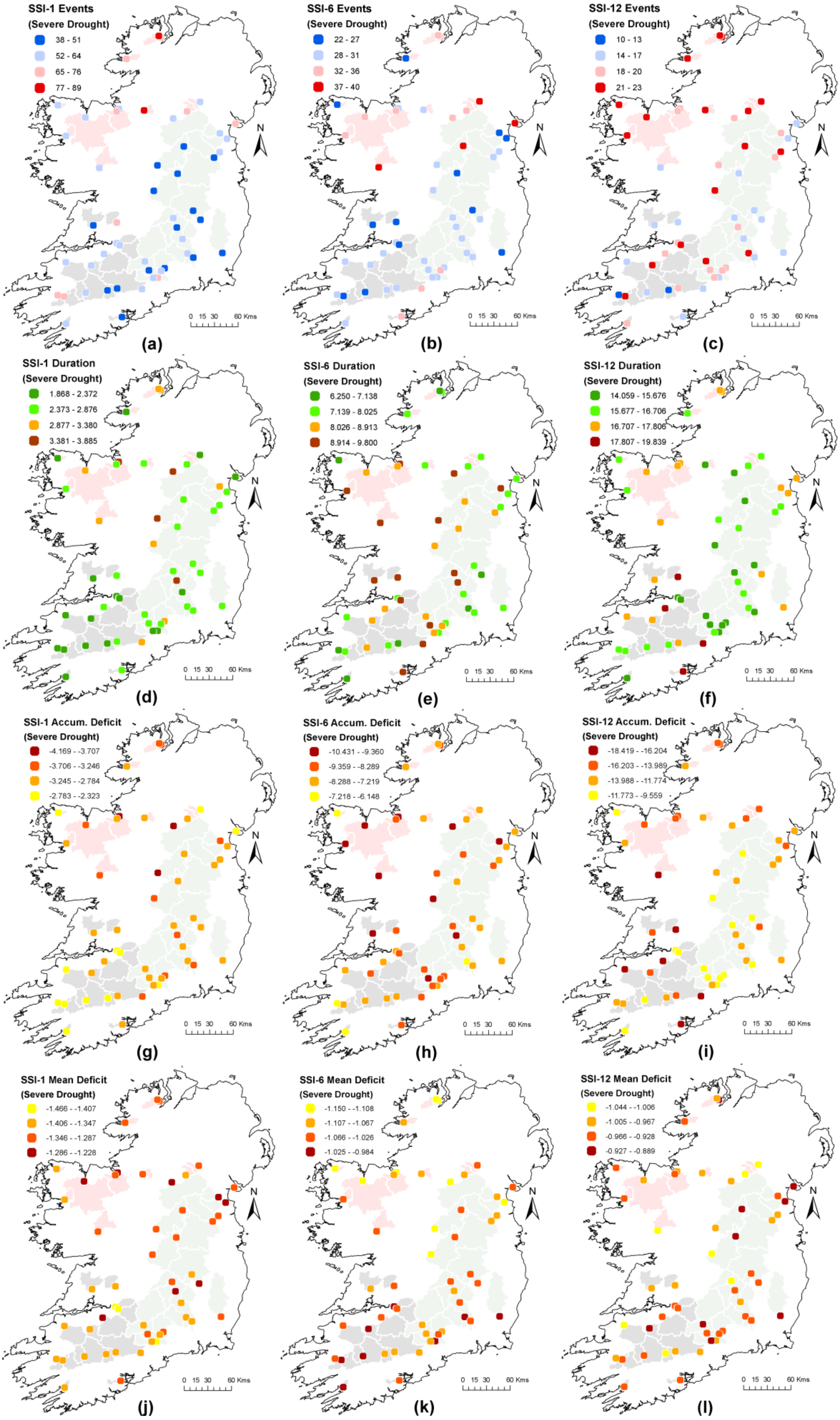


Figure 3.10 As Figure 3.9 but for severe droughts.

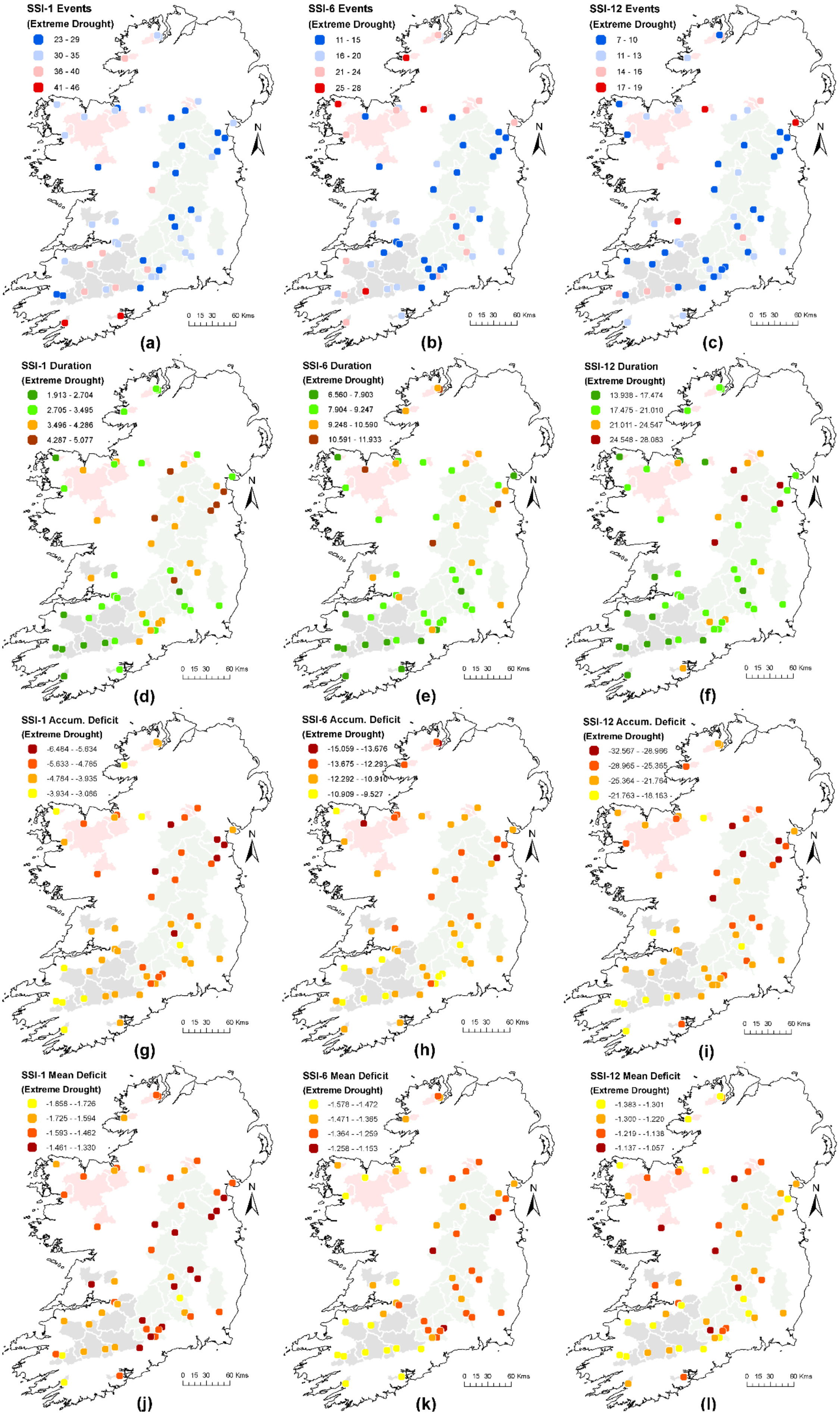


Figure 3.11 As Figure 3.9 but for extreme droughts.

3.3.6 Extreme hydrological drought events

Figure 3.12 displays extreme SSI-3, 6 and 12 drought events for each cluster with details about the number of events, their durations, maximum intensities, and accumulated deficits. For SSI-12, the 1854-1860 drought period is most notable, having the greatest duration and accumulated deficits in each cluster. The event is less prominent for SSI-6, particularly in Cluster 3, and is not distinguishable from other events at SSI-3. Although not as remarkable for SSI-12, the 1975-1977 drought is a prominent SSI-3 and SSI-6 event in terms of deficits and duration for Clusters 1 and 3, with the longest duration of all extreme droughts in both clusters at that accumulation, and the greatest accumulated deficits of all droughts in Cluster 3. The 1933-1935 drought is notable for the intensity and accumulated deficits despite the relatively short duration, particularly for SSI-6 and SSI-12 in Cluster 1. Cluster 3 catchments have the most extreme droughts by accumulated deficit and duration for SSI-3 and SSI-12, whereas for SSI-6 it is Cluster 1. On average, maximum intensity values are most extreme in Cluster 2 for SSI-3 and Cluster 1 for SSI-6 and 12. Across all clusters, there is a remarkable lack of extreme hydrological droughts since the mid-1970s.

Of the top 10 most extreme hydrological droughts per cluster grouping and accumulation period listed in Table 3.3, the 1854-1859 event is the most prominent having the longest duration (53 months) and greatest accumulated deficits (-84.81) for SSI-12. Based on SSI-3, this event fails to make the top ten extreme droughts for Cluster 2. This is primarily due to the length of the drought and the sporadic deficits accumulated over shorter periods during its occurrence. Spatially and temporally, the drought was uneven with Cluster 1 catchments experiencing extreme SSI-12 drought approximately 12 months after Cluster 3, and 9 months after Cluster 2. Despite this, maximum SSI-12 deficits are greatest in Cluster 1 catchments reaching -3.46 SSI.

The 1933-1935 event is the most spatially coherent drought in the record, as it is identified as a top six SSI-3, -6 and -12 event in all clusters. The relatively short duration of this event (23 months for SSI-12), results in high ranks across lower accumulations (consistently within the top two events). Cluster 1 catchments are most impacted with a maximum intensity of -3.43 SSI, the second most extreme of all SSI-12 events across each cluster grouping. Extreme drought conditions consistently began earliest in Cluster 1 catchments, two months before Cluster 2 and 3 catchments in the case of SSI-12 and one month in the case of SSI-3 and 6. Consequently, Cluster 1 catchments experience the greatest accumulated deficits reaching -34.49 for SSI-12.

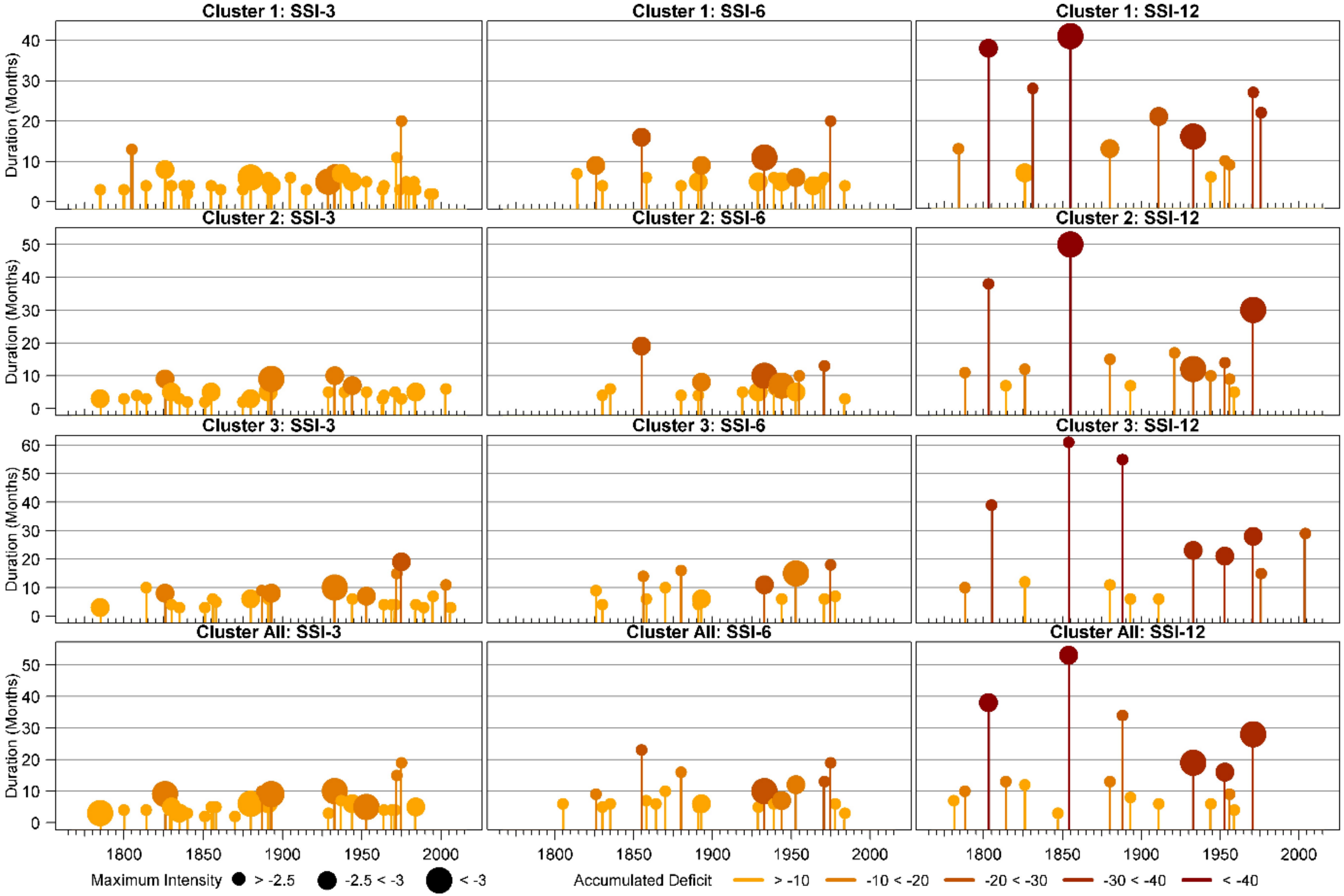


Figure 3.12 Extreme SSI-3, 6 and 12 drought events derived from median flow reconstructions for each cluster and all catchments for the period 1767-2016. For each extreme drought event the duration, maximum intensity and accumulated deficit are provided.

The 1944 drought, although not as extreme as others in terms of duration or deficits, is most significant in Cluster 2 particularly for SSI-3 where accumulated deficits exceed values attained by all other droughts. For SSI-6, the event is notable in all groupings, as it is consistently within the top seven events despite having a relatively short duration (7 months).

Table 3.3 Top 10 SSI-3, 6 and 12 drought events, derived from median flow across all catchments and for clusters during the period 1767-2016. Included are the maximum intensity (Max INT), accumulated SSI deficit (Accum SSI) and duration (Months) of each event.

Cluster 1 (SSI-3)

	Start Date	End Date	Max INT	Accum SSI	Months
1st	07/1975	03/1977	-2.33	-19.90	20
2nd	10/1933	05/1934	-3.00	-15.34	7
3rd	01/1805	02/1806	-2.16	-13.50	13
4th	12/1855	06/1856	-3.42	-12.39	6
5th	03/1929	08/1929	-3.46	-11.61	5
6th	12/1937	07/1938	-2.90	-9.83	7
7th	02/1891	08/1891	-2.17	-8.92	6
8th	07/1826	03/1827	-2.85	-8.90	8
9th	05/1893	09/1893	-2.96	-8.68	4
10th	03/1953	08/1953	-2.41	-8.31	5

Cluster 1 (SSI-6)

	Start Date	End Date	Max INT	Accum SSI	Months
1st	10/1933	09/1934	-3.64	-26.87	11
2nd	07/1975	03/1977	-2.44	-26.75	20
3rd	05/1855	09/1856	-2.53	-25.02	16
4th	06/1826	03/1827	-2.58	-15.47	9
5th	05/1893	02/1894	-2.74	-14.41	9
6th	04/1953	10/1953	-2.72	-11.54	6
7th	05/1944	10/1944	-2.67	-9.64	5
8th	05/1929	10/1929	-2.89	-9.36	5
9th	12/1971	06/1972	-2.11	-9.02	6
10th	02/1858	08/1858	-2.10	-8.23	6

Cluster 1 (SSI-12)

	Start Date	End Date	Max INT	Accum SSI	Months
1st	11/1855	04/1859	-3.46	-70.53	41
2nd	10/1803	12/1806	-2.98	-50.95	38
3rd	09/1831	01/1834	-2.05	-37.59	28
4th	10/1933	02/1935	-3.43	-34.49	16
5th	11/1971	02/1974	-2.24	-33.04	27
6th	01/1976	11/1977	-2.34	-32.34	22
7th	08/1911	05/1913	-2.62	-25.54	21
8th	05/1953	03/1954	-2.18	-15.91	10
9th	10/1784	11/1785	-2.03	-15.32	13
10th	09/1880	10/1881	-2.68	-15.10	13

Cluster 2 (SSI-3)

	Start Date	End Date	Max INT	Accum SSI	Months
1st	03/1944	10/1944	-2.89	-14.09	7
2nd	11/1933	09/1934	-2.81	-13.80	10
3rd	06/1826	03/1827	-2.70	-12.07	9
4th	05/1893	02/1894	-3.32	-11.03	9
5th	06/1984	11/1984	-2.64	-9.14	5
6th	03/1929	08/1929	-2.41	-9.02	5
7th	01/1830	06/1830	-2.74	-8.66	5
8th	03/1953	08/1953	-2.62	-8.43	5
9th	02/1891	07/1891	-2.48	-8.43	5
10th	10/1971	03/1972	-2.04	-7.56	5

Cluster 2 (SSI-6)

	Start Date	End Date	Max INT	Accum SSI	Months
1st	02/1855	09/1856	-2.55	-26.77	19
2nd	11/1933	09/1934	-3.21	-21.46	10
3rd	05/1971	06/1972	-2.28	-21.14	13
4th	11/1955	09/1956	-2.15	-15.54	10
5th	04/1944	11/1944	-3.15	-15.47	7
6th	06/1893	02/1894	-2.66	-11.45	8
7th	04/1953	09/1953	-2.76	-9.80	5
8th	06/1929	11/1929	-2.64	-8.28	5
9th	03/1830	07/1830	-2.21	-7.57	4
10th	01/1835	07/1835	-2.10	-7.05	6

Cluster 2 (SSI-12)

	Start Date	End Date	Max INT	Accum SSI	Months
1st	02/1855	04/1859	-3.10	-68.64	50
2nd	10/1803	12/1806	-2.31	-39.63	38
3rd	09/1971	03/1974	-3.40	-33.23	30
4th	01/1953	03/1954	-2.37	-26.95	14
5th	12/1933	12/1934	-3.35	-26.93	12
6th	05/1956	02/1957	-2.21	-13.02	9
7th	09/1880	12/1881	-2.12	-12.36	15
8th	12/1921	05/1923	-2.21	-12.16	17
9th	08/1944	06/1945	-2.44	-11.82	10
10th	12/1788	11/1789	-2.20	-11.58	11

Cluster 3 (SSI-3)

	Start Date	End Date	Max INT	Accum SSI	Months
1st	07/1975	02/1977	-2.78	-20.47	19
2nd	11/1933	09/1934	-3.10	-16.42	10
3rd	10/1972	01/1974	-2.00	-14.83	15
4th	02/1953	09/1953	-2.73	-14.11	7
5th	11/2003	10/2004	-2.19	-11.96	11
6th	08/1887	05/1888	-2.09	-11.79	9
7th	05/1893	01/1894	-2.86	-10.93	8
8th	07/1826	03/1827	-2.74	-10.31	8
9th	01/1856	07/1856	-2.45	-8.85	6
10th	02/1891	08/1891	-2.24	-8.48	6

Cluster 3 (SSI-6)

	Start Date	End Date	Max INT	Accum SSI	Months
1st	08/1975	02/1977	-2.21	-23.37	18
2nd	11/1933	10/1934	-2.96	-21.83	11
3rd	03/1953	06/1954	-3.01	-19.29	15
4th	03/1856	05/1857	-2.29	-15.08	14
5th	03/1880	07/1881	-2.01	-11.00	16
6th	05/1944	11/1944	-2.22	-9.95	6
7th	12/1971	06/1972	-2.32	-8.40	6
8th	09/1826	06/1827	-2.10	-8.40	9
9th	08/1893	02/1894	-2.52	-8.01	6
10th	03/1858	09/1858	-2.02	-7.67	6

Cluster 3 (SSI-12)

	Start Date	End Date	Max INT	Accum SSI	Months
1st	11/1854	12/1859	-2.41	-82.87	61
2nd	01/1888	08/1892	-2.17	-40.85	55
3rd	11/1971	03/1974	-2.81	-38.64	28
4th	11/1805	02/1809	-2.02	-37.21	39
5th	01/1953	10/1954	-2.54	-34.34	21
6th	12/1933	11/1935	-2.86	-32.85	23
7th	07/2004	12/2006	-2.04	-29.75	29
8th	01/1976	04/1977	-2.14	-23.27	15
9th	12/1788	10/1789	-2.05	-10.93	10
10th	12/1826	12/1827	-2.04	-9.80	12

All (SSI-3)

	Start Date	End Date	Max INT	Accum SSI	Months
1st	07/1975	02/1977	-2.41	-17.47	19
2nd	11/1933	09/1934	-3.22	-16.18	10
3rd	07/1887	05/1888	-2.24	-13.99	10
4th	06/1826	03/1827	-3.10	-13.84	9
5th	05/1893	02/1894	-3.45	-11.64	9
6th	03/1953	08/1953	-3.19	-11.57	5
7th	10/1972	01/1974	-2.03	-10.65	15
8th	04/1944	10/1944	-2.63	-9.60	6
9th	06/1984	11/1984	-2.72	-9.28	5
10th	01/1830	06/1830	-2.85	-9.23	5

All (SSI-6)

	Start Date	End Date	Max INT	Accum SSI	Months
1st	06/1855	05/1857	-2.32	-27.44	23
2nd	11/1933	09/1934	-3.33	-23.24	10
3rd	05/1971	06/1972	-2.30	-21.34	13
4th	08/1975	03/1977	-2.18	-21.02	19
5th	03/1953	03/1954	-2.98	-15.86	12
6th	04/1944	11/1944	-2.65	-13.46	7
7th	03/1880	07/1881	-2.18	-12.46	16
8th	08/1826	05/1827	-2.39	-11.30	9
9th	02/1858	09/1858	-2.15	-9.58	7
10th	08/1893	02/1894	-2.98	-8.32	6

All (SSI-12)

	Start Date	End Date	Max INT	Accum SSI	Months
1st	11/1854	04/1859	-2.71	-84.81	53
2nd	10/1803	12/1806	-2.74	-45.01	38
3rd	10/1971	02/1974	-3.13	-37.88	28
4th	12/1933	07/1935	-3.02	-32.40	19
5th	01/1953	05/1954	-2.64	-31.35	16
6th	01/1888	11/1890	-2.30	-25.76	34
7th	05/1956	02/1957	-2.22	-12.55	9
8th	09/1880	10/1881	-2.50	-12.02	13
9th	12/1788	10/1789	-2.10	-11.41	10
10th	08/1814	09/1815	-2.33	-11.23	13

The 1953-54 drought is another prominent event in the series which, despite a relatively short duration, produced considerable accumulated deficits. The event is registered as a top 10 drought in each cluster and accumulation period. Cluster 3 catchments show the greatest accumulated deficits (-34.34 SSI-12) and duration (maximum of 21 months). The event does not start simultaneously across the three clusters, with Cluster 1 reaching extreme conditions 4 months after Cluster 2 and 3 and ending 7 months earlier compared to SSI-12 in Cluster 3. This highlights the potential for temporal differences in drought event numbers across the island.

The 1975-1977 drought is the most recent extreme identified in our series, coming at the end of a drought rich period during the early to mid-1970s. With a maximum duration of 22 months (Cluster 1, SSI-12) the spatial impact of the event is uneven. Whilst for Cluster 1 and 3 it is identified as a top 10 event for all accumulation periods, this drought does not rank highly over any accumulation period for Cluster 2. The greatest severity is seen in Cluster 3 where it is the top-ranking drought by accumulated deficit for SSI-3 and 6. Whilst extreme drought conditions commenced at a similar time across Cluster 1 and 3 (consistently summer 1975 for SSI-3 and SSI-6 and winter 1975/1976 for SSI-12), the duration was considerably longer for Cluster 1 catchments (7 months in the case of SSI-12 compared to Cluster 3). As a result, accumulated deficits were greatest in this cluster reaching -32.34 for SSI-12.

3.3.6.1 Sensitivity of drought characteristic results to reference period

Sensitivity of drought characteristics to reference period was investigated using four test periods (1767-2016, 1900-1999, 1930-1999, and 1981-2010) to calculate SSI-1, 3, 6 and 12. The indices, derived from median flow series across all catchments, were assessed for numbers of drought events, their durations and accumulated deficits at moderate and severe thresholds. Figure 3.13 shows that the reference period has a discernible impact on all three metrics but particularly on the number of events at 1, 3 and 6 month accumulations and on durations and deficits at 6 and 12 month accumulations.

For occurrence, the 1900-1999 baseline generates the least number of events across all accumulations and severities (n=353, compared with n=323 for the 1981-2010 baseline period, which is recommended for use in indices generation by the WMO). Differences in the number of droughts derived for SSI-1, 3, 6 and 12 range from a minimum of three events between all four reference periods for moderate SSI-12 to a maximum of 16 events between the 1930-1999 and 1981-2010 reference periods for severe SSI-1. All four reference periods produce similar drought duration values for SSI-1 and 3 at moderate and severe intensities. For SSI-6, the 1981-2010 baseline produces longer mean moderate drought and shorter mean severe drought durations. The greatest differences in duration between reference periods are for SSI-12 with severe droughts calculated using the 1900-1999 baseline have a mean duration of 14 months, compared with 7 months for 1981-2010.

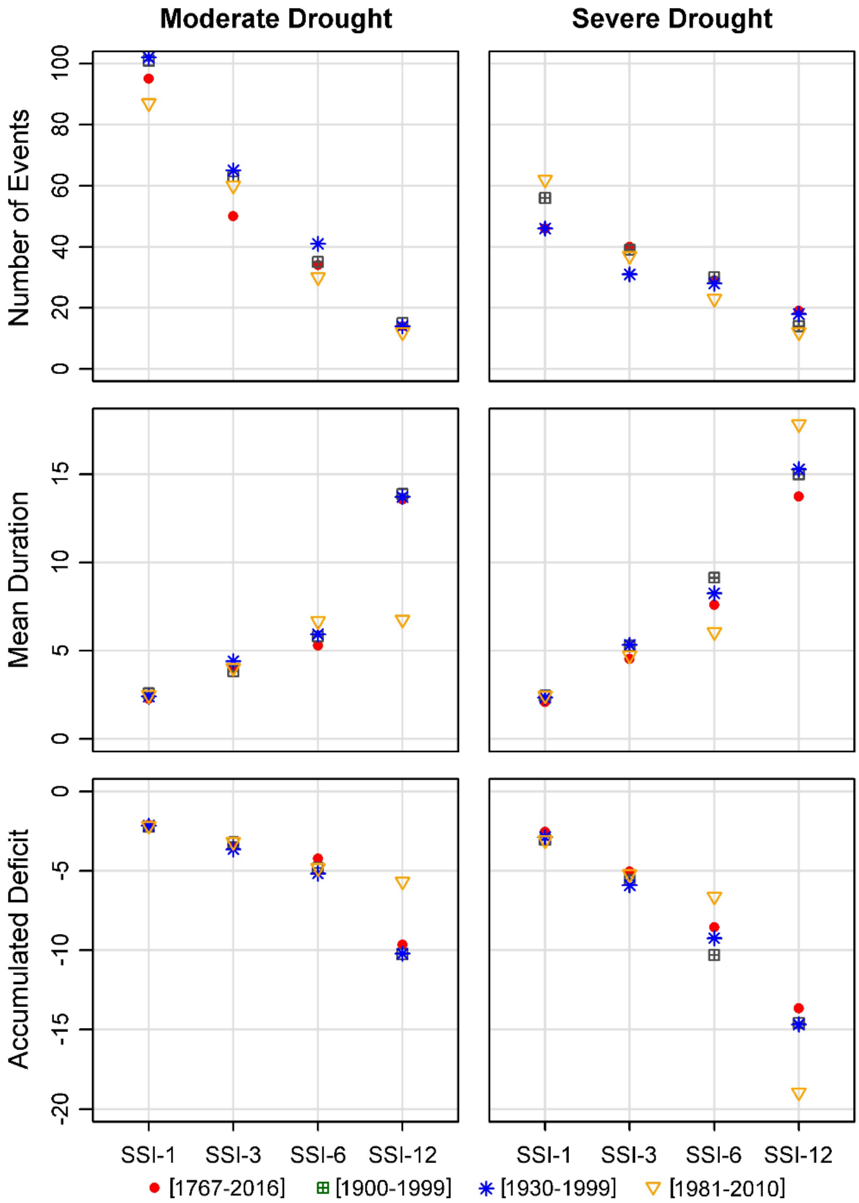


Figure 3.13 The number, duration, and accumulated deficit of drought events for SSI-1, 3, 6 and 12 values derived from median reconstructions for all catchments. Values are derived from the 1767-2016 (red dot), 1900-1999 (dark green square), 1930-1999 (blue star) and 1981-2010 (orange triangle) reference periods.

Accumulated deficits emulate those of duration with SSI-1 and 3 showing similar values for all four reference periods at both severities. The 1981-2010 reference period again deviates from others by producing the least accumulated deficits for severe SSI-6 drought. Similarly, for SSI-12 the 1981-2010 baseline deviates most, producing the least deficits for moderate drought and the most for severe drought. SSI-12 is the most sensitive to the baseline, with 1981-2010 producing a mean accumulated deficit of SSI=-19 compared with mean SSI=-14 for 1767-2016.

3.3.7 Trends in drought characteristics

Trends in the number of events, durations, accumulated and mean deficits of moderate and severe droughts for SSI and SPI at 1, 3, 6 and 12 month accumulations were evaluated for each cluster as well as for all clusters combined. Extreme drought was excluded due to the small number of events. Results for the full period (1767-2016) are displayed in Figure 3.14. For each cluster, increasing trends in the number of moderate and severe drought events are found for SPI- and SSI-1. These trends are significant for all Cluster 2 values, for severe SPI and SSI-1 for Cluster 1 and for moderate SPI-1 for Cluster 3. Whilst no clear patterns are identifiable for moderate and severe SPI-3, the equivalent SSI-3 values display consistent increasing trends. Strong decreasing trends in the number of moderate SPI and SSI-6 and 12 events (Figure 3.14a) are evident for all clusters and all catchments combined (significantly so for Clusters 2 and 3 SPI-12 and Cluster 3 and all catchments combined SSI-12). Trends in the number of severe SPI and SSI-12 events are weaker and are all non-significant.

Decreasing trends in drought duration (Figure 3.14b) are evident for meteorological (SPI) and hydrological (SSI) droughts for most accumulation periods and clusters. Significant ($p \leq 0.05$) decreasing trends in the duration of moderate meteorological droughts are evident for SPI-3 (Cluster 2) and 6 (Clusters 2 and 3). For severe droughts, decreasing trends in duration, significant decreases are evident for SPI-6 (Cluster 3) and SPI-12 (Cluster 3 and all catchments combined). In terms of hydrological droughts, with the exception of SSI-3 severe drought for all catchments combined, only moderate events show significant decreasing trends in duration for SSI-1 (Cluster 1 and 3), SSI-3 (Cluster 1 and 2) and SSI-6 (Cluster 2).

For accumulated deficits (Figure 3.14c), trends are almost the inverse of those found for duration, highlighting the close association between these indices. A significant ($p \leq 0.05$) increasing trend (i.e., towards smaller accumulated deficits) is found for moderate SPI-3 droughts (Cluster 2) and moderate SPI-6 (Cluster 2 and 3). Cluster 3 shows significant increasing trends for severe SPI-6 and SPI-12 whilst the greatest increases evident in SPI-12 are for all catchments combined. For hydrological droughts, changes are again confined to moderate droughts, with significant increasing trends in accumulated deficits in Cluster 3 for SSI-1, Cluster 2 and the all-clusters sample for SSI-3 and Clusters 1 and 2 for SSI-6. Other accumulation periods are also dominated by increasing trends in moderate and severe drought deficits, though these are non-significant. By contrast, mean deficits (Figure 3.14d) for moderate and severe droughts show trends towards more negative values (i.e. more intense droughts), with the most consistent downward trends found in SPI values. The strength of trends is generally greater for moderate drought with Cluster 1 showing significant downward trends for SPI-1, 3 and 6. The largest hydrological trends are found for moderate SSI-1 (significant in Clusters 1, 3 and the all-clusters sample, and for severe SSI-1 and 3 where significant trends are identifiable in Cluster 3 and the all-cluster sample respectively.

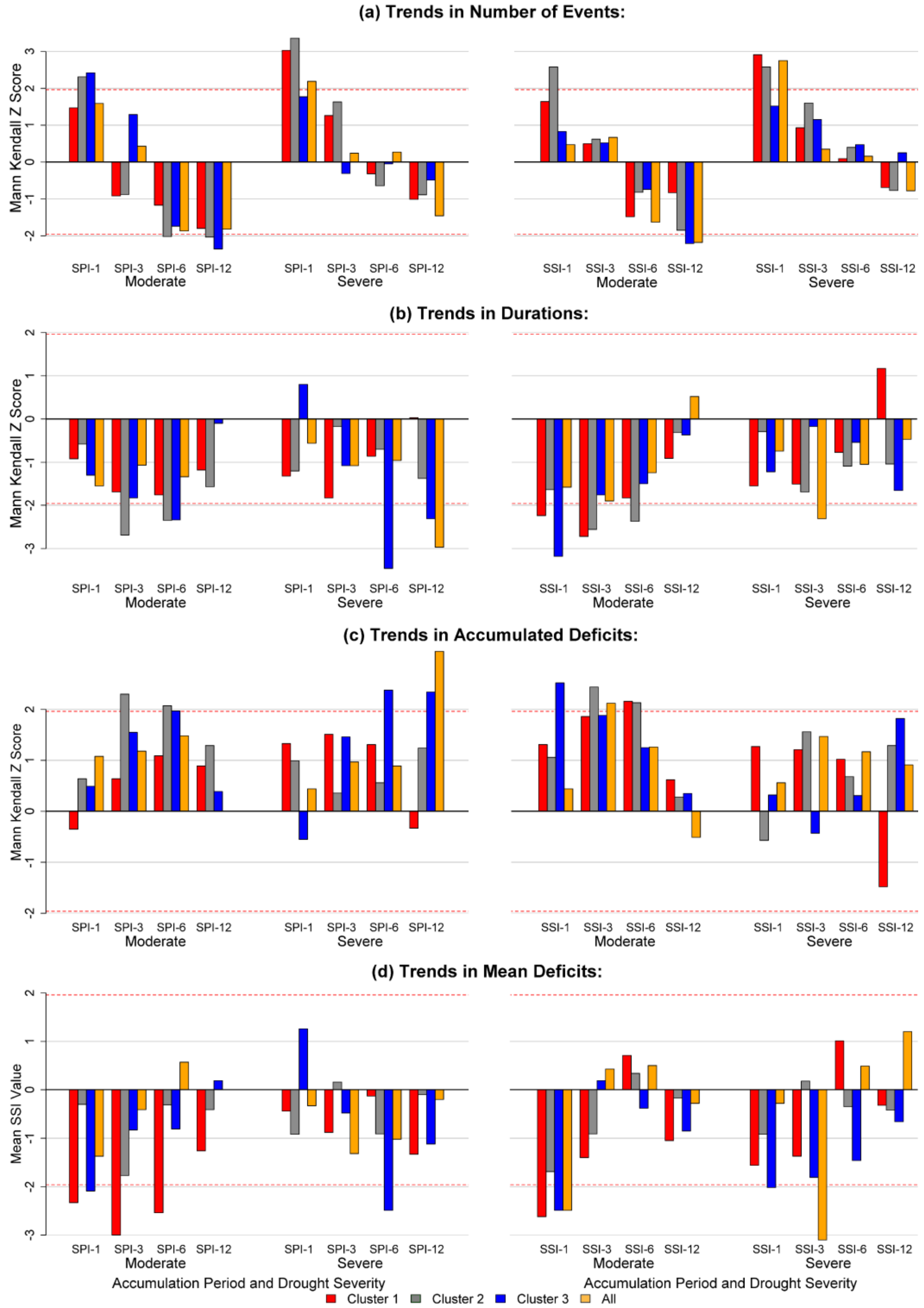


Figure 3.14 Mann-Kendall Zs scores for trends in moderate and severe meteorological (SPI) (left) and hydrological (SSI) (right) drought (a) event numbers, (b) durations, (c) accumulated and (d) mean deficits for each cluster and all catchments (Cluster 1: red, Cluster 2: dark grey, Cluster 3: blue, All Clusters: orange). Event characteristics are derived for accumulation periods of 1, 3, 6, and 12 months. Dashed red horizontal lines represent the 0.05 level significance thresholds (+/- 1.96).

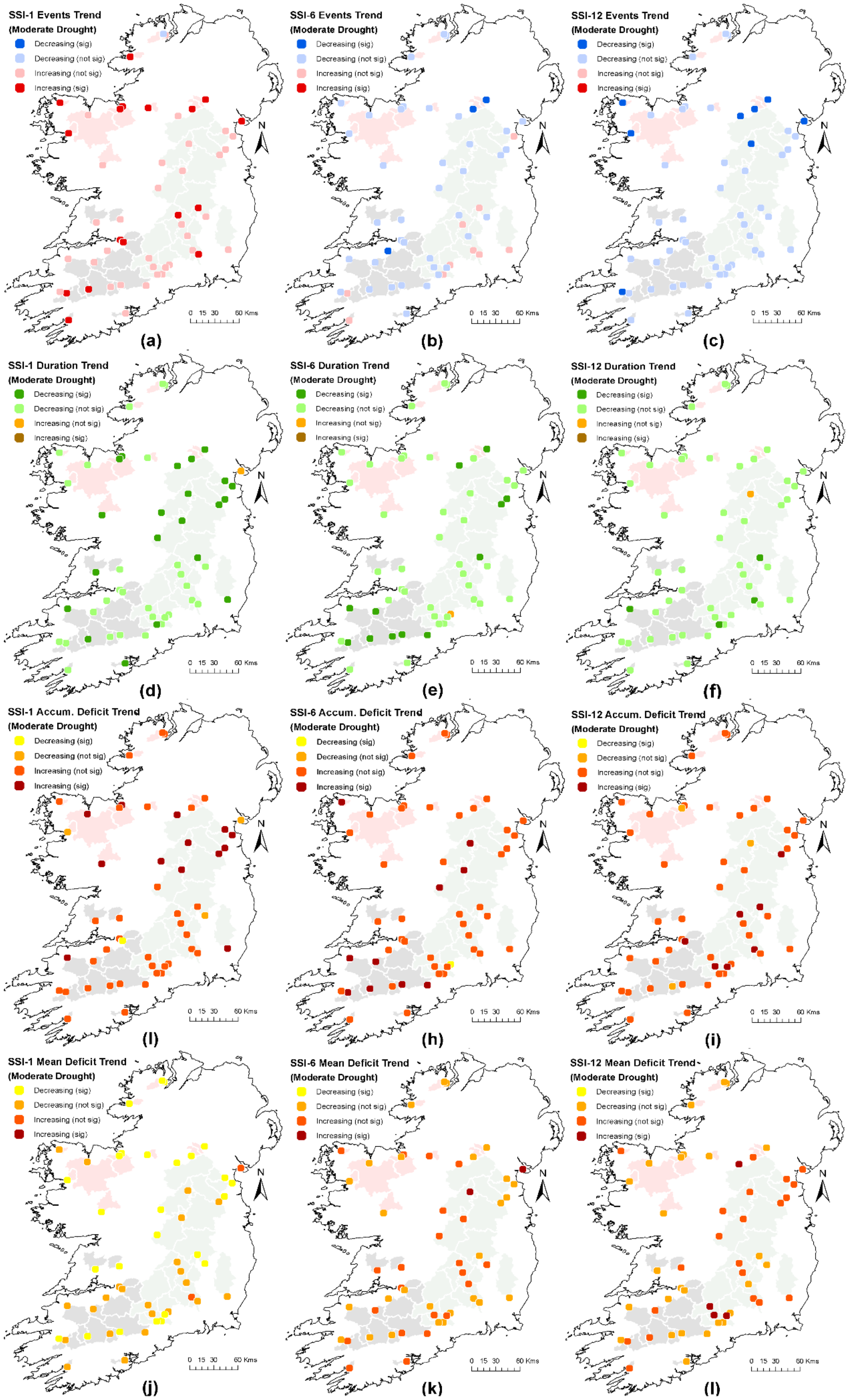


Figure 3.15 Trend direction and significance for moderate drought event numbers, duration, accumulated deficit and mean deficit for each catchment for the period 1767-2016 for SSI-1 (left), SSI-6 (middle) and SSI-12 (right), each superimposed on the cluster membership map shown in Figure 3.1.

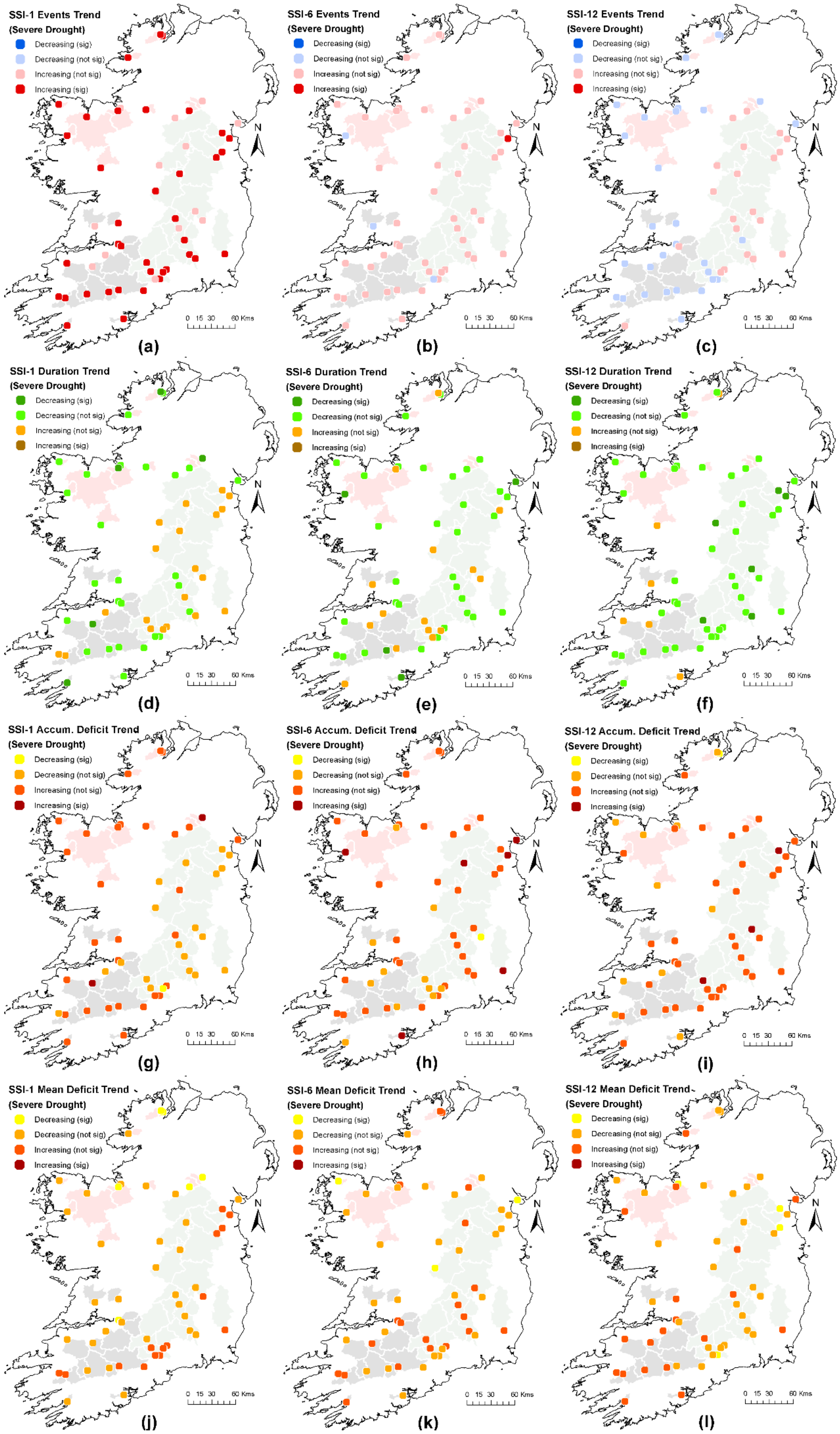


Figure 3.16 As Figure 3.15 but for severe droughts.

Catchment specific trends in the number of hydrological drought events, durations, and deficits for SSI-1, 6 and 12 at moderate and severe intensities were also derived (Figures 3.15 and 3.16). Results align with patterns identified in the cluster analysis described previously, with the number of moderate and severe SSI-1 drought events showing some significant (p≤0.05) increasing trends across catchments. SSI-6 drought shows overall non-significant decreasing/increasing trends for moderate/severe drought whilst SSI-12 shows overall decreasing trends with decreases strongest for moderate drought. Decreasing trends in the duration of moderate SSI-1, 6 and 12 events are identifiable across nearly all catchments with corresponding reductions in accumulated deficits. Mean deficits show more negative values (i.e., more intense droughts) especially for moderate SSI-1.

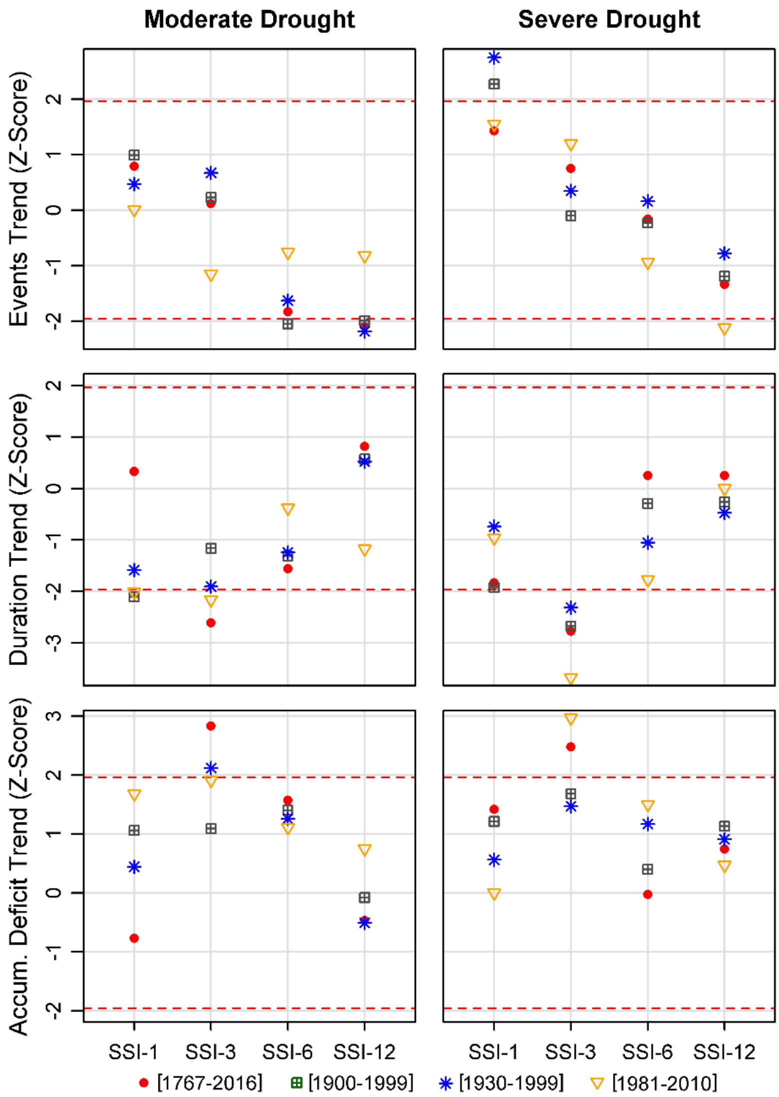


Figure 3.17 Sensitivity of trends in the number, duration and accumulated deficits of moderate (left) and severe (right) drought events to reference period used in fitting SSI indices. Results are presented for accumulation periods of 1, 3, 6 and 12 months for median reconstructions across all catchments. MK Zs scores returned for trends are derived from the 1767-2016 (red dot), 1900-1999 (dark green square), 1930-1999 (blue star) and 1981-2010 (orange triangle) reference periods. Dashed red horizontal lines represent the 0.05 level significance thresholds (+/- 1.96).

3.3.7.1 Sensitivity of trend results to reference period

Sensitivity of trends in numbers of hydrological (SSI) drought events, durations, and deficits to reference period are shown for each cluster in Figure 3.17. Variations in the magnitude, significance and direction of trends, derived for each reference period, are considerable. For the number of drought events, similar trends are identifiable across all four periods with the greatest deviations evident for the 1981-2010 reference period. The most notable differences are apparent for SSI-3 moderate and SSI-3 and 6 severe drought events where the 1981-2010, 1900-1999 and 1930-1999 reference periods generate trend directions opposite to other groupings in each instance. Most reference periods show decreasing trends in drought duration with the notable exception of the 1767-2016 period which generates increasing trends for SSI-1 and 12 moderate and SSI-6 and 12 severe drought). Accumulated deficits are practically the inverse of those found for duration, particularly for moderate drought. The significance of decreasing trends in duration and accumulated deficits is dependent on the reference period used with only SSI-3 showing significant change for both characteristics at moderate and severe intensities.

3.3.7.2 Sensitivity of trends to start and end dates

The sensitivity of trends to the period of record analysed was assessed using SSI-1, 3, 6 and 12 derived from the median flow across all catchments. Trends in the number of hydrological drought events, durations, accumulated and mean deficits were evaluated for moderate and severe droughts across the 1770-2015 period, for a minimum length of 30 years to a maximum of 215 years, incremented at steps of 5 years. Figures 3.10 and 3.11 show results for moderate and severe droughts, respectively. The strong influence of record length on the direction, magnitude, and significance of trends is evident. For moderate droughts, increasing trends in the number of SSI-1 events are seen for tests commencing prior to 1910, with decreasing trends found for tests starting from 1910. Similar patterns are seen for SSI-3, whilst for SSI-6 and 12, tests commencing prior to 1850 also display persistent decreasing trends (significantly ($p \leq 0.05$) for the majority of SSI-12 tests). Almost universal decreases in the duration of moderate SSI-1 and 3 events are evident for all tests ending after 1990, significantly so for the majority of tests with start years after 1950 at both accumulations. For these same test periods consistent increasing trends in accumulated deficit values are evident for SSI-1 and 3, with significant values occurring in SSI-3 for tests commencing before 1795, in 1900 and 1905 and after 1940, matching similar patterns in trends for duration. In contrast, decreasing trends in SSI-1 and 3 mean deficits are largely evident in SSI-1 and 3 for tests ending after 1990, significantly for tests commencing pre-1785 and in 1950 for SSI-1 and between 1850 and 1875 for SSI-3.

