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The Emergence of a Climate Change Signal in Ireland's Rainfall Extremes

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ABSTRACT

Detecting the emergence of anthropogenic climate change signals in precipitation is essential for informing adaptation strategies. This study analyses long-term, quality-assured observations from 36 stations across Ireland (1930–2019) to assess trends and emergence in six seasonal precipitation indices. Using a combination of Mann-Kendall trend testing, Theil-Sen slope estimation, and monthly persistence analysis, robust seasonal changes are identified. Emergence is evaluated by regressing local precipitation indices against global mean surface temperature (GMST), with the resulting signal-to-noise ratio (SNR) classified as normal, unusual, or unfamiliar relative to early industrial (1850–1900) and modern (1950–1980) baselines. The influence of the North Atlantic Oscillation (NAO) is also assessed using commonality analysis. Results show statistically significant intensification of rainfall extremes, particularly in western Ireland during winter and spring, and in the southeast during summer and autumn. Many stations exhibit significant relationships with GMST, with increases in extreme indices (e.g., Rx5day, SDII) ranging from 12% to 27% per °C of warming, often exceeding thermodynamic expectations. Emergence of unusual climate conditions is already evident at several stations relative to the early industrial baseline, and many are nearing this threshold for the modern baseline. While NAO variability strongly modulates winter precipitation extremes in the west, significant GMST relationships in the SNR analysis indicate that these are still robust climate change signals. Commonality analysis reveals that GMST and NAO jointly explain variability in winter PRCPTOT and Rx5day at western stations, suggesting that natural modes of variability like the NAO may not be independent noise but rather embedded within a warming climate signal, complicating the separation of anthropogenic and natural drivers in attribution studies. Findings also challenge projections of widespread summer drying with warming, instead revealing intensification of short-duration extremes in the southeast. As Ireland faces increasingly intense and seasonally variable rainfall extremes, regionally tailored adaptation strategies will be essential.

1 | Introduction

Understanding changes in extreme precipitation is increasingly critical in the context of ongoing climate change. Shifts in the frequency, magnitude, and intensity of rainfall events pose serious challenges for Irish society, particularly through pluvial and fluvial flooding. In recent decades, several high-impact events have highlighted Ireland's vulnerability to intense and persistent rainfall. Notable examples include widespread flooding during the winter of 2015/2016 (McCarthy et al. 2016) and Storm Babet in 2023, which brought record rainfall amounts to southern Ireland and caused severe flooding, particularly in the town of Midleton, County Cork, where substantial damage to residential and commercial property was reported (Clarke et al. 2024).

The Intergovernmental Panel on Climate Change (IPCC) Sixth Assessment Report (AR6) highlights how global warming is altering precipitation patterns worldwide, with extreme rainfall events projected to become more frequent and intense across many regions (IPCC 2023). Globally, increases in the intensity and frequency of heavy precipitation events have been documented across multiple regions and climate regimes (Donat et al. 2016). Therefore, examining how Ireland's precipitation extremes are changing warrants immediate attention. In particular, understanding how extreme rainfall is evolving seasonally is crucial for adapting agricultural practices, water resource management, and flood risk assessment across the country.

Recent Irish research has advanced understanding of long-term trends in annual extremes using an expanded station network (Ryan et al. 2022), but much of the existing research remains limited in its seasonal focus. Earlier studies examining seasonal rainfall trends in Ireland (e.g., Noone et al. 2016; Murphy et al. 2018) primarily analysed seasonal totals, rather than extremes defined by intensity, frequency, or duration. These studies consistently found increasing winter rainfall and decreasing summer rainfall in parts of the country. However, questions remain about how seasonal extremes are changing and how robust those changes are over time.

Ireland's location on the Atlantic margin of western Europe makes it particularly sensitive to changes in large-scale circulation and moisture transport, providing a useful case study for examining emerging precipitation extremes in mid-latitude maritime climates. Few studies have evaluated the magnitude of observed change relative to natural variability, which is essential for informing climate adaptation. Hawkins et al. (2020) demonstrated that significant changes in temperature and precipitation are now detectable across many regions globally, relative to past variability. Using the framework introduced by Frame et al. (2017), they describe how local climates are shifting from "familiar" to "unusual" or even "unknown" relative to pre-industrial conditions. Their work shows that temperatures in Oxford have already become "unknown" compared to the early industrial era, and that annual precipitation totals and extreme rainfall are now emerging from background variability in parts of the UK. Similarly, Ossó et al. (2022) applied this framework to assess the emergence of new climate extremes across Europe using a reference period representative of 'living memory' (1951–1983), focusing on societally relevant impact metrics. They state that 15% of Europe is experiencing more intense winter precipitation events, while in summer, 7% of Europe is experiencing stronger drought-inducing conditions.

In Ireland, an anthropogenic climate change signal has already been detected in annual rainfall indices and seasonal totals (Murphy, Coen, et al. 2023; Murphy, Kettle, et al. 2023). Notably, annual precipitation totals have emerged as unusual for western stations with large increases in winter totals per degree warming in GMST, indicating heightened flood risk. Here, we extend that analysis by examining seasonal extreme precipitation indices, assessing signal emergence relative to both early industrial and modern reference periods, and investigating the influence of the North Atlantic Oscillation. This is achieved by applying the well-established Signal-to-Noise Ratio (SNR) methodology developed by Hawkins et al. (2020) to assess whether, when, and where a climate signal is statistically evident in Ireland's seasonal rainfall extremes. Two reference periods are used: the early industrial baseline (1850–1900) and a more recent reference (1950–1980). The latter was selected due to it being more societally relevant and a period during which major modernisation, including implementation of flood defences and urban expansion, was undertaken nationally, and thus important from an adaptation perspective.

Importantly, spatial and seasonal patterns of emergence may be influenced by large-scale climate drivers. The North Atlantic Oscillation (NAO) is a key mode of atmospheric variability affecting Ireland's climate, particularly in winter and spring. Previous research has linked changes in rainfall intensity and frequency to variations in the NAO (Kiely 1999; Leahy and Kiely 2011), especially in the west of the country. More recent work has also provided updated estimates of short-duration and point rainfall frequencies in Ireland based on national observational datasets (O'Brien et al. 2026; Mateus and Coonan 2023). Therefore, this study also investigates the potential role of the NAO in modulating patterns of change and the emergence of climate change signals.

High-quality, long-term daily precipitation records are essential for detecting trends and signal emergence. Ireland is well positioned in this regard due to recent large-scale data recovery and homogenisation efforts. Several efforts have focused on the recovery of historical meteorological observations across the island of Ireland (e.g., Mateus 2021; Ryan 2020). Ryan (2020) rescued over 3600 station years of daily rainfall data from before 1940, and post-1940 data were obtained from Met Éireann's archives. Quality assurance procedures, including homogenisation and cross-validation, were used to minimise the influence of non-climatic artefacts such as instrument changes or station relocations (Walsh 2016; Ryan 2020; Ryan et al. 2022). This study uses a suite of internationally standardised extreme rainfall indices defined by the Expert Team on Climate Change Detection and Indices (ETCCDI 2024; Frich et al. 2002; Alexander et al. 2006) to examine seasonal extremes and assess both long-term trends and the emergence of climate change signals in Irish precipitation.

This study aims to: (1) analyse long-term trends in seasonal extreme precipitation indices in Ireland over the period 1930–2019; (2) assess the persistence of these trends by examining their sensitivity to varying start dates at a monthly scale; (3) evaluate the emergence of a climate change signal in seasonal rainfall extremes using the signal-to-noise ratio (SNR) framework developed by Hawkins et al. (2020); and (4) investigate the role of the North Atlantic Oscillation (NAO) in influencing patterns of signal emergence in winter and spring. This paper therefore provides the first national-scale assessment of seasonal rainfall extremes and climate signal emergence in Ireland, offering new insights to inform climate adaptation and flood risk management.

2 | Data and Methods

2.1 | Data

To analyse changes in seasonal rainfall extremes, this analysis uses the quality assured daily rainfall dataset for stations across Ireland developed by Ryan et al. (2022) (Figure 1). This dataset

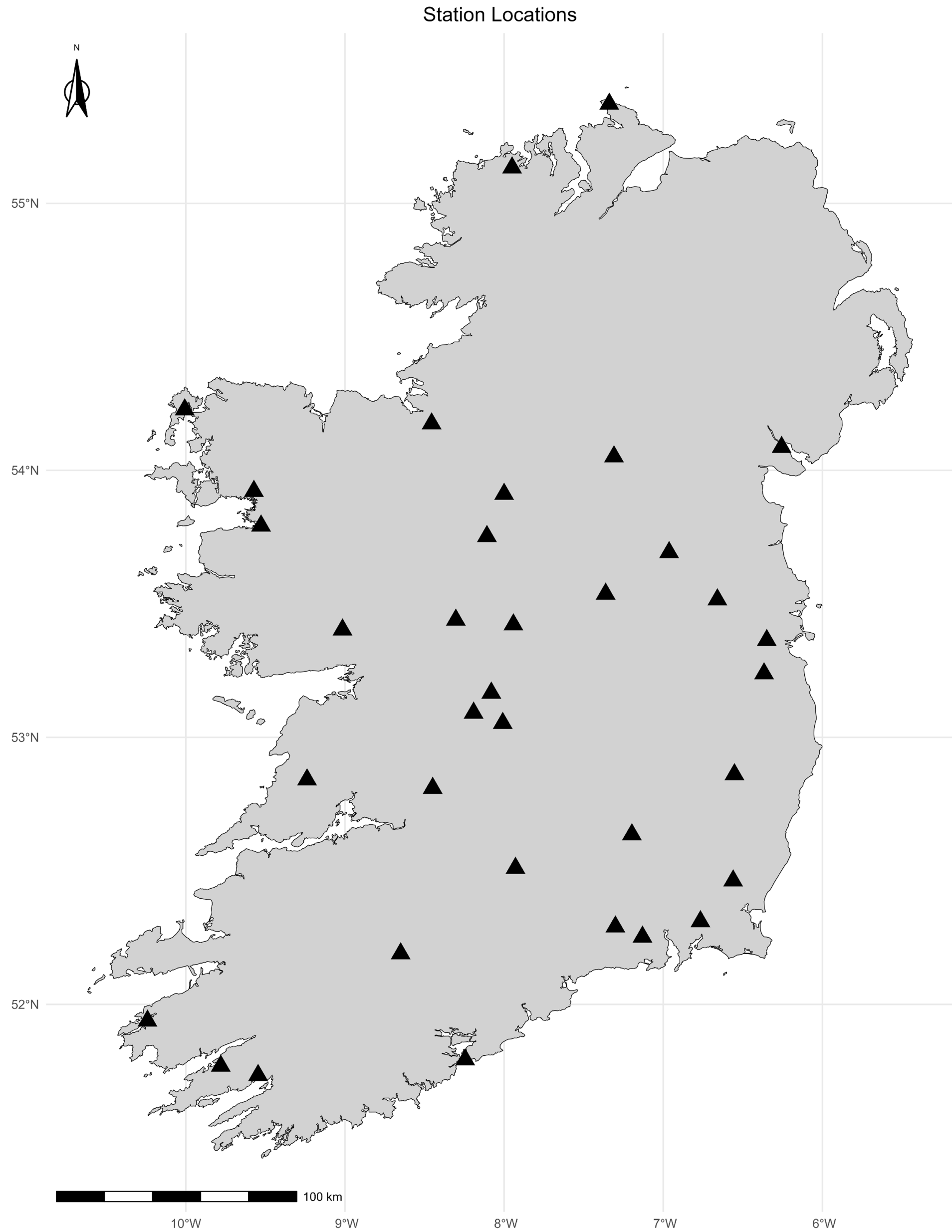

FIGURE 1 | Map of the stations included in this study across Ireland.

was constructed from rescued and digitised daily rainfall data from 1910 to 1940, and 1940 to 2019 daily rainfall data extracted from Met Éireann's database. The pre-1940 daily precipitation data was transcribed from historical manuscripts and printed copies of rainfall registers located in Met Éireann's archives (Ryan 2020). The historical manuscripts were scanned into digital images and then transcribed by students at Maynooth University (Ryan et al. 2018). Quality control assessments on the pre-1940 rescued data were undertaken by Ryan et al. (2022), including basic integrity tests, tolerance tests, temporal, and spatial consistency tests. The post-1940 data also went through similar quality control tests by Walsh (2016). The quality controlled pre-1940 rescued data were added to the database containing post-1940 data to produce continuous station series, with breakpoints identified and adjusted using RHtests software and available metadata (Ryan et al. 2022). The resulting quality assured, homogenised precipitation data series for 36 stations across Ireland is ideal for the investigation for evidence of seasonal trends.

2.2 | Indices

Six precipitation indicators were analysed to determine seasonal trends in extremes (Table 1), selected to allow examination of changes in intensity, frequency, and duration of precipitation events. The indices used in this study are defined by the Expert Team on Climate Change Detection and Indices (ETCCDI, https://www.wcrp-climate.org/etccdi) and were extracted from their website for winter [DJF], spring [MAM], summer [JJA] and autumn [SON]. These indices align with those used in Ryan et al. (2022), except for RX3day, which was included here due to its relevance as a flood-related indicator,

TABLE 1 | List of six precipitation ETCCDI indices used in this study and their description. All indices were calculated seasonally.

ID	Indicator name	Definition	Units
WD	Wet days	Maximum number of consecutive days when precipitation > 1 mm	Days
Rx1day	Max 1-day precipitation amount	Seasonal maximum 1-day precipitation	mm
Rx3day	Max 3-day precipitation amount	Seasonal maximum 3-day precipitation	mm
Rx5day	Max 5-day precipitation amount	Seasonal maximum 5-day precipitation	mm
PRCPTOT	Seasonal total wet-day precipitation	Seasonal total precipitation from days > 1 mm	mm
SDII	Simple daily intensity index	Ratio of seasonal total precipitation to number of wet days (> 1 mm)	mm day^{-1}

thereby facilitating comparison of trend results across different research efforts.