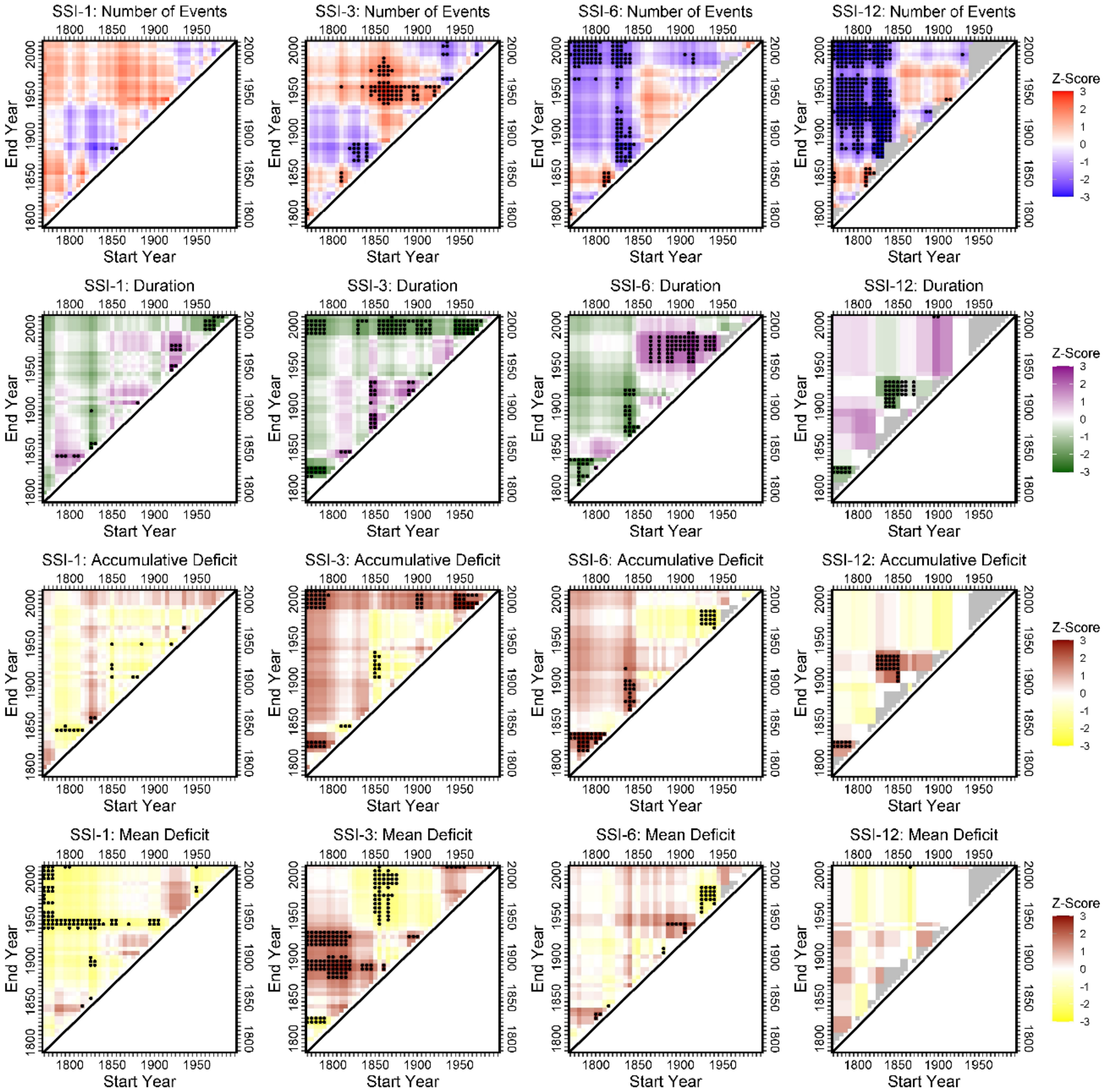


Figure 3.18 MK Zs scores for trends in the number of events, durations, accumulated and mean deficits of moderate hydrological droughts for varying start and end dates. Results are displayed for median reconstructions across all catchments with SSI values, derived from the Tweedie distribution and 1930-1999 reference period. MK Zs values are calculated for periods ranging from 30 to 245 years in 5 year increments for accumulation periods of 1, 3, 6 and 12 months. Black dots indicate test periods for which trends are significant at the 0.05 level.

The strongest (increasing) trends in the number of severe drought events are for SSI-1, especially for tests commencing prior to 1910, particularly those commencing before 1805 and from 1840-1885 (Figure 3.19). Severe SSI-1 drought duration shows decreasing trends for tests commencing post-1930. Increases in accumulated deficit values are evident for the same period. Despite these changes, mean deficit trends show signs of decreasing trends in SSI-1 for start years post-1940 indicating trends towards greater intensity of SSI-1 droughts over this period. Limited significant trends are evident in the number of severe SSI-3 events. SSI-3 duration and accumulated deficit trend values show some significant changes. Of those the most notable are the decreasing/increasing trends in duration/accumulated deficits for start years from 1925 to 1955 and an end year of 2015. Also of note are the largely decreasing trends in duration and increasing trends in accumulated deficits for start year's pre-1800. For severe SSI-3 mean deficits, decreasing trends dominate with significant trends prevalent for start years from 1770 to 1830 and 1880 to 1910. Decreasing trends (significant for start years pre-1890) are widespread in SSI-6 drought durations and are matched by increasing trends in accumulated deficit values. Mean deficits display patterns of overall decreasing trends with significant decreases widely evident for start years between 1890 and 1915 and end years between 1960 and 2000. Finally, it is worth noting that despite some difficulties in trend detection in SSI-12 values, due to the low number of drought events at this accumulation, significant decreasing trends were very prevalent in mean deficit values for test commencing prior to 1830.

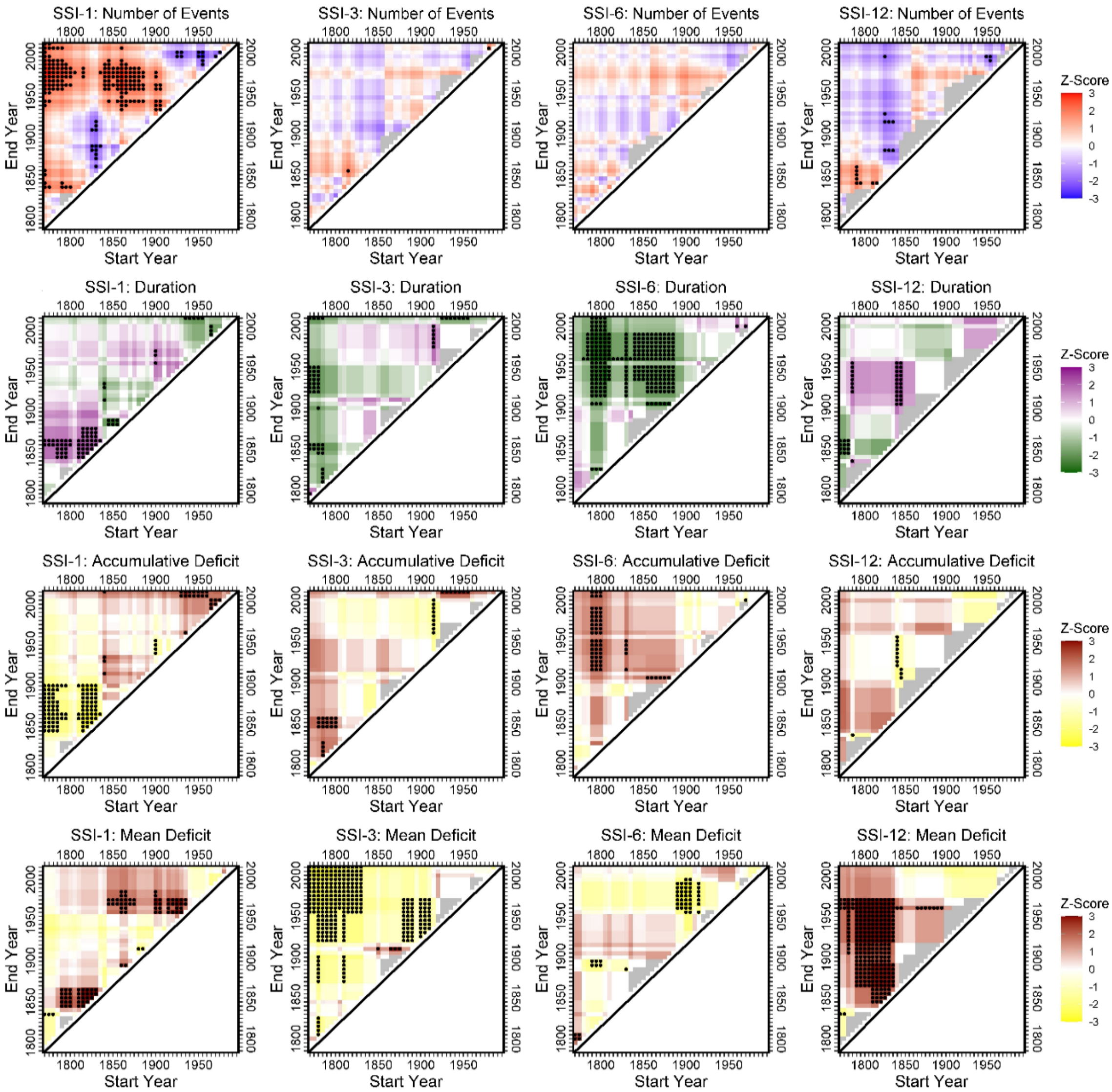


Figure 3.19 As Figure 3.18 but for severe droughts.

3.4 Discussion

This research reconstructs hydrological and meteorological droughts for Irish catchments during the period 1767-2016. Consistent with other studies, we find that catchment characteristics play a critical role in moderating hydrological drought (Barker *et al.*, 2016; Tijdeman *et al.*, 2018; Van Loon and Laaha, 2015). Three distinct clusters of catchments were identified using the Standardised Streamflow Index (SSI). Cluster 1 catchments in the northwest were found to be susceptible to hydrological drought onset with event duration often lowest of the three clusters. Eastern and southeastern, Cluster 3, catchments have the fewest hydrological droughts, but these tend to last longer and produce greater accumulated and reduced mean deficits than other clusters, especially for extreme droughts. Cluster 2 catchments in the southwest had the lowest drought durations overall (marginally lower than Cluster 1), with the number of drought events being intermediate between Cluster 1 and 3.

Examination of the propagation of meteorological to hydrological drought confirmed the importance of groundwater storage in mediating drought incidence. Furthermore, we find a somewhat inverse manifestation of meteorological and hydrological drought across our clusters. Cluster 3 catchments consistently show the lowest frequency of hydrological drought despite having a higher frequency of meteorological drought when compared to other clusters. The opposite is true for Cluster 1 catchments, which experience the highest frequency of hydrological drought with, on average, fewer meteorological droughts than Cluster 3 catchments. Drought duration was generally longer for hydrological events in comparison to meteorological drought, with Cluster 3 catchments showing the greatest drought duration, indicating that these catchments are susceptible to long droughts once deficits become established.

We identified the top 10 droughts for each cluster at 3, 6 and 12 month accumulations. The most notable extreme droughts were the 1803-1806, 1854-1859, 1933-1935, 1944-1945, 1953-1954 and 1975-1977 events. Noone *et al.* (2017) also identified the same post-1850 events as experiencing extreme meteorological drought (except 1944-1945). All three droughts (1806, 1887, and 1893) investigated by Murphy *et al.* (2017) using documentary evidence appear as top ten events here, with 1806 being prominent at the 12-month accumulation in Cluster 1 and 2, and 1887 at 3 and 12 month accumulations in Cluster 3. The 1893 event, which has been described as a ‘relatively forgotten’ drought in France by Caillouet *et al.* (2017), is detectable at 3- and 6-month accumulations in all our clusters. The

Noone and Murphy (2020) assessments of hydrological drought in Ireland also identified 1933-1935, 1944-1945, 1953-1954 and 1971-1977 as notable drought periods. Whilst not as highly ranked, the 1887-1888 and 1891-1894 droughts also emerge as significant events in our study.

European analysis has identified similar historical hydrological droughts to those in this work, particularly in northern/central European regions (Moravec *et al.*, 2019). In the UK, the long drought from 1890-1910, the historic 1933-1934 event, and the drought of 1976 are the most prominent extreme events identified by Marsh *et al.* (2007) and Barker *et al.* (2019) that correspond with droughts identified in our study. The 1854-1859 event was similarly identified as one of the most extreme meteorological, hydrological and soil moisture droughts on the European continent in the last 250 years by Hanel *et al.* (2018). In the UK, the same event ranks highly (Spraggs *et al.*, 2015), with considerable groundwater impacts reported (Marsh *et al.*, 2007). The 1933-1934 drought, which was found to be the most spatially consistent of all events in this study, also had notable impacts on UK flows (Barker *et al.*, 2019) but has less prominence in historic drought records for continental Europe (Moravec *et al.,* 2019). Another notable event identified in our research is the 1953-1954 drought which also impacted central and western Europe (Sheffield *et al.*, 2009). However, for the UK, this drought only impacted Northern Ireland and western Scotland (Barker *et al.*, 2019), highlighting how hydrological drought impacts can vary considerably over relatively small spatial scales, dependent on catchment properties and local climate conditions.

Analysis of trends in the number, duration, mean and accumulated deficits of moderate and severe drought events revealed a complex picture with the direction, magnitude and significance often dependent on the accumulation period used to define drought, the period of record analysed, and the reference period used in fitting standardised indices. The most consistent results identified were for moderate hydrological drought. Decreasing durations and smaller accumulated deficits (i.e., less severe droughts) were found for the full period of record and in the moving window assessment, particularly for tests on SSI-3 values commencing after 1940. However, we find strong negative trends in mean deficits (i.e., more intense droughts) for both moderate and severe meteorological and hydrological droughts over shorter accumulation periods.

Vicente-Serrano *et al.* (2021a) found similar trends for summer SPI-3 for long-term rainfall records in Ireland (1871-2018), particularly in southern and eastern regions, with decreasing trends in the magnitude of August SPI-3 (i.e., increased summer drought), despite predominantly decreasing trends in drought duration. In their assessment of the E-OBS dataset for Europe, Gudmundsson and Seneviratne (2015) found overall decreasing trends in drought event occurrence in northern regions, particularly for SPI-12 with some variance between trends evident in central and western regions. Decreases in drought occurrence at higher accumulations were also found in our study, with significant decreasing trends prevalent for moderate SSI-12 events generated from tests commencing prior to 1850. Hanel *et al.* (2018) however showed that the spatial/temporal variability of drought intensities across the continent may conceal localised impacts, particularly for meteorological to hydrological drought propagation because catchments react differently to drought events (Stoelzle *et al.*, 2014).

Periods marked by an absence of drought are also evident, especially for longer accumulation periods. The period 1767-1800 had few extreme hydrological droughts with the exception of events in 1784-1785 (Cluster 1) and 1788-1789 (Cluster 2 and 3) which rank as top ten droughts for SSI-12. This is consistent with identified SPI-12 droughts from reconstructions of Island of Ireland precipitation by Murphy *et al.* (2020a). Furthermore, a drought-poor period in the late 1700s is also evident in the series generated by Todd *et al.* (2013) from the Kew, Oxford and Spalding rainfall series, for southeast England. Another drought-poor period is evident in 1860-1885, as reported for SPI-12 events by Noone *et al.* (2017). The lack of extreme droughts (particularly for longer accumulation periods) since the mid-1970s found here is consistent with studies showing decreasing trends in meteorological drought in northern European regions for SPI-3, 6, 12, 24 and 36 month accumulations (Gudmundsson and Seneviratne, 2015; Stagge *et al.*, 2017). In the UK, Barker *et al.* (2019) found a decrease in hydrological drought occurrence (SSI-3 and 12) post the 1980s in northern and western catchments, which aligns with our findings. The presence of drought-rich and -poor periods in our reconstructions suggest that a return to an era of more frequent extreme droughts is possible. This raises questions regarding the preparedness of water managers in Ireland for such change. The Irish Water (2021) 25-year plan acknowledges substantial vulnerability to drought due to the major expansion of infrastructure during the current drought-poor period (post mid-1970s) combined with insufficient recognition of the historical propensity for droughts.

There are a number of limitations to note. O'Connor *et al.* (2021b) highlight key assumptions regarding the reconstruction of river flows including land-use change, changes in channel geometry (Slater *et al.*, 2019), and reductions in precipitation and temperature station density in early records (Ryan *et al.*, 2021a), among others. Moreover, Murphy *et al.* (2020b) raise questions about the under measurement of snowfall in early precipitation records. Therefore, pre-1850 results should be treated with caution. Nonetheless, the coherence of drought events across clusters increases confidence in the results, as does consistency with inventories of major droughts in the UK and Western Europe.

There is potential for further research too. For instance, given the typically short (~45 years) records of observed river flow in Ireland, our reconstructions provide a multi-century catalogue of major droughts for stress-testing infrastructure, water and drought management plans. The various indices could also be used for national drought monitoring and reporting of emergent trends (Wilby, 2021). Similarly, there have been considerable efforts in Europe to link drought metrics and impacts to better inform drought monitoring and management (e.g., Bachmair *et al.*, 2016; Haro-Monteagudo *et al.*, 2018; Erfurt *et al.,* 2019; Parsons *et al.,* 2019; Parente *et al.,* 2019; Vicente-Serrano *et al.,* 2021b). As noted by Noone *et al.* (2017), Irish newspaper archives hold valuable information about cross-sectoral drought impacts. Potential therefore exists to systematically identify droughts from newspaper records dating back to the 1700s, to understand vulnerability and identify which metrics and accumulation periods best describe societal impacts at the catchment scale. Such work could shed light on the changing nature of drought vulnerability and inform development of monitoring and early warning systems (Hannaford *et al.*, 2019).

Having a multi-century catalogue of meteorological and hydrological droughts at the catchment scale also offers potential to inform and evaluate climate change adaptation measures with historical events presenting analogies of plausible future extremes. As previously highlighted, the most extreme hydrological events identified here tend to occur before the availability of digital discharge records and, therefore, offer new insight into the range of variability in drought characteristics. Recent research is highlighting the utility of storylines (plausible changes to the factors that impacted the unfolding of past events) for informing adaptation to credible extreme events (Shepherd *et al.*, 2018); others have used such approaches to evaluate how extreme drought events may change in a warmer world (e.g., Chan *et al.,* 2021). Our work provides a foundation for such approaches to adaptation planning across Irish catchments. Finally, future work should examine the climatological drivers behind drought-rich and -poor periods, as well as for the emergent pattern of shorter, sharper droughts identified here over recent decades. The AMO is known to influence summer precipitation variability in Ireland (McCarthy *et al.*, 2015) and has been linked to hydrological drought occurrence in the UK (Svensson and Hannaford, 2019). The role such phenomena play in drought variability, together with impacts of observed temperature increases should be further examined, as changing drought characteristics may have consequences for water management in Ireland, particularly where limited catchment storage increases vulnerability.

3.5 Conclusions

We used reconstructed monthly precipitation and river flows to evaluate historical and hydrological drought in 51 Irish catchments over the period 1767-2016. Using standardised indices of varying accumulation periods applied to reconstructions for individual catchments and cluster groupings we found that physical catchment descriptors such as average rainfall and groundwater storage play a critical role in determining the propagation of meteorological to hydrological drought. Runoff dominated catchments tend to experience the highest drought frequency and intensity, but shorter durations. Groundwater dominated catchments tend to experience droughts of longer duration with greater accumulated deficits and reduced mean deficits. Accounting for the differential signatures of droughts at the catchment scale, the most significant hydrological droughts were identified in 1803-1806, 1854-1859, 1933-1935, 1944-1945, 1953-1954 and 1975-1977. Although not as highly ranked, events in 1826-1827, 1887-1888, 1891-1894 and 1971-1974 also emerged as significant hydrological extremes in our study. However, the evaluation of drought characteristics was shown to be sensitive to the reference period used in standardising drought indices. The most appropriate reference period should be identified with the wavelength of key modes of variability in mind. Here, we recommend a 70-year reference period, which matches observed AMO periodicity. Despite trends in the number of drought events, durations and deficits being additionally sensitive to the period of record tested, we found that shorter droughts show evidence of increasing mean deficits, despite decreasing duration, indicating a tendency towards shorter, more intense hydrological droughts. The dataset developed here offers an important reference set for drought and water management in Ireland, particularly given the paucity of extreme droughts present in the observational records currently used for drought planning (Irish Water, 2021).

Chapter 4 | Linking drought indices to historic newspaper articles

4.1 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, regional and national scales (Wilhite *et al.*, 2007), including reduced agricultural output, freshwater shortages, ecosystem degradation, reduced energy and industrial productivity (Gil *et al.*, 2013; Mosely, 2015; Van Vliet *et al.*, 2016; García-León *et al.*, 2021). The 2018 European drought, for example, resulted in severe impacts across the continent, particularly for crop production, power generation and transportation (Bakke *et al.*, 2020). Given their effects, understanding drought events and their links to 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 data recording drought impacts (Bachmair *et al.*, 2015). Of those undertaken they typically relate to agricultural drought and linking indices to crop yields, with multi-sectoral impact assessments much sparser (Wang *et al.*, 2020b). 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 drought, for both historic and future events (Steinemann *et al.*, 2015; Ekström *et al.*, 2018). For meteorological drought, indices such as the Standardised Precipitation Index (SPI), Standardised Precipitation Evapotranspiration Index (SPEI), Effective Drought Index (EDI), Reconnaissance Drought Index (RDI) and Palmer Drought Severity Index (PDSI) are often used (e.g., Erfurt *et al.*, 2019; Erfurt *et al.*, 2020; Deo *et al.*, 2017; Tsakiris *et al.*, 2007; Lloyd-Hughes and Saunders 2002). For hydrological drought, indices such as the Standardised Streamflow Index (SSI), Total Storage Deficit Index (TSDI) and Palmer Hydrological Drought Index (PHDI) can also be applied (e.g. Vicente-Serrano *et al.*, 2012b; Nie *et al.*, 2018; Karl, 1986). Although indicators provide a means of quantifying and comparing droughts (Vicente-Serrano *et al.*, 2011) their usefulness 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 in case of the modulation and propagation of hydrological droughts by catchment properties (Barker *et al.*, 2016; Rust *et al.*, 2021).

Good quality, long-term precipitation and 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.*, 2021a), however historical records for river flow are not as readily available. One means of addressing this issue is by reconstructing historic river flows using rainfall-runoff models forced with long-term temperature and precipitation series (e.g. Jones, 1984; Spraggs *et al.*, 2015; Crooks and Kay, 2015; Rudd *et al.*, 2017; Hanel *et al.*, 2018; Smith *et al.*, 2019; Noone and Murphy, 2020; O'Connor *et al.*, 2021b).

Drought indicators have been extracted from reconstructed flows to assess historical droughts in a number of studies (e.g. Caillouet *et al.*, 2017; Hanel *et al.*, 2018; Erfurt *et al.*, 2020; Rudd *et al.*, 2017; Moravec *et al.*, 2019; O'Connor *et al.*, 2022a). However, knowledge of drought characteristics alone does not necessarily translate into socio-economic impacts (which can vary depending on drought timing, socio-economic vulnerability, etc). 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.*, 2012a; Gudmundsson *et al.*, 2014; Bachmair *et al.*, 2015; Blauhut *et al.*, 2015), particularly for agricultural impacts (e.g. Stagge *et al.*, 2015a; 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 centralised 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, Murphy *et al.* (2017) demonstrated the value of historical newspaper archives in an analysis of drought impacts across the island over the past 250 years. Noone *et al.* (2017) also used newspaper archives to verify the occurrence and duration of historical droughts, using the former to help verify quantitative drought reconstructions.

The SPI has been shown to be effective in generating strong links between drought occurrence and agricultural impacts (Vincente-Serrano *et al.*, 2012a). Similarly, the SSI has demonstrable utility for linking hydrological drought with groundwater levels, vegetative 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.* (2015a) and Sutanto *et al.* (2019) concluded that logistic regression could generate valuable information on localised impacts, from drought indicators in the UK and Europe, despite the simplicity of the approach.

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). Nonetheless, there is a notable lack of research into trends in drought-related impacts (Kreibich *et al.*, 2019) and vulnerability to droughts (Mechler and Bouwer, 2015). Recent studies have begun to address this knowledge gap. For example, Parsons *et al.* (2019) found an increasing likelihood of agricultural 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.* (2015a) attributed inter-annual variations in agricultural drought impacts across Europe to sampling and reporting bias, impact awareness, changes in 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, particularly in relation to food supply, water supply and human health, highlighting the non-static nature of drought impacts.

In this paper, we related 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 4.2 provides an overview of the datasets and methods employed, Section 4.3 presents the results of our analysis, then Section 4.4 provides a discussion of key results and insights. Finally, conclusions are drawn and suggestions for further research are offered in Section 4.5.

4.2 Data and methods

4.2.1 Meteorological and hydrological data

Meteorological and hydrological data consist of monthly precipitation and river flow reconstructions, produced by O'Connor *et al.* (2021a) for 51 catchments across Ireland[1]. For each catchment we extract precipitation and flow reconstructions for the period 1900-2016. O'Connor *et al.* (2021a) produced uncertainty estimates for flow reconstructions by applying various 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 (O'Connor *et al.*, 2022a). To allow for a comparison of results between both studies, we conduct our analysis using the same clusters (Figure 4.1a). Cluster 1 catchments, located in the wetter northwest of the island, have relatively small areas, low groundwater content, 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. Standardised drought indices for 1900-2016 were applied to median monthly precipitation and flow data in each cluster. These were the Standardised Precipitation Index (SPI; McKee *et al.*, 1993) and Standardised Streamflow Index (SSI; Vicente-Serrano *et al.*, 2012b) 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 (1930-2000) and the Tweedie distribution were used to fit both SPI and SSI following O'Connor *et al.* (2022a).

4.2.2 Drought impact data

Jobbová *et al.* (2022) developed an Irish Drought Impacts Database (IDID) from the Irish Newspaper Archive (INA) spanning the period 1738-2019. The INA is an online newspaper database consisting of over six 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

[1] https://doi.org/10.1594/PANGAEA.914306

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 6,087 drought related articles. Using a modification of European Drought Impact report Inventory (EDII; Stahl *et al.*, 2012) that was 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 categorised under multiple categories the final decision on the associated grouping was determined by the authors to ensure consistency in classifications across the entire dataset. For each drought impact, 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 we retain all but the Human Health and Public Safety and Conflicts categories due to a lack of articles of that nature in the data selected for use in this study. The resulting 13 drought impact categories 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 hydrological-based impact reports (related to aquaculture and fisheries, waterborne transport, energy and industry, tourism and recreation, public water supply, water quality and freshwater ecosystems). We matched the associated year and month of each reported impact in the IDID to the drought indices on that date. 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 4.1b). Impact reports that did not provide a specific location or from which the relevant county could not be derived were excluded from the analysis. 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 sub-category is given in Table 4.1. For each cluster, the cumulative number of drought impact reports were then calculated for each month from 1900-2016.

4.2.3 Model generation and analysis

Logistic regression and Generalised Additive Models (GAMS) have been previously used to link drought indices to impacts (Bachmair *et al.*, 2017; Parsons *et al.*, 2019; Stagge *et al.*, 2015a). 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/non-occurrence 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 typically applied to derive the probability of occurrence from regression models (see Morgan *et al.*, 1988). Logistic regressions were fit using the Generalised Additive Model (GAM) framework which enables logistic regressions to be applied with a smoothing function for selected predictor variables (month values) to account for non-linear components in series (e.g. the seasonal components of monthly SPI/SSI values). To convert the log-odds predicted output to a simple probability output (i.e., to generate impact probability values in the range from 0 to 1) the inverse logit of the predicted values were found. Values could then be easily categorised by their probability 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 hydrological-based articles. Model predictor variables included standardised drought indices, smoothed month values and year values. Month values account for seasonal variations in drought impact reporting probability, whilst year values allow for any trends in the data (cf. Parsons *et al.*, 2019).

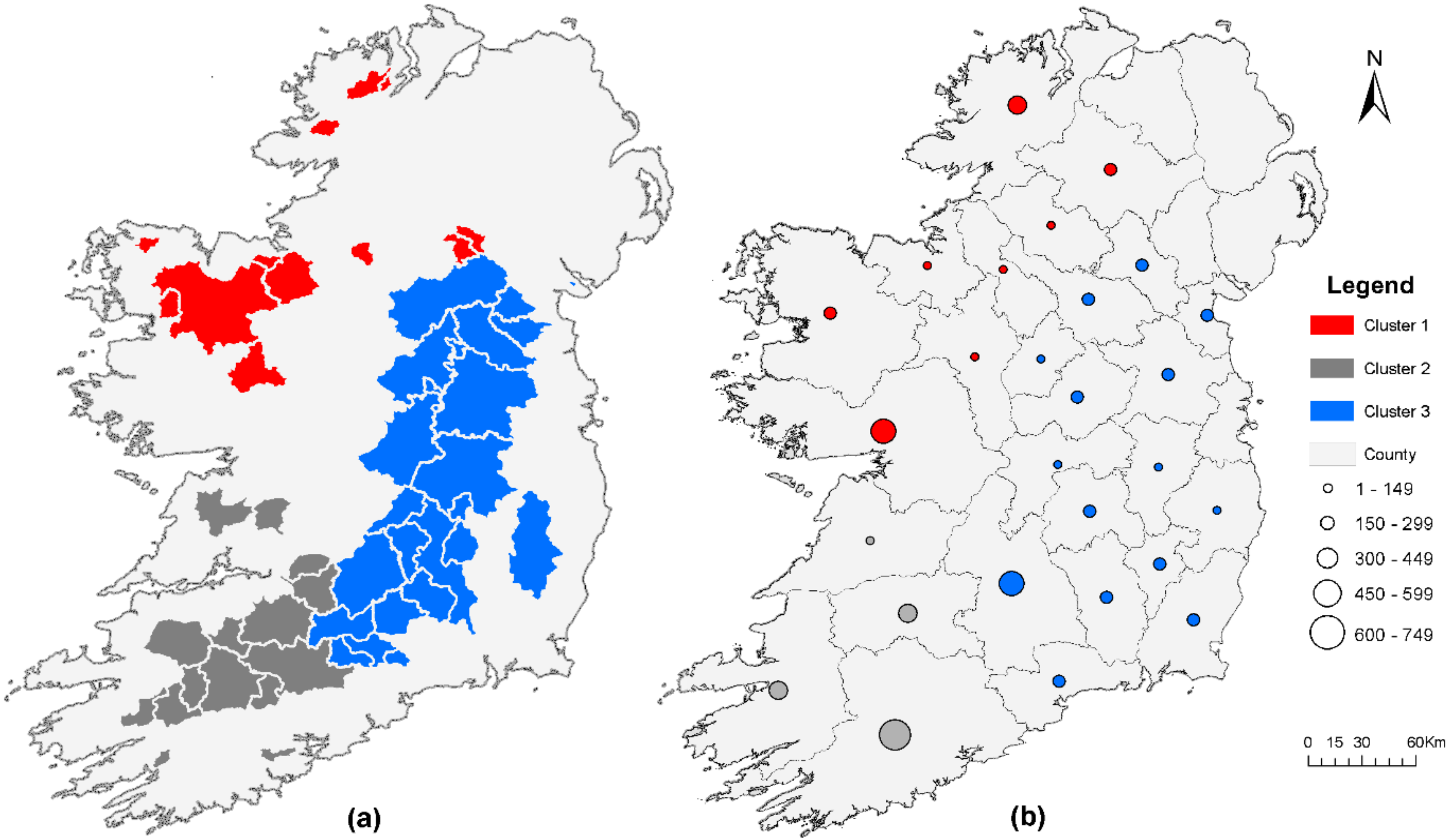


Figure 4.1 Spatial distribution of (a) clusters of catchments used in the analysis and (b) counties and corresponding drought impact article numbers (combined land- and hydrological-based) over the period 1900-2016.

Table 4.1. Breakdown of article numbers based on county, cluster and related article type/grouping.

		Hydrological-Based Articles								Land-Based Articles							
County Name	Cluster No.	Aquaculture and Fisheries	Waterborne Transport	Energy and Industry	Tourism and Recreation	Public Water Supply	Water Quality	Freshwater Ecosystem	Sub-Total	Agriculture & Livestock farming	Terrestrial Ecosystem	Soil System	Wildfires	Air Quality	Forestry	Sub-Total	Total
Carlow	3	3	2	2	1	31	1	9	49	104	2	14	2	0	0	122	171
Cavan	3	13	1	5	2	42	3	27	93	159	4	1	5	0	0	169	262
Clare	2	1	1	14	3	22	1	8	50	43	0	2	3	0	0	48	98
Cork	2	24	0	9	20	147	7	62	269	422	8	13	5	2	0	450	719
Donegal	1	41	0	8	5	105	5	56	220	155	1	3	12	0	0	171	391
Fermanagh	1	9	1	1	1	19	1	15	47	26	2	0	5	0	2	35	82
Galway	1	23	1	3	9	117	7	62	222	217	3	4	7	0	1	232	454
Kerry	2	24	2	1	10	66	3	36	142	243	6	4	0	0	0	253	395
Kildare	3	6	1	1	7	20	1	7	43	72	2	5	4	0	0	83	126
Kilkenny	3	0	0	1	3	46	0	8	58	163	1	5	2	0	0	171	229
Laois	3	2	0	2	2	45	4	15	70	104	2	0	7	0	0	113	183
Leitrim	1	5	3	3	0	22	1	18	52	85	2	4	2	0	0	93	145
Limerick	2	7	0	6	7	83	4	24	131	239	15	3	7	0	1	265	396
Longford	3	2	1	2	2	27	0	10	44	89	1	1	0	0	0	91	135
Louth	3	9	0	1	8	43	0	7	68	76	3	3	5	0	0	87	155
Mayo	1	16	1	4	6	58	6	54	145	94	4	4	8	1	1	112	257
Meath	3	14	0	1	9	45	0	19	88	103	3	5	2	0	0	113	201
Monaghan	3	5	1	5	0	56	3	15	85	105	4	1	4	0	0	114	199
Offaly	3	5	2	2	0	19	0	15	43	63	2	2	1	0	1	69	112
Roscommon	1	2	1	4	3	27	0	19	56	74	2	0	3	1	0	80	136
Sligo	1	11	0	1	3	39	2	15	71	43	1	0	0	0	0	44	115
Tipperary	3	7	0	7	10	87	0	16	127	308	8	4	8	0	0	328	455
Tyrone	1	35	0	1	1	84	5	40	166	66	3	3	3	0	0	75	241
Waterford	3	9	0	0	6	55	1	16	87	145	6	4	4	0	2	161	248
Westmeath	3	6	6	3	4	36	4	26	85	95	5	1	2	0	0	103	188
Wexford	3	0	1	6	3	33	1	7	51	155	5	11	1	0	0	172	223
Wicklow	3	1	0	0	2	31	0	4	38	54	2	4	5	0	2	67	105
Total	-	280	25	93	127	1405	60	610	2600	3502	97	101	107	4	10	3821	6421

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 article numbers. The procedure was as follows: Step 1, the date (month/year) with the highest number of articles was ranked as one ($rank_1 = 1$), the second highest as two ($rank_2 = 2$), etc., 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 1, 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.

$$Reciprocal\ Rank = \sum_{i=1}^{Q} \frac{1}{rank_i} \qquad (1)$$

Reciprocal ranked weights were determined separately for each model. Dependent variable values for each model were represented by the binary occurrence/non-occurrence of monthly drought impact articles (land- or hydrological-based) for each cluster, with final model output returning the probability 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 (R^2adj). 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 and model output assessed for each.

For each cluster, models were used to relate SPI and SSI to predicted impact report probabilities, i.e., the likelihood of a drought related newspaper article for a given SPI or SSI value. To aid interpretation, we classify reported impact probability 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 probability of reported impacts 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 116 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 probabilities at annual and monthly timescales with the latter allowing for assessment of how reported impact likelihood changes within clusters over the course of a year. Annual probabilities were derived by finding the mean of the monthly probabilities 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 non-parametric 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 break point.

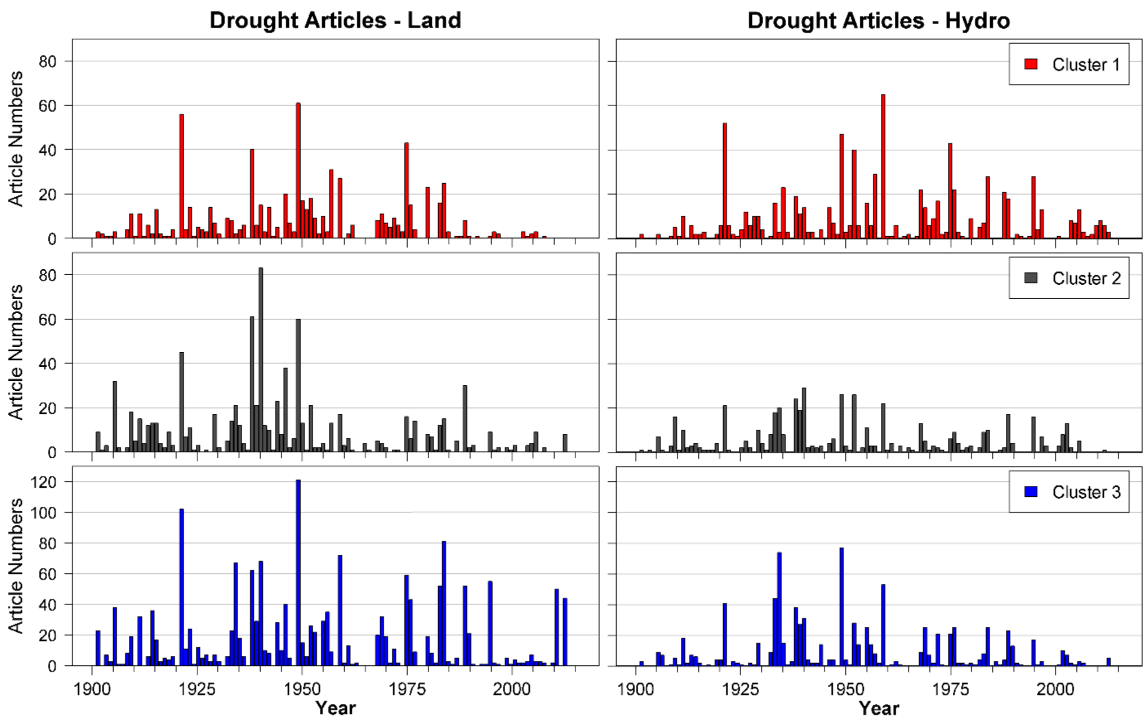


Figure 4.2 Distribution of land-based (left) and hydrological-based (right) drought impact articles (annual totals) for each cluster over the period 1900-2016.

4.3 Results

4.3.1 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 4.3 and 4.4). Across the period there are several extreme events identifiable 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 show less intensity in the SSI equivalent such as the 1911, 1944, and 2003-2004 droughts. Figure 4.2 plots the annual number of articles by cluster over the period 1900-2016. Notable are the high number 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, 1933-1934, 1938, 1940, 1949, 1959 and 1975. Differences in article numbers for certain events are identifiable between clusters and article types. Although some droughts coincide with article occurrence (e.g. the 1933-1934 and 1975 droughts) others show fewer impact articles, despite being classified as severe or extreme droughts by the standardised indices. Conversely, events such as the 1921 and 1949 droughts do not rank among the most extreme droughts in the indices series despite producing some of the highest number of drought articles.

4.3.2 Model performance analysis

Logistic regression and GAMs show the relationship between SPI/SSI and land-/hydrological-based drought impact reports in each cluster. Figure 4.5 displays results of this assessment with R^2adj values for different SPI/SSI accumulation periods plotted for land- and hydrological-based impact reports (lighter coloured bars). For hydrological-based impact reports SSI-2 performed best across all three clusters (R^2adj values of 0.17 ($p<0.01$; Cluster 1), 0.18 ($p< 0.01$; Cluster 2) and 0.17 ($p< 0.01$; Cluster 3)). For land-based impact reports SPI-3 performed best having the highest R^2adj score for Cluster 1 (0.11; $p<0.01$) and 3 (0.17; $p<0.01$). For Cluster 2, SPI-2 performed marginally better than SPI-3 (0.12; $p<0.01$ versus 0.11 ($p<0.01$). For simplicity, SPI-3 was adopted as the best predictor of land-based drought impact reports in all clusters.

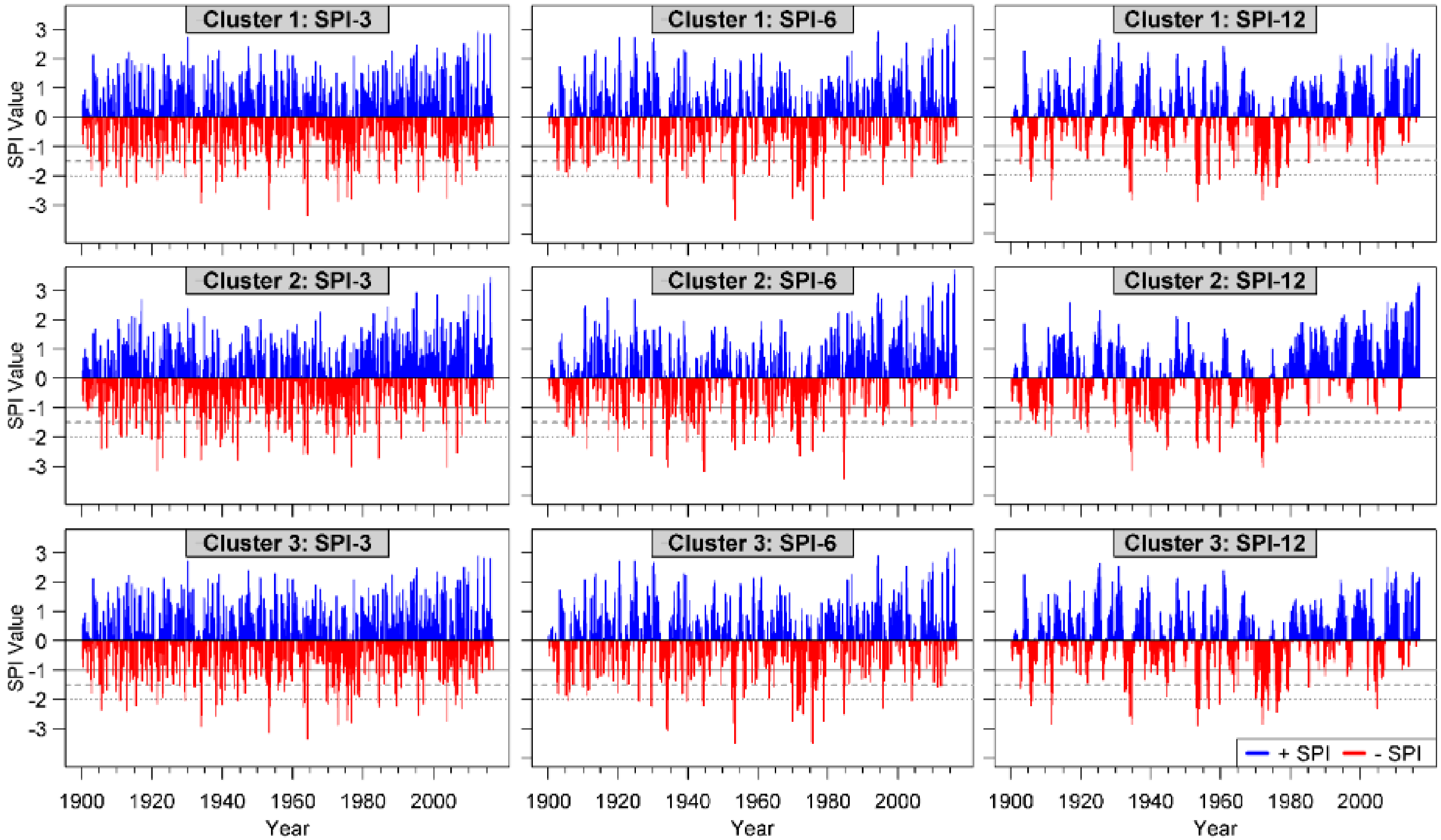


Figure 4.3 Time-series of SPI 3, 6 and 12, derived from median flows for each cluster (1900-2016), using the Tweedie distribution and 1930-1999 reference period. Horizontal lines represent moderate, severe and extreme drought thresholds in all plots.

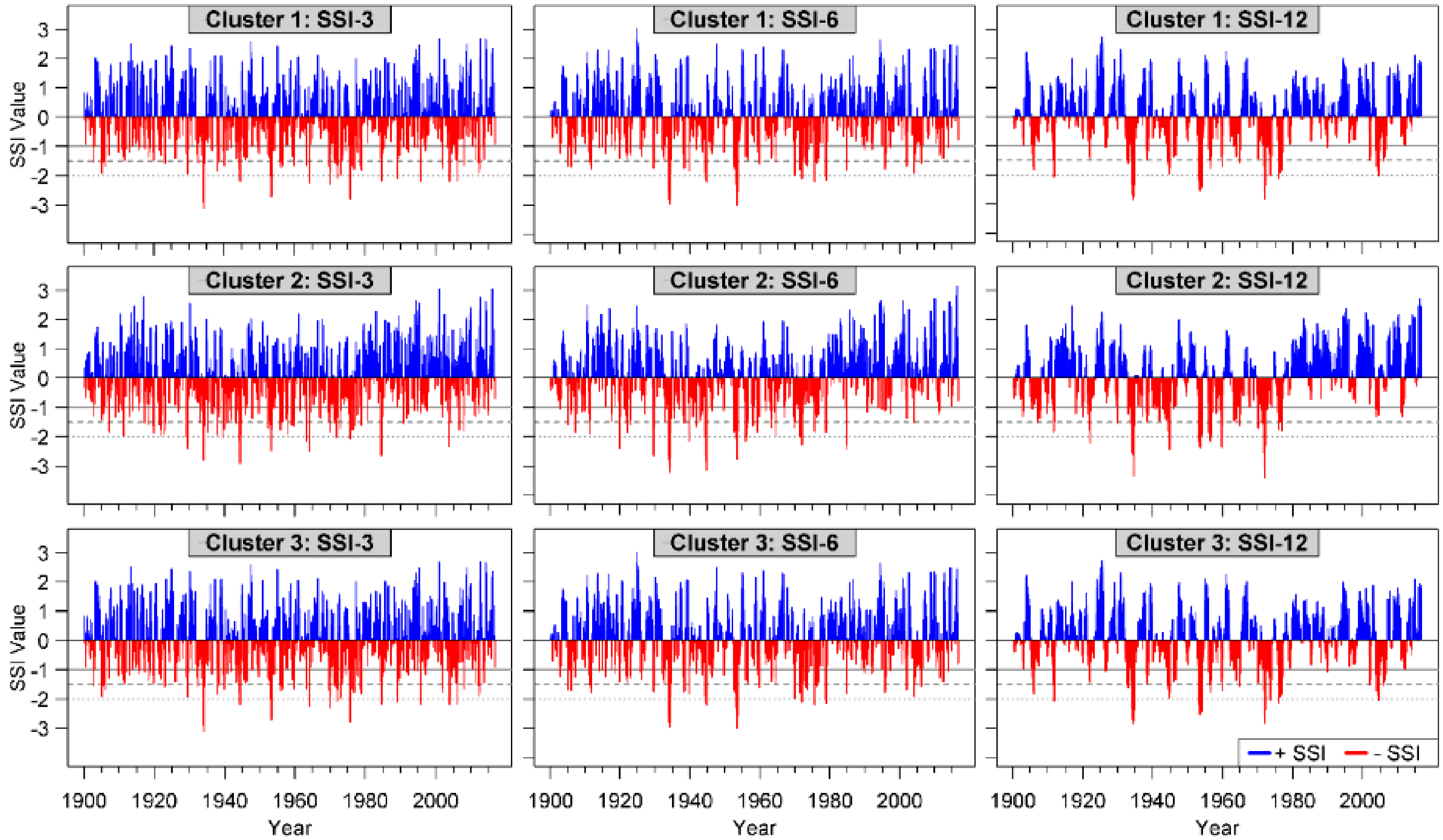


Figure 4.4 As per Figure 4.3 but for SSI 3, 6 and 12.

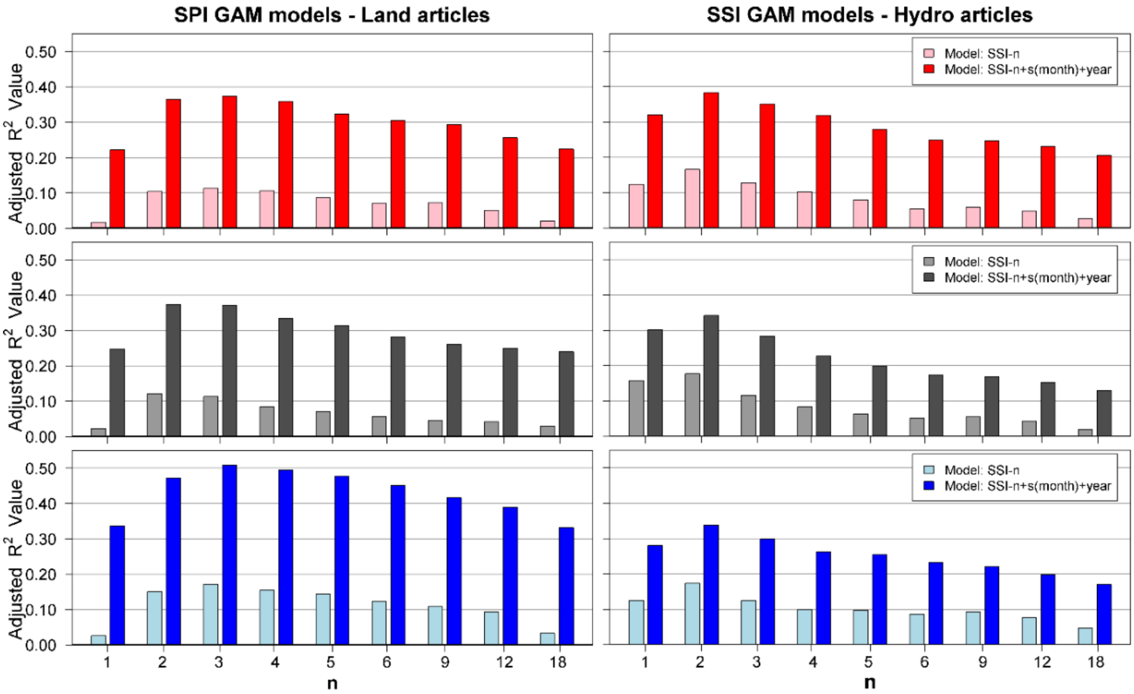


Figure 4.5 Adjusted R^2 values of the logistic regression models for selected SPI/SSI accumulation periods (n) when simulating monthly land- (left) and hydrological-based (right) impact articles for each cluster during 1900-2016. Results are also shown for models including month and year (darker colours).

Following Parson *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 the monthly smoothing by the REML method (see Section 4.2.3). Model performance was again assessed using R^2adj, with results presented in Figure 4.5 (darker coloured bars). Across all clusters, inclusion of month led to significant model improvements. Final model structures for land- and hydrological-based drought impact reports are given in Equations 2 and 3, with additional performance metrics provided in Table 4.2. For reported land-based impacts (Eq. 1) model performance is best for Cluster 3 (R^2adj = 0.51; p<0.01), with Cluster 1 and 2 having R^2adj values of 0.37 (p<0.01). For reported hydrological-based impacts (Eq. 2) model performance is generally lower than for the land-based equivalent with Cluster 1, 2 and 3 having R^2adj values of 0.38, 0.34 and 0.34 (all with p-values of <0.01).

$$\mathrm{SPI-3} + \mathrm{s(month)} + \mathrm{year} \tag{2}$$

$$\mathrm{SSI-2} + \mathrm{s(month)} + \mathrm{year} \tag{3}$$

Receiver Operator Characteristic (ROC) curves, which demonstrate the ability of models to correctly predict the occurrence or non-occurrence of an event, are shown in Figure 4.6 (see Stagge *et al.* (2015a) 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 hydrological-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 hydrological-based impact reports AUC scores are highest for Cluster 1 (0.86) and lowest for Cluster 3 (0.83).