2.3 | Trend Detection

Indices were derived for the fixed period 1930 to 2019 to quantify seasonal trends. The non-parametric Mann-Kendall (MK) test was used to detect monotonic trends (Mann 1945; Kendall 1975). The MK test statistic (MKZs) has a mean of zero and a variance of one. A positive (negative) MKZs value indicates an increasing (decreasing) trend in precipitation. Trends identified were evaluated at a significance level of 0.05, with the null hypothesis of no trend rejected when the absolute value of MKZs exceeded 1.96 (i.e., $|\text{MKZs}| > 1.96$).

The magnitude of change (β) was estimated for each indicator and season at all stations using the relative Theil-Sen slope, expressed as the percentage change over the study period (n years) relative to the long-term mean (μ), following the approach of Yue and Hashino (2007). This was calculated as:

$$\text{TSArel}\,(\%) = \left(\frac{\beta \times n}{\mu}\right) \times 100$$

The median magnitude of trends (TSArel %) was calculated for each indicator and season. To quantify uncertainty in the median trend estimates, 95% confidence intervals were calculated using a non-parametric bootstrap approach (10,000 resamples), providing a robust estimate of the likely range of the true median across stations. Results were visualised using maps that display the direction, magnitude and significance of the trends identified for each indicator at each of the locations across Ireland.

The robustness of trends for the fixed period was further examined by conducting a monthly persistence analysis at each station. This approach involves dropping the start year of analysis iteratively from the full record to a minimum record length of 30 years for each individual month, following the approach of Ryan et al. (2022) and Murphy et al. (2013). The MKZs statistic was calculated for the fixed record 1930 to 2019, then for 1931 to 2019, and so on, enabling an assessment of how stable or sensitive monthly trends are to the chosen start year. This method allows for the identification of specific months that may be driving seasonal trends, as well as any months where opposing signals may be masked in seasonal aggregation. Additionally, plotting MKZ values for all stations and indicators allowed for the identification of any stations exhibiting notable deviations from the general trend patterns. All trend detection analyses were conducted using R statistical software.

2.4 | Observed Emergence and Signal-to-Noise

The emergence of forced climate change signals in the six observed extreme precipitation indices (see Table 1) was examined following the methodology of Hawkins et al. (2020). This approach involves linearly regressing local variations in climate onto annual global mean surface temperature change (GMST) to produce estimates of the signal-to-noise ratio.

$$L(t) = \propto G(t) + \beta$$

where $L(t)$ is the local change in precipitation indices over time, $G(t)$ is a smoothed version of GMST anomalies over the same period, $\propto$ is the linear scaling between L and G, and β is a constant. Significance of $\propto$ was evaluated at the 0.05 level. To calculate $G(t)$, annual anomalies in GMST were derived relative to 1850–1900 (representative of the early industrial era) (Hawkins et al. 2020) and to 1950–1980. The latter was selected due to its greater relevance for contemporary policy, particularly in the context of widespread implementation of flood defences in Ireland since the mid-20th century (OPW 2021). GMST anomalies were derived from the Berkely Earth temperature dataset for 1850–2018 (Rohde et al. 2013) combined with HadSST4 from Kennedy et al. (2019). This data was smoothed using a Loess filter with a span of 0.25. The signal of global temperature change is defined as the smoothed GMST in 2018 ($G_{2018} = 1.18$ or 0.91 K, depending on baseline), the signal of local precipitation change is assumed proportional to GMST ($\propto G$), and the noise is the standard deviation of the residuals ($L - \propto G$). The terminology of Frame et al. (2017) is applied to describe how climate has changed from being normal or familiar (S/N > 1), unusual (S/N > 1 < 2), unfamiliar (S/N > 2 < 3), and unknown (S/N > 3), relative to each baseline. Results were visualised by mapping the spatial distribution of Alpha ($\propto$) values as % change per degree warming in GMST and SNR values across Ireland, highlighting regions and seasons where precipitation changes have most clearly emerged from natural variability. Results for all seasons and indices analysed are provided in the Supporting Information, while the text provides those with strongest relationship with GMST and emergence.

2.5 | Influence of the North Atlantic Oscillation (NAO)

To further investigate potential drivers of the observed emergence in extreme precipitation, the influence of the North Atlantic Oscillation (NAO) was assessed. The analysis focused on winter (Rx5day and PRCPTOT) and spring (Rx5day and SDII) indices, which showed the strongest emergence signals. The NAO is a key mode of atmospheric variability over the North Atlantic and strongly influences storm tracks and precipitation across western Europe, especially in winter (Hurrell 1995). In Ireland, increases in extreme rainfall have previously been linked to NAO variability (Leahy and Kiely 2011). Given this relationship and the spatial overlap with regions of emergence, Hurrell's station-based NAO index (Hurrell et al. 2023) was used to evaluate the extent to which the NAO may be contributing to or modulating these trends.

As a first step, linear regression was performed between the NAO index and the precipitation indices that exhibited significant relationships with GMST in the original SNR analysis. Residuals from this regression were then used to repeat the SNR analysis, allowing for an assessment of how much of the observed emergence could be attributed to NAO variability. However, given that NAO itself may be modulated by anthropogenic climate change (Smith et al. 2025; Liu et al. 2023), regressing out its influence risks removing part of the GMST-driven signal.

To address this, a commonality analysis was conducted to partition the variance in precipitation explained by unique contributions from GMST and NAO, as well as their shared variance. This analysis was applied to stations with statistically significant GMST relationships in the original SNR analysis. GMST was smoothed using a Loess filter (span = 0.25), consistent with the emergence methodology, while the NAO was left unsmoothed to preserve interannual variability. Sensitivity testing was conducted using different combinations of smoothed and unsmoothed predictors to ensure robustness of results. Stations were then classified based on the dominant explanatory factor: NAO-driven (> 60% of the explained variance attributable to NAO), GMST-driven (> 60% attributable to GMST), Shared (> 60% jointly attributable to both NAO and GSMT), or Mixed influence (no explanatory factor exceeds 60% contribution).

3 | Results

3.1 | Fixed Period Trends and Persistence

Trends were assessed for each of the six indices across the network of 36 homogenised daily precipitation series for each season in the fixed period 1930–2019. Results are summarised in Tables 2 and 3, with key spatial trends mapped in Figures 2 and 3. Figures S1–S4 in the Supporting Information provide maps of the fixed period trends in all six indices for each season. Persistence testing evaluated the stability of trends at monthly intervals to identify specific months that were driving seasonal trends, as well as any months where opposing signals may be masked in seasonal aggregation. Key months that drive fixed period seasonal trends are highlighted in Figure 4, with persistence plots for each month and indicator in the Supporting Information (Figures S5 and S16).