Table 4.2 Performance indicators for model (SPI-3 + s(month) + year) generated for land-based impact articles and model (SSI-2 + s(month) + year) generated for hydrological-based impact articles (1900-2016).

Model	Cluster No.	Intercept Co-eff.	Indices Co-eff.	Year Co-eff.	Adjusted R^2	P-value	% Deviance	AUC	AIC	BIC
SPI-3 + s(month) + year	1	24.57	-1.19	-0.01	0.37	0.001	37.59	0.88	13.55	46.09
	2	24.98	-1.04	-0.01	0.37	0.001	35.56	0.85	13.06	45.57
	3	16.92	-1.42	-0.01	0.51	0.002	47.54	0.90	12.68	45.25
SSI-2 + s(month) + year	1	-1.66	-1.28	-0.00	0.38	0.001	36.87	0.86	13.13	45.61
	2	15.29	-1.33	-0.01	0.34	0.001	33.38	0.84	12.69	44.52
	3	13.65	-1.21	-0.01	0.34	0.002	30.95	0.83	12.85	44.45

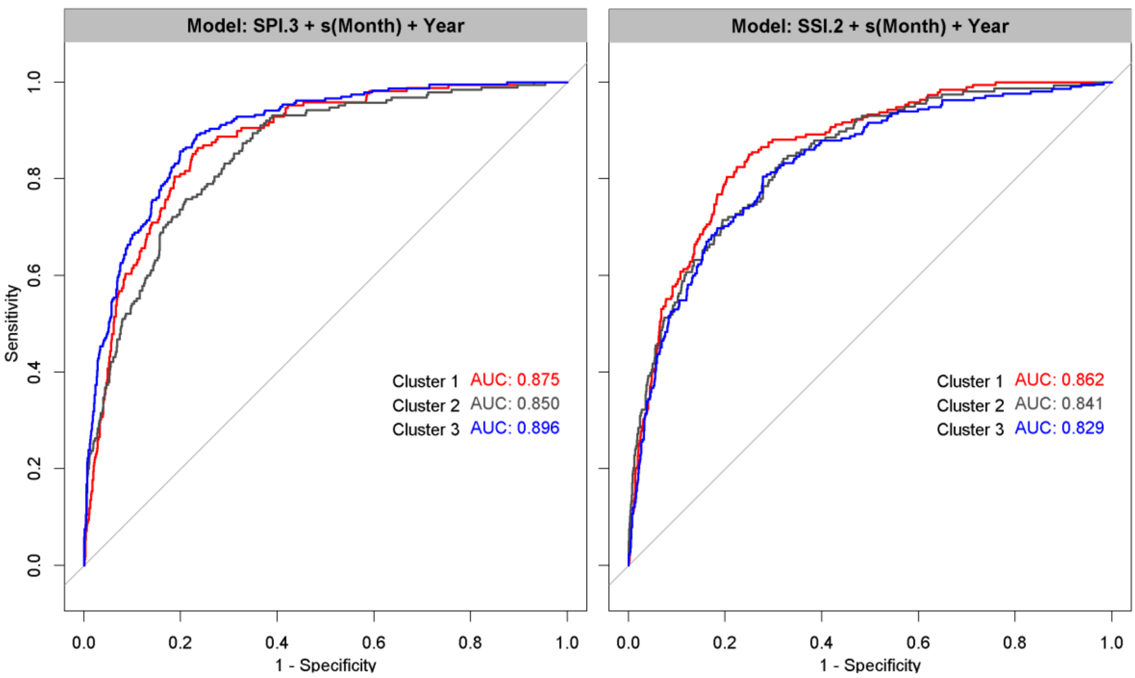


Figure 4.6 Receiver Operating Characteristic (ROC) curves displaying performance of the logistic regression models generated using land-based newspaper articles and SPI-3 indices (left) and for models generated using hydrological-based newspaper articles and SSI-2 indices (right) for each cluster.

4.3.3 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 annualised SPI and SSI at 1, 2, 3, 4, 5, 6, 9, 12 and 18 month accumulations was carried out revealing that SPI-3 and SSI-2 generated the highest likelihoods of drought impacts across clusters, specifically at low deficits. Peak impact likelihood values reduced markedly for SPI and SSI for accumulations above and below 3 and 2 months respectively. Notably however the patterns of differences between impact likelihoods across clusters remained similar for all accumulations. As SPI-3 and SSI-2 produced the highest likelihoods of impacts and the best model scores for land-based and hydrological-based impact reports they were chosen for further analysis. Figure 4.7 shows reported impact probabilities on an annual basis over the period 1900-2016. Cluster 3 has the highest reported impact probabilities for both SPI and SSI values. Clusters 1 and 2 show very similar reported impact probabilities for a 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 4.7 also identifies SPI/SSI thresholds resulting in at least a high likelihood of impact reports (0.60). For land-based impact reports SPI-3 ≤ -2.39 for Cluster 1, ≤ -2.33 for Cluster 2 and ≤ -2.05 for Cluster 3 are identified as thresholds for high impact probabilities on an annual scale. For hydrological-based impact reports in Cluster 3 the equivalent values are SSI-2 ≤ -2.41 for Cluster 1, ≤ -2.08 for Cluster 2 and ≤ -1.92. Cluster 3 is identified as most likely to experience both land- and hydrological-based drought impact reports, whereas Cluster 1 the least likely. Indices values required to reach each land- and hydrological-based drought impact report threshold are given in Table 4.5.

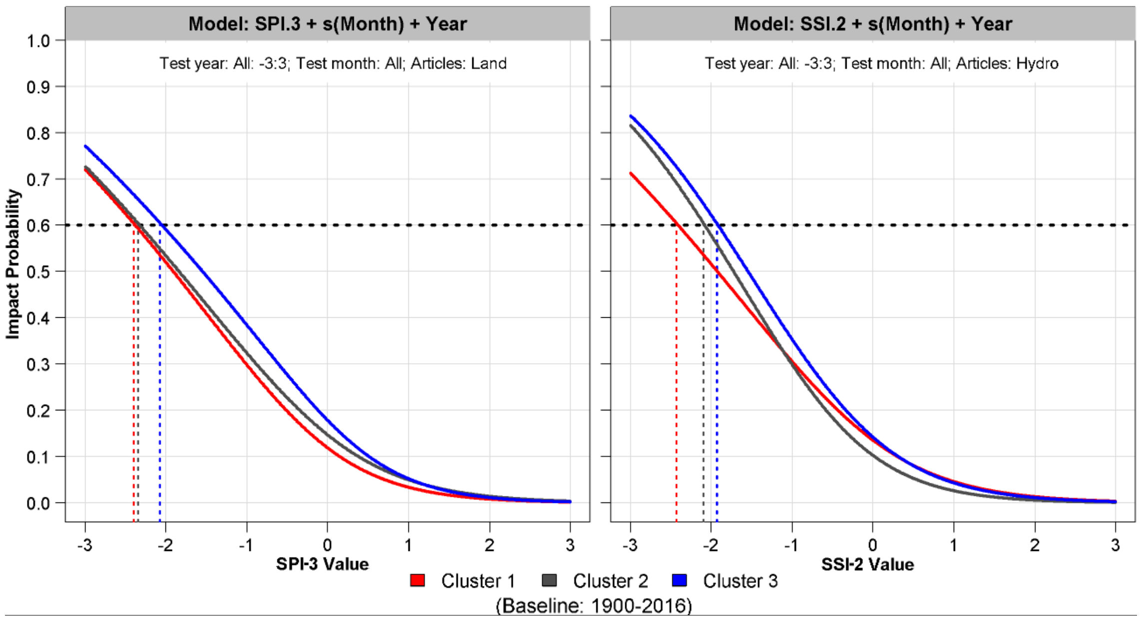


Figure 4.7 Predicted probability of reported impacts (annual) from models generated using land-based impact articles and SPI-3 indices (left) and from models using hydrological-based impact articles and SSI-2 indices (right). Impact likelihoods for each cluster over the period 1900-2016 are shown for indices values ranging from -3 to 3. Indices values resulting in high reported impact probabilities (0.60) are denoted by the dashed horizontal line.

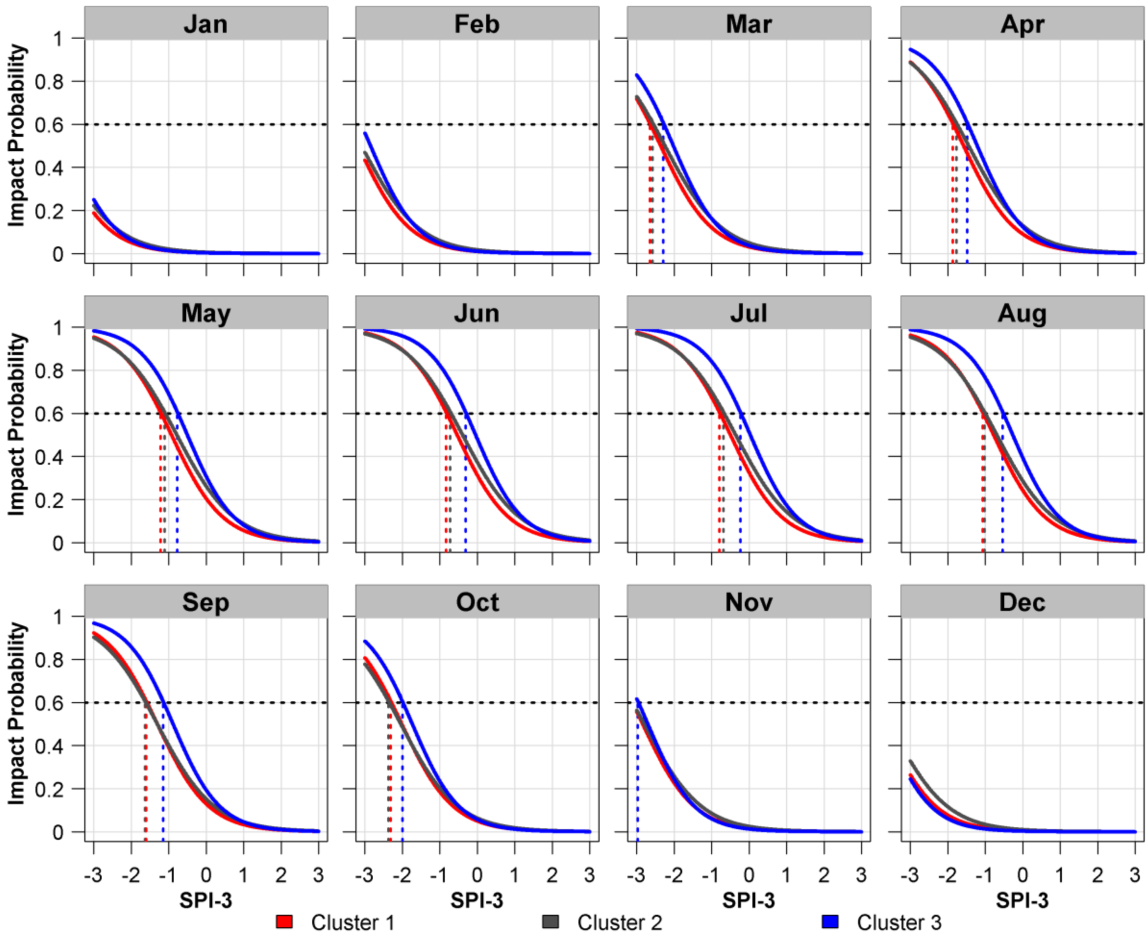


Figure 4.8 Predicted probability of reported impacts (monthly) from models generated using land-based impact articles and SPI-3 indices. Impact likelihoods for each cluster over the period 1900-2016 are shown for indices values ranging from -3 to 3. Indices values for each cluster resulting in a high reported impact probabilities (0.60) are also identified (dashed horizontal line).

Figure 4.8 displays results for monthly likelihoods of land-based drought article occurrence. There are large variations in the probability of reported impacts across months and clusters. December and January show very low to low impact report probabilities, even for extreme deficits in SPI-3. February is the winter month with highest land-based impact report probabilities, reaching moderate probabilities for deficits of -3 SPI-3. From April through October the likelihood of impact reports increases in all clusters. Excluding December, Cluster 3 consistently shows the highest probability of impact reports 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 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 probabilities (-0.78 for Cluster 1, -0.67 for Cluster 2 and -0.23 for Cluster 3). In autumn (SON), the SPI-3 deficits required to reach high reported impact probabilities become more extreme, with

Cluster 3 remaining the most vulnerable. Throughout most months there is little difference in land-based drought impact report probabilities between Clusters 1 and 2.

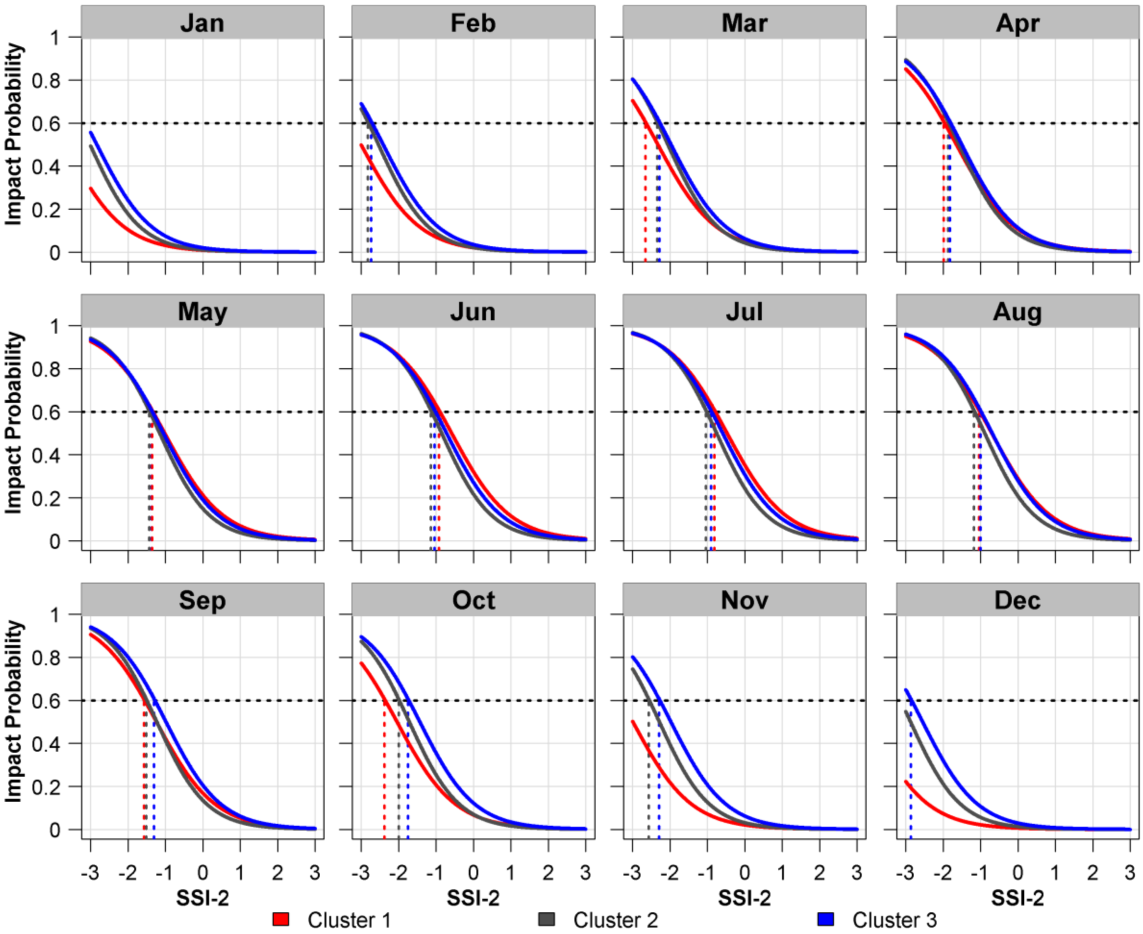


Figure 4.9 As per Figure 4.8 but for hydrological-based impact articles and SSI-2 indices.

Figure 4.9 displays monthly impact likelihoods for hydrological-based impact reports. Significant differences emerged when compared with land-based impact reports. Cluster 3 shows the highest likelihood of reported impacts across most months, particularly in autumn (SON) and winter (DJF). However, during late spring and summer, especially from May to August, Cluster 1 shows the highest likelihood. From May through to August Cluster 2 is least sensitive to hydrological-based impact reports. For SSI-2 values ranging from -3 to 3, no cluster reaches the threshold of high probability of reported impacts for January, with only Cluster 3 reaching this threshold in December and Cluster 2 and 3 in February, but for very extreme SSI-2 deficits. During summer months, deficits of close to -1 SSI-2 are required to reach the 0.6 high probability of reported impacts threshold in most clusters. July is the month most prone to hydrological-based impact reporting, with the most modest SSI-2 deficits resulting in high impact report probabilities (-0.79 for Cluster 1, -1.02 for Cluster 2 and -0.89 for Cluster 3). The lowest reported impact probabilities are in December for

Cluster 1 (low probabilities) and January for Clusters 2 and 3 (moderate probabilities) for SSI-2 values of -3.

4.3.4 Sensitivity of results to impacts baseline

All clusters display a negative year coefficient for land- and hydrological-based impact reports, with the exception of Cluster 1 for hydrological-based reported impacts (Table 4.2). Significant negative trends across all clusters were confirmed using Theil-Sens slope testing, again with the exception of hydrological-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 statistically significant ($p<0.05$) step changes in the number of impact articles for each cluster and impact type (see Table 4.3).

Table 4.3 Step change month and year identified for land- and hydrological-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	0.03	downward
	2	7	1961	0.01	downward
	3	9	1961	0.04	downward
Hydrological -based	1	8	1977	0.59	downward
	2	6	1961	0.33	downward
	3	9	1990	0.07	downward

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 hydrological-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 4.4 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 R^2adj for land-based impact report models occurring in Cluster 2 (from 0.40 to 0.24; both $p<0.01$). The largest reduction in R^2adj for hydrological-based impact models occurs for Cluster 3 (from 0.39 to 0.26; both $p<0.01$). The least change in R^2adj 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 71 % (Cluster 1), 78 % (Cluster 2) and 63 % (Cluster 3) for land- and 58 % (Cluster 1), 68 % (Cluster 2) and 71 % (Cluster 3) for hydrological-based impact reports.

Table 4.4 Performance indicators for model (SPI-3 + s(month) + year) generated for land-based impact articles and model (SSI-2 + s(month) + year) generated for hydrological-based impact articles (1900-1960 & 1961-2016).

Model (Period)	Cluster No.	Intercept Co-eff.	Indices Co-eff.	Year Co-eff.	Adjusted R^2	P-value	% Deviance	AUC	AIC	BIC
SPI-3 +	1	-38.57	-1.04	0.02	0.41	0.028	38.48	0.87	13.45	41.57
s(month) + year	2	-9.91	-1.02	0.00	0.40	0.007	35.46	0.83	12.64	40.63
(1900-1960)	3	-12.52	-1.40	0.01	0.53	0.007	49.06	0.89	12.36	40.35
SSI-2 +	1	-72.11	-1.28	0.04	0.47	0.025	43.76	0.88	12.45	40.51
s(month) + year	2	-12.71	-1.30	0.01	0.35	0.003	32.93	0.82	12.30	39.46
(1900-1960)	3	-44.50	-1.30	0.02	0.39	0.001	34.77	0.83	12.30	39.58
SPI-3 +	1	61.58	-1.40	-0.03	0.37	0.053	40.21	0.89	11.78	38.35
s(month) + year	2	0.89	-0.97	0.00	0.24	0.007	29.03	0.86	11.74	38.20
(1961-2016)	3	-16.43	-1.36	0.01	0.45	0.007	44.32	0.90	11.90	38.72
SSI-2 +	1	9.90	-1.24	-0.01	0.35	0.027	34.61	0.86	11.72	38.14
s(month) + year	2	13.18	-1.20	-0.01	0.28	0.000	30.50	0.86	11.69	38.06
(1961-2016)	3	32.82	-1.02	-0.02	0.26	0.001	25.61	0.82	10.99	35.77

Figure 4.10 shows annual results for reported impact likelihoods for land- and hydrological-based drought, with groupings A and B representing results derived from the 1900-1960 and 1961-2016 baseline periods, respectively for Clusters 1, 2 and 3. Differences between reported impact probability curves are apparent for all three clusters and both impact categories, but particularly for land-based impact reports where agricultural and livestock farming dominate (94% and 85% 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 probability of impact reports for the 1961-2016 period, whilst for values closer to zero the risk is higher for the 1900-1960 period, indicating that the likelihood 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 hydrological-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 probability of hydrological-based impact reports for the 1961-2016 period but only at extreme SSI-2 values.

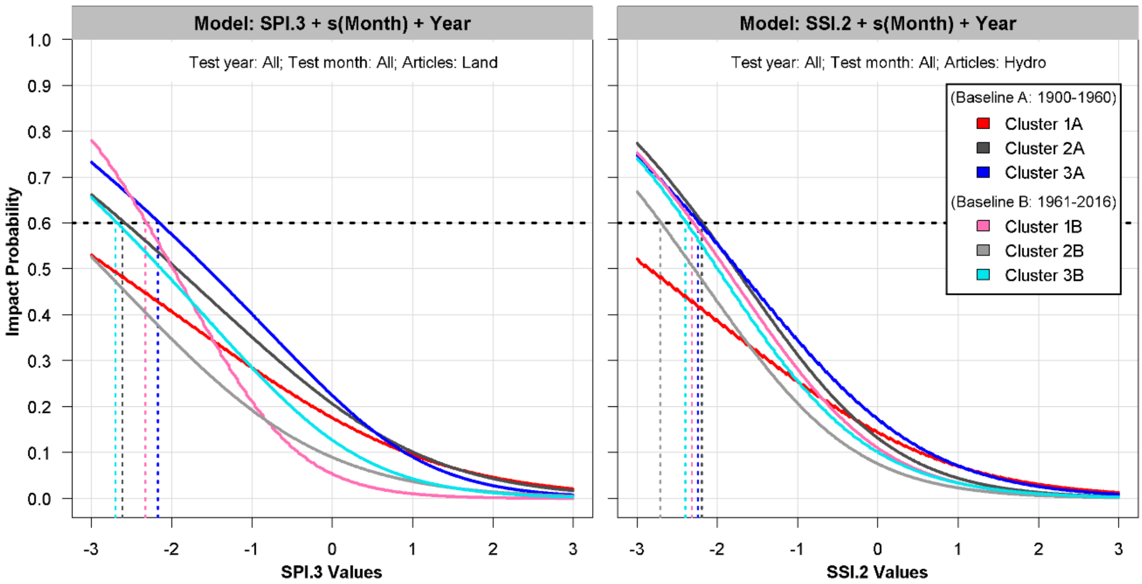


Figure 4.10 Predicted probability of reported impacts (annual) from models generated using land-based impact articles and SPI-3 indices (left panel) and from hydrological-based impact articles and SSI-2 indices (right panel). Impact likelihoods for each cluster over the baseline period A: 1900-1960 (i.e. 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 probabilities (0.60) are also identified (dashed horizontal line).

The reduction in impact report probabilities for the 1961-2016 period is reflected by 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 high impact report probabilities changes from -2.16 SPI-3 for 1900-1960 to -2.61 SPI-3 for 1961-2016. For hydrological-based drought in the same cluster, values change from -2.24 to -2.41 SSI-2. For Cluster 2 catchments the high impact probability for land-based articles occurs at -2.60 SPI-3 for the 1900-1960 period and <-3.00 SPI-3 for the 1961-2016 period. Hydrological-based impact reports change from -2.19 to -2.70 SSI-2. The largest change in deficit thresholds returning high likelihoods of reported impacts is in Cluster 1 for both land- and hydrological-based droughts (<-3.00 to -2.30 SPI-3 and <-3.00 to -2.31 SSI-2). Table 4.5 provides a cluster specific breakdown of SSI-2 and SPI-3 values required to reach each reported impact probability threshold.

Table 4.5 SPI-3 and SSI-2 values producing incremental increasing probabilities of impact reports from very low to very high, for land- and hydrological-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)
	1	>3.00	-0.52	-1.47	-2.39	<-3.00
SPI-3 (1900-2016)	2	>3.00	-0.34	-1.36	-2.33	<-3.00
	3	>3.00	-0.12	-1.08	-2.05	<-3.00
	1	>3.00	-0.43	-1.46	-2.41	<-3.00
SSI-2 (1900-2016)	2	>3.00	-0.58	-1.38	-2.08	-2.92
	3	>3.00	-0.34	-1.18	-1.92	-2.80
	1	>3.00	-0.27	-1.96	<-3.00	<-3.00
SPI-3 (1900-1960)	2	>3.00	0.03	-1.32	-2.60	<-3.00
	3	>3.00	0.13	-1.00	-2.16	<-3.00
	1	>3.00	-0.57	-2.13	<-3.00	<-3.00
SSI-2 (1900-1960)	2	>3.00	-0.46	-1.38	-2.19	<-3.00
	3	>3.00	-0.20	-1.28	-2.24	<-3.00
	1	>3.00	-0.95	-1.66	-2.30	<-3.00
SPI-3 (1961-2016)	2	>3.00	-1.04	-2.30	<-3.00	<-3.00
	3	>3.00	-0.50	-1.57	-2.61	<-3.00
	1	>3.00	-0.60	-1.51	-2.31	<-3.00
SSI-2 (1961-2016)	2	>3.00	-0.95	-1.88	-2.70	<-3.00
	3	>3.00	-0.73	-1.64	-2.41	<-3.00

Figures 4.9 and 4.10 repeat the analysis on a monthly basis for land- and hydrological-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. The opposite is the case for Cluster 1 where at larger deficits the latter period displays greater likelihoods of reported drought impacts whilst at more modest deficits the earlier period dominates. For the 1961-2016 period, high impact report probabilities at the 0.6 threshold are most easily attained in June for Cluster 1 and July for Cluster 2 and 3 with corresponding SPI-3 values of -1.40, -1.73 and -0.79, compared to -0.57, -0.42, 0.01 for equivalent values derived from the 1900-1960 period. The lowest likelihood of reported impacts are 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 with the exception of Cluster 1 (1960-2016) which displays moderate impact report likelihoods. Between baseline periods, impact likelihoods also differ markedly for hydrological-based articles (Figure 4.12). For the

1961-2016 period, Cluster 1 shows the greatest sensitivity to drought impacts from January to April, until August for larger deficits. Also, across the year cluster 1 consistently produces greater likelihoods of reported impacts in this later period in comparison to 1900-1960. As with land-based impact reports, the likelihood of hydrological-based impact reports in cluster 2 is consistently lower for all months for the 1961-2016 period. This is also the case for cluster 3 except for the months of November to January. Similarly, the month with the greatest likelihood of reported hydrological-based impacts for 1961-2016 is June for Cluster 1 and July for Cluster 2 and 3. SSI-2 values required to reach the (0.6) threshold are more extreme with values of -1.21, -1.53 and -1.61 SSI-2 required in Clusters 1 to 3 compared to -0.89, -1.09 and -0.89 SSI-2 for the 1900-1960 period.

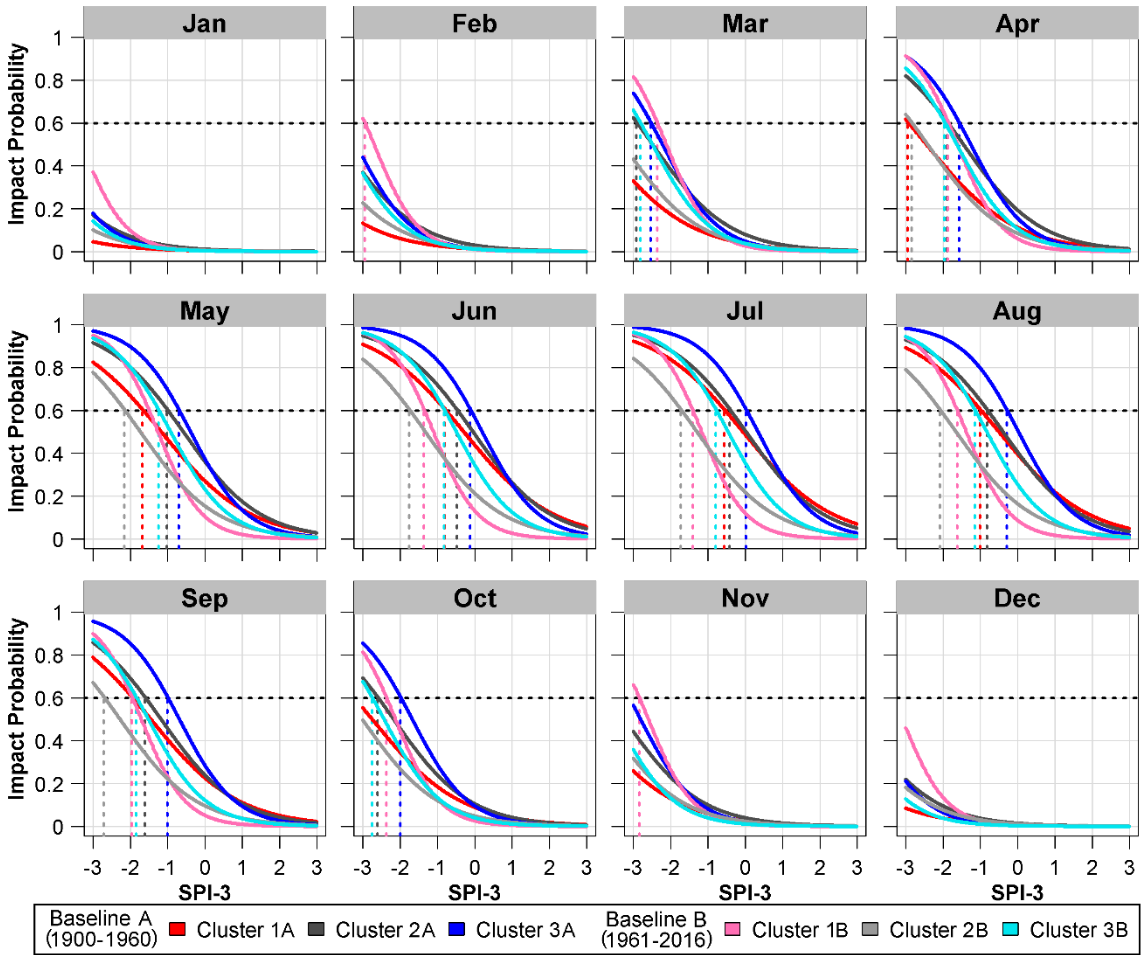


Figure 4.11 Predicted probability of reported impacts (monthly) from models generated using land-based impact articles and SPI-3 indices. Impact likelihoods for each cluster over the baseline period A: 1900-1960 (i.e. Clusters 1A, 2A and 3A) and baseline period B: 1961-2016 (i.e. Clusters 1B, 2B and 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 probabilities (0.60) are also identified (dashed horizontal line).

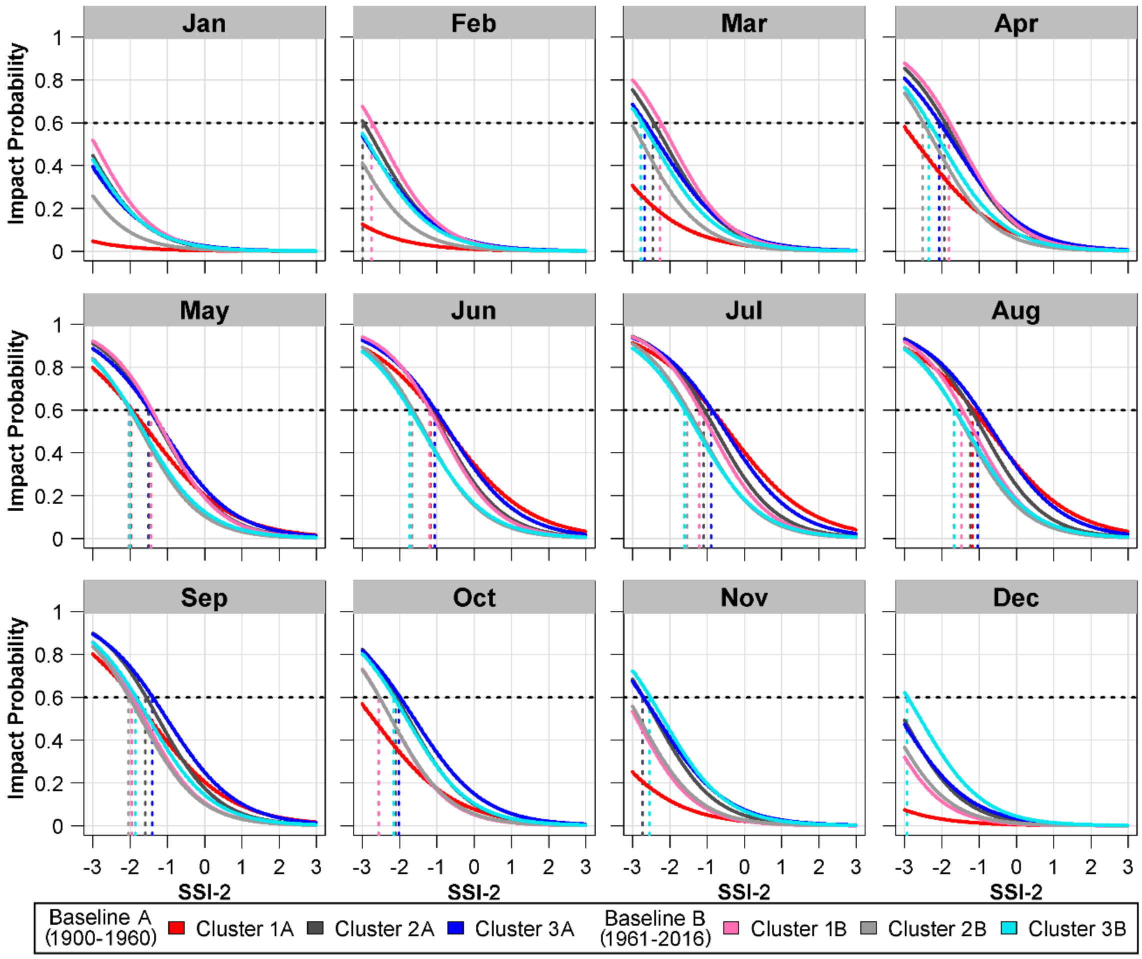


Figure 4.12 As per Figure 4.11 but for hydrological-based impact articles and SSI-2 indices.

4.4 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 link historic newspaper articles with drought indicators using GLMs at the regional scale. The process of model development closely followed Parsons *et al.* (2019) and Stagge *et al.* (2015a) 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 hydrological drought, 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-based model; the weakest was for Cluster 2 in the southwest by a small margin over Cluster 1. For hydrological impact reports Cluster 1 performed the best and Cluster 3 the worst by a small margin over Cluster 2. For these models, catchment characteristics have a greater influence on performance with the faster responding catchments in Cluster 1 producing better results than Cluster 3, which contain considerable groundwater storage (O'Connor *et al.*, 2022a). Overall, we find that models derived from land-based articles and SPI indices perform better than the hydrological-based equivalent, which is unsurprising given the uncertainties associated with flow reconstructions (O'Connor *et al.*, 2021b), non-linear propagation of drought through catchment systems, and the higher reporting of land-based drought impacts. The addition of smoothing to monthly values considerably improved model performance (by a factor of 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 1.5 on average). Performance scores for our models (R^2adj and AUC) compare favourably with similar studies (Parsons *et al.*, 2019; Stagge *et al.*, 2015a).

Our results show that the likelihood of drought impacts being reported is influenced by the location, drought type and time-of-year. On an annual basis Cluster 3 catchments consistently showed the greatest propensity for land- and hydrological-based impact reports, whereas Cluster 1 showed the least likelihood for land- and hydrological-based impact reports at more extreme deficits. At more moderate deficits Cluster 2 showed the least likelihood for hydrological-based impact reports. On a monthly basis, our results indicate large intra-annual variations in the probabilities 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* probability of impact reports in July, brought about by only very modest SPI-3 deficits (not less than -1), indicating a very high vulnerability to drought in that month. Conversely, winter months, when water consumption and crop production decrease, show lower probabilities of drought impacts being reported, with deficits as extreme as <-3 SPI-3 in January resulting in *very low* likelihoods of drought article occurrence in all clusters. Previous studies on drought characterisation in Ireland (e.g. Noone *et al.*, 2017, O'Connor *et al.*, 2022a) have employed a common year-round threshold of -1 SPI to identify the onset of drought events. These finding 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, inaccurately captures drought conditions, particularly over extended periods, and suggests that non-stationary, 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, for hydrological-based impact reports Cluster 1 catchments show the highest likelihood of recorded impacts in summer months. These findings are consistent with O'Connor *et al.* (2022a) who identify Cluster 1 catchments as being the most susceptible to hydrological drought in summer due to the lack of groundwater storage. Conversely Cluster 3 catchments show the highest probabilities of impact reporting from September through April. These catchments tend to have higher groundwater storage and more delayed hydrological drought onset, consistent with higher impact report probabilities from September through April. Cluster 2 displayed relatively lower overall drought impact report likelihoods with reported hydrological-based impacts lowest in this cluster for summer months.

Inclusion of the 'year' predictor variable in our model revealed a falling trend in reported drought impacts across all three clusters for both land- and hydrological-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, with significant changes specifically relating to land-based impact reports. As drought reports in this category are dominated by impacts on agricultural and livestock farming this change may be indicative of either planned or autonomous adaptation in that sector. These results differ to the UK where Parsons *et al.* (2019) found a marked increase in the probability of reported drought impacts in the agricultural sector. Similarly, Stagge *et al.* (2015a) 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 1980s 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 hydrological drought impacts are less extreme but nevertheless notable and coincide with findings by O'Connor *et al.* (2022a) showing reduced hydrological drought occurrence in recent years. However, Cluster 1 catchments contradict this trend, whereby an increased probability 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.*, 2020b). Furthermore, drought vulnerability is also a function of exposure, sensitivity and adaptive capacity (Smit and Wandel, 2006) so accurately apportioning responsibility 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 for better informing 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 probabilities associated with different values of each drought metric for various catchment types. Although we detect a decrease in the probability 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 effects 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.*, 2022) 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 a number of limitations to note. Historic precipitation reconstructions from which SPI indices values 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, relating to the underlying precipitation data and the related 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.,* 2020). Whilst the drought articles have been meticulously assessed and grouped, sources of uncertainty arise from differences in the duration, frequency, spatial extent and regional density of the newspaper publications (see Jobbová *et al.*, 2022). For example some publications were only in print in the early half of the 20th century whilst others commenced in the latter half of the century. The frequency of publication also differed between some newspapers whilst smaller regional publications had a greater local emphasis in reports. Furthermore, drought reporting is dependent on local/national events with more pressing news content impacting the number of and space provided for drought articles. 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 articles numbers, the aforementioned sources of bias would all impact the model performance. Whilst our aggregation of data by catchment clusters helps to limit the impacts of some of these biases, a much 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 may also be considered. For instance, Bachmair *et al.* (2017) demonstrate the utility of machine learning for linking drought impacts and metrics and could potentially better handle the complex, multi-threshold relationships found here, including accounting for non-binary 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, as has been demonstrated for flood impacts (Basnyat *et al.*, 2017; Thompson *et al.*, 2021). Our analysis has shown that indices extremes and article numbers do not always coincide (e.g. the 1945 and 1921 drought events). Examining the relationships between the frequencies of drought impact reporting and evolving drought indices values for such events would be beneficial. Finally, 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 is an additional element to drought monitoring that could potentially produce societal benefits. The development of such a system for Ireland, using these research findings, should be explored further.

4.5 Conclusions

This chapter applied logistic regression and GAMs to link reconstructed SPI and SSI metrics to reported land- and hydrological-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 hydrological-based impacts, respectively. Of the two, the latter consistently demonstrates stronger links to reported impacts on annual timescales. Catchments in the east/southeast show the highest probabilities of land- and hydrological-based impact reports on an annual timescale; catchments in the northwest display the highest hydrological-based impact reporting probabilities at low SSI-2 values during summer months, despite having the lowest equivalent land-based impact reporting likelihoods. Overall, findings show that maximum drought impact likelihoods across the 1900-2016 period occur in July for SPI-3 and SSI-2 with even modest deficits resulting in a *high* likelihood of impact reports, whilst in January indices values of <-3 SPI-3 and SSI-2 only generate a *low* likelihood of impact reports. This suggests that the use of fixed thresholds for identifying drought impacts is not suitable for locations with strong seasonal precipitation and flow cycles, such as Ireland. Changes in impact likelihoods over the last 116 years reveal a falling likelihood of drought impact reports for catchments in the east/southeast and southwest. Northwestern catchments show heightened 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 drought monitoring and warning system both regionally and at the catchment scale in Ireland.

Chapter 5 | Discussion, conclusions and future work

5.1 Introduction

In Chapter 1 a detailed introduction to hydrological drought, its characteristics and relevance in the context of Irish catchments was provided. Subsequently, Chapters 2, 3 and 4 presented the content of the three articles that were prepared and submitted to peer-reviewed journals, as required for a PhD by publication. In each, a detailed introduction to the research topic, with a specific focus on corresponding international studies, was provided followed by an outline of the methodology employed and an analysis of the results obtained. Detailed discussion and conclusion sections were also included which focused on the research findings, limitations and potential future work. In this chapter, a broader assessment of the research is presented, consisting of an examination of how key objectives of the thesis were achieved, the potential impacts of study findings, limitations associated with those study findings and related databases and future research directions. The chapter concludes with some final remarks on the overall achievements of the study.

5.2 Summary of the key research findings

The principal aim of this research was to advance understanding of historical hydrological drought in Ireland. Five key knowledge gaps were identified from the literature review (see Section 1.9). These objectives relate to i) reconstructing river flows to get a better handle on historical drought occurrence in Irish catchments; ii) identifying major drought events and iii) examining the characteristics (severity, duration, maximum intensity, accumulated and mean deficits) of droughts in different catchments; iv) evaluating variability and change in drought characteristics and v) furthering understanding of the temporal and spatial relationships between historic drought and their impacts across the island. The outcomes of each of these objectives are discussed in more detail in the following subsections.

5.2.1 Thesis Objective 1: Reconstructing flows

Using historic gridded precipitation and temperature data and an ensemble of river flow models, generate a database of historic river flow reconstructions for a set of diverse catchments across Ireland – Chapter 2.

One overriding message found in the related literature was that in order to successfully examine historical hydrological drought, long-term flow records are required. In Ireland, as is the case across the rest of Europe, observational records are generally short. Fortunately, previous data rescue efforts have resulted in the availability of multi-centennial precipitation and temperature records for Europe, in the form of gridded datasets (Casty *et al.*, 2007). These data facilitated the generation of historical flow reconstructions in this thesis. Following bias correction of precipitation and temperature data using quantile mapping techniques (Maraun, 2016), the Oudin temperature-based method (Oudin *et al.*, 2005) was used to generate catchment specific potential evapotranspiration. This data was used to force a conceptual rainfall-runoff model and a neural network to generate 250 years of monthly historic flows for 51 catchments across the island of Ireland, thereby addressing objective 1 of the thesis.

In the process of generating the flow reconstructions, uncertainties associated with the hydrological model structure and parameter sets were quantified. The subsequent analysis of flow extremes showed that the highest winter flows all occurred since the 1994/1995 season and that trends towards higher flows are more apparent in recent times. The top three driest years and summer seasons all occurred before 1976 reaffirming Noone and Murphy (2020)'s findings that extended periods of Q95 low-flow deficits in Irish catchments, associated with hydrological drought occurrence, have been lacking in recent decades. Furthermore, exceptional low flow (1855, 1933 and 1971) and high flow (1877, 1872 and 1916) years generally match those in the UK (Jones *et al.*, 2006).

The generation of reconstructed flows was fundamental to realising subsequent objectives and represents one of the longest series of flow reconstructions in Europe. When assessed against observations over the 1980-2016 period, the accuracy of model reconstructions was found to be high in all seasons with observed values typically being contained within derived uncertainty bounds. Some deviations towards greater extremes at peak flows were attributed to arterial drainage work, as shown by Harrigan *et al.* (2014). The flow reconstructions were also evaluated against flows generated using Noone *et al.* (2016)'s homogenised 1850-2010 monthly rainfall database, with results highlighting broad agreement between both series. The reconstructions contain valuable information on historically high and low flow periods at annual, seasonal and monthly scales and represent a considerable addition to scientific knowledge on historic flows on the island of Ireland.

Details on the exact procedures followed to generate the reconstructions and an analysis of the resultant database is found in O'Connor *et al.*, 2021 (see Chapter 2). The flow reconstruction series for each of the 51 catchments are freely available to download at https://doi.org/10.1594/PANGAEA.914306.

5.2.2 Thesis Objective 2: Identify historical events

Using the reconstructed flow series and hydrological drought indices, identify extreme hydrological droughts in the record and classify them based on their duration, maximum intensities and accumulated (total) deficits to produce a catalogue of the most highly ranked extreme events – Chapter 3.

Employing indices values derived from reconstructed flow series, the 10 most extreme hydrological drought events, based on accumulated deficits that occurred in the 51 sample catchments, were identified. The subsequent assessment of these droughts found their principal characteristics including the start and end date, maximum deficits and accumulated deficits of each event. The creation of this catalogue of the most extreme historical events made it possible to determine their most distinctive properties and in the process address thesis objective number 2. The most extreme hydrological droughts, which were identified across most clusters at SSI-3, 6 and 12 included the 1803-1806, 1854-1859, 1933-1935, 1944-1945, 1953-1954 and 1975-1977 events. These droughts compare favourably to those found in other studies investigating meteorological and hydrological drought in Ireland (Noone *et al.*, 2017; Murphy *et al.*, 2020; Noone and Murphy, 2020) and the UK (Marsh *et al.,* 2006; Todd *et al.,* 2013; Spraggs *et al.,* 2015; Hanel *et al.,* 2018) thereby adding confidence that the underlying flow reconstructions are reliable.

The analysis identified distinctive differences in drought characteristics dependent on the chosen cluster and accumulation period. For example, whilst the 1953-1954 (SSI-12) drought commenced in January in the northwest and east/southeast of the island, it did not commence until four months later in the southwest. Furthermore, whilst the total accumulated deficit for the event in the east/southeast reached -34.34 SSI-12 (maximum intensity -2.54) in the northwest it only reached -15.91 SSI-12 (maximum intensity of -2.18). Distinctive characteristics such as those outlined above were identifiable across cluster groupings and derived accumulation periods for each drought, highlighting the uniqueness of each event.

It is notable that, excluding the regionally specific 2003-2004 (Cluster 3; SSI-3), 2004-2006 (Cluster 3; SSI-12) and 1984 (Cluster 2; SSI-3) events, no extreme drought was recorded as a top ten event for the three regional groupings at 3, 6 and 12 month accumulations in the 1977-2016 period, reaffirming findings from Noone *et al.* (2017) and Murphy *et al.* (2020a) that, excluding the most recent summer 2018 and spring 2020 events, there has been a notable absence of extreme droughts in Ireland in recent decades. Further detail on the most extreme droughts identified in the series and their principal characteristics, described by O'Connor *et al.* (2022a), can be found in Chapter 3, with additional catchment specific information available in Appendix III.

5.2.3 Thesis Objective 3: Historical hydrological drought characteristics

Using the reconstructed flow series and hydrological drought indices, examine historical hydrological drought characteristics for catchments across the island, specifically focusing on drought occurrence, duration, mean deficits and accumulated (total) deficits. In the process, examine how catchment characteristics influence the experience of hydrological droughts and the propagation of meteorological to hydrological events – Chapter 3.

Another finding from the literature review presented in Chapter 1 was that studies of spatial and temporal differences in hydrological drought occurrence, drought characteristics and drought propagation at the catchment level have been limited in Ireland. Following the drought identification and classification methodology outlined in Section 1.4, an in-depth analysis of drought occurrence for the 1767-2016 period across the island of Ireland was instigated. Drought characteristics including duration, mean deficits, accumulated deficits and maximum deficits were derived for each catchment and for three cluster groupings for all drought events using the Standardised Precipitation Index (SPI) and Standardised Streamflow Index (SSI) for accumulation periods of 1, 3, 6 and 12 months. Results were compared and contrasted across catchments and clusters to understand the impact of catchment characteristics on the experience of drought and to assess how meteorological drought propagates to hydrological drought.

Using derived hydrological indices and hierarchical cluster analysis three distinct regional clusters of catchments were found, in the northwest, southwest and east/southeast. An analysis of catchment descriptors (Mills *et al.*, 2014) relating to each of the groupings showed that northwestern catchments have relatively high standard period average annual rainfall amounts (SAAR), low groundwater storage (as measured using the baseflow index BFIsoil), high overall peat cover (PEAT) and are smaller in area (AREA) with short main stream lengths (MSL). Catchments in the eastern/southeastern grouping have low average annual rainfall amounts, high groundwater storage and low peat cover with bigger catchment areas matching longer river lengths. Southwestern catchments have annual rainfall amounts similar to northwestern catchments but with greater groundwater storage and less peaty soils.

The analysis of drought indices associated with each cluster grouping found that the lowest number of hydrological drought events occurred in the east/southeast whilst the highest number occurred in the northwest. Hydrological drought durations were longest in east/southeastern catchments, whilst being shortest overall in the wetter southwest. The long duration droughts in east/southeastern produced the greatest accumulated deficits whilst the least occurred in the southwest of the island. A catchment specific assessment of these same characteristics also identified similar spatial patterns.

The finding that more hydrological droughts occur in the wetter northwest as opposed to the drier southeast, highlights the importance of catchment characteristics, in particular groundwater storage, in drought development and meteorological to hydrological drought propagation as identified in other international studies (Van Loon and Laaha, 2015; Barker *et al.*, 2016). The 'flashier' catchments in the northwest of the island respond quicker to meteorological drought conditions resulting in rapid hydrological drought onset. The greater groundwater storage associated with eastern/southeastern catchments (Broderick *et al.*, 2019), results in delayed hydrological drought onset in that region. However, in these catchments, once drought becomes established they are typically of longer duration to the equivalent in the northwest, generating lower mean deficits but greater accumulated deficits. The third catchment grouping in the southwest of the island had similar numbers of hydrological droughts to southeastern catchments but were generally of shorter duration and accumulated limited deficits. These findings represent a considerable addition to understanding of drought and its characteristics in Ireland and have resulted in the achievement of objective 3 of the thesis.

In the process of developing the indices output used in the drought assessment an analysis of suitable probability distributions and reference periods to use when fitting standardised SPI- and SSI-1, 6 and 12 was carried out. This review assessed the performance of three statistical distributions in the generation of median precipitation and flow across all 51 catchments (Gamma, Log-logistic and Tweedie). Results suggested that whilst all three performed well at modelling the distribution of precipitation, for flow Tweedie performed best, matching findings from Svensson *et al.* (2017). Subsequently the influence of the chosen reference period on hydrological drought indices output was analysed. Using the 1767-2016, 1900-1999, 1930-1999 and 1970-1999 reference periods and the Tweedie distribution, moderate and severe SSI-1, 3, 6 and 12 drought events were identified and evaluated in terms of the total number of drought events, their durations and accumulated deficits. Trends in these drought characteristics were also evaluated for each cluster grouping and reference period. Results showed that the chosen reference period can substantially impact drought characteristics and related trends. For example, the 1981-2010 period, which is currently recommended by the World Meteorological Organisation for indices generation (WMO, 2017), produced 16 more severe SSI-1 drought events compared to the 1930-1999 period. These results corroborate similar findings from other international studies including Um *et al.* (2017), Paulo *et al.* (2016) and Núñez *et al.* (2014) and highlight the importance of choosing a suitable reference period in any drought analysis.

5.2.4 Thesis Objective 4: Evaluate trends in historical droughts

Evaluate trends in meteorological and hydrological droughts and their characteristics including occurrence, duration, mean deficits and accumulated deficits for both individual and clustered catchments to better understand variability and change – Chapter 3.

The discussion on trends in hydrometric variables and drought occurrence presented in Section 1.8.3 highlighted that trend direction and magnitudes can vary considerably depending on start/end year and series length, with inter-decadal variability strongly influencing trends (Hannaford *et al.*, 2013). Using the generated flow reconstructions and drought analysis techniques it was possible to investigate the change in catchment-based drought characteristics in Ireland over the last 250 years, thereby achieving thesis objective 4. Moderate and severe, SPI- and SSI-1, 3, 6 and 12 indices values were assessed for trends over the 1767-2016 period for each of the 51 catchments as well as for each catchment cluster.

Despite finding that trend magnitudes, directions and significance were dependent on the drought type (meteorological or hydrological), the period of record analysed and the accumulation period employed, overall patterns of increasing drought occurrence at lower accumulation periods were identified, whilst drought at higher accumulations showed decreasing trends. Drought durations decreased over the entire period, with corresponding accumulated deficit values reducing in tandem. The most notable finding was strong trends towards increasing mean deficits representative of shorter, more intense meteorological and hydrological droughts. Regional trend results for the entire period (1767-2016) suggest that these patterns are amongst the strongest for catchments in the east/southeast of the island matching results by Vicente-Serrano *et al.* (2021a) who found trends towards shorter more intense SPI-3 drought in summer months in the southeastern region.

Of particular interest was the detection of trends towards shorter more intense SSI-1 moderate hydrological drought across all regions. The recent 2018 drought exposed the vulnerability of Irish society to such short drought events, particularly in respect of water access (Falzoi *et al.*, 2019). The possibility of increased occurrence of such droughts poses considerable challenges for water management in Ireland and is something that will require further research. Further analysis relating to this important finding is given in Section 5.3.2 whilst a complete outline of the trend assessment results, relating to O'Connor *et al.* (2022a), can be found in Chapter 3.

5.2.5 Thesis Objective 5: Linking drought indicators to reported impacts

Using derived drought indices, historical impact data and modelling techniques, examine if a relationship exists between meteorological and hydrological drought and recorded impacts at the catchment scale and identify regional differences and changes in the likelihood of reported drought impacts over time – Chapter 4.

Research establishing links between drought indicators and impacts has been limited worldwide, primarily due to a lack of impact data and limited coverage (Bachmair *et al.*, 2015). Using a database of historic drought impact records from newspapers, reconstructed drought indices and logistic regression models it was possible to explore the relationships between drought occurrence and reported impacts on the island of Ireland to achieve thesis objective 5.

Models were generated using SPI and SSI at 1, 2, 3, 4, 5, 6, 9, 12 and 18 month accumulations and model performance scores assessed. Results showed that models generated using SPI-3 perform best for land-based impact reports and SSI-2 perform best for hydrological-based impact reports, with the latter consistently generating better model performance scores (highest R^2adj and AUC values). A subsequent analysis of model output found that the likelihood of land- and hydrological-based impact reporting changed depending on the chosen indices, accumulation period, deficit value, regional grouping and time period. As well as generating the best performance scores, SPI-3 and SSI-2 models produced the highest peak impact likelihood values for land-based and hydrological-based impact reports of all accumulations. For SPI-3/SSI-2 models, catchments in the east/southeast displayed the highest sensitivity to annual land-based and hydrological-based impact reports whilst catchments in the northwest showed the least sensitivity to land-based impact reports and hydrological based impact reports (at lower deficits). At deficits closer to zero hydrological-based impact reports were more likely to occur in southwestern catchments.

The monthly assessment of reported impact likelihoods, found for SPI-3 and SSI-2 models, also identified unique characteristics in northwestern catchments, where in summer months the likelihood of hydrological-based drought impact reports were the highest of all regions despite land-based equivalent being amongst the lowest of all regions at that time. A possible reason for these distinctive findings is that low groundwater storage in the region influences the likelihood of hydrological-based impact reports occurring. This corroborates the findings from O'Connor *et al.,* (2022a), which established that northwestern catchments are unique in terms of their susceptibility to hydrological drought (see Chapter 3).

Another important finding of the study was that, for the three regional groupings, the drought indices deficits required to produce a high likelihood of drought impact reports vary considerably across the year, ranging from -0.23 SPI-3 in July to <-3 SPI-3 in December in southeastern catchments for example. The non-stationarity of reported drought impact likelihoods across the year raises questions regarding the value of set indices thresholds, such as the McKee *et al.* (1993)'s thresholds used in this study, particularly in respect of drought impact assessments where impacts could vary considerably dependent on date of onset and termination of the drought event. As this finding has considerable consequences, in terms of drought analysis methodologies applied worldwide, it is subject to further discussion in Section 5.3.3.

Understanding how the likelihood of reported land-based and hydrological-based drought impacts have changed over the last century was an important part of objective 5. The assessment of temporal change in the likelihood of reported drought impacts over the 1900-2016 period, identified using the Theil-Sens slope test, found decreasing trends, particularly in the east/southeast of the country. Pettitt testing subsequently identified significant downward step changes (reductions in reported impact likelihoods) in reported land-based impacts in 1961 for catchments in the east/southeast and in the southwest respectively whilst in northwestern catchments the step change occurred in June 1985. Similar downward trends in reported hydrological-based impact likelihoods were found however these were not significant in nature.

The analysis of change in reported drought impact likelihoods between 1900-1960 and 1961-2016 found that, for more extreme deficits, catchments in the northwest had an increased likelihood of land- and hydrological-based impacts being reported in the latter period. This was not found to be the case in either the southwest or east/southeast where the likelihood of reported impacts decreased. As both land- and hydrological-based impact reports produced the same trends in the northwest it would suggest that this is not a symptom of catchment characteristics and may relate to external influences. Determining the exact reasoning for the observed increase however is difficult as multiple external factors may influence this change including possible failure in adaptation policies and biases in reporting of impacts in the region. Further discussion regarding this important finding is provided for in section 5.3.3.

5.3 Limitations and potential future work

5.3.1 Monthly flow reconstructions

The generation of monthly flow reconstructions was the first and possibly most important aspect of this research as all subsequent results were derived from these reconstructions. A number of potential limitations relate to the reconstruction process that are important to be aware of. The 51 catchments were carefully chosen using the same criteria as those selected for the Irish Reference Network by Murphy *et al.* (2013), however over the full 250-year period both natural and anthropogenic influences would have impacted catchments with resultant effects on flow. Changes in land-use, (e.g. afforestation/deforestation, agriculture, urbanisation) and to the river channel morphology over time (Slater *et al.*, 2019) affect the accuracy of historical reconstructions.

In Ireland such change has been prevalent in the past with large portions of the landscape being altered by means of arterial drainage (Murphy *et al.*, 2013), which is often associated with the reclamation of poorly drained soils for agricultural use and flood alleviation. Such activities were a large part of the national land-use strategy that was put in place in the mid-twentieth century, associated with the Arterial Drainage Act, 1945 (Bhattarai *et al.*, 2004) and primarily affected midlands and western regions (Hammond, 1981). For those same regions large scale historical peatland drainage and extraction activities have occurred historically (Connolly, 2018). As well as undergoing extraction and drainage peatlands have been subject to considerable land-use change, with conversion into grassland and forestry being most prominent (Eaton *et al.*, 2008). As many of the observational flow records included in this study are relatively recent, often commencing in line with arterial drainage works (Murphy *et al.,* 2013), their is limited knowledge of the impacts these widespread practices have had on catchment flows except for a select number of catchments (e.g.

Harrigan *et al.*, 2014). Such uncertainties therefore must be considered when deploying this database in any analysis.

Possible future work might attempt to quantify the impacts of the sources of uncertainty referred to above by exploring the extent of catchment change using historical maps and or written documentation on changes in the landscape as demonstrated by Lestel *et al.* (2020). It is noted however that Jones (1984) proposes that reconstructed flows may in fact be more useful than actual river flows because the former assumes no land use change beyond the conditions within the model calibration period, whereas actual flows may be impacted by considerable changes over time. For water managers, water resource infrastructure designs are generated based on flows relating to current as opposed to historic conditions and therefore reconstructions generated from models calibrated on observational records, during which time limited land-use change has occurred, may be more useful.

Another potential source of error in flow reconstructions relates to the underlying rainfall series. As precipitation values in the early part of the series have a greater dependence on reanalysis products as opposed to direct measurements (Casty *et al.*, 2005), and as the measurement of snowfall in early precipitation records may be inaccurate (Murphy *et al.*, 2019), the accuracy of precipitation values pre-1850 is less than that of post-1850. Therefore flow values from the early part of the reconstruction series should be used with a degree of caution. One means to assess and/or improve the accuracy of the underlying data is by employing Ryan *et al.* (2021a)'s newly developed daily precipitation series, generated from 118 years of rescued rainfall records, in either an evaluation or directly in the development of catchment-based precipitation values.

An important component of the flow reconstruction process was the bias correction of catchment specific monthly precipitation and temperature Casty data to observed values using quantile mapping techniques. Observed values were extracted for each catchment from 1 x 1 km monthly gridded data provided by Met Eireann (Walsh, 2012). This gridded dataset was constructed using relaxed climatological mean values (weighted averages) away from point source observations with values representative of long term monthly values. Whilst such techniques may have limited impacts on temperature values, due to the large spatial extent of temperatures that can be easily captured by instrumental records, precipitation values, particularly extreme precipitation, which can generate large rainfall accumulations over small spatial areas, are more difficult to replicate. One means to assess this source of uncertainty would be to employ alternative datasets such as ERA5-land reanalysis data which combines modelled values with observations to generate hourly gridded precipitation values at a 0.1° x 0.1° scale. Such data is recommended for hydrological studies due to its high resolution, temporal length and consistency between fields in the data (Muñoz-Sabater *et al.,* 2021) and is known to perform well at replicating precipitation compared to other reanalysis datasets particularly for central Europe (Hassler and Lauer, 2021). The use of this and other observational datasets including satellite data, would help identify uncertainty and potentially increase the accuracy of bias corrected precipitation values, in turn leading to more accurate hydrological model performances.

When generating the neural network models, inputs of temperature and precipitation from the current month, plus precipitation lagged by one, two and three months were found to perform best overall and so were applied across all models to allow for like-to-like comparisons. The use of a number of lagged precipitation predictors as inputs however raises questions regarding the possible overfitting of the models with serial correlation between inputs leading to model misspecification. Analysis of auto correlation plots derived from model covariates suggested that limited autocorrelation was present even over lagged intervals, however such analysis techniques typically relate to linear regression models. Despite this they have been shown to work well with non-linear neural network models by Flores *et al.* (2012). Future work should include a more in-depth analysis of the degree to which serial correlation impacts the generated models and to help determine how model performance has been impacted in this study.

A further source of uncertainty, that affects the quality of the reconstructions, is the hydrological models used to reconstruct river flows. Combined use of Monte Carlo sampling techniques, along with two independent model types allowed uncertainty derived from model structure and parameters to be quantified in the reconstructions presented in this dataset, with generated flows from the two model structures showing good agreement overall. Another component of the model generation process that requires greater examination is the derived performance scores (i.e. log NSE, KGE and PBIAS) and their use in identifying and comparing hydrological model performances. The combination of differing catchment characteristics, differing model types and differing internal structures, determined by the combined use of objective functions, all influence the accuracy of derived model scores, particularly as they are generated from series trained over different period lengths. As a result a direct comparison of scores under non-homogeneous conditions may produce inaccurate representations of the skill of the models. One possible means to address this would be to apply synthetic data of set lengths as inputs to groups of models for catchments with similar characteristics and to compare the results to outputs from the study data. Comparisons of scores between models under such circumstances would provide an additional means for estimating uncertainty in model performances across catchments and would help identify the most and least accurate flow reconstructions across the entire series.

Future work should also examine the sensitivity of reconstructions to the choice of calibration and validation periods used in model development. Broderick *et al.* (2016) highlight the importance of the information content of the calibration period when assessing the transferability of models to conditions outside of which they were trained in the context of understanding future climate impacts. Such decisions are also likely to be important when simulating back in time over multiple centuries. Furthermore, for ideal model testing, years with contrasting seasonal regimes should be included (Broderick *et al.*, 2016). Here the 2001-2016 validation period was consistently employed to allow for comparisons between model outputs however as 2001-2016 has been identified as drought poor alternative periods should be considered. A method that could be trialled to address this is the leave-one-out cross validation approach to training/testing of the data which is known to successfully reduce bias (overestimation) in model performance test scores (Varma and Simon, 2006) and in this instance would allow for the inclusion of drought rich periods, such as 1975/1976, in the testing of model performance.

Whilst the utility of flow reconstructions in drought analysis work has been clearly demonstrated in Chapters 3 and 4 there remain many possible future applications in which they could be used further. Potential exists for a more in-depth analysis of historical high flow periods over the last 250 years. Mirroring the drought analysis presented here, such research could assess the spatial and temporal differences in high flows across the island and provide greater detail on the characteristics of the most extreme high flow periods. An examination of the reconstructed flows' relationships to external atmospheric drivers such as the NAO and AMO could also be carried out.

Opportunities also exist to conduct a much greater analysis of catchment level responses to both high and low flow periods and to form more robust links between flows and catchment characteristics. For example, an assessment of the relationship between extended flow series and catchment descriptor variable values could help identify which descriptors have the greatest influence on historic high and low flow extremes for individual catchments and regional groupings.

In addition, recent years have seen increased focus on the application of seasonal hydrological forecasting methods such as persistence based techniques (e.g. Foran Quinn *et al.*, 2021) and ensemble streamflow forecasting (e.g. Donegan *et al.*, 2021). The availability of historical reconstructions of precipitation and river flows may have potential in extending the sample of analogue conditions for developing ensemble forecasts, which might be conditioned on prevailing circulation characteristics. This could be a novel and beneficial avenue for future research.

Finally, it is worth noting that the methodology employed to generate the dataset is robust and flexible enough that it will be possible to apply the technique in other regions across Europe which have readily accessible observed hydrometric and meteorological data.

5.3.2 Historic drought analysis

In Chapter 3, results from the analysis of hydrological drought over the last 250 years were presented. The evaluated indices employed in this analysis were the SPI and SSI. Whilst one of the most commonly used indices for meteorological assessments (Šebenik *et al.*, 2017), the SPI is disadvantaged by its inability to account for evapotranspiration. In Ireland such differences would primarily arise in warmer summer months where drought impacts have been shown to be higher. It is therefore clear that the inclusion of indices that incorporate evaporative losses (e.g. Standardised Precipitation-Evaporation Index (SPEI); Vicente-Serrano *et al.,* 2010) in future assessments would be advantageous, particularly for examining maximum deficits and the propagation of meteorological to agricultural to hydrological drought.

In this research, while evaporative losses are not included in meteorological drought calculations, they are in assessments of hydrological drought due to the nature of runoff generation. Nonetheless, given the importance of agricultural impacts on the island, it would be beneficial to derive indices that relate to soil moisture deficits in future work. Such an analysis would be sensitive to possible uncertainties in underlying flow data attributable to historical anthropogenic influences on catchments such as arterial drainage works (see discussion in Section 5.3.1) and therefore would need a selection of study catchments known to have limited land-use change. Different indicators and indices could also be trialled to derive hydrological drought characteristics. Results from such an assessment could be used to find the most accurate means of identifying meteorological and hydrological drought at the catchment level across the island and would assist in the calculation of uncertainties in indices values. For example, Q95 (the flow exceeded 95 percent of the time) is an important water management metric that is most commonly used in Ireland (Mandal, 2012) and would be easily discernible from reconstructions. Presently, Q95 is estimated from relatively short observational flow records and is likely not representative of the range of variability that is possible.

A further element of the research that could be expanded upon is the choice of accumulation period. For this study, results were derived from SPI and SSI at 1, 3, 6 and 12 month accumulations. In the UK, hydrological drought events have been identified as commonly occurring over extended periods of years (e.g. Parry *et al.*, 2012; Barker *et al.*, 2016). Considerable potential exists to extend the analysis of drought, including drought characteristics, trends and drought propagation, to indices derived from multi-year accumulation periods.

This research revealed new insights into drought occurrence, their characteristics, trends and propagation across 51 catchments on the island. Regional differences were detected with catchment characteristics found to play an important role in determining drought susceptibility. As well as potential for expanding the drought analysis to further catchments across the island, particularly within Northern Ireland, there exists the possibility to use the catalogue of droughts identified to stress test water infrastructure at the catchment scale for drought conditions equivalent to the most extreme historical events in the record. Such undertakings will be important to evaluate the effectiveness of current drought plans which are based predominantly on drought events identified from short observational records (Irish Water, 2021). This research clearly shows that basing drought planning on observational records alone runs a high risk of underestimating drought risk.

In the process of generating the SPI and SSI drought indices, Gamma, Log-logistic and Tweedie distribution functions were trialled. Like Svensson *et al.* (2017) the Tweedie distribution was determined as being best at matching the distribution of the flow and precipitation values. While this work attempted to evaluate different distributions, this was not exhaustive and further analysis of the performance of other distribution functions should be undertaken. The reference period used for indices generation has also been shown to impact results, particularly in respect of drought characteristics and trends, as found by Um *et al.* (2017). This raises questions regarding which reference period to choose when assessing droughts. In this study the best performing reference period was 70 years (1930-1999) and was found to align with the periodicity of the AMO. There exists considerable scope to investigate the use of differing periods for both grouped and individual catchments to assess for regional differences and to garner better understanding on the relationships between period selection, climate variability, drought characteristics and impacts.

The work presented here provides a foundation for the development of drought monitoring and warning systems in Ireland. In particular, the opportunity now exists to evaluate the links between droughts and key modes of climate variability, with the long records developed offering opportunity to examine the stationarity of such relationships. Further research might also assess how long-term temperature increases have influenced drought deficits since the 1950s to ascertain if climate change is impacting the trend towards shorter, sharper droughts, identified in Chapter 3.

The trend assessment detected changes in drought characteristics over the last 250 years. The key finding is a trend to shorter, more intense droughts becoming more common. International evidence shows short sharp droughts or "flash droughts" events are occurring more frequently elsewhere (Christian *et al.*, 2021). These short duration (typically less than two months) (Christian *et al.*, 2018), rapidly intensifying droughts (Wang and Yuan, 2018) have been identified across the globe and in essence are representative of an intensification of current common regional drought regimes. Whilst not fitting the typical definition of a "flash" drought, the recent 2018 and 2020 events, both of which fall outside this study's period of analysis, were of relatively short length (approximately three months) with severe intensities and appear to coincide with the pattern of projections for the island. In Ireland, minimum, mean and maximum temperatures are projected to increase in future (Nolan and Flanagan, 2020), which will result in increased evapotranspiration. Furthermore, increases in mean autumn and winter rainfall as well as annual heavy rainfall events are expected (Nolan and Flanagan, 2020). When these changes are considered in tandem with the trends identified in this study, the potential for shorter, more extreme drought events increases. In Section 1.3.1 the considerable impacts that the 2018 drought had were highlighted, particularly with regard to water access, agricultural outputs and farmer's incomes, with the former inducing severe strain on infrastructure and the provision of drinking water across the island at the time. These research findings suggest that such events may become more common and more severe and as a result pose a considerable risk. It would therefore be prudent to carry out more research into this topic to help identify the drivers of this change including an assessment of the impact increasing rates of evapotranspiration have on these trends, by employing indices such as SPEI, together with a more detailed analysis of trends using the moving window technique to identify regional patterns of change.

The most extreme hydrological drought events identified in this research occur outside of the majority of observational flow records and therefore provide new insight into the impacts of drought at the catchment level. As future climate projections for Ireland contain considerable uncertainties (Nolan and Flanagan, 2020), examination of the dynamics of these past droughts can help identify plausible characteristics associated with future extremes. Such information will be extremely important in helping to understand drought impacts in Ireland and could potentially be employed to assist in the identification of weaknesses in adaptation plans at local and national scales. Furthermore the generated data as part of this thesis could lay the foundation for the development of climate change adaptation tools, especially drought storylines (Shepherd *et al.*, 2018; Chan *et al.*, 2021) to assist in communication of climate risks using memorable analogues and in navigating the uncertainty associated with future drought projections.

5.3.3 Linking indicators to impacts

Understanding the links between drought indicators and impacts is important in the process of identifying drought vulnerability, evaluating risk and measuring change and has been demonstrated effectively in Chapter 4. Using SPI and SSI along with an historic database of newspaper records of drought impacts, regionally distinctive spatial and temporal patterns of reported impact likelihoods were identified across Ireland for the 1900-2016 period. As this component of the research relied upon flow reconstructions and derived drought indices the limitations discussed in Sections 5.3.1, and 5.3.2 are relevant here too. Further sources of uncertainty arise from the underlying newspaper article data, described in detail by Jobbová *et al.* (2022). The duration, frequency, spatial extent and regional density of the newspaper publications affect article occurrence numbers and may result in biases in the logistic regression model outputs. For example, during drought events, article numbers may increase considerably in regional newspapers as the reporting of local impacts increases. As the density of publications across the island is uneven this may lead to both positive and negative regional biases. Conversely, the number of drought articles published during a drought event is dependent on local/national events at the time and the editor's discretion. With more pressing news content, the number of drought articles for certain events may decrease leading to negative biases. Uncertainty arising from such biases could be reduced if a more stringent policy of publication selection and article evaluation is applied and should be considered in future analyses.

Deciding upon what thresholds signify drought onset and termination remains subjective and a matter of considerable debate (Mo, 2011; Steinemann *et al.*, 2015). This research followed the work of Lennard *et al.* (2016) and Noone *et al.* (2017) in identifying drought onset and termination, at -1 and 0 SI respectively, and identified moderate, severe and extreme droughts based on the thresholds derived by McKee *et al.* (1993). Results in Chapter 4 have shown that the indices values that produce a *high* likelihood of land-based and hydrological-based impact reports are dynamic in nature, i.e. correspond with different deficit values across the year. This raises questions regarding the utility of static thresholds in the identification and analysis of drought, particularly in mid-latitude temperate climate locations such as Ireland where a strong seasonality in mean precipitation and flow results in a change in the deficits needed to induce drought conditions. For example, in southeastern catchments an SPI-3 value of -0.23 resulted in a high likelihood of reported impacts in July, whilst in January a value of -3 SPI-3 failed to register even a moderate likelihood of drought reports. Furthermore, values are dependent on the region, with -0.67 SPI-3 inducing similar likelihoods of impact reports in southwestern catchments in July in comparison to the aforementioned southeastern values. As the deficits required to induce drought are spatially and temporally non-stationary the use of dynamic thresholds, dependent on the season or month and location, should be considered when identifying drought and its characteristics. Taking into consideration the significance of this finding, a study should be instigated to investigate the implementation of such an approach.

Whilst indices are commonly employed for drought assessment across the globe their use has both advantages and disadvantages dependent on the location of application and temporal period under review. Standardised indices such as the SPI are relatively simplistic and their temporal and statistical interpretability allows for easy identification of drought onset, cessation and the analysis of drought characteristics at different timescales (Bloomfield and Marchant, 2013; Tefera *et al.*, 2019). Weaknesses however include a requirement for long time series, that drought events occur at the same frequency at all locations due to the standardisation of the data meaning drought prone regions cannot be easily identified, and that an assumed probability distribution applied over different time periods may result in biases in output particularly when generated over short periods in regions of the globe with strong seasonal precipitation patterns such as Ireland (Llyod Hughes and Saunders, 2002). In regions with more consistent precipitation patterns across the year standardised indices such as the SPI perform better.

Alternatives to standardised indices exist for drought identification including absolute indices which identify drought from raw data (i.e. 15 consecutive days of less than 0.2mm of rainfall in respect of Ireland; Rohan, 1986). Drought identification from this approach is location specific however (differing rainfall deficits represent drought onset in different countries) limiting the ability to compare events (Brogan and Cunnane, 2006) and employs daily data which was not available for this study. Other simple statistical techniques exist to define drought including percentage of normal, deciles and percentiles (Quiring, 2009). Such techniques apply simple calculations and are flexible enough to apply at differing timescales and locations, however deriving drought characteristics and change from outputs for the purpose of comparing events and identifying trends, as was required in this study, is more difficult. Ultimately the combined use of multiple indicators and indices associated with a given region to evaluate drought characteristics, as recommended by the WMO (Svoboda *et al.*, 2016), is the best means to evaluate drought and should be considered as part of any future assessment of drought on the island.

In Chapter 4 results showing a significant reduction in land-based and hydrological-based drought impact reports across the 1900-2016 period for regions across the island of Ireland were presented, with a significant step change identified for land-based impact reports around 1961. A subsequent analysis of the 1900-1960 and 1961-2016 periods found that downward trends in reported impact likelihoods, particularly in agricultural and livestock farming, occurred in all regions bar the northwest where an increased probability of drought impacts being reported at more extreme deficits was detected for the 1961-2016 period. The cause of these changes, whether or not they relate to adaptation policies or other external factors or alternatively if regional and/or temporal biases in the impact reporting data influenced results is not clear. Changes in agricultural practices tied to economic improvements in the mid-twentieth century coupled with land reform policies implemented at the time, including a widespread land improvement program of arterial drainage of poorly drained soils, may have reduced the vulnerability to drought impacts in Ireland over time. An exact reasoning for the differing trends in northwestern catchments post-1960 at more extreme deficits remains uncertain although it has been proposed that it relates to slower economic development in that region. The potential exists for a much more detailed sectoral based analysis of spatial and temporal differences in likelihoods of drought impact reporting and trends at the catchment level to garner greater insight into how these relationships develop, with such information being useful for policy makers and drought managers interested in reducing drought vulnerability. Such an assessment could identify if certain catchments are outliers, affecting regional drought impact vulnerability in the northwest, allowing stakeholders to act on these findings.

As part of this assessment only SPI and SSI indices were employed in the analysis of reported drought impacts due to their selection for the historic drought assessment presented in Chapter 3. As highlighted in Section 5.3.2, the opportunity exists to include other indices for both meteorological and hydrological drought analysis. Such research could then be expanded to include additional indicators in the impact analysis. Of particular interest would be the trialling of SPEI to assess the effect evapotranspiration has on reported drought impact likelihoods, as demonstrated by Bachmair *et al.* (2015). Using an ensemble of indices it would be possible to generate uncertainty bounds on the impact probability values thereby quantifying the uncertainty in the generated data.

This study only applied logistic regression modelling techniques with GAMs, which whilst performing well, do not represent the only approach to linking drought metrics and impacts. Bachmair *et al.* (2017) has shown that different model structures including zero altered negative bi-nominal and random forest machine learning have performed well in the process of linking indices to water related impacts in the southeast of England. As neural networks better handle the complex non-linear components relating indices to impacts and do not require the application of independent weighted values, as were included in the logistic regression models generated here, they offer a potentially fruitful approach to further developing the initial assessment methodology. Alternatively, the indices/impacts relationships could be generated using a non-binary hurdle model with Poisson distribution, which would remove the requirement for model weighting and could deal with the overdispersion caused by excess zero article occurrences in the dependent variable data. In any event the use of an ensemble of models would allow for the quantification of the uncertainty in model output which would be of utility.

Whilst the IDID newspaper archive has demonstrated its utility in determining drought impacts for Irish catchments over the last 116 years, other datasets could be included to bolster the accuracy of the historic record of impacts. Data on harvest volumes and livestock numbers in Ireland exist and when added as predictor inputs in the model generation process could possibly improve the accuracy of model output. Online content could also be included in future analyses, including drought impact reports from social media platforms such as Twitter, with such content being specifically of use for analysing individual events that have occurred in the recent past, as has been demonstrated effectively for a flash flood event in the US state of Maryland by Basnyat *et al.* (2017).

5.4 Concluding remarks

This thesis introduced a new database of monthly flow reconstructions for 51 catchments across the island of Ireland for the 1767-2016 period. It has provided detail on the methodology employed to generate the reconstructions, the most notable extremes in flows in Ireland over the last 250 years and potential uses for the data. The utility of the reconstructions has been demonstrated in the historical catchment-based drought analysis, which identified historical drought events of importance and their principal characteristics, trends in those characteristics and helped develop understanding of how distinctive catchment features, including annual rainfall amounts and groundwater storage, influence drought propagation. The new knowledge gained by this assessment has many potential uses, particularly in relation to stress testing of the resilience of current and planned water resource infrastructure on the island. The quantification and subsequent classification of the main drought characteristics of catchments has provided new insight and a more coherent understanding of drought, its development and its uneven impacts. The analysis of the relationship between drought indices and reported impacts has demonstrated the utility of long-term documentary records and has shown for the first time that distinct regional differences in drought impact reporting exist across the island. The value of this new knowledge is considerable and presents opportunities for future research to advance understanding of drought, vulnerability and associated impacts in Ireland and further afield.

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Appendix I Authorship declaration forms

Maynooth University
National University of Ireland Maynooth

Maynooth University

Department of Geography

This form is to accompany the submission of a PhD that contains research reported in published or unpublished work. **Please include one copy of this form for each co-authored work.** This form along with the published work should, under normal circumstances, appear in an Appendix.

Authorship Declaration Form

Publication Details:

Thesis Chapter/Pages	Chapter 2
Publication title	Reconstructed monthly river flows for Irish catchments 1766–2016
Publication status	Published
Type of publication	Journal article – In the Geoscience Data Journal
Publication citation	O'Connor, P., Murphy, C., Matthews, T. and Wilby, R.L., 2021b. Reconstructed monthly river flows for Irish catchments 1766–2016. *Geoscience Data Journal*, 8(1), pp.34-54. doi.org/10.1002/gdj3.107

Nature/extent of my contribution to the work detailed above is as follows:

Nature/Extent of Contribution	**Lead author**
Study conceptualization, funding acquisition, project administration, resource acquisition, data curation and generation, investigation of background to	☒ Yes

research, methodology generation, coding, result generation and validation, complete formal analysis, writing-draft, visualizations, writing original text, making suggested edits.	☐ No

The following co-authors contributed to the work (all contributing co-authors):

Name	Nature of contribution
Conor Murphy	Lead supervisor, assistance with study conceptualization, assistance with funding acquisition, assistance with resource acquisition, 1st review & suggested edits of original text.
Tom Matthews	Second supervisor, assistance with study conceptualization, 2nd review & suggested edits of text.
Rob Wilby	Assistance with study conceptualization, 3rd review & suggested edits of text.

The undersigned hereby certify that the above declaration correctly reflects the nature and extent of the student's and co-author's contribution to this work

	Name	Signature	Date
Student	Paul O’Connor	Paul O'Connor	**26/01/2022**
Co-author 1	Conor Murphy	Conor Murphy	**26/01/2022**
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Co-author 3	Rob Wilby	Robert Wilby	**28/1/2022**

Maynooth University

Department of Geography

This form is to accompany the submission of a PhD that contains research reported in published or unpublished work. **Please include one copy of this form for each co-authored work.** This form along with the published work should, under normal circumstances, appear in an Appendix.

Authorship Declaration Form

Publication Details:

Thesis Chapter/Pages	Chapter3
Publication title	Historical droughts in Irish catchments 1767-2016
Publication status	Published
Type of publication	Journal article - In the International Journal of Climatology
Publication citation	O'Connor, P., Murphy, C., Matthews, T. and Wilby, R.L., 2022a. Historical droughts in Irish catchments 1767-2016. *International Journal of Climatology*. 1–25. https://doi.org/10.1002/joc.7542

Nature/extent of my contribution to the work detailed above is as follows:

Nature/Extent of Contribution	**Lead author**
Study conceptualization, funding acquisition, project administration, resource acquisition, data curation and generation, investigation of background to research, methodology generation, coding, result generation and validation,	☒ Yes ☐ No

complete formal analysis, writing-draft, visualizations, writing original text, making suggested edits.	

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Conor Murphy	Lead supervisor, assistance with study conceptualization, assistance with funding acquisition, assistance with resource acquisition, 1st review & suggested edits of original text.
Tom Matthews	Second supervisor, assistance with study conceptualization, 3rd review & suggested edits of text.
Rob Wilby	Assistance with study conceptualization, 2nd review & suggested edits of text.

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Co-author 3	Rob Wilby		**28/1/2022**

Maynooth University

Department of Geography

This form is to accompany the submission of a PhD that contains research reported in published or unpublished work. **Please include one copy of this form for each co-authored work.** This form along with the published work should, under normal circumstances, appear in an Appendix.

Authorship Declaration Form

Publication Details:

Thesis Chapter/Pages	Chapter 4
Publication title	Relating drought indices to impacts reported in newspaper articles
Publication status	Article submitted for review
Type of publication	Journal article – In the International Journal of Climatology
Publication citation	O'Connor, P., Murphy, C., Matthews, T. and Wilby, R.L., 2022b. Relating drought indices to impacts reported in newspaper articles. *International Journal of Climatology*. Submitted for review.

Nature/extent of my contribution to the work detailed above is as follows:

Nature/Extent of Contribution	**Lead author**
Study conceptualization, funding acquisition, project administration, resource acquisition, data curation and generation, investigation of background to research, methodology generation, coding, result generation and validation,	☒ Yes ☐ No

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Conor Murphy	Lead supervisor, assistance with study conceptualization, assistance with funding acquisition, assistance with resource acquisition, 1st review & suggested edits of original text.
Tom Matthews	Second supervisor, assistance with study conceptualization, 2nd review & suggested edits of text.
Rob Wilby	Assistance with study conceptualization, 3rd review & suggested edits of text.

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Appendix II Published works and pre-prints

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DATA PAPER

Geoscience Data Journal RMetS WILEY

Reconstructed monthly river flows for Irish catchments 1766–2016

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Abstract

A 250-year (1766–2016) archive of reconstructed river flows is presented for 51 catchments across Ireland. By leveraging meteorological data rescue efforts with gridded precipitation and temperature reconstructions, we develop monthly river flow reconstructions using the GR2M hydrological model and an Artificial Neural Network. Uncertainties in reconstructed flows associated with hydrological model structure and parameters are quantified. Reconstructions are evaluated by comparison with those derived from quality assured long-term precipitation series for the period 1850–2000. Assessment of the reconstruction performance across all 51 catchments using metrics of MAE (9.3 mm/month; 13.3%), RMSE (12.6 mm/month; 18.0%) and mean bias (−1.16 mm/month; −1.7%), indicates good skill. Notable years with highest/lowest annual mean flows across all catchments were 1877/1855. Winter 2015/16 had the highest seasonal mean flows and summer 1826 the lowest, whereas autumn 1933 had notable low flows across most catchments. The reconstructed database will enable assessment of catchment specific responses to varying climatic conditions and extremes on annual, seasonal and monthly timescales.

KEYWORDS

hydrological modelling, Ireland, reconstruction, river flow, time series

Data set

Identifier: https://doi.org/10.1594/PANGAEA.914306

Creator: Irish Climate Analysis and Research UnitS (ICARUS), Department of Geography, Maynooth University, Ireland. [O'Connor, P., Murphy, C., Matthews, T., Wilby, R.L.].

Title: Monthly river flow reconstructions for Ireland 1766–2016.

Publisher: PANGAEA

Publication year: 2020

Resource Type: Dataset

Version: 1.0

1 | INTRODUCTION

Continuous, long-term river flow records are needed for evaluations of hydro-climatic variability and change, historical extremes and catchment processes (Machiwal and Jha, 2006). They also underpin water management and provide a means of stress-testing existing and planned systems to a range of variability and past droughts (Wilby and Murphy, 2019). Unfortunately, there are few continuous and homogeneous river flow records spanning a century or more (Mediero *et al.*, 2015). Instead, available records are often impacted by confounding factors or large amounts of missing data (Wilby *et al.*, 2017).

Various techniques exist for extending observations by reconstructing river flows. This typically involves forcing statistical or conceptual hydrological models with long-term precipitation and temperature/evapotranspiration data provided by reanalysis (e.g. Kuentz *et al.*, 2013; Brigode *et al.*, 2016) or long-term historical data sets (e.g. Jones, 1984; Spraggs *et al.*, 2015; Crooks and Kay, 2015; Rudd *et al.*, 2017; Hanel *et al.*, 2018; Smith *et al.*, 2019; Noone and Murphy, 2020). Others have leveraged international data rescue initiatives to generate gridded historical weather variables (Casty *et al.*, 2007). Whilst these kinds of information have been used to reconstruct river flows in parts of Europe (e.g. Moravec *et al.*, 2019), they have yet to be deployed in the British-Irish Isles.

Here, we develop a data set of reconstructed monthly river flows for 51 catchments across the island of Ireland back to 1766. This was achieved using gridded historical meteorological data, bias corrected to contemporary observations in each catchment. These data provided the input to a conceptual hydrological model and an artificial neural network (ANN), both of which were trained and verified using river flow observations. In addition, we use recently rescued precipitation data to evaluate model reconstructions for selected catchments during the period 1850–2010. The following sections describe the catchments, data sets and modelling approaches, before we present the derived reconstructions.

2 | DATA PRODUCTION METHODS

2.1 | Catchments and data

Reconstructions were generated for 51 catchments (Table 1 and Figure 1) that are relatively free from artificial influences (following criteria applied by Murphy *et al.* (2013): they have at least 25 years of record and acceptable quality rating curves). The catchments are broadly representative of hydro-climatological conditions across the island, with a recognized under-representation of upland catchments along coastal margins (Broderick *et al.*, 2019). Urban extent averages <2% of the combined area of all catchments, which individually vary in size between 10 and 2,418 km^2. However, given the extent of arterial drainage works undertaken in Ireland, it is unavoidable that some catchments have been impacted by such activities. We note which catchments are known to be affected by arterial drainage in Table 1.

Daily flow series were obtained from the Office of Public Works (OPW; http://waterlevel.ie/) and the Environmental Protection Agency (http://www.epa.ie/hydronet/) and then aggregated to monthly mean flows. The average amount of missing data was <6% across the 51 catchments, with a notable outlier of 31% being the Blackwater at Duarrigle (ID: 18050). Of the total missing days (11% overall), the majority have been previously infilled using rainfall–runoff modelling techniques (Murphy *et al.*, 2013). As the remaining missing data only represented 1% of the total, they were not repopulated.

We use gridded (1 × 1 km) monthly precipitation and temperature series (Walsh, 2012) area-averaged for each catchment, alongside concurrent river flow records, to calibrate the hydrological models (see below). Monthly potential evapotranspiration (PET) was estimated from air temperature and radiation following the method of Oudin *et al.* (2005). We favoured this over more physically based methods (e.g. Penman-Monteith), because the latter have greater data requirements (e.g. wind speed, humidity) that cannot be met over the full duration of the reconstruction period. Instead, the sensitivity of monthly river flow simulations to PET estimation methods was tested for periods with complete variable sets. Six PET estimation methods (Penman–Monteith Penman (1948), Monteith (1965), Blaney and Criddle (1950), Hamon (1961), Oudin *et al.* (2005), Thornthwaite (1948) and Kharrufa (1985)) were evaluated using the hydrological model GR2M. This revealed that the Oudin method performed similarly to the Penman–Monteith method, with an average RMSE of 3.6 mm between flows generated from the two methodologies for five catchments for the period 1974–2000 (equating to 4.5% of mean annual flows).

2.2 | Historical gridded precipitation and temperature data

Casty *et al.* (2007) (henceforth Casty data) produced gridded (0.5° × 0.5°) monthly temperature and precipitation series for Europe covering the period 1766–2000 using non-linear principle component regression of a spatial network of available station data against reanalysis data, with independent predictors used for different variables (Casty *et al.*, 2007). Monthly mean temperature and total precipitation were extracted and averaged for grids overlying each catchment for the years 1766–2000. Quantile mapping (Maraun, 2016) was used to

TABLE 1 Details of the 51 catchments for which flow reconstructions were generated

River	Flow station	Waterbody	Arterial	Area	Calibration	GR2M validation scores			ANN validation scores			Ensemble validation scores		
ID	Name	Name	Drainage	km^2	Years	NSE	KGE	PBIAS%	NSE	KGE	PBIAS%	NSE	KGE	PBIAS%
3051	Faulkland	Blackwater (Mon)	Yes	143	1976–2000	0.79	0.69	−16.40	0.78	0.67	−14.80	0.80	0.69	−16.00
6013	Charleville	Dee	Yes	309	1976–2000	0.78	0.75	−12.50	0.82	0.70	−9.10	0.83	0.72	−11.20
6014	Tallanstown	Glyde	Yes	270	1976–2000	0.77	0.75	−8.00	0.82	0.73	−4.50	0.81	0.73	−7.70
6030	Ballygoly	Big	No	10	1975–2000	0.86	0.86	−2.10	0.83	0.78	−1.00	0.86	0.83	−1.80
7009	Navan Weir	Boyne	Yes	1658	1977–2000	0.77	0.73	−9.90	0.81	0.73	−6.40	0.81	0.71	−9.60
7012	Slane Castle	Boyne	Yes	2,408	1961–2000	0.79	0.74	−11.90	0.83	0.71	−8.60	0.84	0.72	−10.90
12001	Scarrawalsh	Slaney	No	1,031	1961–2000	0.76	0.73	−15.10	0.80	0.81	−11.90	0.78	0.74	−14.50
14007	Derrybrock	Stradbally	No	115	1980–2000	0.83	0.77	−10.10	0.88	0.79	−8.80	0.86	0.75	−10.30
14019	Levitstown	Barrow	No	1697	1961–2000	0.81	0.74	−12.40	0.86	0.79	−8.00	0.84	0.74	−11.60
15001	Annamult	Kings	No	445	1972–2000	0.87	0.90	−1.00	0.88	0.82	1.10	0.89	0.87	−0.30
15003	Dinin Bridge	Dinin	No	140	1972–2000	0.87	0.86	−7.40	0.84	0.75	−8.90	0.88	0.82	−7.80
15005	Durrow Ft. Br.	Erkina	No	379	1972–2000	0.78	0.68	−11.90	0.83	0.72	−8.50	0.82	0.68	−10.60
15006	Brownsbarn	Nore	No	2,418	1972–2000	0.87	0.88	−3.90	0.90	0.87	0.30	0.91	0.87	−2.10
15007	Kilbricken	Nore	No	340	1982–2000	0.82	0.71	−11.30	0.81	0.68	−8.60	0.82	0.70	−10.70
16008	New Bridge	Suir	No	1,090	1961–2000	0.85	0.84	−6.90	0.86	0.87	−2.40	0.88	0.84	−5.40
16009	Caher Park	Suir	No	1583	1962–2000	0.86	0.87	−7.50	0.90	0.93	−3.20	0.89	0.89	−6.20
16010	Anner	Anner	No	437	1973–2000	0.80	0.89	−1.20	0.84	0.92	2.90	0.85	0.91	0.60
16011	Clonmel	Suir	No	2,144	1962–2000	0.88	0.89	−0.10	0.89	0.94	3.20	0.90	0.90	1.10
16012	Tar Bridge	Tar	No	230	1969–2000	0.83	0.83	0.80	0.83	0.89	2.00	0.85	0.85	1.30
16013	Fourmilewater	Nire	No	94	1973–2000	0.69	0.85	−0.80	0.82	0.84	−1.20	0.80	0.86	−1.50
18002	Ballyduff	Blackwater	No	2,334	1972–2000	0.90	0.91	6.00	0.87	0.86	10.30	0.91	0.92	7.40
18003	Killavullen	Blackwater	No	1,257	1972–2000	0.91	0.88	0.80	0.92	0.95	3.80	0.93	0.91	1.60
18006	Cset Mallow	Blackwater	No	1,052	1978–2000	0.88	0.83	−0.20	0.89	0.88	3.80	0.90	0.85	1.10
18050	Duarrigle	Blackwater	No	250	1982–2000	0.89	0.86	−5.50	0.89	0.84	−5.00	0.90	0.85	−5.30
19001	Ballea	Owenboy	No	103	1973–2000	0.85	0.76	−16.30	0.82	0.74	−12.60	0.85	0.75	−14.50
21002	Coomhola	Coomhola	No	65	1976–2000	0.90	0.83	−6.40	0.92	0.89	−4.70	0.93	0.87	−5.30
22006	Flesk	Flesk (Laune)	No	329	1990–2000	0.84	0.75	−7.20	0.91	0.84	−6.40	0.89	0.80	−6.60
22035	Laune Bridge	Laune	Yes	560	1992–2000	0.81	0.73	−6.10	0.87	0.84	−6.30	0.86	0.78	−6.40
23002	Listowel	Feale	Yes	647	1975–2000	0.93	0.90	2.80	0.92	0.87	3.40	0.94	0.89	3.40
24008	Castleroberts	Maigue	Yes	806	1977–2000	0.89	0.83	−0.40	0.88	0.83	3.30	0.90	0.82	0.90

(Continues)

TABLE 1 (Continued)

River	Flow station	Waterbody	Arterial	Area	Calibration	GR2M validation scores			ANN validation scores			Ensemble validation scores		
ID	Name	Name	Drainage	km^2	Years	NSE	KGE	PBIAS%	NSE	KGE	PBIAS%	NSE	KGE	PBIAS%
24030	Danganbeg	Deel	Yes	259	1981–2000	0.92	0.90	1.70	0.91	0.90	4.20	0.93	0.90	2.80
25001	Annacotty	Mulkear	Yes	648	1973–2000	0.88	0.82	−1.50	0.88	0.82	0.00	0.89	0.82	−1.00
25002	Barrington Br.	Newport (Mun)	Yes	230	1961–2000	0.91	0.92	−0.90	0.91	0.94	0.70	0.92	0.93	−0.20
25006	Ferbane	Brosna	No	1,163	1961–2000	0.83	0.79	−10.40	0.86	0.80	−6.80	0.87	0.78	−9.50
25030	Scarriff	Graney	Yes	279	1973–2000	0.86	0.81	−6.80	0.86	0.83	−4.10	0.87	0.82	−5.50
25034	Rochfort	L. Ennell Trib	Yes	11	1976–2000	0.81	0.84	−7.90	0.85	0.81	−7.60	0.86	0.82	−8.30
26021	Ballymahon	Inny	No	1,099	1973–2000	0.83	0.86	−4.10	0.84	0.88	−0.60	0.88	0.85	−3.40
26029	Dowra	Shannon	Yes	117	1976–2000	0.86	0.85	−8.80	0.83	0.81	−8.00	0.86	0.84	−8.20
26058	Ballyrink Br.	Inny Upper	Yes	60	1982–2000	0.75	0.82	4.50	0.85	0.82	4.40	0.85	0.82	2.60
27002	Ballycorey	Fergus	Yes	511	1961–2000	0.83	0.74	−8.70	0.84	0.81	−6.90	0.85	0.75	−8.50
30007	Ballygaddy	Clare	No	470	1975–2000	0.89	0.85	−7.50	0.91	0.90	−4.30	0.91	0.86	−6.40
32012	Newport Weir	Newport	No	146	1982–2000	0.90	0.85	−6.00	0.90	0.89	−3.80	0.91	0.87	−4.80
33001	Glenamoy	Glenamoy	Yes	76	1978–2000	0.93	0.95	−0.50	0.87	0.94	0.00	0.93	0.96	0.30
34001	Rahans	Moy	No	1975	1970–2000	0.90	0.92	−4.60	0.89	0.94	−1.90	0.92	0.92	−4.00
35002	Billa Bridge	Owenbeg	No	81	1972–2000	0.86	0.88	4.70	0.87	0.92	5.60	0.88	0.90	5.30
35005	Ballysadare	Ballysadare	No	640	1961–2000	0.89	0.90	−2.30	0.90	0.90	−2.10	0.91	0.90	−2.40
36015	Anlore	Finn	No	153	1973–2000	0.84	0.76	−9.50	0.79	0.65	−10.40	0.84	0.73	−9.80
36019	Belturbet	Erne	No	1,492	1961–2000	0.83	0.85	−5.60	0.79	0.77	−7.60	0.86	0.80	−6.90
38001	Clonconwal	Ownea	No	111	1973–2000	0.93	0.87	−4.00	0.93	0.88	−4.50	0.94	0.88	−3.60
39006	Lennan	Claragh	No	245	1977–2000	0.85	0.88	8.00	0.85	0.87	7.90	0.86	0.88	8.00
39009	Aghawoney	Fern O/L	Yes	207	1973–2000	0.91	0.90	−1.00	0.91	0.88	−2.20	0.92	0.90	−1.20

Note: Included are calibration periods for each catchment, together with logNSE, KGE and PBIAS scores for the validation period (2001–2016) for ANN, GR2M and Ensemble median simulations.