3.1.1 | Winter and Spring

Fixed-period analysis reveals a west–east gradient in winter indices, with significant increasing trends concentrated in western Ireland and non-significant decreasing trends in the east and south. PRCPTOT and Rx5day show the highest rates of significant increases (16.7% of stations). While the median change across all stations for these two indicators is −1.85% and 3.52%, respectively, western stations with significant increases show much larger median increases of 18.84% (CI: 14.34 to 31.16) and 18.38% (CI: 16.42 to 25.74), underscoring the intensity of change in that region. Rx1day and Rx3day show more variability, with more stations experiencing significant decreasing trends (8.3%) than increasing ones (2.8% and 5.6%, respectively). WD and SDII show moderate, though often insignificant, increases. Winter fixed period results indicate subtle changes in the frequency and intensity of winter rainfall, complementing the more robust trends observed in PRCPTOT and Rx5day. Monthly persistence testing shows February is the primary driver of these trends, with robust increases in Rx5day (Figure 4) and Rx3day from the 1950s to 1960s and recent WD increases from the late 1990s onward in the west. December and January exhibit weak or inconsistent signals, with only short-lived intensifications in a few stations. This indicates that fixed-period winter trends may mask important intra-seasonal variability.

TABLE 2 | Direction of change and proportion of statistically significant (5% level) winter and spring trends for 1930–2019 fixed period extreme precipitation indices.

	Winter			Spring		
Indicator	**Pos.(sig.) %**	**Neg.(sig.) %**	**Magnitude (CI)**	**Pos.(sig.) %**	**Neg.(sig.) %**	**Magnitude (CI)**
WD	58.3 (8.3)	36.1 (8.3)	0 (0, 3.78)	75 (22.2)	22.2 (2.8)	8.44 (4.05, 12.22)
Rx1day	63.8 (2.8)	36.1 (8.3)	−1.66 (5.46, 1.84)	86.1 (25)	13.9 (0)	9.54 (5.57, 13.10)
Rx3day	50 (5.6)	50 (8.3)	−0.37 (−6.60, 5.38)	75 (22.2)	25 (2.8)	6.89 (4.69, 11.51)
Rx5day	55.6 (16.7)	44.4 (0)	3.52 (−3.39, 10.55)	88.8 (22.2)	11.1 (0)	10.25 (5.32, 13.37)
PRCPTOT	52.8 (16.7)	47.2 (2.8)	−1.85 (−6.48, 6.45)	94.4 (33.3)	5.6 (0)	13.37 (9.85, 19.11)
SDII	55.6 (5.6)	44.4 (0)	1.57 (−2.17, 4.93)	86.1 (16.7)	13.9 (2.8)	4.24 (2.56, 8.44)

Note: Direction and significance tested using modified Mann–Kendall (MKZs) and magnitude tested with the relative Theil-Sen approach (TSArel). Magnitude of change is based on the median of the test statistics alongside 95% confidence intervals, derived via non-parametric bootstrapping.

TABLE 3 | Direction of change and proportion of statistically significant (5% level) summer and autumn trends for 1930–2019 fixed period extreme precipitation indices.

	Summer			Autumn		
Indicator	**Pos.(sig.) %**	**Neg.(sig.) %**	**Magnitude (CI)**	**Pos.(sig.) %**	**Neg.(sig.) %**	**Magnitude (CI)**
WD	27.8 (2.8)	72.2 (11.1)	−6.56 (10.31, 0)	55.6 (5.6)	4.44 (5.6)	0 (2.31, 0)
Rx1day	61.1 (5.6)	38.9 (5.6)	2.60 (2.80, 7.15)	63.8 (11.1)	36.1 (5.6)	1.72 (2.64, 8.03)
Rx3day	38.9 (5.6)	61.1 (5.6)	−2.38 (−5.34, 1.73)	66.6 (11.1)	33.3 (0)	4.71 (0.33, 12.14)
Rx5day	38.9 (2.8)	61.1 (13.9)	−2.22 (−4.78, 0.95)	72.2 (11.1)	25 (0)	5.30 (2.44, 9.28)
PRCPTOT	22.2 (0)	77.8 (2.8)	−6.07 (9.21, −3.83)	72.2 (2.8)	27.8 (0)	3.62 (1.37, 6.34)
SDII	50 (16.7)	50 (8.3)	0.55 (5.88, 4.40)	61.1 (13.9)	38.9 (8.3)	1.49 (−1.90, 6.70)

Note: Direction and significance tested using modified Mann–Kendall (MKZs) and magnitude tested with the relative Theil-Sen approach (TSArel). Magnitude of change is based on the median of the test statistics alongside 95% confidence intervals, derived via non-parametric bootstrapping.

Spring precipitation trends are predominantly positive across all indicators, with very few decreasing trends. The spatial distribution indicates broad national increases, with statistically significant increases concentrated in the western half of the country across all indicators. PRCPTOT exhibits the most significant increases, with 33.3% of stations showing statistically significant positive trends. It also has the largest median increase in magnitude of any indicator or season, at 13.37%. Stations with significant increases located in the west show a median increase of 26.57% (CI: 23.22 to 34.32), highlighting the region's sensitivity to spring rainfall changes.

Short-duration extremes follow a similar spatial pattern with significant increases concentrated in the west. Rx1day shows significant increases at 25% of stations, and at 22.2% of stations for Rx3day and Rx5day. Western stations with significant trends show a median increase of 20.41% (CI: 18.28 to 30.13) for Rx1day, 21.11% (CI: 16.43 to 31.38) for Rx3day, and 22.51% (CI: 20.21 to 29.91) for Rx5day. WD also reflects increasing frequency, with 22.2% of stations showing significant increases. SDII shows a consistent, though slightly weaker pattern, with 16.7% of stations showing significant increases.

March and early April are the dominant contributors to fixed period trends. March shows persistent increases post-1990 across multiple indicators, following a dip in the mid-1970s (see Figure 4). April displays a mixed pattern with increasing trends from the 1960s–1970s, then declining from the 1980s onward, particularly at western stations for PRCPTOT and SDII (Figure 4). May trends are more limited and less persistent, particularly for tests commencing after 1990.

3.1.2 | Summer and Autumn

Summer reveals pronounced regional divergence. Fixed-period data show overall declines in WD, with 11.1% of stations, primarily in the southeast, exhibiting significant decreases. These southeast stations show a median decrease in number of wet days of −25.04% (CI: −31.89 to −17.24). Conversely, SDII increases at 16.7% of stations in the same region. These stations exhibit a median increase in magnitude of 17.66% (CI: 11.38 to 25.27), indicating a shift toward less frequent but more intense rainfall. Rx1day and Rx3day reveal decreases in the west and increases in the southeast, although few are statistically significant. Rx5day is dominated by decreasing trends at 13.9% of stations, predominantly in the west, with a median decrease in magnitude of −14.38% (CI: −19.22 to −11.13). PRCPTOT reveals little change overall, with few significant trends detected. This, combined with the contrasting trends in frequency and intensity indicators, suggests that extreme events are contributing more heavily to summer totals. Persistence testing echoes these signals in summer. June trends peak in the 1960s–1970s then decline, suggesting reduced rainfall frequency. July and August show consistent SDII and short duration extreme increases from the 1960s onward (see Figure 4). These findings reinforce the fixed-period signals of a shift toward shorter, more intense summer rainfall events.