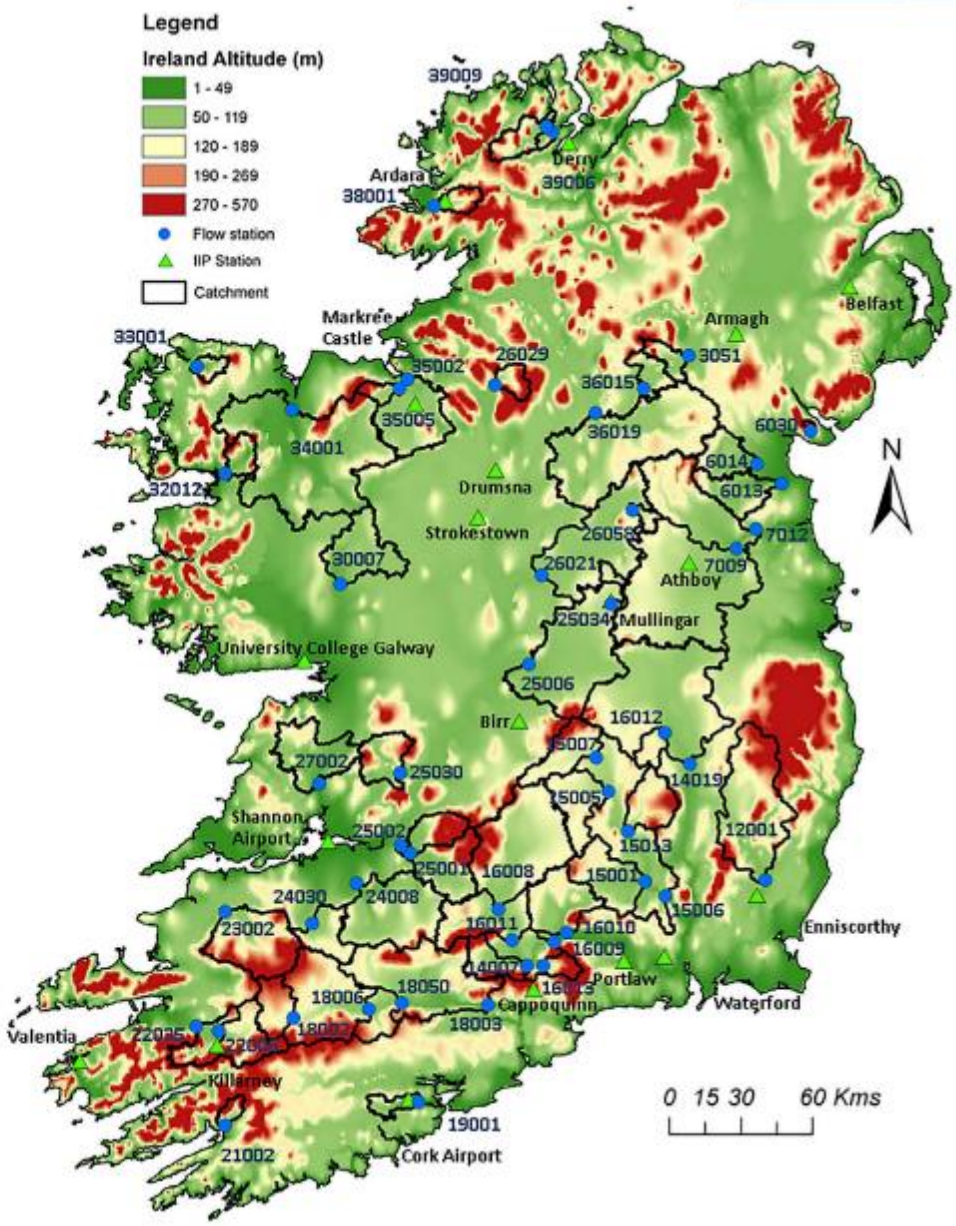


FIGURE 1 The 51 study catchments along with the locations of corresponding flow stations and island of Ireland precipitation (IIP) series synoptic stations

bias correct Casty data to catchment averages using the aforementioned gridded (1 × 1 km) monthly precipitation and temperature series. We perform quantile mapping by interpolating the empirical quantiles using local linear least square regression to robustly estimate the values of the quantile–quantile relationship between the Casty and observed data for each catchment. For values outside the historical range, a constant correction—equivalent to the highest quantile in that series—was applied (Boé *et al.*, 2007). Bias correction was carried out on a monthly basis using the 'qmap' R package (Gudmundsson, 2016). Sample bias correction plots for nine catchments are shown in Figure 2 (temperature) and Figure 3 (precipitation). Across the 51 catchments, the bias adjustment produced minimal change in mean annual temperature values (−0.15°C). Precipitation corrections were more substantial, with a mean increase of 94.2 mm/year (7.7% of mean annual

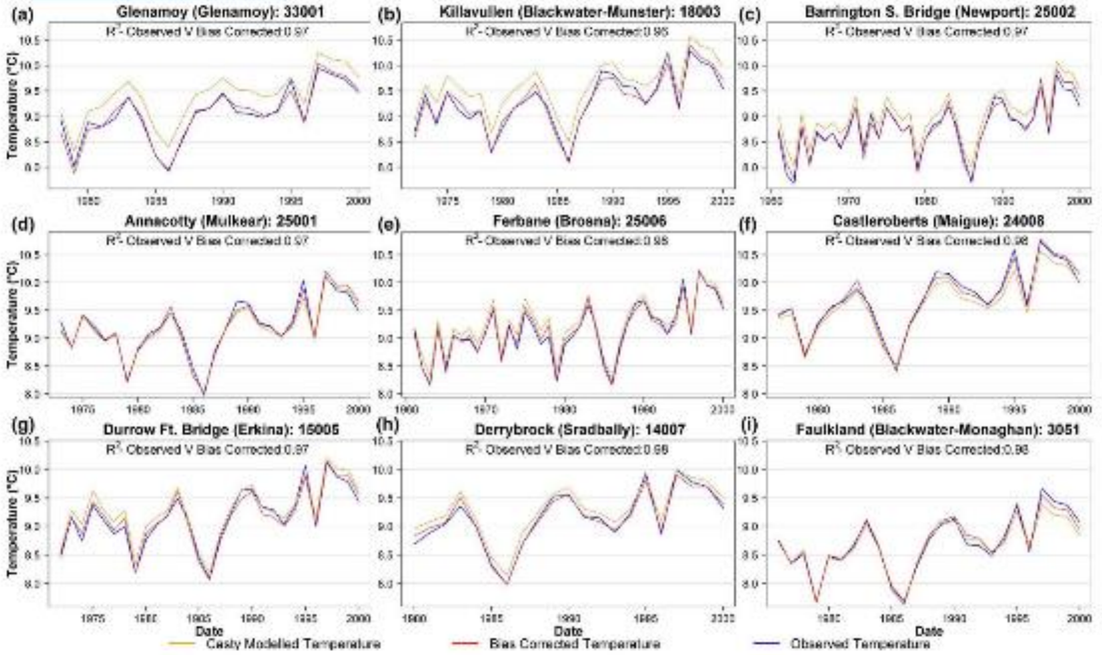


FIGURE 2 Annual bias corrected Casty temperature for nine catchments from the start of the respective observations up until the year 2000. R^2 scores between bias corrected and observed temperature values are also provided

precipitation). Once bias corrected, observed temperature and precipitation were appended to each catchment series to bring values up to 2016. The Oudin method was then used to derive PET estimates from the Casty temperature data for each catchment.

2.3 | Hydrological models and calibration procedures

To ascertain the contribution to uncertainty generated by model structure, two model types were implemented—a conceptual hydrological model (GR2M) and an empirical based Artificial Neural Network (ANN). These models are explained below.

2.3.1 | The GR2M conceptual model

GR2M is a simple water balance model (Mouelhi *et al.*, 2006), originally developed for French catchments, now available via the airGR R hydrological modelling package (Coron *et al.*, 2017). The monthly flow model contains two reservoirs representing a soil store and routing reservoir (Figure 4) governed by two parameters: the production store capacity and groundwater exchange coefficient. GR2M has been widely deployed across diverse catchment types and applications (e.g. Louvet *et al.*, 2016), including for flow reconstructions (Dieppois *et al.*, 2016).

For each catchment, GR2M was calibrated and validated on observed data before using the bias corrected Casty data to reconstruct flows. A split record for calibration/validation was applied as this allows direct comparison between GR2M and ANN model outputs on a catchment-by-catchment basis. Calibration for all catchments (including a 1-year warm-up period) was undertaken from the start of the flow record up to December 2000. This time interval captures periods of large flow variability ranging from the drought rich 1970s to the flood rich 1980s. Validation was undertaken using the 15 years postcalibration (2001–2016) for all catchments (see Table 1).

Uncertainty in GR2M model parameters was sampled using Monte Carlo methods. For each parameter, 20,000 values were randomly drawn from a uniform distribution of [0–2500] for the production store capacity and [0–2] for the groundwater exchange coefficient. Each parameter set was used to simulate flows for the calibration period (yielding a 20,000-member ensemble). The performance of parameter sets was evaluated using two objective functions to ensure robust performance across the flow regime: the Nash Sutcliffe Efficiency (NSE) (Nash and Sutcliffe, 1970) derived from log transformed flows (logNSE) and the modified Kling Gupta Efficiency (KGE) derived from raw flows (Gupta *et al.*, 2009; Kling *et al.*, 2012). Two steps were then

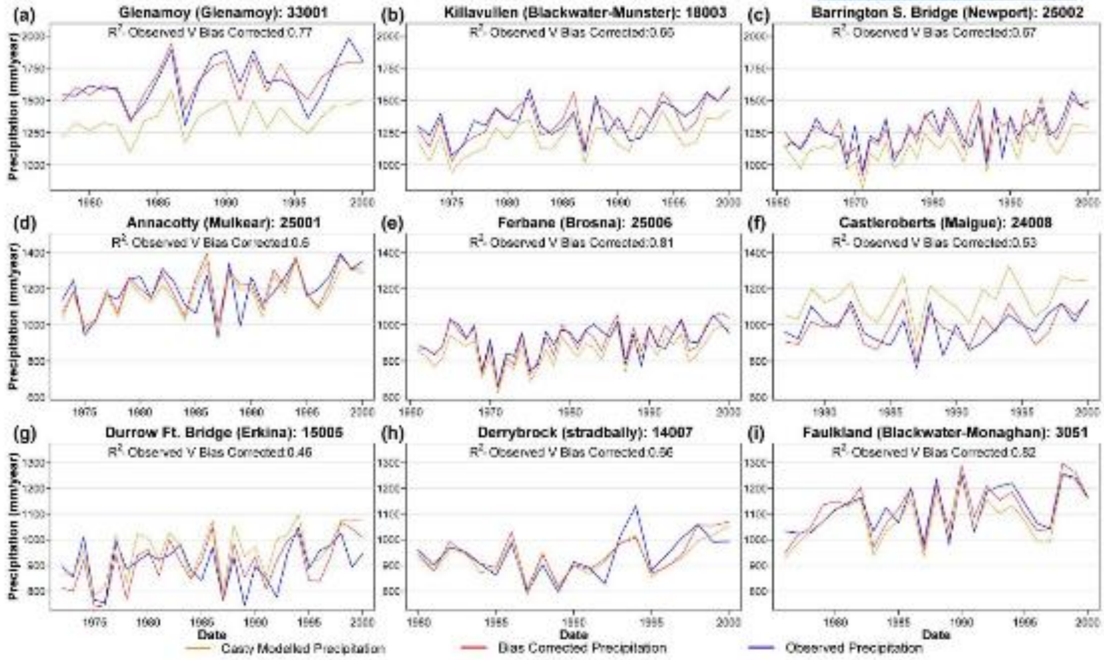
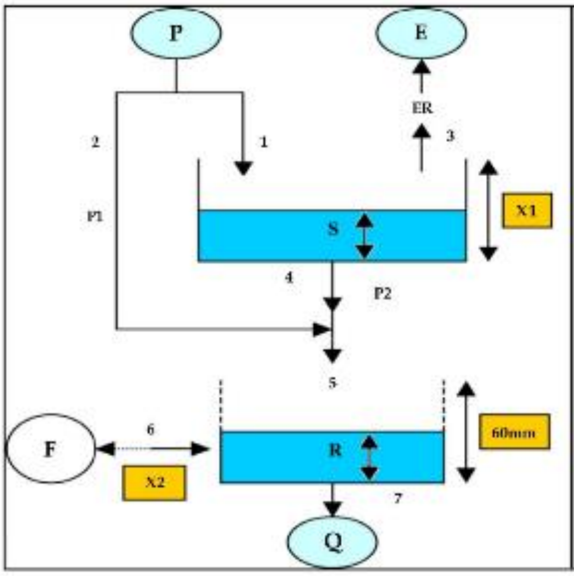


FIGURE 3 Annual bias corrected Casty precipitation values for nine catchments from the start of the respective observations up until the year 2000. R^2 scores between bias corrected and observed precipitation values are also provided



$$(1)\quad S_1 = \frac{S + X_1\varphi}{1 + \varphi\frac{S}{X_1}} \quad \text{with} \quad \varphi = \tanh\frac{P}{X_1}$$

$$(2)\quad S_2 = \frac{S_1(1-\Psi)}{1 + \Psi\left(1 - \frac{S_1}{X_1}\right)} \quad \text{with} \quad \Psi = \tanh\frac{E}{X_1}$$

$$(3)\quad S = \frac{S_2}{\left[1 + \left(\frac{S_2}{X_1}\right)^3\right]^{1/3}} \quad ; \quad P_2 = S_2 - S$$

$$(4)\quad P_1 = P + S - S_1$$

$$(5)\quad R_1 = R + P_1 + P_2$$

$$(6)\quad R_2 = X_2 . R_1$$

$$(7)\quad Q = \frac{{R_2}^2}{R_2 + 60} \quad ; \quad R = R^2 - Q$$

FIGURE 4 Outline of the structure of the GR2M model together with relevant equations defining the model structure. (Adapted from Mouelhi *et al.* (2013) and Lespinas *et al.* (2014))

undertaken to determine which parameter sets to retain. First, objective function scores were ranked by their performance, with the top 400 sets from each being retained. Second, retained simulations were evaluated by their absolute per cent bias (PBIAS) relative to observed flows, with the 200 best performing parameter sets for both logNSE and KGE retained. The median (henceforth GR2M median) and 95th percentile confidence intervals of GR2M simulated flows, retained from this process, were then determined.

2.3.2 | The ANN Model

ANNs have been widely used for rainfall–runoff modelling (Dawson and Wilby, 1998; Dastorani *et al*., 2010). A backpropagation ANN was developed here using the neuralnet R package (Fritsch *et al*., 2019), with different combinations of inputs and neurons tested with two hidden layers. The same calibration and validation periods for individual catchments were employed as those for the GR2M, again using observed data to generate the model. When determining the ANN structure, input data were limited to observed variables that were also available for the full reconstruction period (temperature, precipitation and PET). Lagged variables (e.g. precipitation from previous months) were also included. The best performing ANN inputs were found to be temperature and precipitation from the current month, plus precipitation lagged by one, two and three months. An example ANN structure which generated the best efficiency scores for one catchment is shown in Figure 5.

Uncertainty in ANN model structure was explored by varying combinations of neurons in one or two hidden layers. Neuron permutations, varying from one to twenty for each hidden layer (giving 420 independent model structures in total), were used to simulate flows for the given calibration period. Each model structure was then independently evaluated using logNSE and KGE and ranked in order of performance. As per the GR2M model, the top 400 ANN model structures according to each objective function were identified and those which subsequently produced the 200 lowest PBIAS scores were retained. The median (henceforth ANN median) and 95th percentile confidence intervals of simulated flows were then obtained.

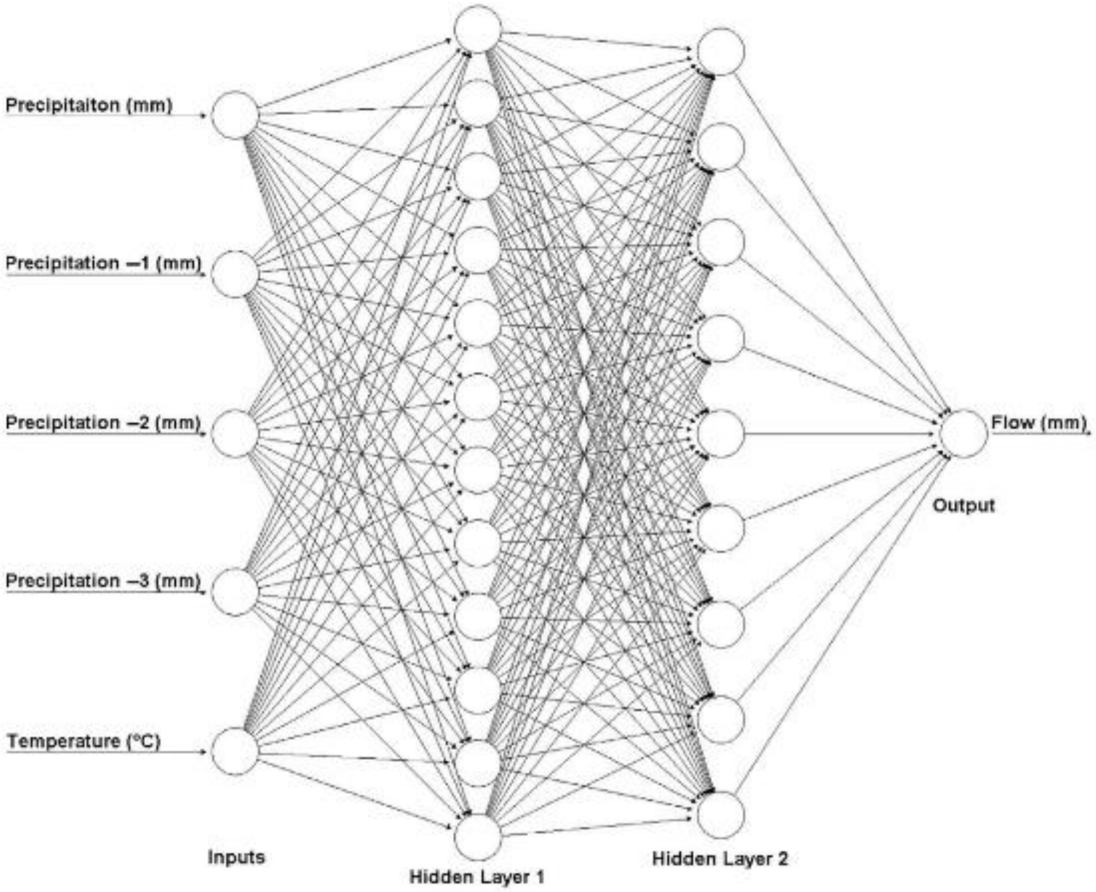


FIGURE 5 Schematic of a typical ANN model structure employed with five inputs, two hidden layers (with 12 and 9 neurons respectively) and monthly flow output. Negative one, two and three values represent the number of lagged months for precipitation

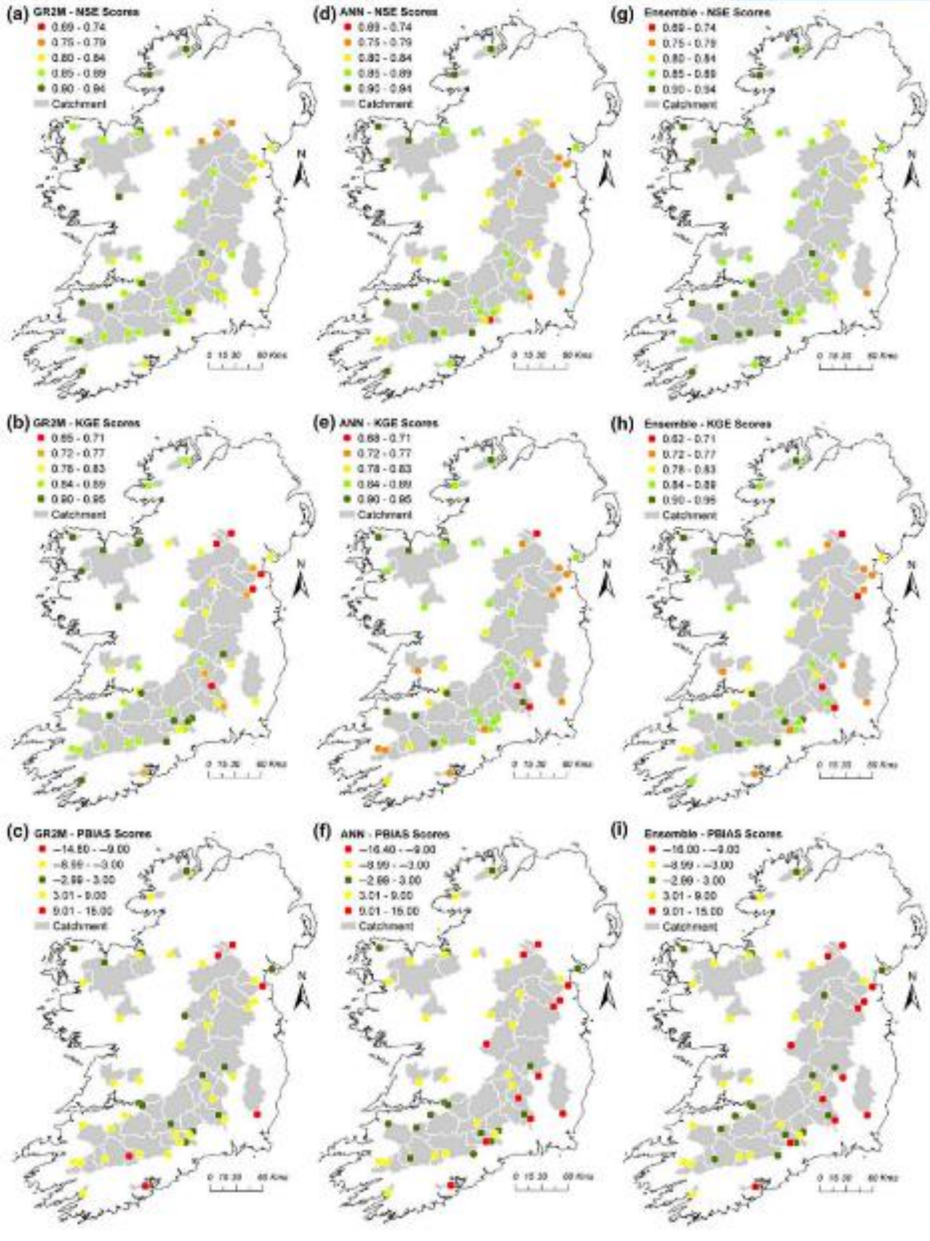


FIGURE 6 Maps of logNSE, KGE and PBIAS scores for GR2M, ANN and Ensemble median simulations for all 51 catchments. Scores are derived from the observed versus modelled flows for the independent validation period (2001–2016) for each catchment

Finally, a mixed ensemble was derived from both GR2M and ANN model structures and parameters by combining the 200 retained simulations from each. The median (henceforth Ensemble median) and 95th percentile confidence intervals of simulated flows were obtained and used to evaluate model reconstructions.

2.3.3 | Validation results

Figure 6 displays the performance of the GR2M, ANN and Ensemble median simulations for all 51 catchments for the 2001–2016 validation period according to logNSE, KGE and PBIAS scores. The ANN and GR2M simulations perform equally well with average logNSE, KGE and PBIAS scores across all 51 catchments of 0.86, 0.83 and −3.04% for GR2M median and 0.85, 0.83 and −4.97% for ANN median. The combined Ensemble median returned scores of 0.87, 0.83 and −4.38%. Individual catchment results also show similar performance for both model types.

Skill scores for GR2M, ANN and Ensemble median simulations during validation for each catchment are provided in Table 1. Poorest performances are evident for the Nire at Fourmilewater (ID: 16013) which has a logNSE score of 0.69 (ANN median) and the Finn at Anlore (ID: 36015) with a KGE score of 0.65 (GR2M median). PBIAS scores vary between catchments with the largest bias evident for the Blackwater at Faulkland (ID: 3051) (−16.4%; ANN median) and a minimum of 0% for the Glenamoy at Glenamoy (ID: 33001) (GR2M median). PBIAS values are generally higher for the ANN median.

Observed and simulated monthly flows for the validation period for nine catchments are shown in Figure 7. This subset represents a spread of the best (top row), average (middle row) and worst (bottom row) performing catchments. The proportion of observed variance (R^2) captured by the Ensemble median simulation for each catchment is also provided—varying between 0.88 and 0.93 for the nine sample catchments. The average Ensemble median R^2 value across all 51 catchments for the same validation period is 0.90. ANN and GR2M median simulations show good agreement for the majority of catchments. Whilst observed flows are largely contained within the uncertainty bounds for each of the catchment reconstructions, some discrepancies are apparent in peak values. Arterial drainage works have been identified as a probable cause of this, with previous work showing the tendency for elevated peak flows following drainage (Harrigan *et al.*, 2014). Peak flows also tend to be underestimated for smaller catchments where gridded rainfall may not capture flood generating precipitation adequately.

3 | RECONSTRUCTED FLOWS

3.1 | Assessment of reconstructed flows

Following calibration and validation with observed data, bias corrected Casty data (precipitation/temperature and Oudin PET) were input to the hydrological models to reconstruct monthly river flows back to 1766. The following sub-sections present the resulting annual, seasonal and monthly flow reconstructions across all 51 catchments.

3.1.1 | Annual flow reconstructions

The median of annual reconstructed flows for all 51 catchments from 1766 is shown in Figure 8. GR2M and ANN median reconstructions show close agreement ($R^2 = 0.97$). In Figure 8 and subsequent plots, observed flows from 1980 onward are displayed as, by this year, observed values are available for over 84% of catchments. Overall, the percentage of median annual observed flow values across all 51 catchments contained within the uncertainty ranges of the median ensemble (henceforth the containment value) is 97%. Observed and Ensemble median simulated series across all catchments show close agreement ($R^2 = 0.81$). Some divergence is evident between modelled and observed flows around 1989 due to differences between Casty and observed precipitation at that time.

3.1.2 | Seasonal and monthly flow reconstructions

Seasonal and monthly flow reconstructions for all 51 catchments are displayed in Figures 9 and 10, respectively, with reconstructions showing strong agreement with observations for 1980–2016 in all seasons. There is some evidence that summer flows are over-estimated in 1989, consistent with annual flows. For all other periods and seasons, observed flows lie within uncertainty estimates (minimum containment value is 89%) and show good agreement with reconstructions (R^2 between Ensemble median values and observations range from a high of 0.9 in summer [JJA] to a low of 0.76 in autumn [SON]). Close agreement is also evident between GR2M and ANN median reconstructions ($R^2 > 0.91$) in all seasons. It is notable from Figure 9 that GR2M reconstructions for spring and summer are slightly higher and autumn values lower than ANN reconstructions.

Monthly reconstructions are displayed in Figure 10 for all 51 catchments. Good agreement is evident between GR2M and ANN median reconstructions ($R^2 > 0.84$ in all months). GR2M median reconstructions are slightly higher than the ANN in April, May, June and July, whilst GR2M output in September, October and November is lower than the ANN equivalent, concurrent with summer and autumn differences between GR2M and ANN values identified above. As expected, performance of monthly simulations is poorer than for seasonal and annual time steps. Monthly observed flows generally lie within uncertainty estimates (mean containment value across all months is 68%) and show satisfactory agreement with observations (R^2 for Ensemble median values vs. observations range between 0.56 in April and 0.91 in July).

3.2 | Comparison with reconstructions from long-term precipitation series

Monthly river flow reconstructions generated with the bias corrected Casty data were evaluated against reconstructions based on monthly precipitation data for stations within the

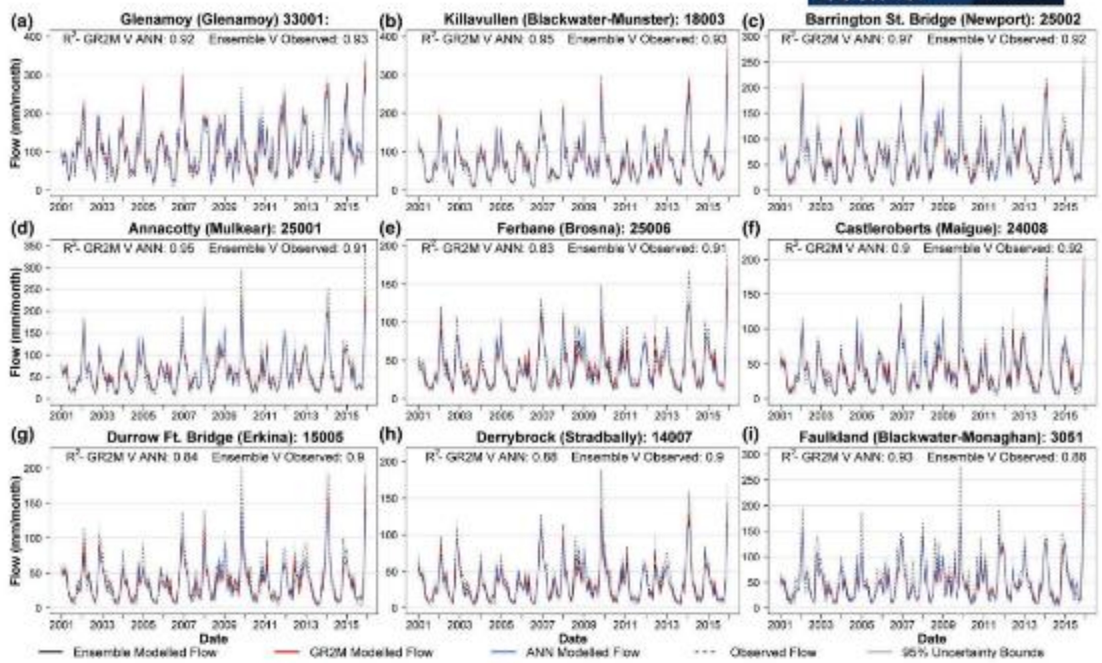


FIGURE 7 Observed and simulated annual mean flows for nine sample catchments representing best (top row), average (middle row) and worst (bottom row) performing models. Plotted are the GR2M (red), ANN (blue) and Ensemble median (black) simulations, together with observed flows (dashed dark-grey). 95% uncertainty range (grey) is derived from the Ensemble median simulations

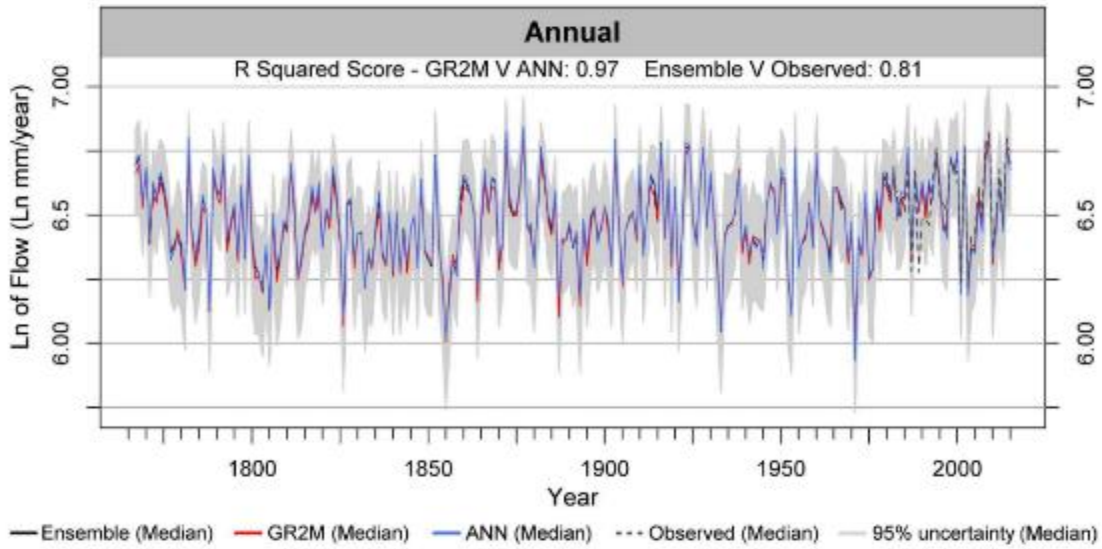


FIGURE 8 Median annual flow values across all 51 catchments for the period 1766–2016 for GR2M (red), ANN (blue) and Ensemble median (black) reconstructions. The median of observed flows across the catchment sample for years 1980–2016 are in dark-grey, whilst 95% uncertainty ranges (grey) are derived from the ensemble simulations

Island of Ireland Precipitation (IIP) network 1850–2010 (Noone *et al.*, 2016). For each catchment, we identified the nearest IIP station (see Figure 1) and then bias corrected data to catchment average precipitation, as per the Casty data. Bias corrected precipitation, together with bias corrected monthly temperature/PET derived from the Casty data, was

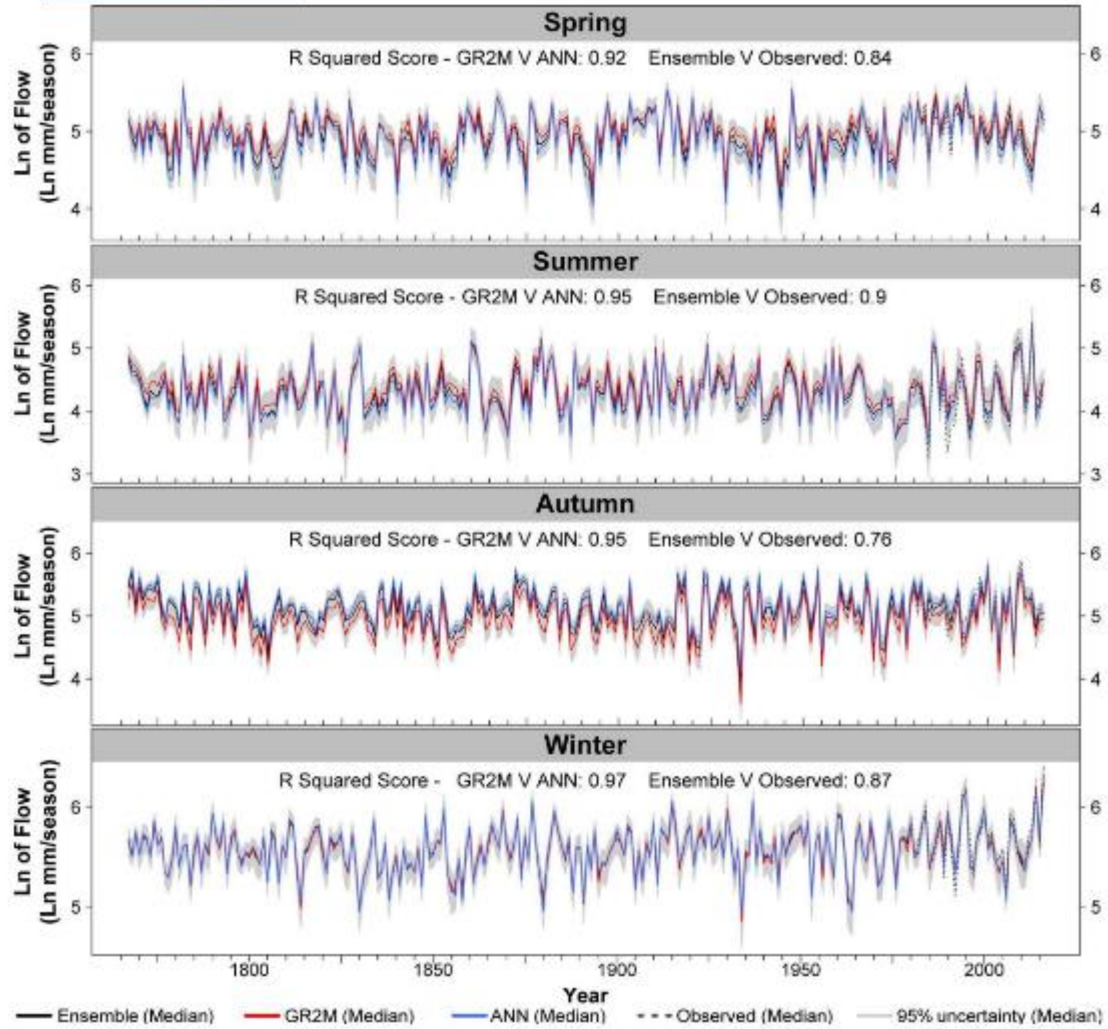


FIGURE 9 As in Figure 8 but for seasonal median flows: Winter [DJF], spring [MAM], summer [JJA], autumn [SON]

used to reconstruct flows back to 1850, using the same methods as described above. Although some of the IIP data are likely contained within the Casty gridded precipitation (so there is a degree of circularity), it was deemed important to compare both data sources, given the different methods used in their construction.

Figure 11 shows the Ensemble median annual mean flow reconstructions from 1850 to 2016 for four exemplar catchments, using Casty precipitation or IIP as input. Strong agreement between the reconstructions is evident despite the different input data with IIP reconstructions largely contained within the uncertainty ranges of the Casty reconstructions. Across the four case study catchments, the R^2 between IIP and Casty reconstructed annual mean flows varies between 0.70 and 0.77. Differences between flows generated from the two data sources are not unexpected given that IIP data are station based and often located outside catchment boundaries, whereas Casty data are gridded.

3.3 | High- and low-flow assessment

The most notable extreme flow years for seasonal and annual Casty reconstructions were identified (Table 2), with the top five highest and lowest flow year across all catchments displayed for calendar years (1767–2016) as well as winter and summer seasons (1767–2016). The percentage anomaly relative to the mean of the full record is also provided. The most exceptional high-flow years across the

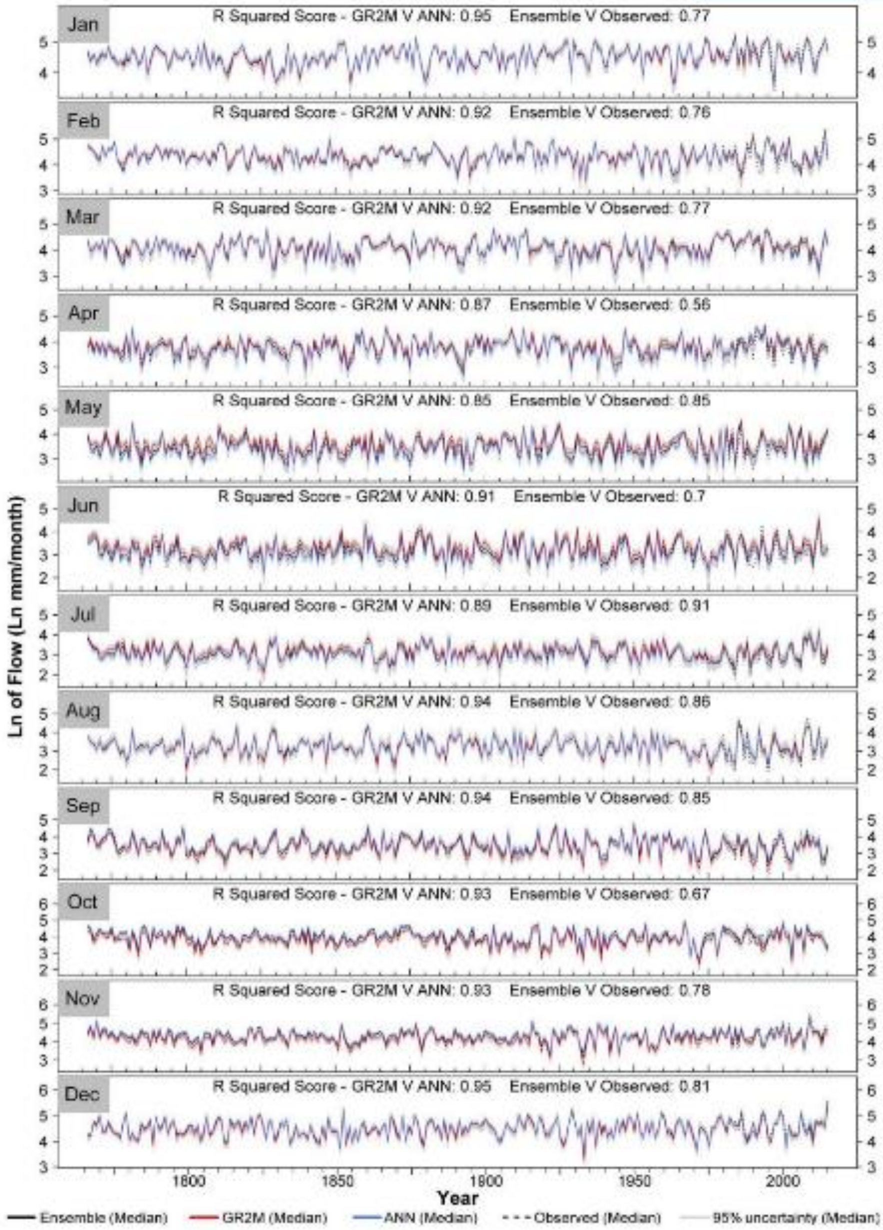


FIGURE 10 As in Figure 8 but for monthly median flows

sample include 1877, 1872 and 1916, whilst the most notable winter seasons include 2015/16, 1994/95 and 2013/14. In terms of exceptional low-flow years, 1855, 1933 and 1971 standout across the catchments, whereas 1826, 1975 and 1887 dominate the most notable low-flow years for summer. Annual flow anomalies across all 51 catchments range from 150% to 58% of the long-term mean for all catchments, whilst seasonally winter and summer extreme anomalies range from 173% to 37% of the respective long-term seasonal mean values. Our extreme years and seasons show considerable agreement with a similar evaluation of reconstructed river flows (1865–2002) in the United Kingdom (Jones *et al.*, 2006), with the previously identified exceptional high- and low-flow seasons and years (1865–2002) all found at least once in the top five equivalent events for multiple catchments in that series.

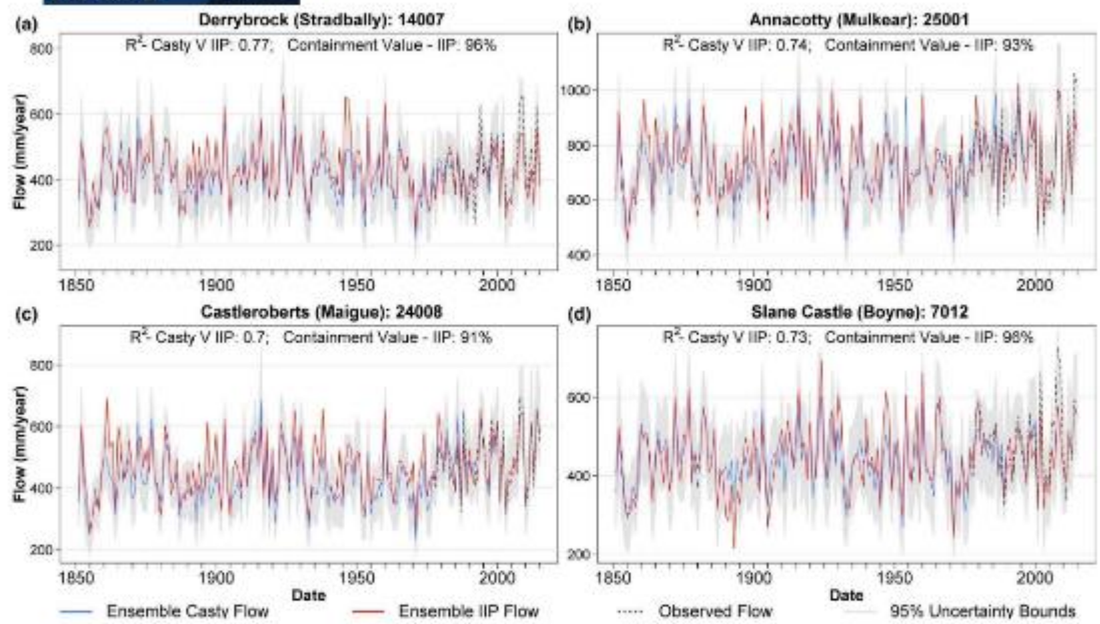


FIGURE 11 Reconstructed annual mean flow values for four sample catchments. Ensemble median simulations generated using Casty precipitation data (blue), and Island of Ireland Precipitation (IIP) data (red), together with observed flows (dashed dark-grey) are displayed for each catchment

4 | DATA SET ACCESS, USES AND LIMITATIONS

The derived monthly flow reconstructions (December 1766 to November 2016 inclusive) for the 51 catchments are freely available for download from the PANGAEA data centre (https://doi.org/10.1594/PANGAEA.914306). Data are presented as five individual tab-delimited text files (ASCII), representing reconstructions for each catchment from the GR2M, ANN and Ensemble median simulations, along with 2.5% and 97.5% quantiles derived from the Ensemble simulation. Also included is a table providing the geographical co-ordinates of all 51 flow stations.

4.1 | Potential uses

The reconstructed flow series provide a resource for assessing the impacts of extreme meteorological events, such as drought, on river flows across Ireland, extending the work of Noone *et al.* (2017) and Noone and Murphy (2020). Our reconstructions could also inform spatio-temporal assessments of variability plus support detection of multi-centennial changes in river flows (e.g. Wilby, 2006). Furthermore, the multi-centennial time scale of our reconstructions offers the potential to examine how modes of ocean and climate variability influence river flows over extended periods. For example, it is known that Atlantic multidecadal variability exerts an important control on Ireland's climate (McCarthy *et al.*, 2015), but its impact on river flows is less clear. Our long-term data set offers the means to explore any potential control, including its stationarity. In turn, this could help facilitate improved seasonal forecasting (e.g. Wedgbrow *et al.*, 2002).

This work represents the first reconstruction of monthly flows for a large number of Irish catchments using long-term reanalysis data and observations. Given the uncertainties involved, this data set should be treated as a benchmark and evaluated and improved by future products. The approach to flow reconstruction adopted here is easily transferable to other catchments in Europe (i.e. the domain of Casty data). By taking advantage of observed runoff data, available from the Global Runoff Data Centre (https://www.bafg.de/GRDC/EN/Home/homepage_node.html), it would be possible to generate similar archives of monthly flow reconstructions for the entire continent.

4.2 | Limitations

There are several recognized limitations to reconstructed river flows. First, arterial drainage has had a pervasive impact on Irish rivers. Catchments in this data set that have been drained tend to have higher peak flows during winter months than captured by the reconstructions. This is consistent with the findings of Harrigan *et al.* (2014) for the

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TABLE 2 Years with the five highest and lowest annual (calendar), winter [DJF] (year given for January) and summer [JJA] flows for the period of reconstructions 1767–2016 across all 51 catchments

Station (ID)	Top 5 High Flow Years										Top 5 Low Flow Years									
	Annual					Winter (December to February)					Annual					Summer (June to August)				
	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
3051	2015	2002	1877	1954	2009	2016	1995	1994	2014	1937	1933	1826	1855	1953	1971	1826	1975	1983	1800	1870
	150%	145%	144%	138%	137%	193%	172%	166%	161%	159%	59%	62%	62%	65%	65%	33%	33%	35%	37%	39%
6013	1877	1966	2002	1782	1872	2016	1877	1994	1883	1915	1953	1971	1933	1975	1855	1975	1826	1887	1995	1870
	154%	150%	146%	141%	138%	170%	158%	154%	151%	151%	53%	57%	62%	63%	64%	30%	32%	38%	39%	42%
6014	2002	1877	1966	1782	1872	2016	1877	1883	1994	1915	1953	1971	1855	1933	1826	1975	1826	1995	1887	1870
	160%	152%	146%	138%	136%	174%	153%	151%	151%	148%	55%	57%	63%	63%	64%	35%	36%	43%	44%	47%
6030	2002	1877	2015	1782	1872	2016	2013	1994	1877	1990	1933	1826	1953	1887	1911	1995	1800	1826	1949	1983
	173%	142%	141%	137%	137%	201%	173%	163%	161%	158%	61%	64%	65%	67%	69%	24%	28%	28%	31%	31%
7009	1877	1924	1782	1872	1960	2016	2014	1877	1995	1994	1971	1953	1855	1933	1826	1975	1826	1995	1887	1870
	142%	137%	135%	135%	133%	173%	151%	147%	146%	145%	57%	61%	66%	67%	68%	36%	38%	42%	44%	45%
7012	1877	1924	1782	1872	1965	2016	1877	2014	1937	1995	1971	1953	1855	1933	1826	1975	1826	1887	1995	1870
	152%	141%	140%	138%	138%	180%	164%	163%	161%	158%	56%	60%	64%	64%	65%	32%	34%	41%	41%	43%
12001	1960	1930	1872	1924	2009	2016	1877	1995	1994	1930	1971	1953	1905	1788	1855	1975	1826	1995	1887	1984
	158%	150%	148%	146%	145%	192%	177%	177%	170%	169%	55%	62%	64%	66%	66%	37%	38%	42%	44%	44%
14007	1924	1877	1872	1960	1903	1915	2014	1995	2016	1883	1971	1953	1855	1788	1933	1975	1826	1995	1887	1870
	155%	145%	144%	143%	141%	171%	169%	168%	165%	160%	53%	62%	64%	66%	67%	38%	40%	43%	45%	47%
14019	1924	1960	2008	1877	1872	2014	2016	1995	1915	1994	1971	1953	1855	1905	1933	1975	1826	1995	1887	1870
	149%	144%	142%	141%	140%	175%	173%	170%	165%	162%	57%	65%	67%	69%	70%	43%	46%	47%	52%	53%
15001	1877	1872	1924	1928	1903	1930	1995	1877	1915	1937	1971	1953	1855	1788	1826	1826	1975	1984	1870	1887
	160%	155%	153%	152%	151%	193%	192%	190%	190%	184%	51%	54%	59%	60%	64%	32%	33%	35%	36%	36%
15003	1924	2009	1872	1877	1916	2014	1995	1915	2016	1937	1971	1953	1788	1855	1933	1826	1975	1870	1887	1995
	150%	148%	147%	147%	147%	179%	177%	173%	164%	162%	50%	57%	61%	64%	64%	24%	24%	27%	28%	28%
15005	1877	1872	1903	1916	1924	1930	1915	1937	2016	1877	1953	1971	1855	1788	1933	1826	1984	1887	1975	1870
	152%	145%	142%	142%	141%	180%	175%	174%	174%	171%	57%	61%	62%	67%	67%	39%	40%	43%	43%	46%
15006	1877	1872	1924	1928	1903	1915	1995	2016	1930	1877	1971	1953	1855	1788	1933	1826	1975	1984	1887	1870
	152%	146%	145%	144%	143%	178%	178%	176%	174%	172%	57%	60%	65%	66%	68%	39%	41%	42%	44%	45%
15007	1872	1877	1954	1903	1924	2016	1995	1937	2014	1915	1971	1953	1855	1933	1826	1826	1984	1800	1870	1975
	142%	142%	141%	140%	140%	177%	173%	172%	172%	168%	57%	58%	59%	61%	65%	37%	39%	43%	43%	44%

(Continues)

TABLE 2 (Continued)

Station (ID)	Top 5 High Flow Years: Annual 1	2	3	4	5	Winter (December to February) 1	2	3	4	5	Top 5 Low Flow Years: Annual 1	2	3	4	5	Summer (June to August) 1	2	3	4	5
16008	1877	1872	1903	1923	1954	2016	1937	1995	1877	2014	1953	1855	1971	1933	1826	1984	1826	1870	1887	1975
	144%	143%	140%	139%	139%	180%	168%	167%	161%	161%	58%	59%	60%	65%	67%	38%	40%	44%	47%	48%
16009	1877	2009	1872	1903	1916	2016	1995	1937	1915	2014	1855	1971	1953	1933	1826	1826	1984	1870	1975	1887
	147%	144%	143%	143%	142%	189%	184%	175%	172%	170%	60%	61%	62%	66%	68%	45%	45%	51%	51%	52%
16010	2009	1877	1928	1903	1916	1930	2016	1915	1995	1994	1855	1971	1788	1953	1893	1826	1984	1870	1975	1887
	153%	152%	152%	148%	145%	189%	189%	187%	181%	179%	61%	64%	66%	67%	68%	44%	47%	50%	50%	51%
16011	1877	1903	2009	1928	1872	2016	1995	1915	1994	1937	1971	1855	1953	1933	1788	1826	1984	1975	1870	1887
	143%	141%	141%	140%	139%	185%	181%	172%	168%	167%	64%	65%	67%	69%	71%	51%	52%	56%	57%	57%
16012	1928	2009	1877	1903	1960	1995	2016	1915	1930	1925	1855	1971	1826	1933	1887	1826	1984	1887	1975	1870
	143%	141%	140%	138%	138%	188%	187%	170%	169%	168%	65%	66%	70%	71%	72%	47%	50%	53%	53%	56%
16013	1928	2009	1938	1903	1960	1930	1995	2016	1915	1994	1971	1933	1855	1788	1887	1826	1984	1870	1800	1887
	152%	148%	147%	145%	145%	196%	185%	185%	184%	182%	63%	66%	67%	68%	69%	38%	40%	43%	45%	46%
18002	1916	2009	1877	2000	1872	2016	2014	1995	1915	1994	1971	1855	1933	1788	1826	1826	1984	1887	1975	1870
	151%	142%	140%	139%	135%	209%	188%	184%	163%	162%	56%	61%	69%	70%	71%	44%	45%	50%	50%	51%
18003	1916	2009	2000	1877	1994	2016	2014	1995	1915	1994	1971	1855	1788	1826	1921	1984	1826	1887	1975	1870
	150%	143%	141%	138%	138%	215%	199%	189%	170%	167%	54%	61%	67%	69%	69%	38%	39%	45%	45%	47%
18006	1916	2009	2000	1994	2002	2016	2014	1995	1915	1994	1971	1855	1826	1933	1788	1984	1826	1887	1975	1800
	145%	144%	141%	140%	139%	217%	205%	191%	177%	173%	58%	62%	68%	69%	70%	42%	43%	47%	47%	48%
18050	2009	2002	2008	2000	1872	2016	2014	1995	1915	1994	1971	1855	1788	1826	1921	1826	1984	1800	1975	1944
	142%	139%	139%	138%	137%	203%	200%	185%	179%	172%	58%	62%	69%	69%	70%	40%	41%	42%	43%	44%
19001	2009	1982	1928	2000	1872	2016	1995	2014	1915	1994	1971	1855	1788	1933	1854	1984	1826	1887	1870	1975
	159%	153%	151%	150%	149%	233%	211%	203%	188%	187%	48%	57%	63%	63%	65%	37%	38%	40%	41%	42%
21002	2009	1982	1872	1914	1916	2016	1995	1915	2014	1994	1971	1855	1955	1788	1887	1800	1976	1955	1975	1864
	142%	136%	134%	134%	134%	203%	178%	168%	167%	164%	60%	70%	71%	72%	72%	33%	39%	42%	42%	46%
22006	1916	1872	1982	2000	2002	2016	2014	1995	1915	1994	1971	1855	1933	1788	1921	1800	1976	1975	1984	2006
	137%	135%	135%	135%	135%	199%	187%	183%	175%	169%	62%	66%	69%	71%	72%	45%	47%	51%	54%	54%
22035	2000	1872	1916	1982	1994	2016	2014	1995	1915	1994	1971	1855	1933	1788	1921	1800	1975	1984	1826	1976
	137%	136%	135%	135%	131%	202%	182%	176%	168%	163%	62%	67%	72%	73%	73%	51%	53%	56%	57%	58%
23002	2008	2015	1986	1916	1872	2014	2016	1995	1915	1994	1971	1855	1788	1826	1921	1800	1984	1826	1975	1976

TABLE 2 (Continued)

Station (ID)	Top 5 High Flow Years – Annual 1	2	3	4	5	Winter (December to February) 1	2	3	4	5	Top 5 Low Flow Years – Annual 1	2	3	4	5	Summer (June to August) 1	2	3	4	5
	157%	145%	141%	140%	138%	215%	205%	195%	187%	177%	56%	61%	68%	68%	68%	35%	38%	39%	39%	39%
24008	1916	2014	2009	1986	2008	2016	2014	1995	1994	1915	1971	1855	1933	1788	1826	1984	1826	1975	1887	1870
	160%	154%	151%	148%	148%	228%	224%	212%	180%	176%	53%	58%	63%	66%	66%	37%	38%	42%	43%	45%
24030	1916	1986	1994	2000	2008	2014	2016	1995	1994	1915	1971	1855	1826	1933	1921	1984	1826	1887	1870	1975
	156%	153%	151%	151%	150%	228%	226%	213%	189%	188%	51%	56%	64%	64%	65%	35%	36%	42%	44%	44%
25001	1916	2008	1986	1954	1877	1995	2016	2014	1937	1994	1855	1933	1971	1953	1826	1984	1826	1800	1870	2006
	141%	140%	138%	137%	136%	185%	180%	177%	163%	161%	63%	63%	63%	67%	69%	42%	44%	47%	48%	50%
25002	2008	1872	1877	1994	1916	1995	2016	2014	1994	1937	1971	1933	1855	1953	1826	1984	1826	1800	1870	2006
	141%	138%	137%	135%	134%	186%	167%	164%	163%	162%	62%	64%	65%	67%	68%	30%	34%	38%	39%	41%
25006	2014	1877	1872	1924	1954	2016	2014	1937	1995	1877	1971	1855	1933	1953	1826	1826	1975	1984	1995	1887
	144%	143%	140%	140%	138%	194%	181%	179%	168%	163%	59%	66%	66%	67%	68%	44%	46%	47%	50%	51%
25030	2015	1986	2014	2009	1994	2016	2014	1995	1994	1937	1855	1933	1971	2003	1826	1984	1826	1800	2006	1870
	157%	145%	144%	140%	139%	219%	210%	201%	177%	162%	59%	63%	63%	63%	66%	39%	40%	41%	42%	46%
25034	2014	1872	1924	1960	1877	2016	2014	1995	1915	1937	1971	1855	2003	1826	1933	1975	1826	1995	1887	1870
	145%	140%	140%	140%	139%	190%	165%	158%	154%	152%	54%	66%	67%	68%	68%	30%	33%	35%	40%	41%
26021	2015	1924	2014	1877	2002	2016	2014	1937	2007	1995	1971	1855	1933	1826	1805	1975	1826	1984	1887	1995
	141%	139%	139%	138%	135%	196%	163%	159%	153%	148%	58%	65%	65%	67%	70%	35%	37%	42%	44%	45%
26029	2015	1986	2002	1992	1877	2016	2014	1995	1937	1994	1933	1855	2001	1826	1805	1800	1826	1984	1821	1983
	144%	138%	134%	133%	131%	183%	173%	164%	154%	152%	64%	65%	65%	69%	73%	30%	34%	34%	35%	37%
26058	2002	1877	1924	2015	2014	2016	2014	1937	2007	1995	1971	1855	1933	1826	1805	1975	1826	1887	1995	1984
	143%	140%	139%	138%	136%	195%	166%	153%	144%	143%	58%	62%	62%	65%	68%	33%	34%	42%	43%	44%
27002	2009	2015	2008	1872	1986	2016	2014	1995	1994	1915	1855	1971	1933	1921	1826	1984	1826	1975	1800	1887
	160%	150%	148%	139%	139%	221%	199%	192%	168%	165%	57%	58%	63%	64%	66%	33%	34%	39%	40%	41%
30007	2015	1986	1950	1954	2002	2016	2014	1995	1937	1994	1855	1933	1826	1805	1921	1826	1984	1887	1870	1978
	154%	148%	140%	140%	138%	197%	169%	165%	164%	153%	58%	62%	65%	68%	68%	38%	39%	46%	49%	49%
32012	2015	1986	2008	1949	2011	2016	2014	1995	1994	1937	1855	1933	1826	1805	1971	1800	1826	1984	1983	1976
	147%	142%	137%	130%	130%	180%	178%	165%	154%	151%	64%	65%	71%	73%	73%	42%	46%	48%	50%	52%
33001	2015	1986	2008	1992	1949	2014	2016	1995	1994	2000	1855	1933	1826	1805	1971	1800	1983	1995	1984	1968
	149%	141%	131%	128%	127%	185%	177%	166%	151%	147%	65%	66%	74%	76%	76%	34%	35%	44%	45%	46%

(Continues)

TABLE 2 (Continued)

Station (ID)	Top 5 High Flow Years: Annual 1	2	3	4	5	Winter (December to February) 1	2	3	4	5	Top 5 Low Flow Years: Annual 1	2	3	4	5	Summer (June to August) 1	2	3	4	5
34001	2015	1986	1950	2008	1877	2016	2014	1995	1937	1950	1855	1933	1805	1826	2003	1826	1984	1975	1800	1887
	143%	141%	138%	138%	136%	185%	175%	159%	156%	149%	60%	63%	68%	69%	70%	41%	45%	49%	51%	51%
35002	2015	2008	2002	1986	1949	2016	2014	1995	2015	1994	1855	1933	1805	1826	1921	1800	1826	1995	1983	1984
	150%	146%	145%	136%	132%	187%	181%	167%	156%	154%	63%	64%	70%	70%	75%	40%	43%	43%	47%	47%
35005	2015	2002	2008	1986	1950	2016	2014	1937	1995	2015	1855	1933	1805	1826	1921	1826	1984	1800	1995	1975
	149%	144%	143%	140%	137%	190%	186%	164%	163%	153%	62%	63%	66%	66%	69%	38%	42%	46%	46%	47%
36015	1877	1954	1998	2002	1782	1995	2016	1937	1994	1877	1933	1826	1855	1971	1921	1975	1826	1983	1800	1870
	146%	145%	142%	141%	138%	169%	164%	158%	157%	153%	57%	60%	60%	63%	65%	27%	28%	31%	32%	33%
36019	2002	1877	2015	1954	1998	2016	2014	1937	1995	2007	1971	1933	1826	1855	1953	1826	1975	1984	1870	1887
	155%	146%	141%	139%	138%	179%	166%	158%	154%	153%	58%	59%	61%	61%	65%	24%	24%	31%	33%	34%
38001	2015	1949	2011	1992	1986	1995	2014	2016	1994	2015	1933	1855	1805	1826	1864	1800	1821	1995	1983	1984
	145%	139%	136%	132%	131%	183%	180%	165%	162%	160%	63%	64%	69%	70%	75%	29%	37%	37%	40%	40%
39006	2015	1990	1949	1992	1999	2016	1995	2015	2014	1994	1855	1933	1826	1805	1911	1800	1995	1983	1824	1984
	167%	141%	138%	138%	137%	189%	185%	179%	176%	173%	60%	63%	66%	67%	70%	34%	34%	36%	37%	38%
39009	2015	1949	1990	1992	1999	2016	1995	2015	2014	1994	1855	1933	1805	1826	1911	1800	1983	1995	1984	1824
	165%	140%	140%	138%	138%	186%	184%	177%	175%	173%	60%	62%	67%	67%	71%	32%	34%	34%	35%	36%

Note: The percentage anomaly relative to the long-term mean (1767–2016) is provided in each case. Values highlighted in progressively darker blue represent the top three occurring high flow events, whilst those in red represent the top three occurring low-flow events.

Boyne catchment. Hence, our reconstructions may be useful for quantifying the impact of arterial drainage on flow response. Moreover, we note that there is limited knowledge about how arterial drainage affects low-flow and drought responses—again, our reconstructions may provide a useful point of reference.

Changes in land use can have considerable impacts on flows over time (Yan *et al.*, 2013). Lack of metadata on historical land-use change hinders the quantification of such impacts. Moreover, Slater *et al.* (2019) highlight that rivers are treated as conduits of fixed conveyance by models even though changes in channel geometry and structure are known to occur in response to periods of hydro-climatic variability. Here, we assume that land-use and channel geomorphology remain static over the period of reconstruction; a common assumption attached to long-term flow reconstructions. Jones (1984) asserts that such assumptions can be justified. Water resource infrastructure designs are based on flows relating to current land use as opposed to historical conditions, suggesting that catchment response tuned to present conditions are a useful resource.

Second, potential biases or inaccuracies in precipitation data could propagate into the reconstructed flow series. The gridded Casty data set employed in this study was generated using both reanalysis and observed precipitation values, with principle component regression to interpolate across space. Interpolation of station data is more uncertain before the 1900s as the number of stations decreases rapidly prior to this time. Casty *et al.* (2005) highlight that European wide precipitation patterns in the early part of their series should be treated with caution, especially before 1800 when station numbers are low. For Ireland, we believe that data prior to 1850 should be treated with caution due to the sparseness of observed precipitation records on the island. A further source of uncertainty relates to the quality of early precipitation observations. Murphy *et al.* (2019) show that pre-1870 winter precipitation observations in the United Kingdom were likely affected by under-catch of snowfall due to gauge design and observer practice. It is likely that early Irish precipitation totals are affected by the same biases during winter months (Murphy *et al.*, 2020).

Third, the sensitivity of hydrological model parameters to prevailing climatic conditions during the calibration period can result in uncertainties when models are used to simulate conditions different to those used for training. Broderick *et al.* (2016) showed that changes in climatic conditions can affect model performance depending on catchment, model type and assessment criteria. A shift from relatively wet to dry conditions resulted in poorer results. Future work should assess the robustness of monthly reconstructions to the wetness or dryness of periods used for training.

5 | SUMMARY

This paper presents a data set of monthly river flow reconstructions back to 1766 for 51 Irish catchments. Gridded reconstructions of monthly precipitation and temperature, bias corrected to observed catchment data sets, are used with derived PET to force a conceptual hydrological model and an Artificial Neural Network to generate monthly flows spanning more than 250 years. Reconstructed flows are subject to uncertainties associated with hydrological response to arterial drainage and land-use change, together with potential biases in early precipitation observations and non-stationary hydrological model parameters. With these caveats in mind, the data set is suitable for examining hydrological responses to arterial drainage, tracking hydrological variability and change, or testing the robustness of water plans and/or contextualizing modern hydrological droughts.

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OPEN PRACTICES

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RESEARCH ARTICLE

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Historical droughts in Irish catchments 1767–2016

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Abstract

Recent prolonged dry periods in summer 2018 and spring 2020 have reawakened interest in drought in Ireland, prompting questions regarding historical drought occurrence and potential long-term risks. Employing 250 years of monthly precipitation and flow reconstructions, we investigate historical drought in Irish catchments evaluating the characteristics (number of events, duration, and deficits) of moderate, severe, and extreme droughts as well as the propagation of meteorological to hydrological drought. Using standardized indices, we identify three distinct catchment types. Cluster 1 catchments, located in the wetter northwest are characterized by small areas, low groundwater storage, and the highest frequency of hydrological drought relative to other catchments. Cluster 3 catchments, located in the drier east and southeast have larger areas, greater groundwater storage, the highest frequency of meteorological drought but the least hydrological droughts. However, once established, droughts in Cluster 3 tend to be more persistent with large accumulated deficits. Cluster 2 catchments, located in the southwest and west, are intermediate to Clusters 1 and 3, with hydrological droughts typically of shorter durations, reduced accumulated deficits but greater mean deficits. The most extreme droughts based on accumulated deficits across all catchments occurred in 1803–1806, 1854–1859, 1933–1935, 1944–1945, 1953–1954, and 1975–1977. Although not as severe, droughts in 1887–1888, 1891–1894, and 1971–1974 also appear as significant extremes. Changes in drought characteristics reveal a complex picture with the direction, magnitude, and significance of trends dependent on the accumulation period used to define drought, the period of record analysed, and the reference period used to standardize indices. Of particular note is a tendency towards shorter, more intense meteorological and hydrological droughts. Our findings offer important insight for drought and water management in Ireland given the paucity of extreme droughts in short observed river flow records.

KEYWORDS
drought analysis, drought propagation, hydrological drought, Ireland, meteorological drought, reconstruction

1 | INTRODUCTION

Drought is a complex hazard (Van Loon *et al.*, 2016), typically characterized by the component of the hydrological cycle affected (e.g., atmosphere [meteorological], soil moisture [agricultural], or river flows [hydrological] droughts) (Haile *et al.*, 2020). Impacts can unfold slowly, with propagation of meteorological to hydrological drought dependent on controls governing catchment response, including land cover, geology, and rainfall–runoff relationships (Lorenzo-Lacruz *et al.*, 2013; Wong *et al.*, 2013; Barker *et al.*, 2016; Huang *et al.*, 2017; Guo *et al.*, 2020). Recently, there has been greater attention to evaluating historical droughts, facilitated by increased information availability from data rescue efforts (Noone *et al.*, 2017; Tanguy *et al.*, 2021); use of extreme droughts for stress testing models of water supply systems (Wilby and Murphy, 2019; Murphy *et al.*, 2020b); interest in placing recent extremes in a long-term context (Lhotka *et al.*, 2020; Moravec *et al.*, 2021); and evaluations of variability and change in drought occurrence and characteristics (Hanel *et al.*, 2018; Vicente-Serrano *et al.*, 2021a).

Although most work has focused on meteorological drought, increasingly researchers are using long-term precipitation and temperature records to study hydrological droughts for periods before systematic river flow measurements. For example, Caillouet *et al.* (2017) reconstructed 140 years (1871–2011) of river flow for 600 French catchments. This information was then screened for hydrological droughts using a threshold level approach, and uncovered well known European droughts of 1921, 1945, 1949, 1954, 1976, and 1989–1990 events, as well as less well-known events in 1878 and 1893. Multicentennial reconstructions have been produced elsewhere in Europe (Hanel *et al.*, 2018; Moravec *et al.*, 2019; Erfurt *et al.*, 2020) and assessed for drought occurrence using hydrological drought indicators. An overarching theme of these studies is that, despite variations in temporal and spatial extents, extreme hydrological droughts have been a regular feature in long-term reconstructions for mainland Europe.

Trends in meteorological drought across Europe have been extensively investigated (e.g., Gudmundsson and Seneviratne, 2015; Stagge *et al.*, 2017; Hänsel *et al.*, 2019; Oikonomou *et al.*, 2020; Vicente-Serrano *et al.*, 2021a). However, research into hydrological drought trends are less common (Sutanto and Van Lanen, 2020) because long records are not as readily available for observed river flow as for meteorological variables (Mediero *et al.*, 2015). Across Europe, trends in low flows have been found to vary considerably between regions with a general lack of clear patterns (Stahl *et al.*, 2010; Van Loon, 2015). Such inconsistencies are the result of changing temporal characteristics of precipitation deficits which impact directly on low flows and result in spatio-temporal variability in hydrological drought intensities (Hanel *et al.*, 2018).

Historical droughts in UK catchments have also been the subject of much research (e.g., Jones and Lister, 1998; Jones *et al.*, 2006; Spraggs *et al.*, 2015; Wilby *et al.*, 2015; Parry *et al.*, 2016). For instance, Rudd *et al.* (2017) assessed hydrological drought over the period 1891–2015 and found that, while there was considerable spatial and temporal variability between individual events, few changes in drought characteristics were identifiable. More recently, Barker *et al.* (2019) assessed hydrological drought occurrence in 108 UK catchments for the same period and found regionally distinctive drought characteristics. Significant drought episodes included 1890–1910, 1921–1922, 1933–1934, in the 1940s, and early 1970s prior to the notable 1975–1976 event. Overall, evidence of trends in hydrological drought occurrence and severity in the UK is limited (Hannaford, 2015).

Research in Ireland has focused on historical meteorological drought (e.g., Wilby *et al.*, 2016; Noone *et al.*, 2017; Murphy *et al.*, 2018; 2020a), with relatively little attention to long-term hydrological drought. One exception is Noone and Murphy (2020) who used rescued and transcribed monthly precipitation data (Noone *et al.*, 2017) to reconstruct river flows in 12 catchments during the period 1850–2015. Drought events were identified using the low flow Q95 threshold, with major episodes in 1887–1888, 1891–1894, 1902–1912, 1933–1934, 1944, 1953, and 1971–1976. Murphy *et al.* (2013) investigated trends in observed river flows for 43 catchments. However, they found that the short records hindered robust assessment, highlighting the value of reconstruction techniques for understanding multidecadal (or even multicentennial) variability and change in river flows.

Recently, O'Connor *et al.* (2021) produced monthly reconstructions of river flow for 51 catchments in Ireland. We employ these reconstructions to assess historical meteorological and hydrological drought by fitting standardized indices to precipitation series and reconstructed river flows spanning the period 1767–2016. As well as identifying major drought events, we evaluate changes in drought characteristics (severity, duration, maximum intensity, accumulated and mean deficits) and investigate regional controls on drought propagation. This is the first assessment of multicentennial drought properties for Ireland—a place where drought has been popularly overlooked as a recurrent threat to water security and the wider socio-economy.

The remainder of the paper is structured as follows: section 2 describes the catchments, datasets and methods employed. Section 3 presents the results, with details

TABLE 1 Details of the 51 study catchments

River flow station ID	Station name	Waterbody name	Cluster No.	SPI-1 vs. SSI-1	SPI-3 vs. SSI-1	SPI-6 vs. SSI-1	SPI-12 vs. SSI-1	SAAR (mm)	BFIsoil (index)	Area (km^2)
21002	Coomhola	Coomhola	2	0.98	0.65	0.46	0.32	2,158	0.37	65
38001	Clonconwal	Ownea	1	0.97	0.68	0.48	0.34	1795	0.28	111
22006	Flesk	Flesk (Laune)	2	0.96	0.71	0.51	0.35	1741	0.39	329
26029	Dowra	Shannon	1	0.96	0.69	0.48	0.34	1,546	0.46	117
33001	Glenamoy	Glenamoy	1	0.95	0.68	0.47	0.33	1,509	0.29	76
35002	Billa Bridge	Owenbeg	1	0.95	0.73	0.53	0.38	1,458	0.42	81
22035	Laune Bridge	Laune	2	0.94	0.75	0.55	0.38	1858	0.64	560
23002	Listowel	Feale	2	0.94	0.74	0.53	0.37	1,388	0.31	647
3051	Faulkland	Blackwater (Mon)	1	0.93	0.76	0.57	0.41	1,049	0.42	143
18050	Duarrigle	Blackwater	2	0.93	0.75	0.53	0.36	1,511	0.41	250
32012	Newport Weir	Newport	1	0.93	0.76	0.55	0.39	1,652	0.59	146
6030	Ballygoly	Big	1	0.92	0.75	0.54	0.38	1,106	0.45	10
39006	Lennan	Claragh	1	0.92	0.76	0.54	0.38	1,435	0.44	245
39009	Aghawoney	Fern O/L	1	0.92	0.76	0.55	0.39	1,485	0.4	207
18006	Cset Mallow	Blackwater	2	0.91	0.77	0.56	0.38	1,311	0.5	1,055
15003	Dinin Bridge	Dinin	3	0.90	0.76	0.56	0.39	992	0.38	299
16013	Fourmilewater	Nire	3	0.90	0.78	0.57	0.39	1,303	0.54	94
25002	Barrington S Br.	Newport (Mun)	2	0.90	0.77	0.56	0.38	1,229	0.54	222
25030	Scarriff	Graney	2	0.90	0.78	0.57	0.40	1,183	0.54	280
36015	Anlore	Finn	1	0.90	0.77	0.58	0.41	1,009	0.42	154
25001	Annacotty	Mulkear	2	0.89	0.78	0.58	0.39	1,138	0.52	648
15007	Kilbricken	Nore	3	0.88	0.81	0.60	0.42	1,078	0.59	340
18003	Killavullen	Blackwater	2	0.87	0.81	0.61	0.42	1,287	0.46	1,257
24030	Danganbeg	Deel	2	0.87	0.80	0.60	0.41	1,013	0.53	259
35005	Ballysadare	Ballysadare	1	0.87	0.81	0.61	0.43	1,212	0.61	640
16012	Tar Bridge	Tar	3	0.84	0.85	0.67	0.48	1,222	0.63	230
18002	Ballyduff	Blackwater	2	0.84	0.83	0.63	0.44	1,213	0.62	2,334
30007	Ballygaddy	Clare	1	0.84	0.84	0.65	0.45	1,097	0.65	470
16011	Clonmel	Suir	3	0.83	0.84	0.65	0.45	1,072	0.67	2,144
27002	Ballycorey	Fergus	2	0.83	0.84	0.64	0.44	1,262	0.7	511
12001	Scarrawalsh	Slaney	3	0.82	0.86	0.67	0.47	1,068	0.72	1,031
14007	Derrybrock	Stradbally	3	0.82	0.84	0.67	0.47	869	0.64	95
15001	Annamult	Kings	3	0.82	0.83	0.63	0.43	955	0.51	444
15006	Brownsbarn	Nore	3	0.82	0.83	0.64	0.45	950	0.63	2,418
16008	New Bridge	Suir	3	0.82	0.84	0.65	0.44	1,002	0.64	1,090
16009	Caher Park	Suir	3	0.82	0.85	0.65	0.45	1,047	0.63	1,583
19001	Ballea	Owenboy	2	0.82	0.84	0.65	0.45	1,199	0.68	103
6014	Tallanstown	Glyde	3	0.81	0.85	0.67	0.48	913	0.63	270
14019	Levitstown	Barrow	3	0.81	0.85	0.67	0.47	839	0.62	1,697

(Continues)

TABLE 1 (Continued)

River flow station ID	Station name	Waterbody name	Cluster No.	SPI-1 vs. SSI-1	SPI-3 vs. SSI-1	SPI-6 vs. SSI-1	SPI-12 vs. SSI-1	SAAR (mm)	BFIsoil (index)	Area (km^2)
24008	Castleroberts	Maigue	2	0.81	0.84	0.64	0.45	948	0.54	806
34001	Rahans	Moy	1	0.81	0.86	0.65	0.45	1,290	0.78	1975
6013	Charleville	Dee	3	0.80	0.84	0.67	0.48	880	0.62	309
25034	Rochfort	L. Ennell Trib	3	0.80	0.85	0.68	0.47	958	0.76	11
26058	Ballyrink Br.	Inny Upper	3	0.80	0.87	0.68	0.49	971	0.77	60
7012	Slane Castle	Boyne	3	0.79	0.85	0.68	0.48	888	0.68	2,408
16010	Anner	Anner	3	0.79	0.86	0.69	0.48	961	0.62	437
25006	Ferbane	Brosna	3	0.78	0.86	0.68	0.47	898	0.71	1,163
7009	Navan Weir	Boyne	3	0.77	0.85	0.68	0.48	869	0.71	1,684
15005	Durrow Ft. Br.	Erkina	3	0.75	0.86	0.69	0.48	889	0.71	379
36019	Belturbet	Erne	3	0.74	0.86	0.67	0.47	991	0.79	1,492
26021	Ballymahon	Inny	3	0.73	0.87	0.71	0.50	942	0.83	1,099

Note: The cluster number, Pearson correlation value between SSI-1 and SPI-1, 3, 6, and 12 month accumulation values, standard period average annual rainfall (SAAR) value, base flow index (BFIsoil) and area (km^2) are displayed. Rows are ordered by correlation scores between SPI-1 and SSI-1 from highest (blue) to lowest (red) allowing correlation scores at higher SPI accumulations, SAAR, BFI and area values to be compared. All correlation values are significant ($p \leq .05$).

about the characteristics of historical droughts across catchments then an assessment of variability and change. Section 4 discusses the detected trends, study caveats, potential applications, and scope for further research. Finally, section 5 concludes with a summary of key findings.

2 | DATA AND METHODS

2.1 | Catchments and data

We evaluate historical droughts for 51 catchments across Ireland, employing reconstructed monthly precipitation and discharge estimates for each catchment for the period 1767–2016, derived by O'Connor *et al.* (2021). The choice of end year was determined by the availability of concurrent hydrological and meteorological data. The sample represents diverse hydrological conditions in Ireland, including catchments that have good quality data and limited evidence of disturbance/river regulation during the period of the observational record (Murphy *et al.*, 2013). Table 1 lists the catchments considered and Figure 1 shows their spatial distribution. Full details of the construction of the long-term precipitation and discharge series are provided by O'Connor *et al.* (2021). Briefly, monthly gridded ($0.5° \times 0.5°$) reconstructed precipitation and temperature datasets developed by Casty *et al.* (2007) were bias-corrected to observed catchment data, before being used to force a conceptual hydrological model and an Artificial Neural Network to reconstruct monthly river flows. We employ the ensemble median of the reconstructed discharge series for each of the 51 catchments assessed.

To aid interpretation, we employ hierarchical agglomerative clustering to identify a reduced subset of catchments following previous studies (e.g., Schmitt *et al.*, 2007; Berhanu *et al.*, 2015; Clubb *et al.*, 2019). Clustering was undertaken based on the Standardized Streamflow Index (SSI; see section 2.2) with Euclidean distance determining dissimilarities between catchments and Ward's (Ward Jr, 1963) linkage criterion used to identify clusters. Silhouette information (Rousseeuw, 1987), which interprets the consistency of clustered data, was also derived to confirm the optimum number of clusters. Median SPI and SSI series were extracted for catchments comprising each identified cluster.

Physical catchment descriptors (PCDs), derived by Mills *et al.* (2014), were compiled for each cluster grouping to determine the importance of catchment characteristics in modifying the occurrence and propagation of hydrological droughts. The PCDs were the standard period average annual rainfall, 1961–1990 (SAAR); baseflow index derived using catchment soil type (BFIsoil); Taylor-Schwartz measurement of mainstream slope

(TAYSLO); proportion of area covered by peat (PEAT); proportion of time soils are typically wet (FLATWET); and mainstream length in kilometres (MSL). These six PCDs were previously used by Broderick *et al.* (2019) to classify Irish catchments.

2.2 | Standardized drought indices

We derive the standardized precipitation index (SPI; McKee *et al.*, 1993) and standardized streamflow index (SSI; Vicente-Serrano *et al.*, 2012) for the 51 catchments and clusters for the period 1767–2016 using the "SCI" package in R (Gudmundsson and Stagge, 2016). Both SPI and SSI series were extracted for accumulation periods of 1, 3, 6, and 12 months. Two key decisions when applying standardized indices are (a) the statistical distribution and (b) the reference period for standardizing data. The effect of distribution has been previously investigated (Vicente-Serrano *et al.*, 2012; Bloomfield and Marchant, 2013; Soľáková *et al.*, 2014; Stagge *et al.*, 2015; Svensson *et al.*, 2017). We evaluate the performance of three distributions when deriving the SPI and SSI, namely the Gamma distribution, commonly used for

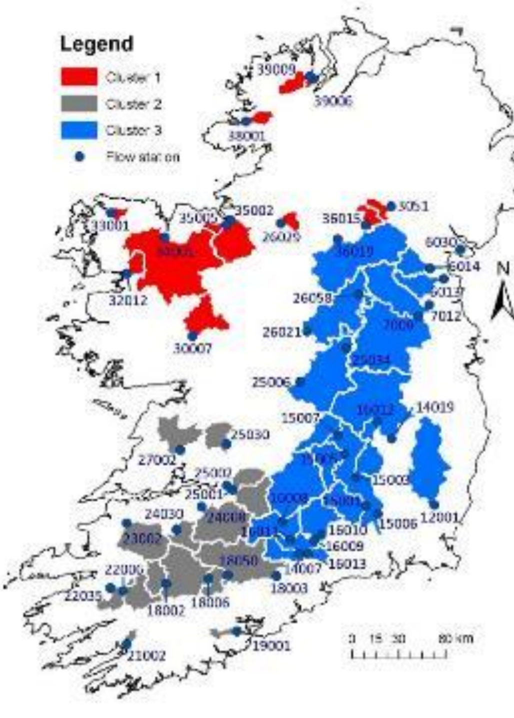

FIGURE 1 Catchment areas with flow station codes and cluster membership [Colour figure can be viewed at wileyonlinelibrary.com]

long-term precipitation series (Shiau, 2020); the Log-logistic distribution, which has been used in fitting precipitation and streamflow series (e.g., (Vicente-Serrano and Begueria, 2016); and the Tweedie distribution, which has been found to perform well for SSI (Svensson *et al.*, 2017) due to the ability to constrain the lower bound to zero (Tweedie, 1984).

Others have highlighted the importance of the reference period used to derive SPI for the detection of historical droughts (Núñez *et al.*, 2014; Paulo *et al.*, 2016; Um *et al.*, 2017). The selection of a representative benchmark is particularly important for Ireland given the influence of low-frequency ocean–atmosphere variability (Murphy *et al.*, 2013; McCarthy *et al.*, 2015). Here, the optimum reference period, which most closely matched average conditions, was specified by minimizing the mean of positive and negative SSI values for 1, 3, 6, and 12 month accumulations for different start years (1767–1990) and reference period durations (30–250 years). We found the reference period 1930–1999 to be optimum. Moreover, a 70-year window is consistent with the wavelength of the Atlantic Multidecadal Oscillation (AMO), which has been shown to modulate the frequency of drought across northwestern Europe (Sutton and Dong, 2012; Wilby *et al.*, 2015). To test the sensitivity of our results to the reference period, we considered three other periods: 1767–2016 (250 years), 1900–1999 (100 years), and 1981–2010 (30 years), with the latter as recommended by the World Meteorological Organisation (WMO, 2017).

We categorize drought severity for both SPI and SSI following McKee *et al.* (1993) with values of −1.00 to −1.49 representing moderate drought, −1.50 to −1.99 representing severe drought, and values ≤−2.00 representing extreme drought. We examine the occurrence of hydrological droughts across the 51 catchments over the period 1767–2016 by generating heatmaps for SSI accumulations over 3 (SSI-3), 6 (SSI-6), and 12 (SSI-12) months. For each drought category (i.e., moderate, severe, and extreme) and accumulation period we extract meteorological (SPI) and hydrological (SSI) drought indices. Individual droughts commence when the respective standardized index falls below the drought category's upper value and terminate when recovered to zero. Events are categorized as moderate, severe, or extreme according to the maximum deficit recorded. For each drought index, accumulation period, and severity category we derive the following statistics:

- Number of events: sum of drought event numbers.
- Duration: number of months from the start until the end of the drought event.
- Maximum intensity: minimum index value attained during the event.

- Accumulated deficit: sum of monthly deficits during the drought event.
- Mean deficit: accumulated deficit divided by duration.

For our assessment of *extreme* historical droughts we focus on event duration, accumulated deficit, and maximum intensity; for our analysis of *average* historical drought characteristics we investigate the number of events (total), drought durations (mean), accumulated deficits (mean), and mean deficits (mean) for each catchment cluster.

Trends in the number of events (per year), duration (months), and deficits (accumulated and mean) of moderate and severe droughts for both SSI and SPI at 1, 3, 6, and 12 month accumulations were assessed for all catchments and clusters using a modified version of the Mann–Kendall (MK) test (Yue and Wang, 2004) which employs variance correction to address serial correlation. Trends were evaluated at the 0.05 significance level with a MK Z statistic >1.96 indicating a significant positive trend and a score <-1.96 indicating a significant negative trend. Following Wilby (2006) and Murphy *et al.* (2013), the sensitivity of trends to the period of record was evaluated by considering different start and end dates with a minimum record length of 30 years.

Finally, we examine the propagation of meteorological to hydrological drought using a similar approach to Barker *et al.* (2016). We compute Pearson correlation coefficients between SSI-1 and SPI- 1, 3, 6, 12 for each catchment within each cluster. Stronger correlations between SSI-1 and SPI series over longer accumulation periods indicate a delay in drought propagation from precipitation to discharge, signalling a nonlinear drought response due to catchment storage.

3 | RESULTS

3.1 | Fitting standardized indices

To select the most appropriate distribution for deriving SPI and SSI, the Gamma, Tweedie, and Log-logistic distribution functions were evaluated for 1, 3, 6, and 12 month accumulations using median precipitation and river flow series. Following Svensson *et al.* (2017), function performance was assessed using Anderson–Darling and Shapiro–Wilk scores (see Table S1, Supporting Information). Although the Gamma and Tweedie functions performed well for standardized precipitation, Tweedie performed markedly better for flow standardization. Visual assessment of the fitted distributions was also undertaken (see Figures S1 and S2). All three functions replicate the distribution of precipitation but the Tweedie and Log-Logistic are better for flow. The Tweedie function was best at capturing the lower tails of flow distributions, particularly in summer months, so was selected for use as in Barker *et al.* (2018). Sample plots of SPI and SSI indices for each distribution for the mid-1970s drought (Figure S3) indicate that sensitivity to distribution is greatest for maximum drought intensity over shorter accumulation periods.

3.2 | Cluster analysis

The optimum number of catchment clusters was determined through visual and numerical assessment of the height between nodes in the dendrogram derived from the agglomerative cluster analysis. We determined that a three-cluster grouping best distinguished SSI values (at 1, 3, 6, and 12 month accumulations) across the 51 catchments. K-means clustering, with the use of silhouette information, also confirmed three groups as optimal. Figure 1 displays each of the clusters and catchment IDs, with further details of cluster membership given in Table 1. Cluster 1 catchments ($n = 13$) tend to be in the northwest and are relatively small and wet, with low groundwater storage (characterised by BFIsoil), steeper slopes, and a higher proportion of peat and wetter soils (see Figure 2a). Catchments in Cluster 2 ($n = 15$) tend to be in the southwest and are intermediate between Cluster 1 and 3 in terms of the PCDs evaluated. Cluster 3 catchments ($n = 23$) are in the east and southeast, tend to be larger and drier, have greater groundwater storage, with shallow slopes and a low proportion of peat cover.

3.3 | Drought propagation

The propensity for meteorological drought to propagate to hydrological drought was assessed for catchments in each cluster by deriving Pearson correlation scores between SSI-1 and SPI-1, 3, 6, and 12 over the full period of reconstructions. Boxplots of derived Pearson scores for each of the clusters are displayed in Figure 2b. Cluster 1 catchments show strongest correlations between SSI-1 and SPI-1, consistent with their low groundwater storage and more rapid propagation of drought. Cluster 3 catchments have strongest correlations between SSI-1 and SPI-3, but remain strong for SPI accumulations over 6 and 12 months, highlighting the slower propagation of drought in larger catchments with greater groundwater storage. Cluster 2 catchments are intermediate, with correlations between SSI and SPI decreasing for longer accumulation periods. In terms of the influence of PCDs, we find a strong association between SAAR and likelihood of

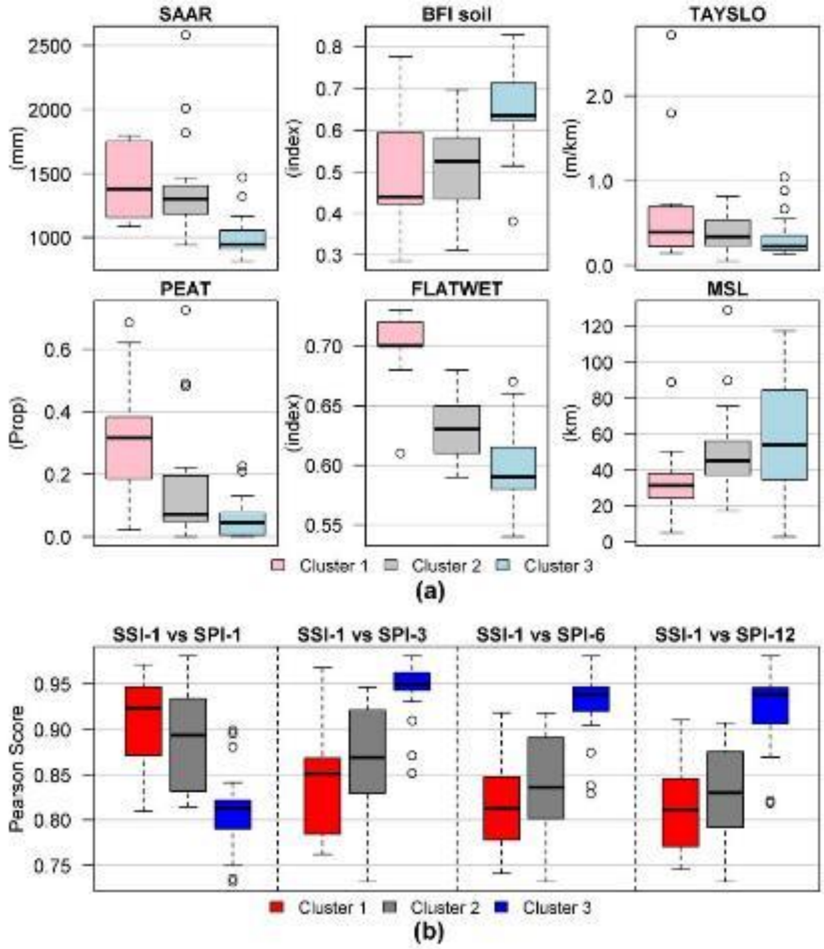

FIGURE 2 (a) Distributions of the six physical catchment descriptors for each cluster and (b) Pearson correlation coefficients scores between SSI-1 and SPI-1, 3, 6, and 12 for each cluster [Colour figure can be viewed at wileyonlinelibrary.com]

a drought, with total annual rainfall correlating strongly with the risk of drought occurrence at 1-month accumulation (Table 1). Also evident is the link between groundwater storage and delayed drought onset, whereby catchments with greater groundwater storage (higher BFIsoil) show stronger correlations between SSI-1 and SPI over longer accumulations.

3.4 | Historical hydrological droughts

Figure 3 displays SSI-1, 3, 6, and 12 generated from the median flow values of each cluster. The variability of SSI between clusters is apparent with different responses in drought event intensity as a function of accumulation period. High variability in SSI-1 values is a feature of the short accumulation period, resulting in more moderate, severe, and extreme events. This is evidenced by SSI values falling below the previously defined McKee *et al.* (1993) thresholds more frequently than for other accumulation periods. Persistent and extreme droughts are more easily detected in the SSI-12 series which produces the lowest number of events across all intensities. Differences in drought intensities between catchment groupings are also visible. For example, while Cluster 1 and 2 catchments register an extreme SSI-6 drought in 1984, this event only reaches severe classification in Cluster 3. Furthermore, while Cluster 2 catchments experience no SSI-12 drought exceeding moderate intensity in the period 1978–2016, both Cluster 1 and 3 return at least one severe and one extreme event. Cluster 1 generates the most hydrological droughts of all intensities (102 SSI-12 events), followed by Cluster 2 (94 SSI-12 events), and Cluster 3 generating the least (83 SSI-12 events).

Figure 4 displays heatmaps of SSI-3, 6, and 12 for the full 250-year period for individual catchments, organized by cluster membership. The most prominent events include the 1803–1806, 1855–1859, 1887–1890, 1933–1935, 1953–1954, 1971–1974, and 1975–1977 droughts. Conversely, the periods 1860–1885 and 1978–2004 were

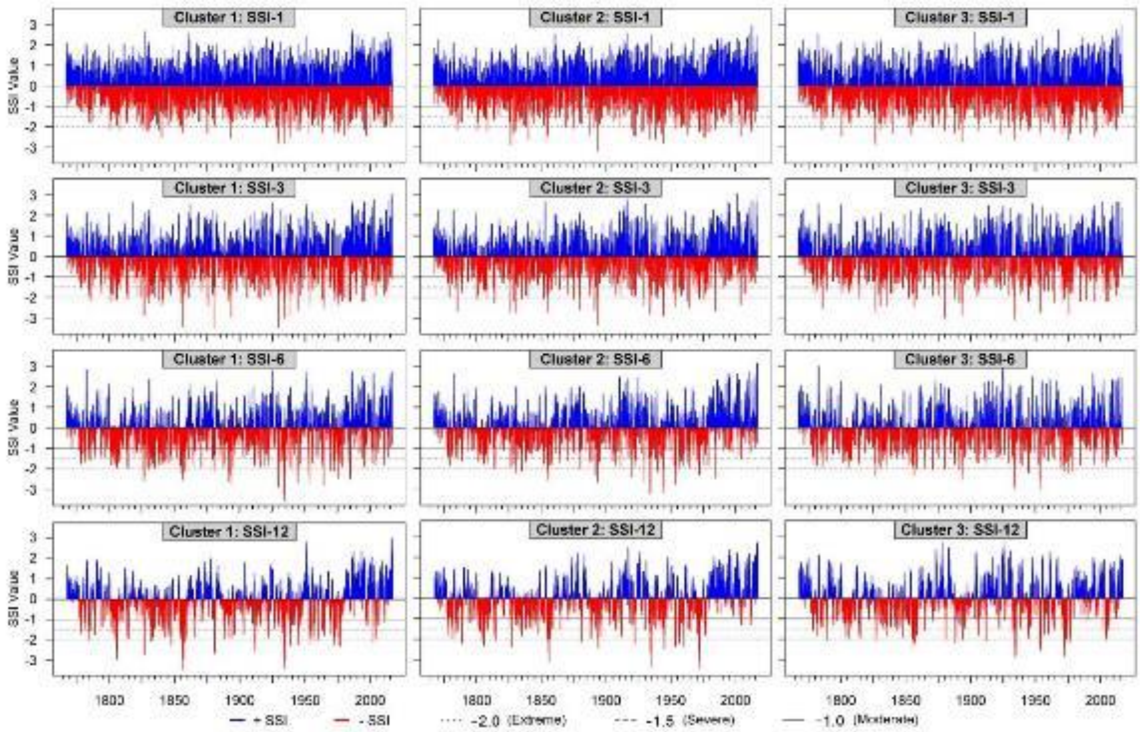

FIGURE 3 Time-series of SSI-1, 3, 6, and 12 derived from median flows for each cluster for the period 1767–2016, using the Tweedie distribution and 1930–1999 reference period. Horizontal lines represent moderate (SSI = −1), severe (SSI = −1.5), and extreme (SSI = −2) drought thresholds [Colour figure can be viewed at wileyonlinelibrary.com]

notably drought poor. Catchment specific variations in drought durations and deficits align closely within clusters, particularly in the case of Cluster 1 which differ noticeably from Cluster 2 and 3. For example, in the SSI-6 and 12 reconstructions, the 1921–1923 drought shows much greater intensity in Cluster 1 compared with other clusters. Differences between Cluster 2 and 3 are also evident. For instance, deficits in the 2004 drought (SSI-12) were severe/extreme in most Cluster 3 catchments but less so in Cluster 2 catchments. Although differences in drought numbers, durations, and deficits *between* clusters are considerable, similarities in drought characteristics for catchments *within* clusters are high.

3.5 | Meteorological and hydrological drought characteristics

A summary of moderate, severe, and extreme meteorological (SPI) and hydrological (SSI) historical drought characteristics is presented in Figure 5. For equivalent intensities and accumulations, the number of SSI drought events (Figure 5a) is consistently lower than for SPI. Although the number of SPI events is often highest in Cluster 3 catchments, SSI event numbers are consistently lower, indicating that meteorological droughts in Cluster 3 do not always translate into hydrological drought. Conversely, Cluster 1 catchments have the highest overall number of SSI drought events despite the number of SPI drought events being similar to Cluster 3, suggesting that the former are more vulnerable to hydrological drought onset. Cluster 2 catchments consistently have the lowest meteorological drought numbers but register more hydrological droughts than Cluster 3. Mean drought duration statistics (Figure 5b) show that SSI events tend to persist longer than corresponding SPI events. However, for Cluster 3 catchments SSI drought durations are longer, suggesting this cluster is susceptible to more persistent droughts once deficits become established.

Accumulated deficit statistics (Figure 5c) indicate that, on average, SSI events produce greater deficits than SPI events. Drought deficits are typically greatest in Cluster 1 for meteorological drought but rank behind Cluster 3 for hydrological drought, highlighting that while more susceptible to drought, Cluster 1 catchments recover quicker than Cluster 3 catchments. Cluster 2 catchments

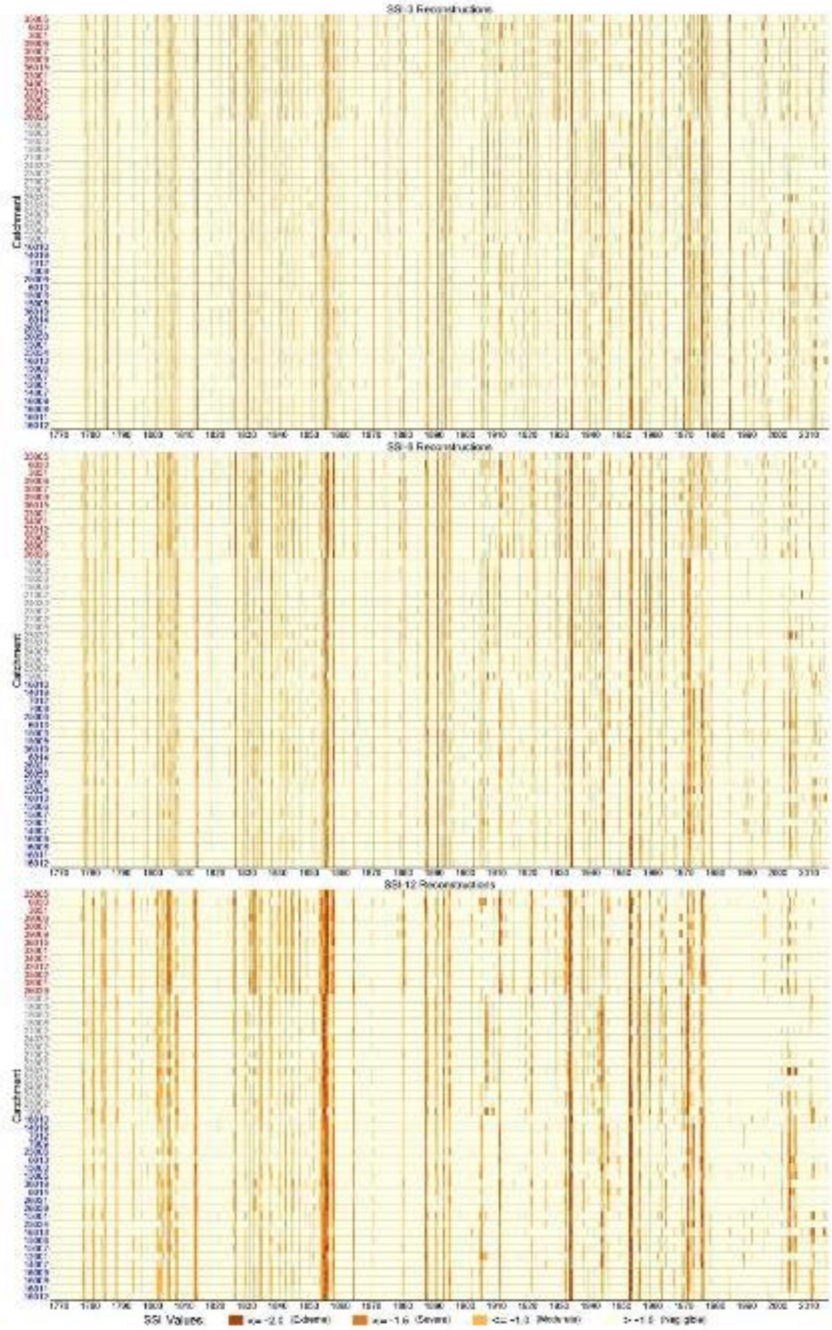

FIGURE 4 Heatmaps of SSI-3, 6, and 12 reconstructions for all 51 catchments grouped by cluster (Cluster 1, red; Cluster 2, dark grey; Cluster 3, blue). Colour coded are the main drought severity categories (moderate: −1.00 to −1.49; severe: −1.50 to −1.99; extreme: ≤−2.00) [Colour figure can be viewed at wileyonlinelibrary.com]

tend to show intermediate accumulated deficits. Cluster 3 catchments consistently show lower accumulated deficit values for SSI-1, 3, 6, and 12 compared to equivalent SPI accumulations which is directly related to longer drought durations in this grouping. Mean drought deficit statistics (Figure 5d) indicate that most SPI events produce greater mean deficits than equivalent SSI events. For almost all SSI accumulation periods, mean drought deficits in Cluster 3 catchments are less than Clusters 1 and 2 despite being equal or greater than the equivalent SPI mean deficits. This results from longer drought durations in these catchments.