Autumn shows few significant fixed-period trends overall. SDII increases (13.9%) appear localised to eastern stations. These stations show a median increase of 18.82% (CI: 12.13 to 20.69), compared to a much smaller overall median of 1.49%, indicating localised intensification of rainfall events as reported in summer. Rx1day, Rx3day, and Rx5day also show significant increases at 11.1% of stations, again predominantly in the east and southeast. PRCPTOT and WD reveal minimal change and lack coherent spatial signals.

Persistence testing reveals October's widespread drying signal beginning in the 1990s (Figure 4). SDII and PRCPTOT show significant decreases, especially in the south and southeast, diverging from fixed-period signals. September and November show limited trend persistence. September's decreases in early start years shift toward neutral or positive values over time, while November displays some significant increasing trends during mid-century that fade after the 1990s.

3.2 | Emergence of Climate Change Signals

The previous section identified fixed-period trends and evaluated their robustness across varying start dates. However, the urgency for adaptation is driven not only by trend presence but by the magnitude of change relative to natural variability. This section examines the signal-to-noise ratio (SNR) in seasonal

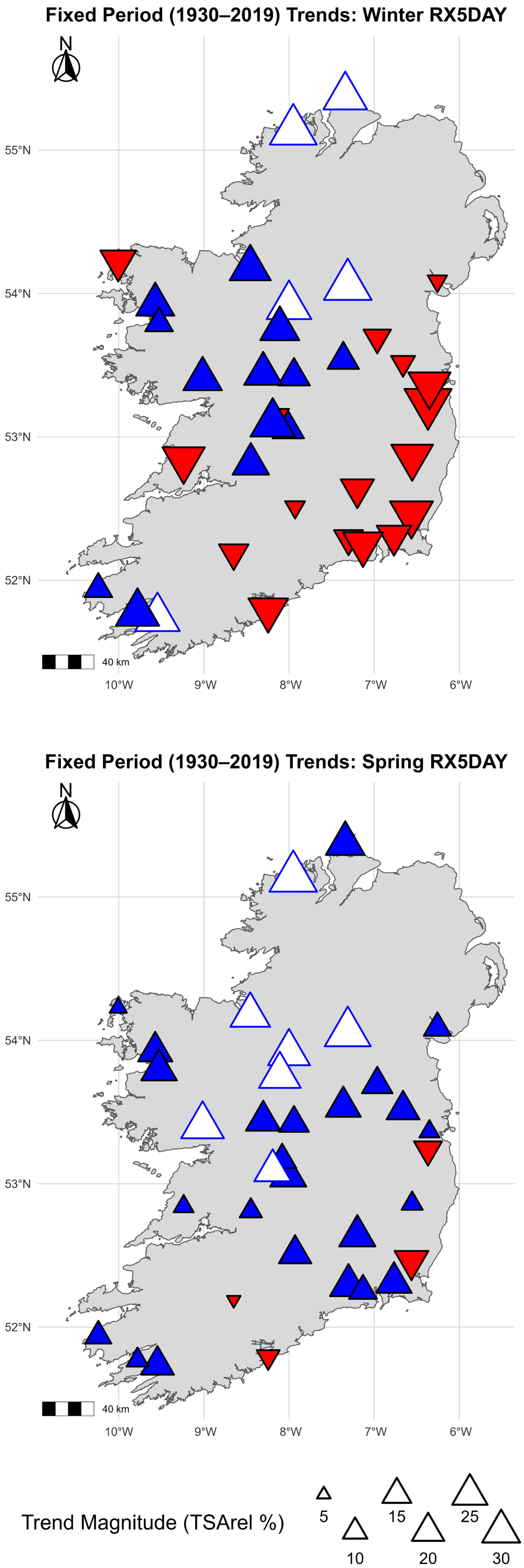

FIGURE 2 | Legend on next page.

FIGURE 2 | Magnitude and direction of trends for 1930–2019 fixed period for winter (Rx5day and PRCPTOT) and spring (Rx5day and PRCPTOT) precipitation indices. Blue triangles represent increasing trends and red decreasing trends, with magnitude proportional to size. Magnitude derived using the relative Theil-Sen Approach TSArel (%). Significant trends (5% level) shown by white triangles and derived from the Modified Mann–Kendall (MKZs). [Colour figure can be viewed at wileyonlinelibrary.com]

precipitation indices against two baselines: the early industrial period (1850–1900) and a modern reference (1950–1980) to establish if observed changes can be associated with anthropogenic climate change. Figures 5 and 6 map the SNR values for each station for indices showing the strongest emergence, while Figure 7 shows the SNR range across each station. Result statistics for all indices and stations analysed are provided in Supporting Information (Tables S1–S48), along with SNR maps for each season and indicator (Figures S17–S24).

3.2.1 | Emergence in Winter and Spring

Winter indices reflect similar spatial patterns to those observed in the fixed-period trend analysis, with increases concentrated in the western half of the country. PRCPTOT and Rx5day in particular show clear signs of climate change emergence in this region. Relative to the early industrial baseline, five stations are classified as unusual for PRCPTOT, with four additional stations nearing the threshold (SNR: 0.82–0.97). For Rx5day, six stations are classified as unusual, with four approaching the threshold (SNR: 0.83–0.94). These stations show significant GMST relationships, with increases ranging from 18.2% ± 17.2% to 27.4% ± 19.6% for PRCPTOT and 18.7% ± 15.3% to 21.8% ± 16.4% for Rx5day per degree warming in GMST. Relative to the 1950–1980 baseline, increasing trends in the west are beginning to emerge from natural variability. Nine stations for PRCPTOT (SNR: 0.63–0.84) and eleven for Rx5day (SNR: 0.6–0.82) exhibit statistically significant relationships with GMST. ∝ ranges from increases of 16.8% ± 15.8% to 26.1% ± 18.0% (PRCPTOT) and 12.7% ± 12.5% to 20.5% ± 15% (Rx5day) per degree of warming since 1950–1980.

Spring indices also show emergence of climate change signals in the west, consistent with fixed-period trends. PRCPTOT, SDII, Rx1day, Rx3day, and Rx5day all exhibit significant relationships with GMST at western stations, with estimated increases ranging from 12.9% ± 12.7% to 27.2% ± 20.5% per degree of warming since the early industrial period. Four stations for each of these indicators are classified as unusual relative to this baseline, with several others nearing the threshold. Relative to the 1950–1980 baseline, many western stations are approaching the threshold for emergence (SNR > 1). Notably, eight and seven stations for SDII and Rx5day, respectively, exhibit strong, statistically significant relationships with GMST. ∝ ranges from increases of 10.7% ± 10.2% to 20.1% ± 12.1% (SDII) and 16.7% ± 14.7% to 23.8% ± 16.6% (Rx5day) per degree of warming since the 1950–1980 period.

3.2.2 | Emergence in Summer and Autumn

In summer, emerging climate change signals are most evident in SDII, particularly in the southeast. Six stations reveal significant relationships with GMST, with ∝ showing increases of 16.9% ± 14.9% to 25.4% ± 18.4% per degree of warming since the early industrial period. Four of these stations are classified as unusual, with a fifth station just below the threshold (SNR: 0.93). Relative to the 1950–1980 baseline, similarly, six stations reveal significant relationships with GMST.