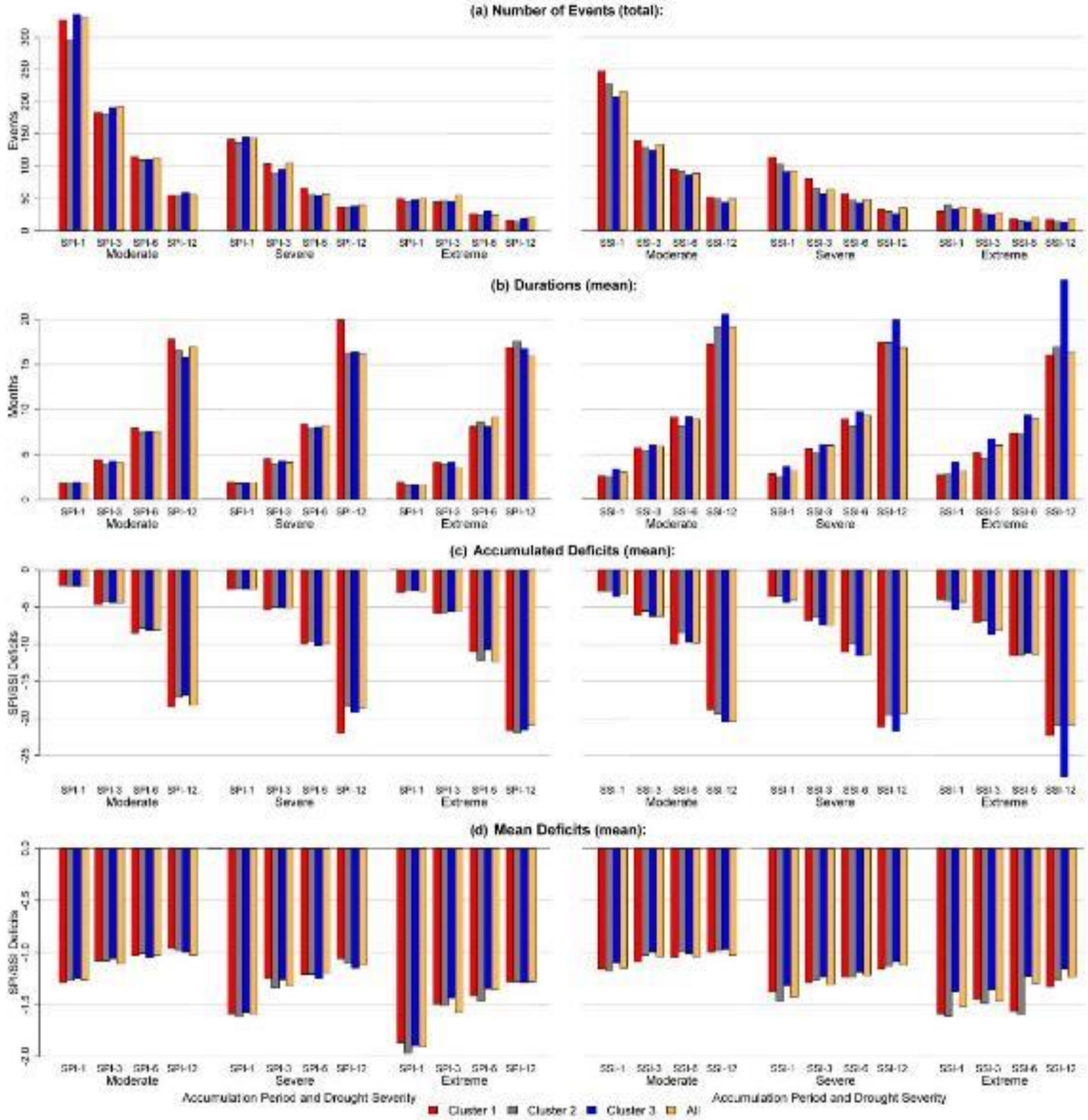

FIGURE 5 Meteorological (SPI) and hydrological (SSI) droughts, (a) total number of events, (b) mean durations, (c) mean accumulated deficits and (d) mean deficits for moderate, severe, and extreme droughts derived from median SPI and SSI series for each cluster grouping (Cluster 1, red; Cluster 2, dark grey; Cluster 3, blue; all clusters, orange). SPI and SSI event characteristics are derived for accumulation periods of 1, 3, 6, and 12 months [Colour figure can be viewed at wileyonlinelibrary.com]

Numbers of moderate, severe, and extreme hydrological drought events, their durations, accumulated deficits and mean deficits, for SSI-1, 6, and 12, were also derived for each catchment. Results display similar patterns to those found in the cluster analysis above, albeit with catchment specific variations (see Figures S4–S6). The Inny at Ballymahon (ID: 26021; Cluster 3) has the least number of moderate, severe, and extreme drought events for SSI-1, 6, and 12, whereas the Shannon at Dowra (ID: 26029; Cluster 1) has the most (n = 740). Catchments in the southwest have on average the shortest drought durations, the greatest mean deficits, and least accumulated deficits, with the Blackwater at Killavullen (ID: 18050; Cluster 2) having the shortest mean drought duration

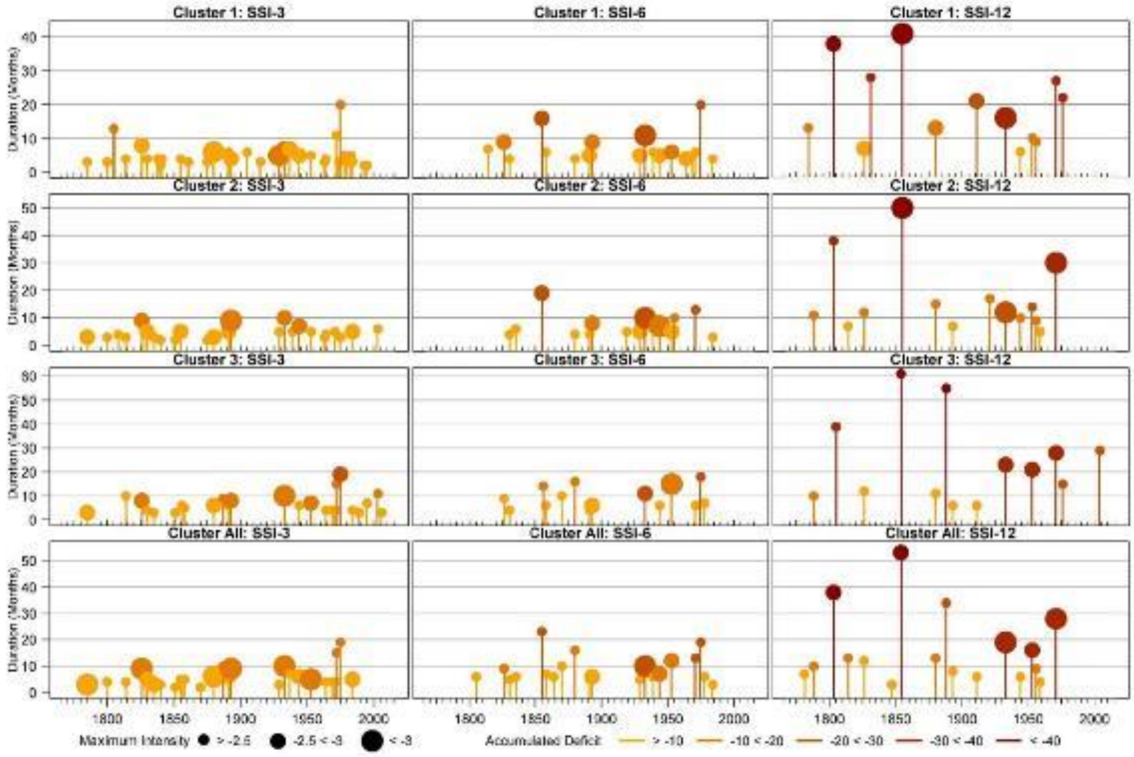

FIGURE 6 Extreme SSI-3, 6, and 12 drought events derived from median flow reconstructions for each cluster and all catchments for the period 1767–2016. For each extreme drought event the duration, maximum intensity, and accumulated deficit are provided [Colour figure can be viewed at wileyonlinelibrary.com]

and least accumulated deficits (8.27 months; −9.94 SSI). The Coomhola at Coomhola (ID: 21002) has the greatest mean deficits (−1.30 SSI) and is a Cluster 2 catchment. At the other extreme, the Erne at Belturbet (ID: 36019) has the longest durations (12.33 months), the Glyde at Tallanstown (ID: 6014) has the greatest accumulated deficits (−13.65 SSI) and the Erkina at Durrow (ID: 15005) has the least mean deficits (−1.14 SSI), with all three catchments belonging to Cluster 3. Overall, catchments in the northwest display the most variability in numbers of hydrological drought events, durations, and deficits.

3.6 | Extreme hydrological drought events

Figure 6 displays extreme SSI-3, 6, and 12 drought events for each cluster with details about the number of events, their durations, maximum intensities, and accumulated deficits. For SSI-12, the 1854–1860 drought period is most notable, having the greatest duration and accumulated deficits in each cluster. The event is less prominent for SSI-6, particularly in Cluster 3, and is not distinguishable from other events at SSI-3. Although not as remarkable for SSI-12, the 1975–1977 drought is a prominent SSI-3 and SSI-6 event in terms of deficits and duration for Clusters 1 and 3, with the longest duration of all extreme droughts in both clusters at that accumulation, and the greatest accumulated deficits of all droughts in Cluster 3. The 1933–1935 drought is notable for the intensity and accumulated deficits despite the relatively short duration, particularly for SSI-6 and SSI-12 in Cluster 1. Cluster 3 catchments have the most extreme droughts by accumulated deficit and duration for SSI-3 and SSI-12, whereas for SSI-6 it is Cluster 1. On average, maximum intensity values are most extreme in Cluster 2 for SSI-3 and Cluster 1 for SSI-6 and 12. Across all clusters, there is a remarkable lack of extreme hydrological droughts since the mid-1970s.

Of the top 10 most extreme hydrological droughts per cluster grouping and accumulation period listed in Table 2, the 1854–1859 event is the most prominent having the longest duration (53 months) and greatest accumulated deficits (−84.81) for SSI-12. Based on SSI-3, this

TABLE 2 Top 10 SSI-3, 6, and 12 drought events, derived from median flow across all catchments and for clusters during the period 1767–2016. Included are the maximum intensity (Max INT), accumulated SSI deficit (Accum SSI) and duration (months) of each event

Cluster 1 (SSI-3)	Start date	End date	Max INT	Accum SSI	Months	Cluster 1 (SSI-6)	Start date	End date	Max INT	Accum SSI	Months	Cluster 1 (SSI-12)	Start date	End date	Max INT	Accum SSI	Months
1st	07/1975	03/1977	−2.33	−19.90	20	1st	10/1933	09/1934	−3.64	−26.87	11	1st	11/1855	04/1859	−3.46	−70.53	41
2nd	10/1933	05/1934	−3.00	−15.34	7	2nd	07/1975	03/1977	−2.44	−26.75	20	2nd	10/1803	12/1806	−2.98	−50.95	38
3rd	01/1805	02/1806	−2.16	−13.50	13	3rd	05/1855	09/1856	−2.53	−25.02	16	3rd	09/1831	01/1834	−2.05	−37.59	28
4th	12/1855	06/1856	−3.42	−12.39	6	4th	06/1826	03/1827	−2.58	−15.47	9	4th	10/1933	02/1935	−3.43	−34.49	16
5th	03/1929	08/1929	−3.46	−11.61	5	5th	05/1893	02/1894	−2.74	−14.41	9	5th	11/1971	02/1974	−2.24	−33.04	27
6th	12/1937	07/1938	−2.90	−9.83	7	6th	04/1953	10/1953	−2.72	−11.54	6	6th	01/1976	11/1977	−2.34	−32.34	22
7th	02/1891	08/1891	−2.17	−8.92	6	7th	05/1944	10/1944	−2.67	−9.64	5	7th	08/1911	05/1913	−2.62	−25.54	21
8th	07/1826	03/1827	−2.85	−8.90	8	8th	05/1929	10/1929	−2.89	−9.36	5	8th	05/1953	03/1954	−2.18	−15.91	10
9th	05/1893	09/1893	−2.96	−8.68	4	9th	12/1971	06/1972	−2.11	−9.02	6	9th	10/1784	11/1785	−2.03	−15.32	13
10th	03/1953	08/1953	−2.41	−8.31	5	10th	02/1858	08/1858	−2.10	−8.23	6	10th	09/1880	10/1881	−2.68	−15.10	13
Cluster 2 (SSI-3)	**Start date**	**End date**	**Max INT**	**Accum SSI**	**Months**	**Cluster 2 (SSI-6)**	**Start date**	**End date**	**Max INT**	**Accum SSI**	**Months**	**Cluster 2 (SSI-12)**	**Start date**	**End date**	**Max INT**	**Accum SSI**	**Months**
1st	03/1944	10/1944	−2.89	−14.09	7	1st	02/1855	09/1856	−2.55	−26.77	19	1st	02/1855	04/1859	−3.10	−68.64	50
2nd	11/1933	09/1934	−2.81	−13.80	10	2nd	11/1933	09/1934	−3.21	−21.46	10	2nd	10/1803	12/1806	−2.31	−39.63	38
3rd	06/1826	03/1827	−2.70	−12.07	9	3rd	05/1971	06/1972	−2.28	−21.14	13	3rd	09/1971	03/1974	−3.40	−33.23	30
4th	05/1893	02/1894	−3.32	−11.03	9	4th	11/1955	09/1956	−2.15	−15.54	10	4th	01/1953	03/1954	−2.37	−26.95	14
5th	06/1984	11/1984	−2.64	−9.14	5	5th	04/1944	11/1944	−3.15	−15.47	7	5th	12/1933	12/1934	−3.35	−26.93	12
6th	03/1929	08/1929	−2.41	−9.02	5	6th	06/1893	02/1894	−2.66	−11.45	8	6th	05/1956	02/1957	−2.21	−13.02	9
7th	01/1830	06/1830	−2.74	−8.66	5	7th	04/1953	09/1953	−2.76	−9.80	5	7th	09/1880	12/1881	−2.12	−12.36	15
8th	03/1953	08/1953	−2.62	−8.43	5	8th	06/1929	11/1929	−2.64	−8.28	5	8th	12/1921	05/1923	−2.21	−12.16	17
9th	02/1891	07/1891	−2.48	−8.43	5	9th	03/1830	07/1830	−2.21	−7.57	4	9th	08/1944	06/1945	−2.44	−11.82	10
10th	10/1971	03/1972	−2.04	−7.56	5	10th	01/1835	07/1835	−2.10	−7.05	6	10th	12/1788	11/1789	−2.20	−11.58	11
Cluster 3 (SSI-3)	**Start date**	**End date**	**Max INT**	**Accum SSI**	**Months**	**Cluster 3 (SSI-6)**	**Start date**	**End date**	**Max INT**	**Accum SSI**	**Months**	**Cluster 3 (SSI-12)**	**Start date**	**End date**	**Max INT**	**Accum SSI**	**Months**
1st	07/1975	02/1977	−2.78	−20.47	19	1st	08/1975	02/1977	−2.21	−23.37	18	1st	11/1854	12/1859	−2.41	−82.87	61
2nd	11/1933	09/1934	−3.10	−16.42	10	2nd	11/1933	10/1934	−2.96	−21.83	11	2nd	01/1888	08/1892	−2.17	−40.85	55
3rd	10/1972	01/1974	−2.00	−14.83	15	3rd	03/1953	06/1954	−3.01	−19.29	15	3rd	11/1971	03/1974	−2.81	−38.64	28
4th	02/1953	09/1953	−2.73	−14.11	7	4th	03/1856	05/1857	−2.29	−15.08	14	4th	11/1805	02/1809	−2.02	−37.21	39
5th	11/2003	10/2004	−2.19	−11.96	11	5th	03/1880	07/1881	−2.01	−11.00	16	5th	01/1953	10/1954	−2.54	−34.34	21
6th	08/1887	05/1888	−2.09	−11.79	9	6th	05/1944	11/1944	−2.22	−9.95	6	6th	12/1933	11/1935	−2.86	−32.85	23
7th	05/1893	01/1894	−2.86	−10.93	8	7th	12/1971	06/1972	−2.32	−8.40	6	7th	07/2004	12/2006	−2.04	−29.75	29

TABLE 2 (Continued)

Cluster 3 (SSI-3)	Start date	End date	Max INT	Accum SSI	Months	Cluster 3 (SSI-6)	Start date	End date	Max INT	Accum SSI	Months	Cluster 3 (SSI-12)	Start date	End date	Max INT	Accum SSI	Months
8th	07/1826	03/1827	−2.74	−10.31	8	8th	09/1826	06/1827	−2.10	−8.40	9	8th	01/1976	04/1977	−2.14	−23.27	15
9th	01/1856	07/1856	−2.45	−8.85	6	9th	08/1893	02/1894	−2.52	−8.01	6	9th	12/1788	10/1789	−2.05	−10.93	10
10th	02/1891	08/1891	−2.24	−8.48	6	10th	03/1858	09/1858	−2.02	−7.67	6	10th	12/1826	12/1827	−2.04	−9.80	12
All Clusters (SSI-3)	**Start date**	**End date**	**Max INT**	**Accum SSI**	**Months**	**All Clusters (SSI-6)**	**Start date**	**End date**	**Max INT**	**Accum SSI**	**Months**	**All Clusters (SSI-12)**	**Start date**	**End date**	**Max INT**	**Accum SSI**	**Months**
1st	07/1975	02/1977	−2.41	−17.47	19	1st	06/1855	05/1857	−2.32	−27.44	23	1st	11/1854	04/1859	−2.71	−84.81	53
2nd	11/1933	09/1934	−3.22	−16.18	10	2nd	11/1933	09/1934	−3.33	−23.24	10	2nd	10/1803	12/1806	−2.74	−45.01	38
3rd	07/1887	05/1888	−2.24	−13.99	10	3rd	05/1971	06/1972	−2.30	−21.34	13	3rd	10/1971	02/1974	−3.13	−37.88	28
4th	06/1826	03/1827	−3.10	−13.84	9	4th	08/1975	03/1977	−2.18	−21.02	19	4th	12/1933	07/1935	−3.02	−32.40	19
5th	05/1893	02/1894	−3.45	−11.64	9	5th	03/1953	03/1954	−2.98	−15.86	12	5th	01/1953	05/1954	−2.64	−31.35	16
6th	03/1953	08/1953	−3.19	−11.57	5	6th	04/1944	11/1944	−2.65	−13.46	7	6th	01/1888	11/1890	−2.30	−25.76	34
7th	10/1972	01/1974	−2.03	−10.65	15	7th	03/1880	07/1881	−2.18	−12.46	16	7th	05/1956	02/1957	−2.22	−12.55	9
8th	04/1944	10/1944	−2.63	−9.60	6	8th	08/1826	05/1827	−2.39	−11.30	9	8th	09/1880	10/1881	−2.50	−12.03	13
9th	06/1984	11/1984	−2.72	−9.28	5	9th	02/1858	09/1858	−2.15	−9.58	7	9th	12/1788	10/1789	−2.10	−11.41	10
10th	01/1830	06/1830	−2.85	−9.23	5	10th	08/1893	02/1894	−2.98	−8.32	6	10th	08/1814	09/1815	−2.33	−11.23	13

event fails to make the top 10 extreme droughts for Cluster 2. This is primarily due to the length of the drought and the sporadic deficits accumulated over shorter periods during its occurrence. Spatially and temporally, the drought was uneven with Cluster 1 catchments experiencing extreme SSI-12 drought approximately 12 months after Cluster 3, and 9 months after Cluster 2. Despite this, maximum SSI-12 deficits are greatest in Cluster 1 catchments reaching −3.46 SSI.

The 1933–1935 event is the most spatially coherent drought in the record, as it is identified as a top six SSI-3, -6, and -12 event in all clusters. The relatively short duration of this event (23 months for SSI-12), results in high ranks across lower accumulations (consistently within the top two events). Cluster 1 catchments are most impacted with a maximum intensity of −3.43 SSI, the second most extreme of all SSI-12 events across each cluster grouping. Extreme drought conditions consistently began earliest in Cluster 1 catchments, 2 months before Clusters 2 and 3 catchments in the case of SSI-12 and 1 month in the case of SSI-3 and 6. Consequently, Cluster 1 catchments experience the greatest accumulated deficits reaching −34.49 for SSI-12.

The 1944 drought, although not as extreme as others in terms of duration or deficits, is most significant in Cluster 2 particularly for SSI-3 where accumulated deficits exceed values attained by all other droughts. For SSI-6, the event is notable in all groupings, as it is consistently within the top seven events despite having a relatively short duration (7 months).

The 1953–1954 drought is another prominent event in the series which, despite a relatively short duration, produced considerable accumulated deficits. The event is registered as a top 10 drought in each cluster and accumulation period. Cluster 3 catchments show the greatest accumulated deficits (−34.34 SSI-12) and duration (maximum of 21 months). The event does not start simultaneously across the three clusters, with Cluster 1 reaching extreme conditions 4 months after Cluster 2 and 3 and ending 7 months earlier compared to SSI-12 in Cluster 3. This highlights the potential for temporal differences in drought event numbers across the island.

The 1975–1977 drought is the most recent extreme identified in our series, coming at the end of a drought rich period during the early to mid-1970s. With a maximum duration of 22 months (Cluster 1, SSI-12) the spatial impact of the event is uneven. While for Cluster 1 and 3 it is identified as a top 10 event for all accumulation periods, this drought does not rank highly over any accumulation period for Cluster 2. The greatest severity is seen in Cluster 3 where it is the top-ranking drought by accumulated deficit for SSI-3 and 6. While extreme drought conditions commenced at a similar time across Clusters 1 and 3 (consistently summer 1975 for SSI-3 and SSI-6 and winter 1975/1976 for SSI-12), the duration was considerably longer for Cluster 1 catchments (7 months in the case of SSI-12 compared to Cluster 3). As a result, accumulated deficits were greatest in this cluster reaching −32.34 for SSI-12.

3.6.1 | Sensitivity of drought characteristic results to reference period

Sensitivity of drought characteristics to reference period was investigated using four test periods (1767–2016, 1900–1999, 1930–1999, and 1981–2010) to calculate SSI-1, 3, 6, and 12. The indices, derived from median flow series across all catchments, were assessed for numbers of drought events, their durations, and accumulated deficits at moderate and severe thresholds. Figure 7 shows that

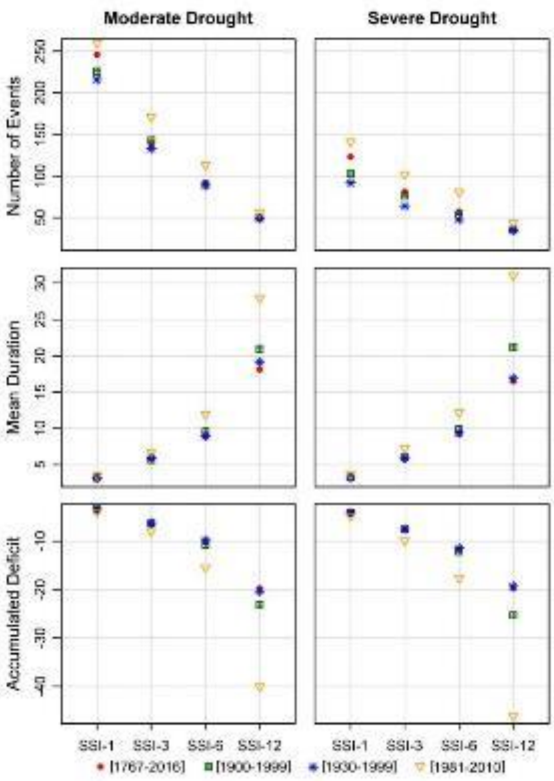

FIGURE 7 The number, duration, and accumulated deficit of drought events for SSI-1, 3, 6, and 12 values derived from median reconstructions for all catchments. Values are derived from the 1767–2016 (red dot), 1900–1999 (dark green square), 1930–1999 (blue star), and 1981–2010 (orange triangle) reference periods [Colour figure can be viewed at wileyonlinelibrary.com]

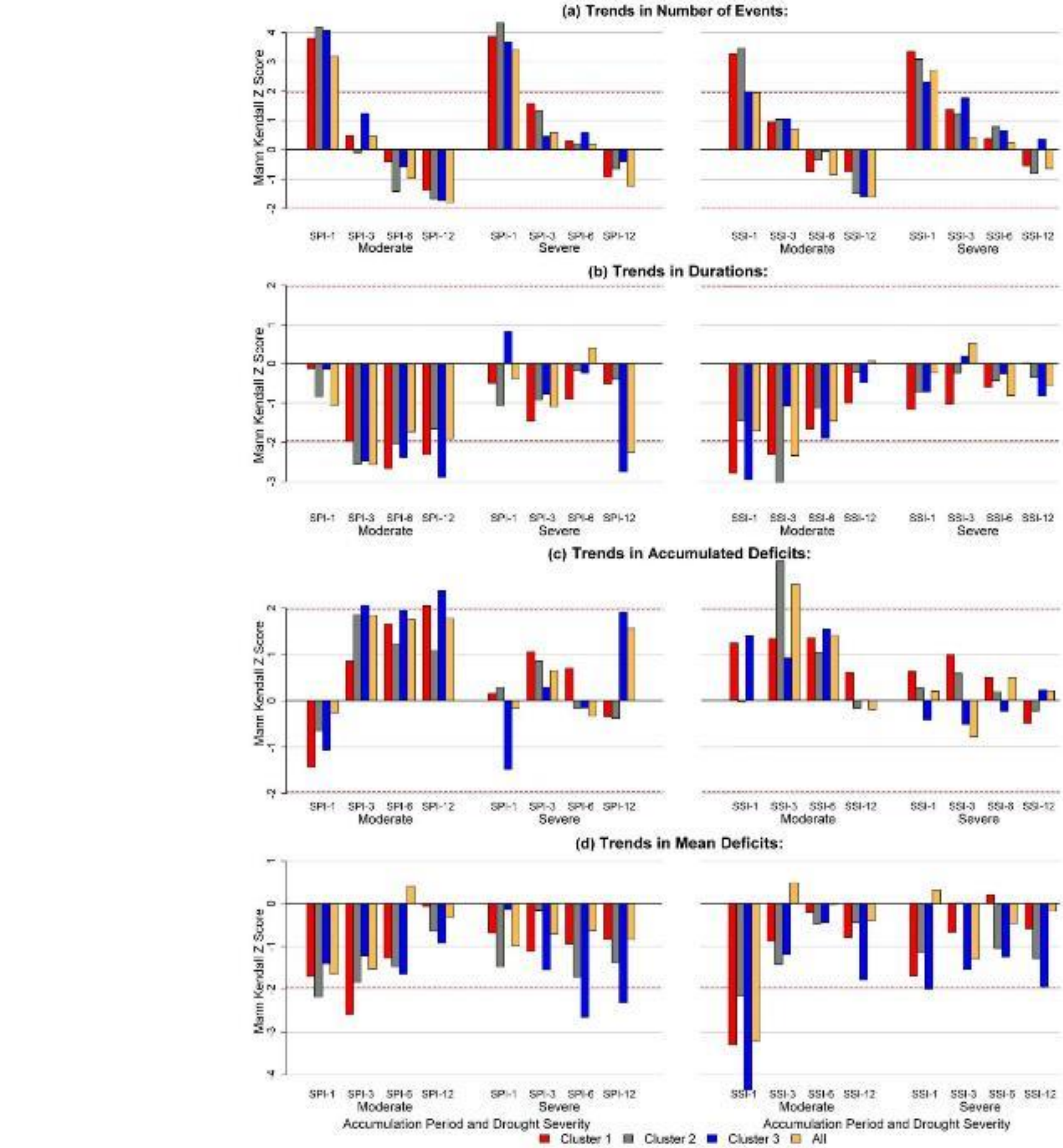

FIGURE 8 Mann–Kendall *Zs* scores for trends in moderate and severe meteorological (SPI) (left) and hydrological (SSI) (right) drought (a) number of events, (b) durations, (c) accumulated and (d) mean deficits for each cluster and all catchments (Cluster 1, red; Cluster 2, dark grey; Cluster 3, blue; all clusters, orange). Event characteristics are derived for accumulation periods of 1, 3, 6, and 12 months. Dashed red horizontal lines represent the 0.05 level significance thresholds (±1.96) [Colour figure can be viewed at wileyonlinelibrary.com]

the reference period has a discernible impact on all three metrics but particularly on the number of events at 1, 3, and 6 month accumulations and on durations and deficits at 6 and 12 month accumulations.

For occurrence, the 1930–1999 baseline consistently generates the least number of events across all accumulations and severities ($n = 726$, compared with $n = 968$ for the 1981–2010 reference). Differences in the number of droughts derived for SSI-1, 3, 6, and 12 range from a minimum of seven events between all four reference periods for moderate SSI-12 to a maximum of 49 events between the 1930–1999 and 1981–2010 reference periods for severe SSI-1. All four references produce similar drought duration values for SSI-1 and 3 at moderate and severe intensities. For SSI-6, the 1981–2010 baseline produces longer mean drought durations. The greatest differences in duration between reference periods are for SSI-12. Severe droughts calculated using the 1930–1999 baseline have a mean duration of 17 months, compared with 31 months for 1981–2010.

Accumulated deficits emulate those of duration with SSI-1 showing similar values for all four reference periods at both severities. The 1981–2010 reference period again deviates from others by producing greater accumulated deficits for SSI-3 and 6. SSI-12 is very sensitive to the baseline, with 1930–1999 producing a mean accumulated deficit of SSI = −19 compared with mean SSI = −46 for 1981–2010. For each accumulation period and severity category the 1981–2010 reference period generates the greatest deficits overall while the 1930–1999 period generates the least (excluding moderate SSI-12 droughts).

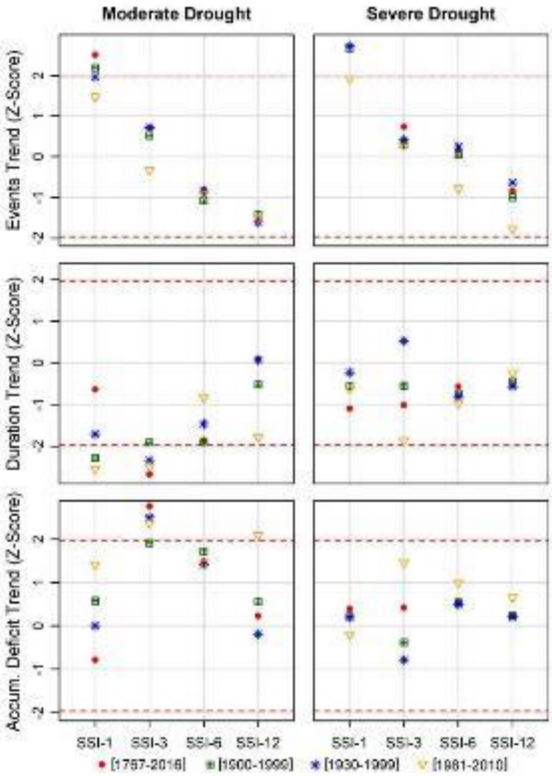

FIGURE 9 Sensitivity of trends in the number, duration and accumulated deficits of moderate (left) and severe (right) drought events to reference period used in fitting SSI indices. Results are presented for accumulation periods of 1, 3, 6, and 12 months for median reconstructions across all catchments. MK *Zs* scores returned for trends are derived from the 1767–2016 (red dot), 1900–1999 (dark green square), 1930–1999 (blue star), and 1981–2010 (orange triangle) reference periods. Dashed red horizontal lines represent the 0.05 level significance thresholds (±1.96) [Colour figure can be viewed at wileyonlinelibrary.com]

3.7 | Trends in drought characteristics

Trends in the number of events, durations, accumulated and mean deficits of moderate and severe droughts for SSI and SPI at 1, 3, 6, and 12 month accumulations were evaluated for each cluster as well as for all clusters combined. Extreme drought was excluded due to the small number of events. Results for the full period (1767–2016) are displayed in Figure 8. For each cluster, a significant ($p \leq .05$) increasing trend in the number of moderate and severe drought events is found for SPI and SSI-1, but nonsignificant trends are found for SPI and SSI-3 (increasing except for Cluster 2 SPI-3) and SPI and SSI-6 (decreasing for moderate and increasing for severe SPI and SSI). Strong decreasing trends in the number of moderate SPI and SSI-12 drought events (Figure 8a) are evident for all clusters and all catchments combined. Trends in the number of severe SPI and SSI-12 events are weaker and are all nonsignificant.

Decreasing trends in duration (Figure 8b) are evident for meteorological (SPI) and hydrological (SSI) droughts for most accumulation periods and clusters. Significant ($p \leq .05$) decreasing trends in the duration of moderate meteorological droughts are evident for SPI-3 and 6 (all clusters) and SPI-12 (Clusters 1 and 3). For severe droughts, despite overall decreasing trends in duration, significant decreases are limited to SPI-12 in Cluster 3. In terms of hydrological droughts only moderate events show significant decreasing trends in duration for SSI-1 (Clusters 1 and 3) and SSI-3 (Clusters 1 and 2). No significant changes in duration are found for severe hydrological droughts for any accumulation period.

For accumulated deficits (Figure 8c), trends are almost the inverse of those found for duration, highlighting the close association between these indices. A significant ($p \leq .05$) increasing trend (i.e., towards smaller accumulated deficits) is found for moderate SPI-3 droughts (Cluster 3) and moderate SPI-12 (Clusters 1 and 3), however this does not translate into significant increases in SSI-3 or 12 for either cluster. For hydrological droughts, changes are again confined to moderate droughts, with significant increasing trends in accumulated deficits in SSI-3 for Cluster 2 and the all-clusters sample. Other accumulation periods are also dominated by increasing trends in moderate drought deficits, though these are nonsignificant. By contrast, mean deficits (Figure 8d) for moderate and severe droughts show trends towards more negative values (i.e., more intense droughts), with the exception of severe SSI-6 droughts in Cluster 1. The strength of trends is generally greater for hydrological drought. Specifically, the largest hydrological trends are found for SSI-1 in all clusters, and for Cluster 3 for all severe drought accumulation periods.

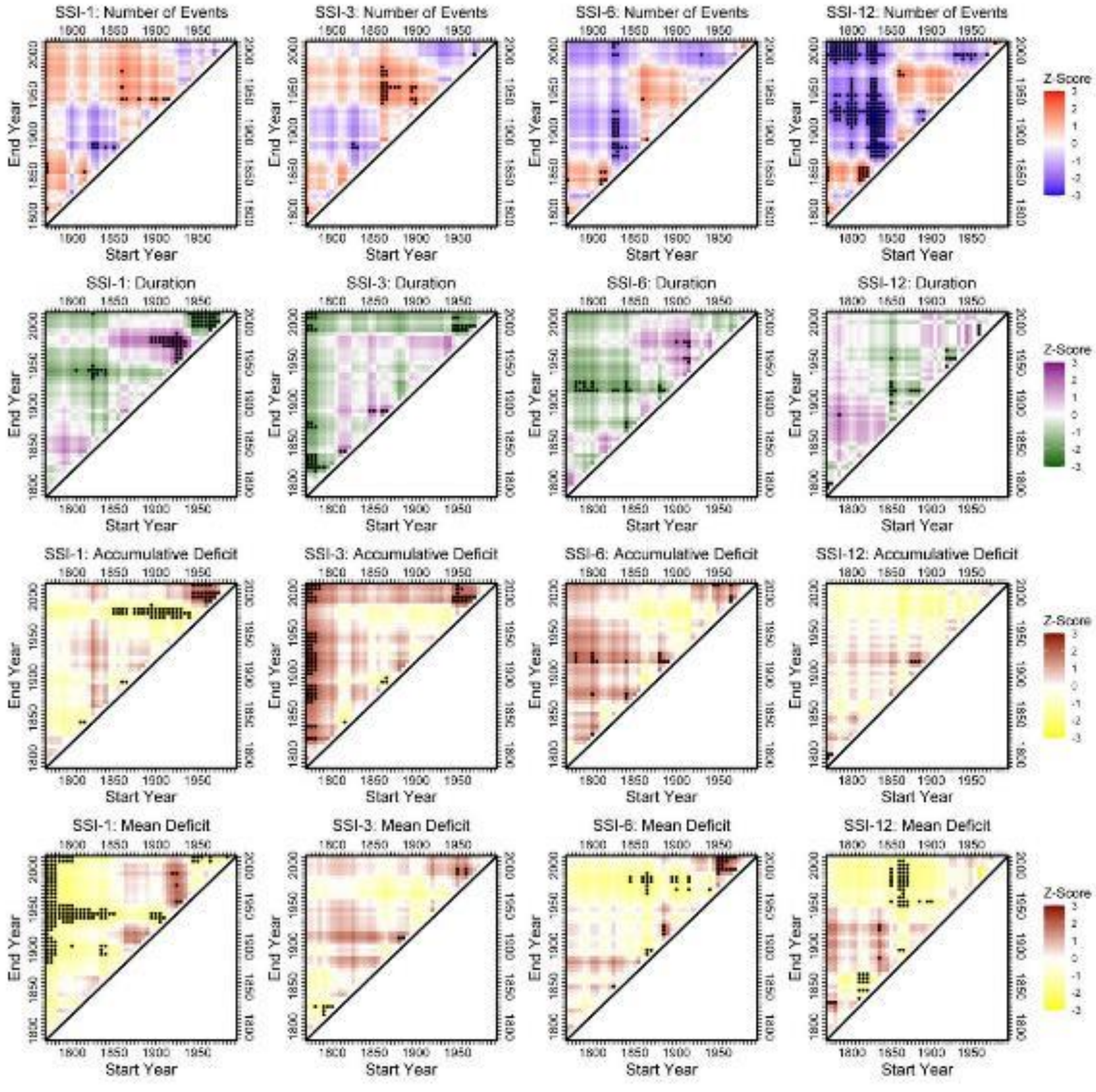

FIGURE 10 MK *Zs* scores for trends in the number of events, durations, accumulated and mean deficits of moderate hydrological droughts for varying start and end dates. Results are displayed for median reconstructions across all catchments with SSI values, derived from the Tweedie distribution and 1930–1999 reference period. MK *Zs* values are calculated for periods ranging from 30 to 245 years in 5 year increments for accumulation periods of 1, 3, 6, and 12 months. Black dots indicate test periods for which trends are significant at the 0.05 level [Colour figure can be viewed at wileyonlinelibrary.com]

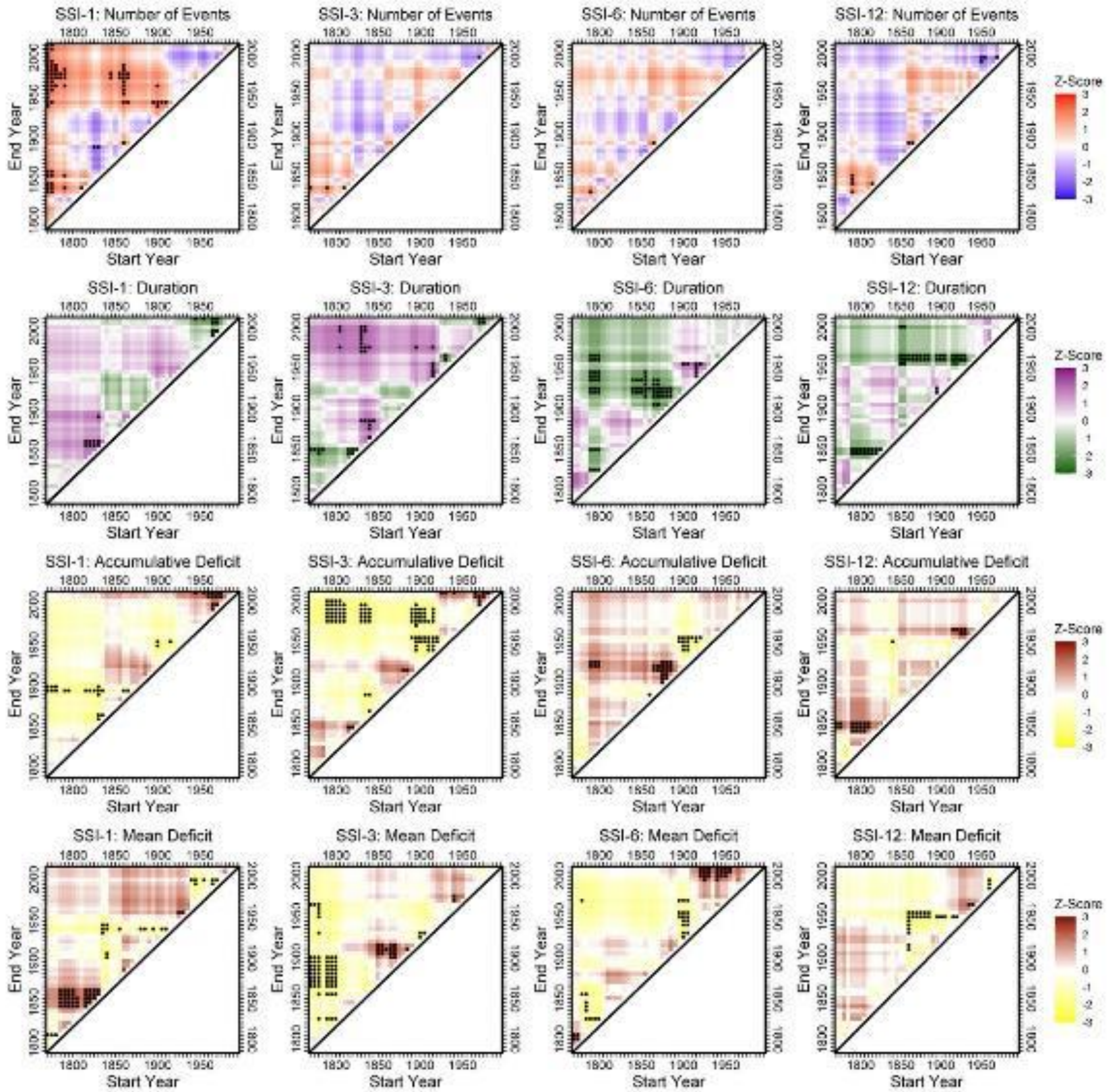

FIGURE 11 As Figure 10 but for severe droughts [Colour figure can be viewed at wileyonlinelibrary.com]

Catchment specific trends in numbers of hydrological droughtevents, durations, and deficits for SSI-1, 6, and 12 at moderate and severe intensities were also derived (Figures S7 and S8). Results align with patterns identified in the cluster analysis described above, with the number of moderate and severe SSI-1 drought events showing significant ($p \leq .05$) increasing trends across catchments. SSI-6 drought shows overall nonsignificant increasing trends while SSI-12 shows decreasing trends with decreases strongest for moderate drought. Decreasing trends in the duration of moderate SSI-1, 6, and 12 events are identifiable across nearly all catchments with corresponding reductions in accumulated deficits. Mean deficits show more negative values (i.e., more intense droughts) especially for moderate SSI-1.

3.7.1 | Sensitivity of trend results to reference period

Sensitivity of trends in numbers of hydrological (SSI) drought events, durations, and deficits to reference period are shown for each cluster in Figure 9. Variations in the magnitude, significance and direction of trends, derived for each reference period, are considerable. For the number of drought events, similar trends are identifiable across all four periods with the greatest deviations evident for the 1981–2010 reference period. The most notable differences are apparent for SSI-3 moderate and SSI-6 severe drought events where the 1981–2010 period gives decreasing trends while other reference periods produce increasing trends. Most reference periods show decreasing trends in moderate drought duration (the 1767–2016 and 1930–1999 periods show weak increasing trends for SSI-12). The significance of decreasing trends in duration and accumulated deficits is dependent on the reference period used for both moderate and severe events. Furthermore, the direction of change in accumulated deficits is also sensitive to the reference period.

3.7.2 | Sensitivity of trends to start and end dates

The sensitivity of trends to the period of record analysed was assessed using SSI-1, 3, 6, and 12 derived from the median flow across all catchments. Trends in the number of hydrological drought events, durations, accumulated and mean deficits were evaluated for moderate and severe droughts across the 1770–2015 period, for a minimum length of 30 years to a maximum of 215 years, incremented at steps of 5 years. Figures 10 and 11 show results for moderate and severe droughts, respectively. The strong influence of record length on the direction, magnitude, and significance of trends is evident. For moderate droughts, increasing trends in the number of SSI-1 events are seen for tests commencing prior to 1920, with decreasing trends found for tests starting after 1920. Similar patterns are seen for SSI-3, while for SSI-6 and 12, tests commencing prior to 1860 also display persistent decreasing trends (significantly for many SSI-12 tests). Significant decreases in the duration of moderate SSI-1 and 3 events are evident for start years after 1945 while SSI-1 tests with start years between 1895 and 1940 and end years in the 1950s and 1980s show significant ($p \leq .05$) decreasing trends, with a notable shift in duration trends in recent decades. For SSI-1, significant increases in accumulated deficit values are evident for tests commencing after 1945, similar to trends in duration. In contrast, decreases in SSI-1 mean deficits are identified for tests commencing pre-1845 and post-1945, significantly for a number of these.

The strongest (increasing) trends in the number of severe drought events are for SSI-1, especially for tests commencing prior to 1910, as well as those commencing before 1795 and from 1855–1865 (Figure 11). Severe SSI-1 drought duration shows decreasing trends for tests commencing post-1945. Increases in accumulated deficit values are evident for the same period. Despite these changes, mean deficit trends show significant decreases in SSI-1 for start years from 1940 to 1975 indicating trends towards greater intensity of SSI-1 droughts over this period. While limited significant trends are evident in the number of severe SSI-3 events, some significant changes are evident for SSI-3 duration, accumulated deficits and mean deficits. For duration, increases are evident for tests commencing prior to 1925, but decreases after 1965. Similarly, for severe SSI-3 accumulated deficits, decreases are evident for tests commencing prior to 1925, but increases after 1960.

4 | DISCUSSION

This research reconstructs hydrological and meteorological droughts for Irish catchments during the period 1767–2016. Consistent with other studies, we find that catchment characteristics play a critical role in moderating hydrological drought (Van Loon and Laaha, 2015; Barker *et al.*, 2016; Tijdeman *et al.*, 2018). Three distinct clusters of catchments were identified using the standardized streamflow index (SSI). Cluster 1 catchments in the northwest were found to be susceptible to hydrological drought onset with event duration often lowest of the three clusters. Eastern and southeastern, Cluster 3, catchments have the fewest hydrological droughts, but these tend to last longer and produce greater accumulated and reduced mean deficits than other clusters, especially for extreme droughts. Cluster 2 catchments in the southwest had the lowest drought durations overall, with the number of drought events being intermediate between Clusters 1 and 3.

Examination of the propagation of meteorological to hydrological drought confirmed the importance of groundwater storage in mediating drought incidence. Furthermore, we find a somewhat inverse manifestation of meteorological and hydrological drought across our clusters. Cluster 3 catchments consistently show the lowest frequency of hydrological drought despite having a higher frequency of meteorological drought when compared to other clusters. The opposite is true for Cluster 1 catchments, which experience the highest frequency of hydrological drought with, on average, fewer meteorological droughts than Cluster 3 catchments. Drought duration was generally longer for hydrological events in comparison to meteorological drought, with Cluster 3 catchments showing the greatest drought duration, indicating that these catchments are susceptible to long droughts once deficits become established.

We identified the top 10 droughts for each cluster at 3, 6, and 12 month accumulations. The most notable extreme droughts were the 1803–1806, 1854–1859, 1933–1935, 1944–1945, 1953–1954, and 1975–1977 events. Noone *et al.* (2017) also identified the same post-1850 events as experiencing extreme meteorological drought (except 1944–1945). All three droughts (1806, 1887, and 1893) investigated by Murphy *et al.* (2017) using documentary evidence appear as top 10 events here, with 1806 being prominent at the 12-month accumulation in Clusters 1 and 2, and 1887 at 3 and 12 month accumulations in Cluster 3. The 1893 event, which has been described as a "relatively forgotten" drought in France by Caillouet *et al.* (2017), is detectable at 3- and 6-month accumulations in all our clusters. The Noone and Murphy (2020) assessments of hydrological drought in Ireland also identified 1933–1935, 1944–1945, 1953–1954, and 1971–1977 as notable drought periods. While not as highly ranked, the 1887–1888 and 1891–1894 droughts also emerge as significant events in our study.

European analysis has identified similar historical hydrological droughts to those in this work, particularly in northern/central European regions (Moravec *et al.*, 2019). In the UK, the long drought from 1890 to 1910, the historic 1933–1934 event, and the drought of 1976 are the most prominent extreme events identified by Marsh *et al.* (2007) and Barker *et al.* (2019) that correspond with droughts identified in our study. The 1854–1859 event was similarly identified as one of the most extreme meteorological, hydrological and soil moisture droughts on the European continent in the last 250 years by Hanel *et al.* (2018). In the UK, the same event ranks highly (Spraggs *et al.*, 2015), with considerable groundwater impacts reported (Marsh *et al.*, 2007). The 1933–1934 drought, which was found to be the most spatially consistent of all events in this study, also had notable impacts on UK flows (Barker *et al.*, 2019) but has less prominence in historic drought records for continental Europe (Moravec *et al.*, 2019). Another notable event identified in our research is the 1953–1954 drought which also impacted central and western Europe (Sheffield *et al.*, 2009). However, for the UK, this drought only impacted Northern Ireland and western Scotland (Barker *et al.*, 2019), highlighting how hydrological drought impacts can vary considerably over relatively small spatial scales, dependent on catchment properties and local climate conditions.

Analysis of trends in the number, duration, mean and accumulated deficits of moderate and severe drought events revealed a complex picture with the direction, magnitude and significance often dependent on the accumulation period used to define drought, the period of record analysed, and the reference period used in fitting standardized indices. The most consistent results identified were for shorter accumulation periods (1 and 3 months) at moderate intensity. Decreasing durations and smaller accumulated deficits (i.e., less severe droughts) were found for the full period of record and in the moving window assessment for tests commencing after 1940. However, we find strong negative trends in mean deficits (i.e., more intense droughts) for both moderate and severe meteorological and hydrological droughts, especially over shorter accumulation periods.

Vicente-Serrano *et al.* (2021a) found similar trends for summer SPI-3 for long-term rainfall records in Ireland (1871–2018), particularly in southern and eastern regions, with decreasing trends in the magnitude of August SPI-3 (i.e., increased summer drought), despite predominantly decreasing trends in drought duration. In their assessment of the E-OBS dataset for Europe, Gudmundsson and Seneviratne (2015) found overall decreasing trends in drought event occurrence in northern regions, particularly for SPI-12 with some variance between trends evident in central and western regions. Overall decreases in drought occurrence, particularly at higher accumulations, including SSI-12 were also found in our study for trends commencing in the latter half of 20th century, however their significance is limited. Hanel *et al.* (2018) showed that the spatial/temporal variability of drought intensities across the continent may conceal localized impacts, particularly for meteorological to hydrological drought propagation because catchments react differently to drought events (Stoelzle *et al.*, 2014).

Periods marked by an absence of drought are also evident, especially for longer accumulation periods. The period 1767–1800 had few extreme hydrological droughts with the exception of events in 1784–1785 (Cluster 1) and 1788–1789 (Clusters 2 and 3) which rank as top 10 droughts for SSI-12. This is consistent with identified SPI-12 droughts from reconstructions of Island of Ireland precipitation by Murphy *et al.* (2020a). Furthermore, a drought-poor period in the late 1700s is also evident in the series generated by Todd *et al.* (2013) from the Kew, Oxford, and Spalding rainfall series, for southeast England. Another drought-poor period is evident in 1860–1885, as reported for SPI-12 events by Noone *et al.* (2017). The lack of extreme droughts (particularly for longer accumulation periods) since the mid-1970s found here is consistent with studies showing decreasing trends in meteorological drought in northern European regions for SPI-3, 6, 12, 24, and 36 month accumulations (Gudmundsson and Seneviratne, 2015; Stagge *et al.*, 2017). In the UK, Barker *et al.* (2019) found a decrease in hydrological drought occurrence (SSI-3 and 12) post the 1980s in northern and western catchments, which aligns with our findings. The presence of drought-rich and

-poor periods in our reconstructions suggests that a return to an era of more frequent extreme droughts is possible. This raises questions regarding the preparedness of water managers in Ireland for such change. The Irish Water (2021) 25-year plan acknowledges substantial vulnerability to drought due to the major expansion of infrastructure during the current drought-poor period (post mid-1970s) combined with insufficient recognition of the historical propensity for droughts.

There are a number of limitations to note. O'Connor *et al.* (2021) highlight key assumptions regarding the reconstruction of river flows including land-use change, changes in channel geometry (Slater *et al.*, 2019), and reductions in precipitation and temperature station density in early records (Ryan *et al.*, 2021), among others. Moreover, Murphy *et al.* (2020b) raise questions about the under measurement of snowfall in early precipitation records. Therefore, pre-1850 results should be treated with caution. Nonetheless, the coherence of drought events across clusters increases confidence in the results, as does consistency with inventories of major droughts in the UK and western Europe.

There is potential for further research too. For instance, given the typically short (~45 years) records of observed river flow in Ireland, our reconstructions provide a multicentury catalogue of major droughts for stress-testing infrastructure, water and drought management plans. The various indices could also be used for national drought monitoring and reporting of emergent trends (Wilby, 2021). Similarly, there have been considerable efforts in Europe to link drought metrics and impacts to better inform drought monitoring and management (e.g., Bachmair *et al.*, 2016; Haro-Monteagudo *et al.*, 2018; Erfurt *et al.*, 2019; Parente *et al.*, 2019; Parsons *et al.*, 2019; Vicente-Serrano *et al.*, 2021b). As noted by Noone *et al.* (2017), Irish newspaper archives hold valuable information about cross-sectoral drought impacts. Potential therefore exists to systematically identify droughts from newspaper records dating back to the 1700s, to understand vulnerability and identify which metrics and accumulation periods best describe societal impacts at the catchment scale. Such work could shed light on the changing nature of drought vulnerability and inform development of monitoring and early warning systems (Hannaford *et al.*, 2019).

Having a multicentury catalogue of meteorological and hydrological droughts at the catchment scale also offers potential to inform and evaluate climate change adaptation. As previously highlighted, the most extreme hydrological events identified here tend to occur before the availability of digital discharge records and, therefore, offer new insight into the range of variability in drought characteristics. Recent research is highlighting the utility of storylines (plausible changes to the factors that impacted the unfolding of past events) for informing adaptation to credible extreme events (Shepherd *et al.*, 2018); others have used such approaches to evaluate how extreme drought events may change in a warmer world (e.g., Chan *et al.*, 2021). Our work provides a foundation for such approaches to adaptation planning across Irish catchments. Finally, future work should examine the climatological drivers behind drought-rich and -poor periods, as well as for the emergent pattern of shorter, sharper droughts identified here over recent decades. The AMO is known to influence summer precipitation variability in Ireland (McCarthy *et al.*, 2015) and has been linked to hydrological drought occurrence in the UK (Svensson and Hannaford, 2019). The role such phenomena play in drought variability, together with impacts of observed temperature increases should be further examined, as changing drought characteristics may have consequences for water management in Ireland, particularly where limited catchment storage increases vulnerability.

5 | CONCLUSIONS

We used reconstructed monthly precipitation and river flows to evaluate historical and hydrological drought in 51 Irish catchments over the period 1767–2016. Using standardized indices of varying accumulation periods applied to reconstructions for individual catchments and cluster groupings we found that physical catchment descriptors such as average rainfall and groundwater storage play a critical role in determining the propagation of meteorological to hydrological drought. Runoff dominated catchments tend to experience the highest drought frequency and intensity, but shorter durations. Groundwater dominated catchments tend to experience droughts of longer duration with greater accumulated deficits and reduced mean deficits. Accounting for the differential signatures of droughts at the catchment scale, the most significant hydrological droughts were identified in 1803–1806, 1854–1859, 1933–1935, 1944–1945, 1953–1954, and 1975–1977. Although not as highly ranked, events in 1826–1827, 1887–1888, 1891–1894, and 1971–1974 also emerged as significant hydrological extremes in our study. However, the evaluation of drought characteristics was shown to be sensitive to the reference period used in standardizing drought indices. The most appropriate reference period should be identified with the wavelength of key modes of variability in mind. Here, we recommend a 70-year reference period, which matches observed AMO periodicity. Despite trends in the number of drought events, durations and deficits being additionally sensitive to the period of record tested, we found that shorter droughts show evidence of increasing mean deficits, despite decreasing duration, indicating a tendency towards shorter, more intense hydrological droughts. For longer accumulation periods, we found a lack of significant trends and, at times, a lack of coherence between trends in meteorological and hydrological drought even within the same types of catchment (cluster). The dataset developed here offers an important reference set for drought and water management in Ireland, particularly given the paucity of extreme droughts present in the observational records currently used for drought planning (Irish Water, 2021).

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AUTHOR CONTRIBUTIONS

Paul O'Connor: Conceptualization; data curation; formal analysis; investigation; methodology; project administration; resources; software; validation; visualization; writing – original draft. **Conor Murphy:** Conceptualization; 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.

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Relating drought indices to impacts reported in newspaper articles

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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 Standardised Precipitation Index (SPI) with land-based impacts and the Standardised Streamflow Index (SSI) with hydrological-based impacts by matching total reported articles per month with concurrent drought indices. Using logistic regression we find SPI-3 links best to probabilities of land-based impact occurrence; SSI-2 links best with the hydrological impacts. Catchments in the east/southeast display the highest sensitivity to land-based impacts. While the likelihood of hydrological-based impacts is greatest in the east/southeast overall, in summer months it is greatest in the northwest, despite the likelihood of summer land-based impacts being lowest for this region. This is possibly due to low groundwater storage in these catchments. Moreover, the likelihood of news-worthy drought impacts has changed over the last 116 years. More severe deficits are required to induce a high likelihood (0.6) of land- and hydrological-based impacts in east/southeast and southwestern catchments during 1961-2016 compared with 1900-1960. Largest changes emerge in the southwest with SPI-3 values of -2.60 (<-3.00) required to reach the high impact likelihood threshold in the pre (post) 1961 period. Even greater reductions are found for hydrological impacts in the southwest with SSI-2 values associated with high impact likelihood reducing from -2.19 to -2.70. Conversely, for catchments in the northwest more moderate drought deficits result in a high impact probability for both land-based (from <-3.00 to -2.30 SPI-3) and hydrological impacts (from <-3.00 to -2.31 SSI-2) for the 1961-2016 period. These findings show the value of newspaper archives for

understanding regional sensitivities to drought and will be of interest in Ireland and further afield.

Keywords: Drought impacts, newspaper records, SSI, SPI, meteorological drought, hydrological drought, Ireland.

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, regional and national scales (Wilhite *et al.*, 2007), including reduced agricultural output, freshwater shortages, ecosystem degradation, reduced energy and industrial productivity (Gil *et al.*, 2013; Mosely, 2015; Van Vliet *et al.*, 2016; García-León *et al.*, 2021). The 2018 European drought, for example, resulted in severe impacts across the continent, particularly for crop production, power generation and transportation (Bakke *et al.*, 2020). Given their effects, understanding drought events and their links to 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 limited impact data availability and coverage (Bachmair et al., 2015). Of those undertaken they typically relate to agricultural drought and linking indices to crop yields, with multi-sectoral 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 drought, for both historic and future events (Steinemann *et al.*, 2015; Ekström *et al.*, 2018). For meteorological drought, indices such as the Standardised Precipitation Index (SPI), Standardised Precipitation Evapotranspiration Index (SPEI), Effective Drought Index (EDI), Reconnaissance Drought Index (RDI) and Palmer Drought Severity Index (PDSI) are often used (e.g., Erfurt *et al.*, 2019; Erfurt *et al.*, 2020; Deo *et al.*, 2017; Tsakiris *et al.*, 2007; Lloyd-Hughes and Saunders 2002). For hydrological drought, indices such as the Standardised Streamflow Index (SSI), Total Storage Deficit Index (TSDI) and Palmer Hydrological Drought Index (PHDI) can also be applied (e.g. Vicente-Serrano *et al.*, 2012; Nie *et al.*, 2018; Karl, 1986). Although indicators provide a means of quantifying and comparing droughts (Vicente-Serrano *et al.*, 2011) their usefulness 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 in case of the modulation and propagation of hydrological droughts by catchment properties (Barker *et al.*, 2016; Rust *et al.*, 2021).

Good quality, long-term precipitation and 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 issue is by reconstructing historic river flows using rainfall-runoff models forced with long-term temperature and precipitation series (e.g. Jones, 1984; Spraggs *et al.*, 2015; Crooks and Kay, 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; Hanel *et al.*, 2018; Erfurt *et al.*, 2020; Rudd *et al.*, 2017; Moravec *et al.*, 2019; O'Connor *et al.*, 2022). However, knowledge of drought characteristics alone does not necessarily translate into socio-economic impacts (which can vary depending on drought timing, socio-economic vulnerability, etc). 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), particularly for agricultural impacts (e.g. 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 centralised 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, Murphy *et al.* (2017) demonstrated the value of historical newspaper archives in an analysis of drought impacts across the island over the past 250 years. Noone *et al.* (2017) also used newspaper archives to verify the occurrence and duration of historical droughts, using the former to help verify quantitative drought reconstructions.

The SPI has been shown to be effective in generating strong links between drought occurrence and agricultural impacts (Vincente-Serrano *et al.*, 2012). Similarly, the SSI has demonstrable utility for linking hydrological drought with groundwater levels, vegetative 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 localised impacts, from drought indicators in the UK and Europe, despite the simplicity of the approach.

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). Nonetheless, there is a notable lack of research into trends in drought-related impacts (Kreibich *et al.*, 2019) and vulnerability to droughts (Mechler and Bouwer, 2015). Recent studies have begun to address this knowledge gap. For example, Parsons *et al.* (2019) found an increasing likelihood of agricultural 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 inter-annual variations in agricultural drought impacts across Europe to sampling and reporting bias, impact awareness, changes in 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, particularly in relation to food supply, water supply and human health, highlighting the non-static nature of drought impacts.

In this paper, we related monthly drought indicators and 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, produced by O'Connor *et al.* (2021) for 51 catchments across Ireland[1]. For each catchment we extract precipitation and flow reconstructions for the period 1900-2016. O'Connor *et al.* (2021) produced uncertainty estimates for flow reconstructions by applying various 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 (O'Connor *et al.*, 2022). To allow for a

[1] https://doi.org/10.1594/PANGAEA.914306

comparison of results between both studies, we conduct our analysis using the same clusters (Figure 1a). Cluster 1 catchments, located in the wetter northwest of the island, have relatively small areas, low groundwater content, 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. Standardised drought indices for 1900-2016 were applied to median monthly precipitation and flow data in each cluster. These were the Standardised Precipitation Index (SPI; McKee *et al.*, 1993) and Standardised 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 (1930-2000) and the Tweedie distribution was used to fit both SPI and SSI following O'Connor *et al.* (2022).

2.2 Drought Impact Data

Jobbová *et al.* (2022) developed an Irish Drought Impacts Database (IDID) from the Irish Newspaper Archive (INA) spanning the period 1738-2019. The INA consists of over six million pages of searchable content from 100 titles for the Island of Ireland. Using the search term '*drought*', the authors systematically identified all newspaper articles containing reference to drought. Using a modification of European Drought

Impact report Inventory (EDII; Stahl *et al.*, 2012), returned articles were assigned to 15 drought impact categories and associated impact sub-categories, with the possibility of each article being assigned to one or more categories depending on impacts described. 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. We further grouped the 15 drought impact categories into two simple categories signified as land-based impacts (related to agriculture and livestock farming, terrestrial ecosystems, soil systems, wildfires, air quality, and forestry) and hydrological-based impacts (related to aquaculture and fisheries, waterborne transport, energy and industry, tourism and recreation, public water supply, water quality and freshwater ecosystems). We matched the associated year and month of each reported impact in the IDID to the drought indices on that date. Impact reports in the IDID are not systematically compiled for catchments, therefore, we tallied reports for each county and assigned them to one of our three clusters of catchments (see Figure 1b). When a county straddles two clusters, impacts were 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 sub-category is given in Table S1. For each cluster, the cumulative number of drought impact reports were then calculated for each month from 1900-2016.

2.3 Model generation and analysis

Logistic regression and Generalised Additive Models (GAMS) have been previously used to link drought indices to impacts (Bachmair *et al.*, 2017; Parsons *et al.*, 2019; Stagge *et al.*, 2015). 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/non-occurrence 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 typically applied to derive the probability of occurrence from regression models (see Morgan *et al.*, 1988). Logistic regressions were fit using the Generalised Additive Model (GAM) framework which enables logistic regressions to be applied with a smoothing function for selected predictor variables (month values) to account for non-linear components in series (e.g. the seasonal components of monthly SPI/SSI values). To convert the log-odds predicted output to a simple probability output (i.e., to generate impact probability values in the range from 0 to 1) the inverse logit of the predicted values were found. Values could then be easily categorised by their probability 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 hydrological-based articles. Model predictor variables included standardised drought indices, smoothed month values and year values. Month values account for seasonal variations in drought impact probability, whilst 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 article numbers. The procedure was as follows: Step 1, the date (month/year) with the highest number of articles was ranked as one ($rank_1$ = 1), the second highest as two ($rank_2$ = 2), etc., 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 1, 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.

$$Reciprocal\ Rank = \sum_{i=1}^{Q} \frac{1}{rank_i} \qquad (1)$$

Reciprocal ranked weights were determined separately for each model. Dependent variable values for each model were represented by the binary occurrence/non-occurrence of monthly drought impact articles (land- or hydrological-based) for each cluster, with final model output returning the probability 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, 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 (R^2_{adj}). Subsequently, models were regenerated with the inclusion of smoothed monthly values (to account for seasonality of impact) 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 probabilities, i.e., the likelihood of a drought related newspaper article for a given SPI or SSI value. To aid interpretation, we classify impact probability 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 probability of impacts threshold (≥0.60) as it represents an above average likelihood of impact occurrence. We identify temporal and spatial variations in drought impacts for each catchment cluster over the full 116 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 impact probabilities at annual and monthly timescales with the latter allowing for assessment of how impact likelihood changes within clusters over the course of a year. Annual probabilities were derived by finding the mean of the monthly probabilities for each year across the 1900-2016 period. Finally, we assess homogeneity in drought impact likelihoods by identifying any significant change points in the drought impact series for each cluster, using the non-parametric Pettitt (1979) test. Theil-Sen slope estimates (Sen, 1968) were also calculated to identify significant trends in the series. We subsequently investigate how impact 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 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 there are several extreme events identifiable 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 show less intensity in the SSI equivalent such as the 1911, 1944, and 2003-2004 droughts. Figure 2 plots the annual number of articles by cluster over the period 1900-2016. Notable are the high number 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, 1933-1934, 1938, 1940, 1949, 1959 and 1975. Differences in article numbers for certain events are identifiable between clusters and article types. Although some droughts coincide with article occurrence (e.g. the 1933-1934 and 1975 droughts) others show fewer impact articles, despite being classified as severe or extreme droughts by the standardised indices. Conversely, events such as the 1921 and 1949 droughts do not rank among the most extreme droughts in the indices series despite producing some of the highest number of drought articles.

3.2 Model performance analysis

Logistic regression and GAMs show the relationship between SPI/SSI and land-/hydrological-based drought impacts in each cluster. Figure 3 displays results of this assessment with R^2_{adj} values for different SPI/SSI accumulation periods plotted for land- and hydrological-based impacts (lighter coloured bars). For hydrological-based impacts SSI-2 performed best across all three clusters (R^2_{adj} values of 0.17 ($p<0.01$; Cluster 1), 0.18 ($p< 0.01$; Cluster 2) and 0.17 ($p< 0.01$; Cluster 3)). For land-based impacts SPI-3 performed best having the highest R^2_{adj} score for Cluster 1 (0.11; $p<0.01$) and 3 (0.17; $p<0.01$). For Cluster 2, SPI-2 performed marginally better than SPI-3 (0.12; $p<0.01$ versus 0.11 ($p<0.01$). For simplicity, SPI-3 was adopted as the best predictor of land-based drought impacts in all clusters.

Following Parson's *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 the monthly smoothing by the REML method (see Section 2.3). Model performance was again assessed using R^2_{adj}, 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 hydrological-based drought impacts are given in Equations 2 and 3, with additional performance metrics provided in Table 1. For land-based impacts (Eq. 1) model performance is best for Cluster 3 ($R^2_{adj} = 0.51$; $p<0.01$), with Cluster 1 and 2 having R^2_{adj} values of 0.37 ($p<0.01$). For hydrological-based impacts (Eq. 2) model performance is generally lower than for land-based impacts with Cluster 1, 2 and 3 having R^2_{adj} values of 0.38, 0.34 and 0.34 (all with p-values of <0.01).

$$\mathrm{SPI{-}3} + \mathrm{s(month)} + \mathrm{year} \qquad (2)$$

$$\mathrm{SSI{-}2} + \mathrm{s(month)} + \mathrm{year} \qquad (3)$$

Receiver Operator Characteristic (ROC) curves, which demonstrate the ability of models to correctly predict the occurrence or non-occurrence 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 hydrological-based models show good skill at correctly classifying drought impacts, with the former performing marginally better overall. For land-based drought impacts AUC scores are highest for Cluster 3 (0.90) and lowest for Cluster 2 (0.85). For hydrological-based drought impacts AUC scores are highest for Cluster 1 (0.86) and lowest for Cluster 3 (0.83).

3.3 Linking indices to impacts

Derived models were used to determine the likelihood of impact (article) occurrence at annual and monthly timescales for specified SPI-3 for land- and SSI-2 for hydrological-based impacts. Figure 5 shows impact probabilities on an annual basis over the period 1900-2016. Cluster 3 has the highest impact probabilities for both SPI and SSI values. Cluster 1 and 2 show very similar impact probabilities for a given SPI value. For SSI-2, Cluster 1 shows a higher likelihood of impacts 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 impacts (0.60). For land-based impacts SPI-3 $\leq$ -2.39 for Cluster 1, $\leq$ -2.33 for Cluster 2 and $\leq$ -2.05 for Cluster 3 are identified as thresholds for high impact probabilities on an annual scale. For hydrological-based impacts in Cluster 3 the equivalent values are SSI-2 ≤ -2.41 for Cluster 1, ≤ -2.08 for Cluster 2 and ≤ -1.92. Cluster 3 is identified as most likely to experience both land- and hydrological-based drought impacts, whereas Cluster 1 the least likely. Indices values required to reach each land- and hydrological-based drought impact threshold are given in Table 4.

Figure 6 displays results for monthly likelihoods of land-based drought article occurrence. There are large variations in impact probability across months and clusters. December and January show very low to low impact probabilities, even for extreme deficits in SPI-3. February is the winter month with highest land-based impact probabilities, reaching moderate impact probabilities for deficits of -3 SPI-3. From April through October the likelihood of impacts increases in all clusters. Excluding December, Cluster 3 consistently shows the highest probability of impacts in all months. The 0.6 threshold (dashed black horizontal lines) helps identify SPI-3 deficit values resulting in a high impact likelihood. Notably, in summer (JJA) months only very modest SPI-3 deficits (not less than -1 SI) are required to reach this threshold for land-based impacts in Cluster 3. July (closely followed by June) is the month most prone to impacts, with the most modest SPI-3 deficits resulting in high impact probabilities (-0.78 for Cluster 1, -0.67 for Cluster 2 and -0.23 for Cluster 3). In autumn (SON), the SPI-3 deficits required to reach high impact probabilities become more extreme, with Cluster 3 remaining the most vulnerable to impacts. Throughout most months there is little difference in land-based drought impact probabilities between Clusters 1 and 2.

Figure 7 displays monthly impact likelihoods for hydrological-based impacts. Significant differences emerged when compared with land-based impacts. Cluster 3 shows the highest likelihood of impacts across most months, particularly in autumn (SON) and winter (DJF). However, during late spring and summer, especially from May to August, Cluster 1 shows the highest likelihood of impacts. From May through to August Cluster 2 is least sensitive to hydrological-based impacts. For SSI-2 values ranging from -3 to 3, no cluster reaches the threshold of high probability of impacts for January, with only Cluster 3 reaching this threshold in December and Cluster 2 and 3 in February, but for very extreme SSI-2 deficits. During summer months, deficits of close to -1 SSI-2 are required to reach the 0.6 high impact probability threshold in most clusters. July is the month most prone to hydrological-based impacts, with the most modest SSI-2 deficits resulting in high impact probabilities (-0.79 for Cluster 1, -1.02 for Cluster 2 and -0.89 for Cluster 3). The lowest impact probabilities are in December for Cluster 1 (low impact probabilities) and January for Clusters 2 and 3 (moderate impact probabilities) for SSI-2 values of -3.

3.4 Sensitivity of results to impacts baseline

All clusters display a negative year coefficient for land- and hydrological-based impacts, with the exception of Cluster 1 for hydrological-based impacts (Table 1). Significant negative trends across all clusters were confirmed using Theil-Sens slope testing, again with the exception of hydrological-based 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 statistically significant ($p<0.05$) step changes in the number of impact articles for each cluster and impact type (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 hydrological-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 changing impact likelihood 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 R^2_{adj} for land-based impact models occurring in Cluster 2 (from 0.40 to 0.24; both $p<0.01$). The largest reduction in R^2_{adj} for hydrological-based impact models occurs for Cluster 3 (from 0.39 to 0.26; both $p<0.01$). The least change in R^2_{adj} 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 71 % (Cluster 1), 78 % (Cluster 2) and 63 % (Cluster 3) for land- and 58 % (Cluster 1), 68 % (Cluster 2) and 71 % (Cluster 3) for hydrological-based impacts.

Figure 8 shows annual results for impact likelihoods for land- and hydrological-based drought, with darker/lighter lines representing results for the 1900-1960 and 1961-2016 period, respectively. Differences between impact probability curves are apparent for all three clusters and both impact categories, but particularly for land-based impacts. For both Clusters 2 and 3 the 1961-2016 period returns lower likelihoods of drought impacts. For Cluster 1 however larger SPI-3 deficits produce a greater probability of impacts for the 1961-2016 period, whilst for values closer to zero the risk is higher for the 1900-1960 period, indicating that the likelihood of impacts has increased for extreme droughts and decreased for more moderate droughts. For SSI-2 both Cluster 2 and 3 show lower likelihoods of hydrological-based drought impact for the 1961-2016 period, however the reduction is not as large as seen for land-based impacts. Cluster 1 also shows a higher probability of hydrological-based impacts for the 1961-2016 period but only at extreme SSI-2 values.

The reduction in impact probabilities for the 1961-2016 period is reflected by 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 impacts, the SPI-3 value associated with high impact probabilities changes from -2.16 SPI-3 for 1900-1960 to -2.61 SPI-3 for 1961-2016. For hydrological-based drought in the same cluster, values change from -2.24 to -2.41 SSI-2. For Cluster 2 catchments the high impact probability for land-based articles occurs at -2.60 SPI-3 for the 1900-1960 period and <-3.00 SPI-3 for the 1961-2016 period. Hydrological-based impacts change from -2.19 to -2.70 SSI-2. The largest change in deficit thresholds returning high impact likelihoods is in Cluster 1 for both land- and hydrological-based droughts (<-3.00 to -2.30 SPI-3 and <-3.00 to -2.31 SSI-2). Table 4 provides a cluster specific breakdown of SSI-2 and SPI-3 values required to reach each impact probability threshold.

Figures 9 and 10 repeat the analysis on a monthly basis for land- and hydrological-based 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. The opposite is the case for Cluster 1 where at larger deficits the latter period displays greater likelihoods of drought impacts whilst at more modest deficits the earlier period dominates. For the 1961-2016 period, high impact probabilities at the 0.6 threshold are most easily attained in June for Cluster 1 and July for Cluster 2 and 3 with corresponding SPI-3 values of -1.40, -1.73 and -0.79, compared to -0.57, -0.42, 0.01 for equivalent values derived from the 1900-1960 period. The lowest likelihood of impacts are 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 likelihoods at -3

SPI-3 with the exception of Cluster 1 (1960-2016) which displays moderate impact likelihoods. Between baseline periods, impact likelihoods also differ markedly for hydrological-based articles (Figure 10). For the 1961-2016 period, Cluster 1 shows the greatest sensitivity to drought impacts from January to April, until August for larger deficits. Also, across the year cluster 1 consistently produces greater likelihoods of impacts in this later period in comparison to 1900-1960. As with land-based impacts, the likelihood of hydrological-based impacts in cluster 2 is consistently lower for all months for the 1961-2016 period. This is also the case for cluster 3 except for the months of November to January. Similarly, the month with the greatest likelihood of hydrological-based impacts for 1961-2016 is June for Cluster 1 and July for Cluster 2 and 3. SSI-2 values required to reach the (0.6) threshold are more extreme with values of -1.21, -1.53 and -1.61 SSI-2 required in Clusters 1 to 3 compared to -0.89, -1.09 and -0.89 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 link historic newspaper articles with 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 impact data. Our model evaluation highlighted the strong relationship between short accumulation SPI/SSI periods and drought impacts in Ireland. Overall, SPI-3 was best at modelling land-based drought impacts 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 agricultural impacts. For hydrological drought, SSI-2 generated the best model performance scores.

Model performance varied by region, but overall Cluster 3 in the east/southeast produced the best performing land-based impact model; the weakest was for Cluster 2 in the southwest by a small margin over Cluster 1. For hydrological impacts Cluster 1 performed the best and Cluster 3 the worst by a small margin over Cluster 2. For these models, catchment characteristics have a greater influence on performance with the faster responding catchments in Cluster 1 producing better results than Cluster 3, which contain considerable groundwater storage (O'Connor *et al.*, 2022). Overall, we find that models derived from land-based articles and SPI indices perform better than the hydrological-based equivalent, which is unsurprising given the uncertainties associated with flow reconstructions (O'Connor *et al.*, 2021), non-linear propagation of drought through catchment systems, and the higher reporting of land-based drought impacts. The addition of smoothing to monthly values considerably improved model performance (by a factor of 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 1.5 on average). Performance scores for our models (R^2_{adj} and AUC) compare favourably with similar studies (Parsons *et al.*, 2019; Stagge *et al.*, 2015).

Our results highlight important spatial and temporal variations in drought impact probabilities. On an annual basis Cluster 3 catchments consistently showed the greatest propensity for land- and hydrological-based impacts, whereas Cluster 1 showed the least likelihood for land-based impacts and the least likelihood for hydrological-based impacts at more extreme deficits. At more moderate deficits

Cluster 2 showed the least likelihood for hydrological-based impacts. On a monthly basis, our results indicate large intra-annual variations in drought impact probabilities across all clusters. Winter months show very low to low probabilities of drought impacts being reported, despite the importance of winter deficits in generating hydrological drought (Van Loon *et al.*, 2010). In all clusters and for both impact categories, summer months show the highest impact likelihood. For land-based impacts, all clusters display a high probability of impacts in July, brought about by only very modest SPI-3 deficits (not less than -1), indicating a very high vulnerability to drought. For instance, values as moderate as -0.23 SPI-3 in Cluster 3 in July can result in a high likelihood of drought impacts. Previous studies on drought characterisation in Ireland (e.g. Noone *et al.*, 2017, O'Connor *et al.*, 2022) have employed a threshold of -1 SPI to identify the onset of drought events. Our results indicate that such thresholds may be too conservative given the emergence of reported impacts for events with modest deficits. Cluster 1 catchments show the lowest likelihood of land-based impacts across clusters. These results coincide with those of Wilby *et al.* (2015) who identified the east and southeast region as drier and more drought prone.

We find a close relationship between hydrological drought impacts and catchment characteristics. Despite revealing the lowest likelihood of land-based impacts, for hydrological-based impacts Cluster 1 catchments show the highest likelihood of recorded impacts 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. Conversely Cluster 3 catchments show the highest impact probabilities from September through April. These catchments tend to have higher groundwater storage and more delayed hydrological drought onset, consistent with higher impact probabilities from September through April. Cluster 2 displayed relatively lower overall drought impact likelihoods with hydrological-based impacts lowest in this cluster for summer months.

Inclusion of the 'year' predictor variable in our model revealed a falling trend in drought impacts across all three clusters for both land- and hydrological-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. These results differ to the UK where Parsons *et al.* (2019) found a marked increase in the probability of 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. However, it should also be noted that the period since the 1980s 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 land-based impacts is lower for Clusters 2 and 3. Changes in hydrological 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 probability of drought impacts 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 responsibility for such changes is not possible without a more in-depth analysis.

Linking drought metrics and impacts at the regional scale opens the possibility for better informing 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 impacts and identifies thresholds for impact probabilities associated with different values of each drought metric for various catchment types. Although we detect a decrease in impact probability for some catchment clusters in recent decades, this may be an artefact of reduced drought occurrence in that period given the widespread and significant effects 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.*, 2022) provides an unprecedented resource for investigating drought impacts in Ireland, as well as new opportunities for evaluating societal effects and responses to drought events. Nonetheless, newspaper archives can be subject to biases in reporting with differences in the frequency of publication, changing spatial density of coverage and the possibility that smaller regional publications may have greater local emphasis on reporting, possibly affecting results (see Jobbová *et al.* (2022) for a full discussion). Our aggregation of data by catchment clusters helps to limit the impacts of some of these biases. Possibilities for future work include the application of other drought metrics such as SPEI and/or low flow indicators. Alternative modelling approaches may also be considered. For instance, Bachmair *et al.* (2017) demonstrate the utility of machine learning for linking drought impacts and metrics and could potentially better handle the complex, multi-threshold relationships found here, including accounting for non-binary 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, as has been demonstrated for flood impacts (Basnyat *et al.*, 2017; Thompson *et al.*, 2021). Our analysis has shown that indices extremes and article numbers do not always coincide (e.g. the 1945 and 1921 drought events). Examining the relationships between the frequencies of drought impact reporting and evolving drought indices values for such events would be beneficial. Finally, 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 is an additional element to drought monitoring that could potentially produce 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 land- and hydrological-based drought impacts as inferred from newspaper reports covering the period 1900-2016 in 51 catchments in Ireland. We find that SPI-3 and SSI-2 are most closely related to reported land- and hydrological-based impacts, respectively, with the latter consistently demonstrating stronger links to impacts on annual timescales. Catchments in the east/southeast show the highest probabilities of land- and hydrological-impacts on an annual timescale; catchments in the northwest display the highest hydrological-based impacts at low SSI-2 values during summer months, despite having the lowest equivalent land-based impacts. Overall, we find that maximum drought impact likelihoods across the 1900-2016 period occur in July for SPI-3 and SSI-2 with even modest deficits resulting in high impacts. Changes in impact likelihoods over the last 116 years reveal a falling likelihood of drought impacts for catchments in the east/southeast and southwest. North-western catchments show heightened impact likelihoods for more extreme drought deficits in recent decades. The results reported here have the potential to inform the development of a drought monitoring and warning system both regionally and at the catchment scale in Ireland.

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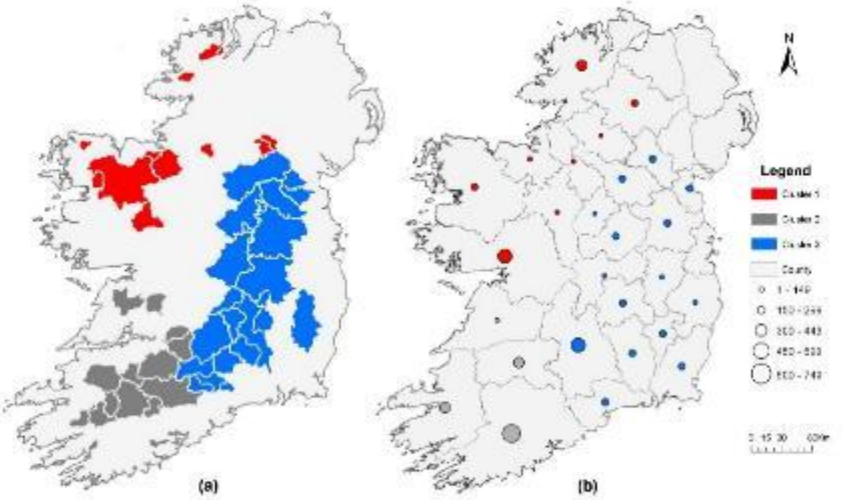

Figure 1. Spatial distribution of (a) clusters of catchments used in the analysis and (b) counties and corresponding drought impact article numbers (combined land- and hydrological-based) over the period 1900-2016.

2187x1320mm (38 x 38 DPI)

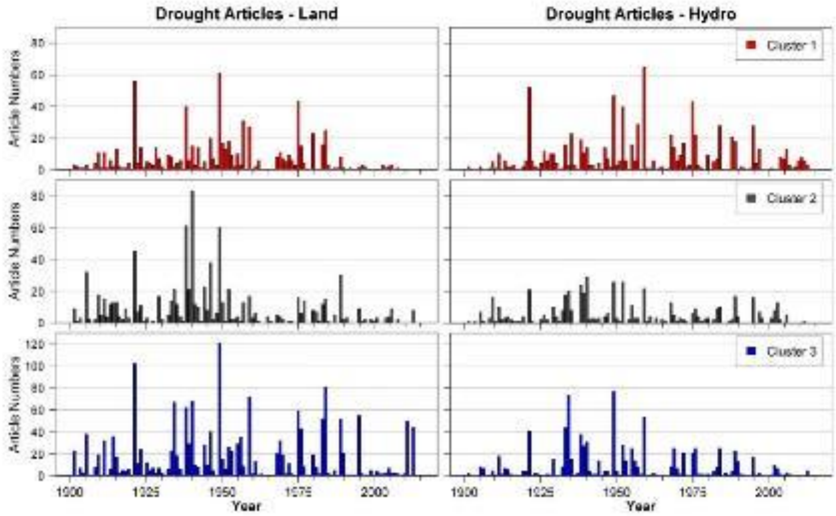

Figure 2. Distribution of land-based (left) and hydrological-based (right) drought impact articles (annual totals) for each cluster over the period 1900-2016.

3042x1863mm (38 x 38 DPI)

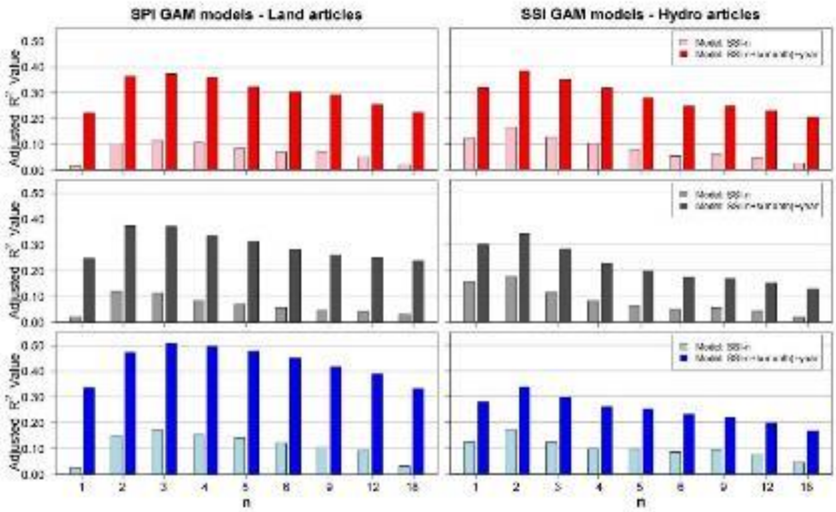

Figure 3. Adjusted R^2 values of the logistic regression models for selected SPI/SSI accumulation periods (n) when simulating monthly land- (left) and hydrological-based (right) impact articles for each cluster during 1900-2016. Results are also shown for models including month and year (darker colours).

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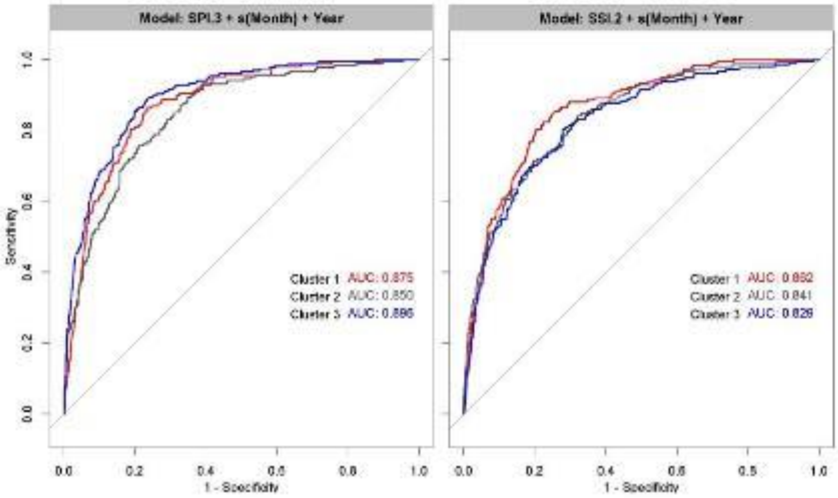

Figure 4. Receiver Operating Characteristic (ROC) curves displaying performance of the logistic regression models generated using land-based newspaper articles and SPI-3 indices (left) and for models generated using hydrological-based newspaper articles and SSI-2 indices (right) for each cluster.

1737x1029mm (38 x 38 DPI)

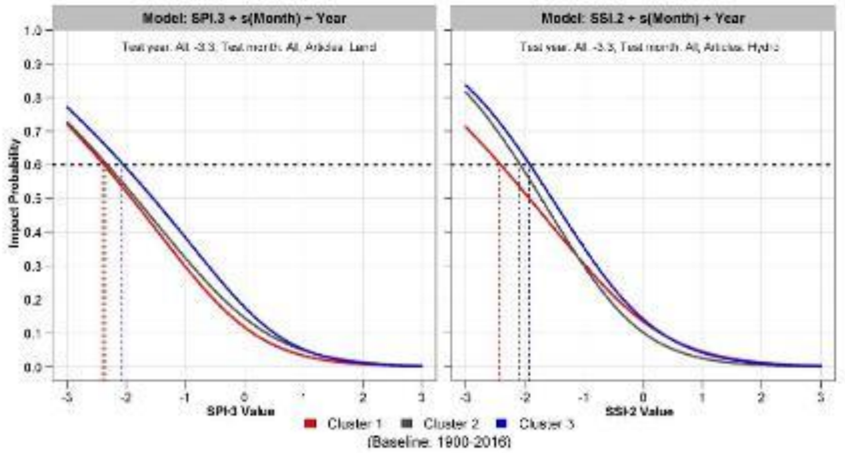

Figure 5. Predicted probability of impacts (annual) from models generated using land-based impact articles and SPI-3 indices (left) and from models using hydrological-based impact articles and SSI-2 indices (right). Impact likelihoods for each cluster over the period 1900-2016 are shown for indices values ranging from -3 to 3. Indices values resulting in high impact probability (0.60) are denoted by the dashed horizontal line.

1736x931mm (38 x 38 DPI)

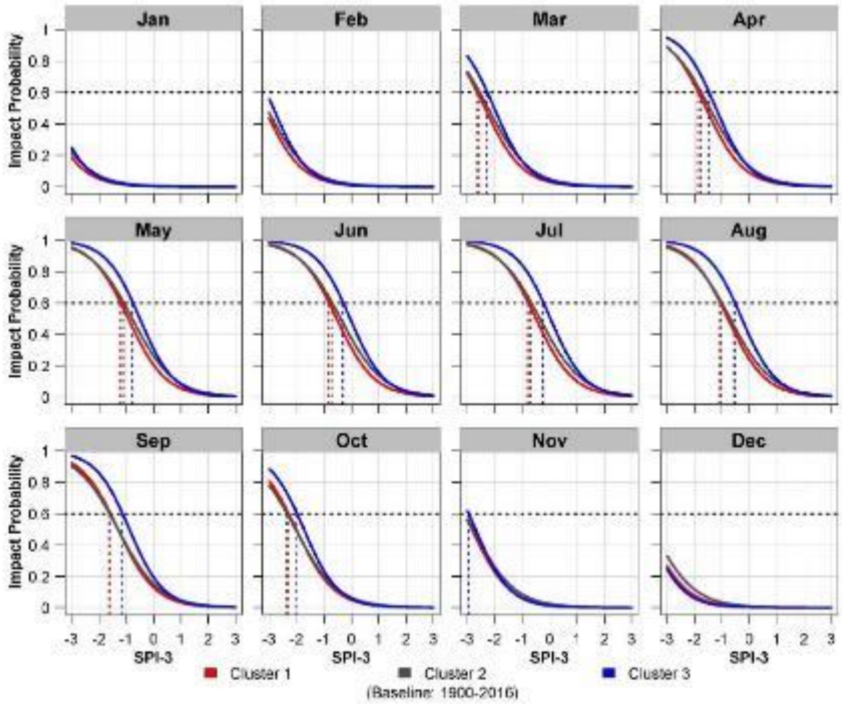

Figure 6. Predicted probability of impacts (monthly) from models generated using land-based impact articles and SPI-3 indices. Impact likelihoods for each cluster over the period 1900-2016 are shown for indices values ranging from -3 to 3. Indices values for each cluster resulting in a high impact probability (0.60) are also identified (dashed horizontal line).

2058x1727mm (38 x 38 DPI)

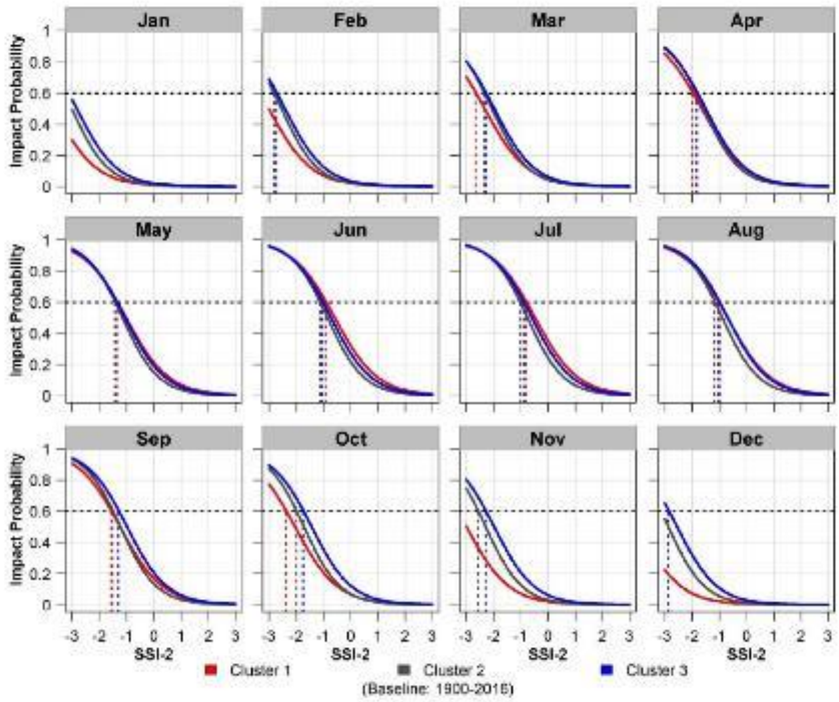

Figure 7. As in Figure 6 but for hydrological-based impact articles and SSI-2 indices.

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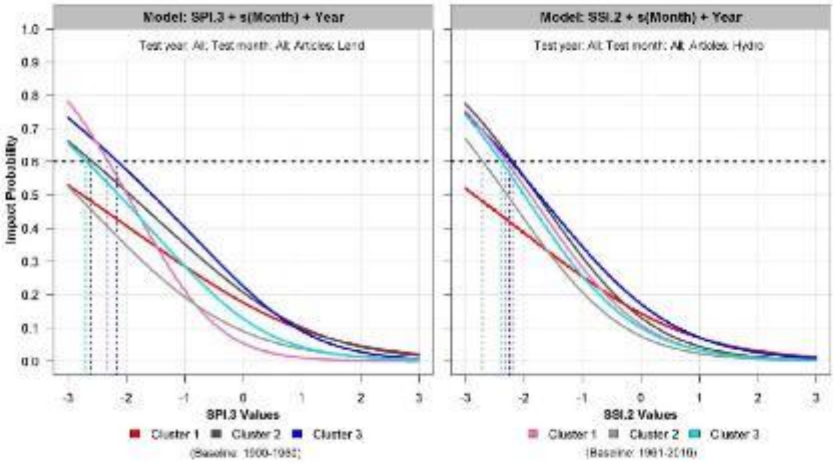

Figure 8. Predicted probability of impacts (annual) from models generated using land-based impact articles and SPI-3 indices (left) and from hydrological-based impact articles and SSI-2 indices (right). Impact likelihoods for each cluster over the period 1900-1960 (darker colours) and 1961-2016 (lighter colours) are shown for indices values ranging from -3 to 3. Indices values for each cluster resulting in a high impact probability (0.60) are also identified (dashed horizontal line).

1753x973mm (38 x 38 DPI)

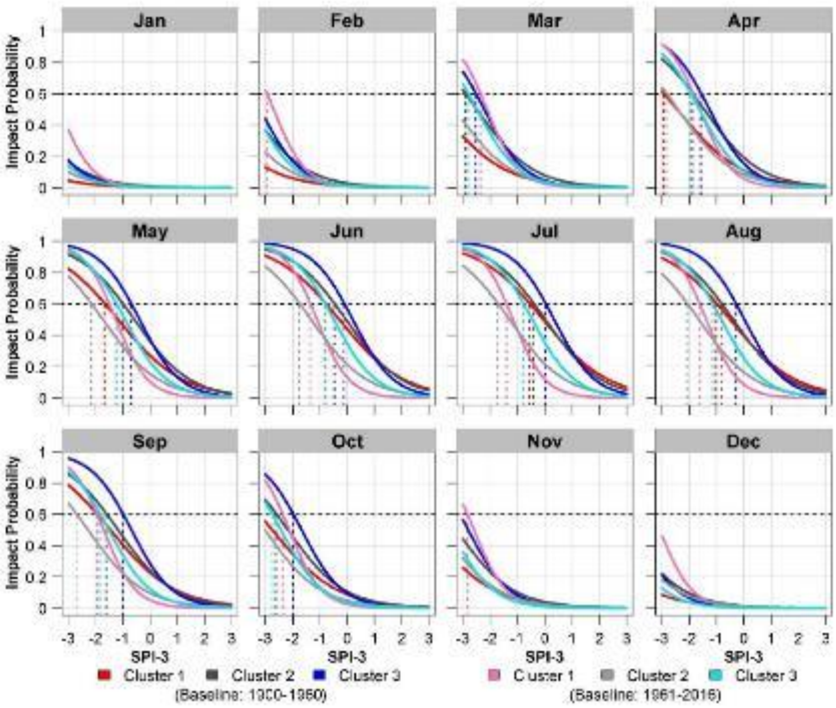

Figure 9. Predicted probability of impacts (monthly) from models generated using land-based impact articles and SPI-3 indices. Impact likelihoods for each cluster over the periods 1900-1960 (darker colours) and 1961-2016 (lighter colours) are shown for indices values ranging from -3 to 3. Indices values for each cluster resulting in a high impact probability (0.60) are also identified (dashed horizontal line).

2064x1732mm (38 x 38 DPI)

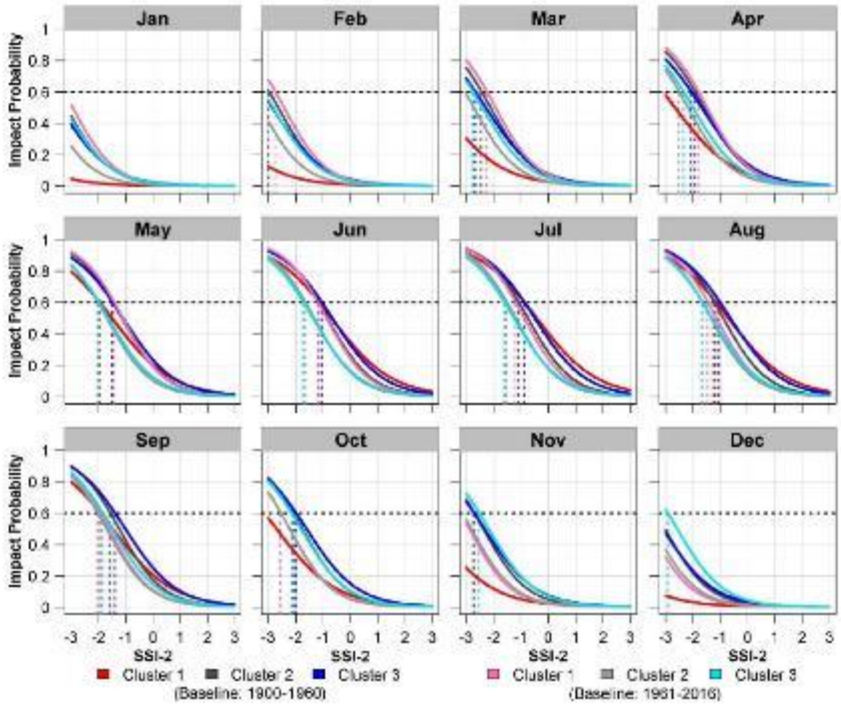

Figure 10. As in Figure 9 but for hydrological-based impact articles and SSI-2 indices.

2061x1729mm (38 x 38 DPI)

Table 1. Performance indicators for model (SPI-3 + s(month) + year) generated for land-based impact articles and model (SSI-2 + s(month) + year) generated for hydrological-based impact articles (1900-2016).

Model	Cluster No.	Intercept Co-eff.	Indices Co-eff.	Year Co-eff.	Adjusted R^2	P-value	% Deviance	AUC	AIC	BIC
SPI-3 + s(month) + year	1	24.57	-1.19	-0.01	0.37	0.001	37.59	0.88	13.55	46.09
	2	21.98	-1.04	-0.01	0.37	0.001	35.56	0.85	13.06	45.57
	3	16.92	-1.42	-0.01	0.51	0.002	47.54	0.90	12.68	45.25
SSI-2 + s(month) + year	1	-1.66	-1.28	-0.00	0.38	0.001	36.87	0.86	13.13	45.61
	2	15.29	-1.33	-0.01	0.34	0.001	33.38	0.84	12.69	44.52
	3	13.65	-1.21	-0.01	0.34	0.002	30.95	0.83	12.85	44.45

Table 2. **Step change month and year identified for land- and hydrological-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	0.03	downward
	2	7	1961	0.01	downward
	3	9	1961	0.04	downward
Hydrological -based	1	8	1977	0.59	downward
	2	6	1961	0.33	downward
	3	9	1990	0.07	downward

Table 3. Performance indicators for model (SPI-3 + s(month) + year) generated for land-based impact articles and model (SSI-2 + s(month) + year) generated for hydrological-based impact articles (1900-1960 & 1961-2016).

Model (Period)	Cluster No.	Intercept Co-eff.	Indices Co-eff.	Year Co-eff.	Adjusted R^2	P-value	% Deviance	AUC	AIC	BIC
SPI-3 +	1	-38.57	-1.04	0.02	0.41	0.028	38.48	0.87	13.45	41.57
s(month) + year	2	-9.91	-1.02	0.00	0.40	0.007	35.46	0.83	12.64	40.63
(1900-1960)	3	-12.52	-1.40	0.01	0.53	0.007	49.06	0.89	12.36	40.35
SSI-2 +	1	-72.11	-1.28	0.04	0.47	0.025	43.76	0.88	12.45	40.51
s(month) + year	2	-12.71	-1.30	0.01	0.35	0.003	32.93	0.82	12.30	39.46
(1900-1960)	3	-44.50	-1.30	0.02	0.39	0.001	34.77	0.83	12.30	39.58
SPI-3 +	1	61.58	-1.40	-0.03	0.37	0.053	40.21	0.89	11.78	38.35
s(month) + year	2	0.89	-0.97	0.00	0.24	0.007	29.03	0.86	11.74	38.20
(1961-2016)	3	-16.43	-1.36	-0.01	0.45	0.007	44.32	0.90	11.90	38.72
SSI-2 +	1	9.90	-1.24	-0.01	0.35	0.027	34.61	0.86	11.72	38.14
s(month) + year	2	13.18	-1.20	-0.01	0.28	0.000	30.50	0.86	11.69	38.06
(1961-2016)	3	32.82	-1.02	-0.02	0.26	0.001	25.61	0.82	10.99	35.77

Table 4. SPI-3 and SSI-2 values producing incremental increasing impact probabilities from very low to very high, for land- and hydrological-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)
	1	>3.00	-0.52	-1.47	-2.39	<-3.00
SPI-3 (1900-2016)	2	>3.00	-0.34	-1.36	-2.33	<-3.00
	3	>3.00	-0.12	-1.08	-2.05	<-3.00
	1	>3.00	-0.43	-1.46	-2.41	<-3.00
SSI-2 (1900-2016)	2	>3.00	-0.58	-1.38	-2.08	-2.92
	3	>3.00	-0.34	-1.18	-1.92	-2.80
	1	>3.00	-0.27	-1.96	<-3.00	<-3.00
SPI-3 (1900-1960)	2	>3.00	0.03	-1.32	-2.60	<-3.00
	3	>3.00	0.13	-1.00	-2.16	<-3.00
	1	>3.00	-0.57	-2.13	<-3.00	<-3.00
SSI-2 (1900-1960)	2	>3.00	-0.46	-1.38	-2.19	<-3.00
	3	>3.00	-0.20	-1.28	-2.24	<-3.00
	1	>3.00	-0.95	-1.66	-2.30	<-3.00
SPI-3 (1961-2016)	2	>3.00	-1.04	-2.30	<-3.00	<-3.00
	3	>3.00	-0.50	-1.57	-2.61	<-3.00
	1	>3.00	-0.60	-1.51	-2.31	<-3.00
SSI-2 (1961-2016)	2	>3.00	-0.95	-1.88	-2.70	<-3.00
	3	>3.00	-0.73	-1.64	-2.41	<-3.00

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