Multiple stations in the southeast region exhibit large ∝ values (15.1% ± 13.7%–23.9 ± 16.9% per degree warming) but remain within the bounds of natural variability (SNR: 0.64–0.98). One of these stations in the mid-west shows a decrease of −13.4% ± 12.7% per degree warming but is still within the bounds of natural variability (SNR: −0.62). Other summer indices show no significant relationships with GMST at most stations and no clear signs of emergence relative to either baseline.

Autumn patterns are similar to those in summer, with SDII showing the strongest signals in the southeast. Relative to both baselines, five southeast stations reveal significant relationships with GMST. ∝ ranges from increases of 15.5% ± 12.0% to 22.4% ± 12.2% per degree warming relative to early industrial and 13.0% ± 12.3% to 20.0% ± 11.3% relative to 1950–1980. Four southeast stations are classified as unusual relative to the early industrial baseline, and no stations exceed the SNR > 1 threshold relative to the 1950–1980 baseline. In the west, one station shows a decrease of −11.3% ± 10.1% per degree warming since early industrial and −10.3% ± 9.3% since 1950–1980, although it does not cross the unusual threshold. Rx1day and Rx3day also show emerging climate change signals in the southeast, with five stations revealing a significant relationship with GMST relative to both baselines. Three southeast stations emerge as unusual in these indicators relative to the early industrial baseline. Relative to 1950–1980, many stations in the southeast are nearing emergence (SNR: 0.60–0.92), but none meet the unusual threshold. In contrast, PRCPTOT and WD show no significant relationship with GMST and no signs of emergence in autumn, while Rx5day shows only limited signals.

3.3 | Influence of the North Atlantic Oscillation (NAO)

Results indicate that in winter (Rx5day and PRCPTOT) NAO variability plays a substantial role in shaping precipitation extremes in western Ireland. When the NAO signal was removed, SNR values for all western stations dropped below the emergence threshold, suggesting that the observed emergence in these cases is strongly modulated by the interannual to decadal variability associated with the NAO. However, this does not imply that emergence is solely driven by the NAO. Commonality analysis reveals that GMST and NAO jointly explain variability in winter at all western stations (see Figure 8), with all western stations classified as NAO-driven for PRCPTOT and predominantly Mixed for Rx5day. This

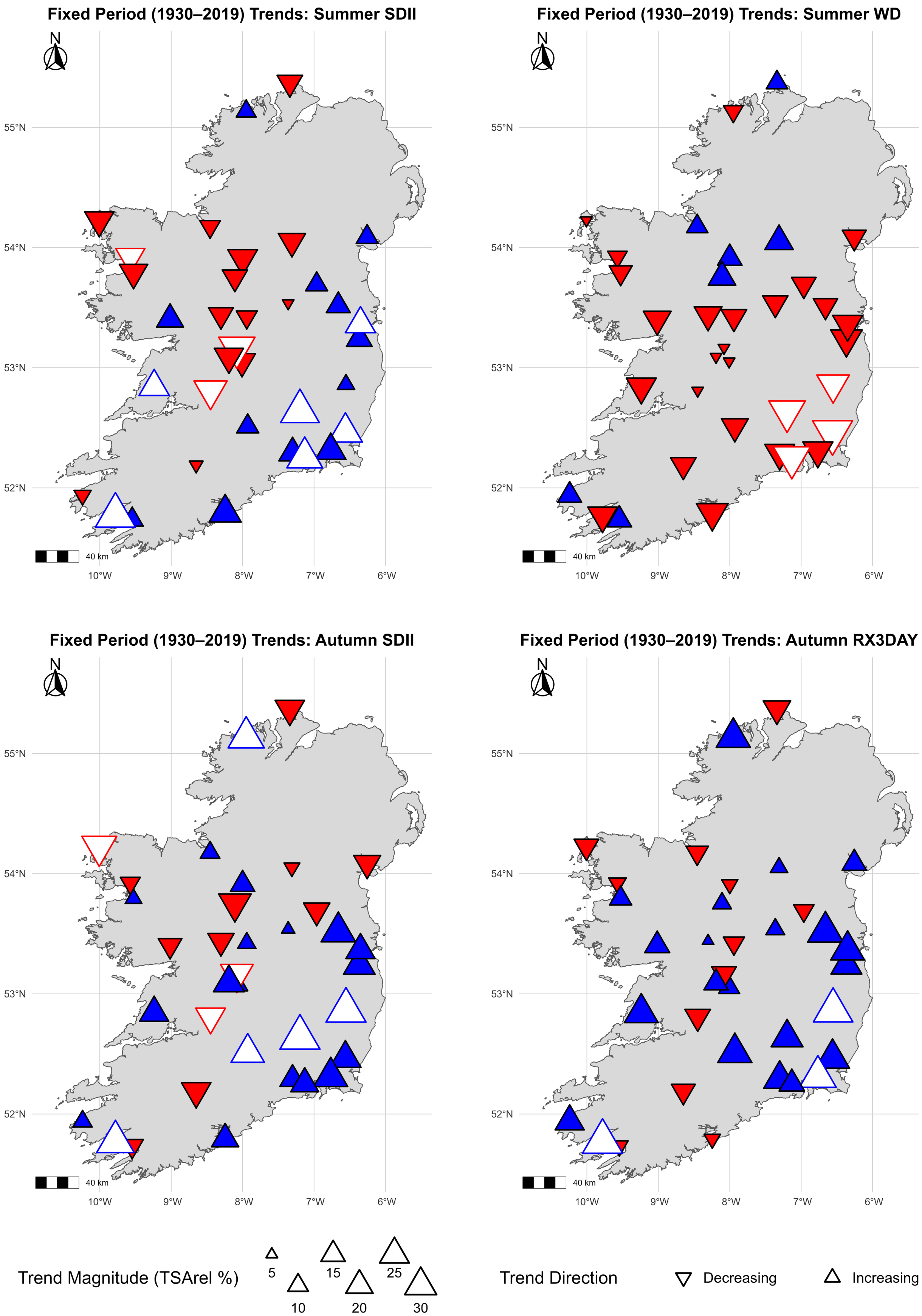

FIGURE 3 | Legend on next page.

FIGURE 3 | Magnitude and direction of trends for 1930–2019 fixed period for summer (SDII and WD) and autumn (SDII and Rx3day) precipitation indices. Blue triangles represent increasing trends and red decreasing trends, with magnitude proportional to size. Magnitude derived using the relative Theil-Sen Approach TSArel (%). Significant trends (5% level) shown by white triangles and derived from the Modified Mann–Kendall (MKZs). [Colour figure can be viewed at wileyonlinelibrary.com]

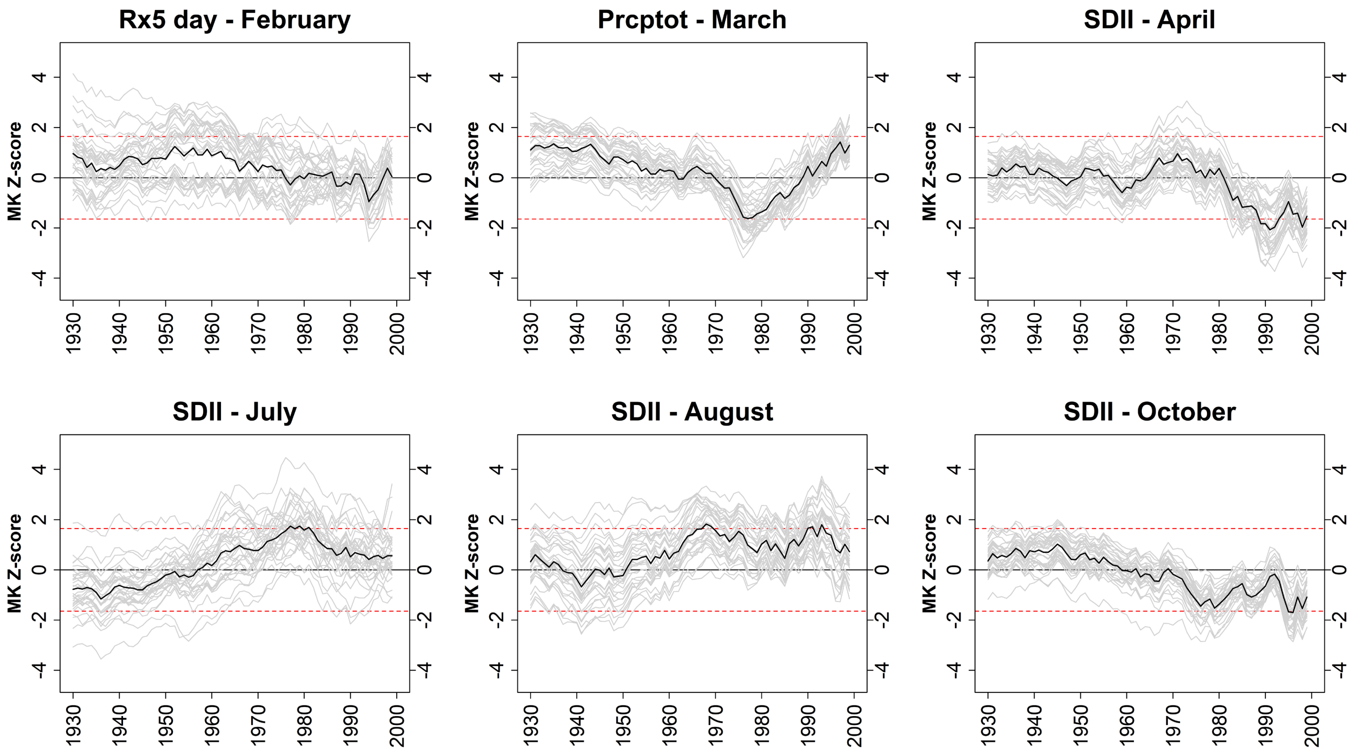

FIGURE 4 | Persistence of monthly precipitation trends for selected months and indicators across Ireland (1930–2019). Each plot shows the Mann-Kendall trend statistic (MKZ) for varying start years, highlighting the temporal stability of trends at individual stations. Plots were selected based on key months that drive fixed period seasonal trends. The grey lines represent MKZ values for each of the 36 rainfall stations for varying start years. The black line represents the mean trend across all stations. The dashed red lines at +1.96/−1.96 represent thresholds above/below which trends are significantly increasing or decreasing at the 0.05 level. [Colour figure can be viewed at wileyonlinelibrary.com]

suggests that the NAO is not merely background noise but may be partially embedded within the broader climate change signal, complicating the separation of anthropogenic and natural influences. In contrast, spring indices retained robust SNR emergence at many stations even after the NAO signal was removed. As shown in Figure 8, all western stations were classified as GMST-driven, indicating that spring emergence is less modulated by the NAO and is more likely to reflect a direct climate change signal. Importantly, the NAO analysis confirms that anthropogenic warming remains a key driver of SNR emergence in both winter and spring, even though the NAO strongly modulates the expression of these signals, particularly in winter.

Sensitivity testing revealed that smoothing the NAO index, as done with GMST, significantly reduced its explanatory power in winter, shifting classifications toward GMST or Shared. This suggests that the unsmoothed NAO better captures the high-frequency variability that influences winter precipitation extremes. In contrast, in spring, smoothing the NAO tended to inflate the shared variance with GMST, likely due to overlapping low-frequency trends between the two signals. These findings underscore the importance of preserving interannual variability in the NAO when assessing its influence on seasonal precipitation patterns.

4 | Discussion

Seasonal rainfall extremes in Ireland exhibit clear, spatially distinct trends. Over the fixed period (1930–2019), robust increases in seasonal total wet-day precipitation and short-duration extremes are evident, especially in winter and spring, with western Ireland consistently showing the most statistically significant and spatially coherent trends. Key indices such as PRCPTOT, Rx5day, and wet days (WD) highlight this intensification, and persistence testing reveals that these seasonal changes are often dominated by a few critical months, notably February in winter, and March and April in spring. Fixed-period results show declining rainfall frequency (WD) in the southeast during summer, even as short-duration intensity (SDII) and extremes become more pronounced, indicating a shift toward less frequent but more intense rainfall events. Monthly analysis points to July and August as the key contributors to this intensification.

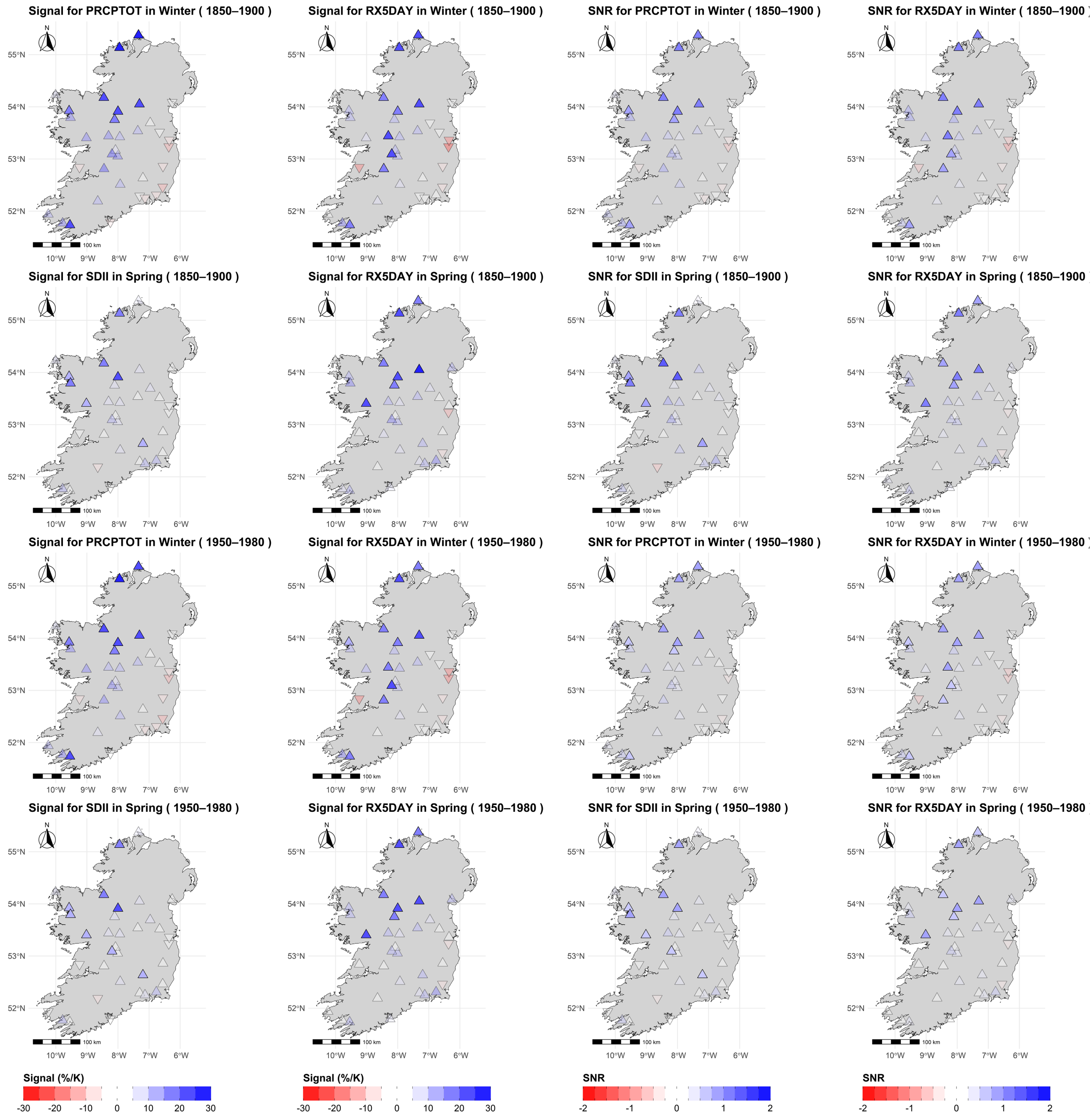

FIGURE 5 | Signal (left) and signal-to-noise ratio (right) for winter (PRCPTOT and Rx5day) and spring (SDII and Rx5day) precipitation indices. The signal is presented % change per degree warming in GMST based on Alpha (∝) values. The top two rows are results relative to 1850–1900 baseline and the bottom two rows are relative to the 1950–1980 baseline. Signal-to-noise ratio (SNR) values are interpreted following the terminology of Frame et al. (2017), where SNR > 1 indicates a climate signal emerging from background variability ("familiar"), SNR > 2 indicates "unfamiliar" conditions, and SNR > 3 indicates "unknown" conditions. The direction of the opaque triangles representing each station show the direction of change, while transparent triangles indicate no significant (5% level) relationship with GMST. [Colour figure can be viewed at wileyonlinelibrary.com]

Autumn also exhibits increasing trends concentrated in the southeast, particularly in intensity and multi-day extremes. Although a notable finding in persistence testing is that October shows signs of drying in recent decades.

These findings build on previous studies. The most recent study on extreme precipitation concluded increasing annual extremes are evident in the southeast (Ryan et al. 2021). Research on seasonal totals (Noone et al. 2016; Hoppe and Kiely 1999) has concluded that precipitation is increasing in the west of the island. This assessment reveals that winter and spring increases are concentrated in the west, while summer and autumn increases are more prominent in the southeast. Using a longer observational record and a broader station network than previous seasonal analyses and a range of seasonal indices strengthens confidence in these spatial patterns.

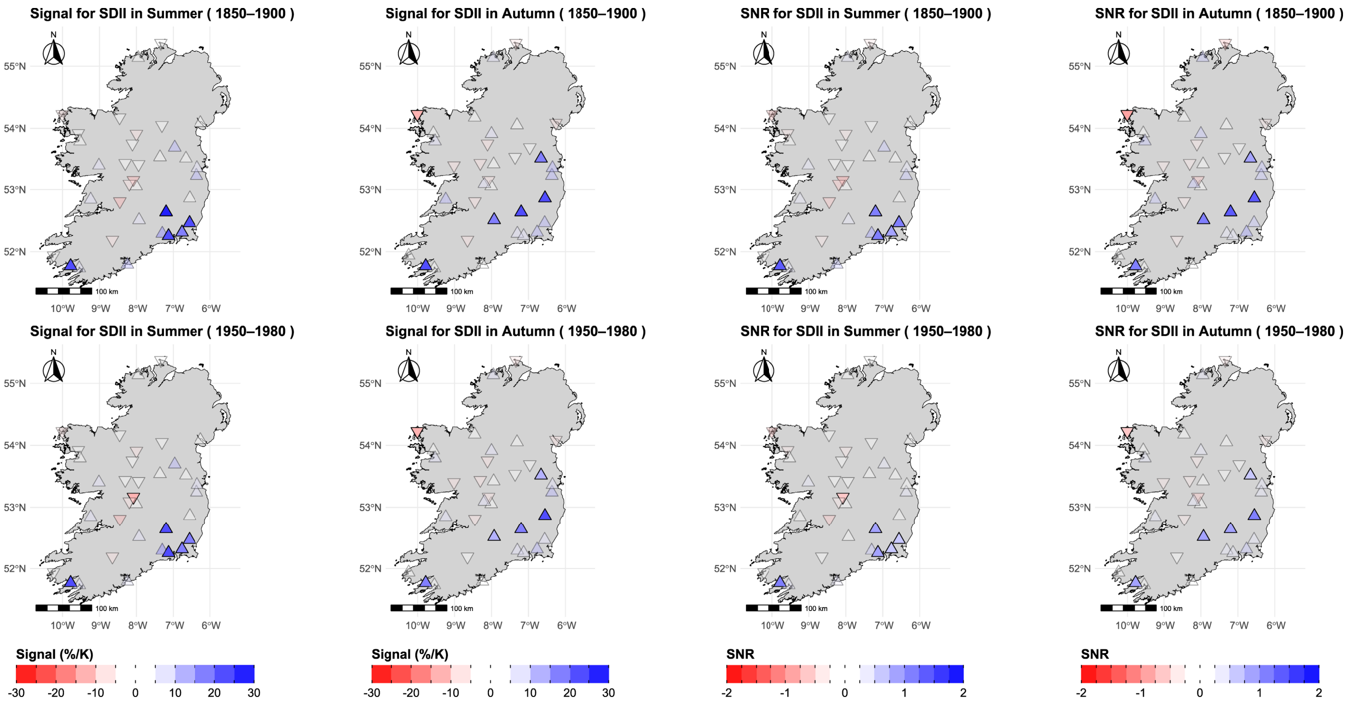

FIGURE 6 | Signal (left) and signal-to-noise ratio (right) for summer (SDII) and autumn (SDII) precipitation indices. The signal is presented % change per degree warming in GMST based on Alpha (∝) values. The top row is results relative to 1850–1900 baseline and the bottom row is relative to the 1950–1980 baseline. Signal-to-noise ratio (SNR) values are interpreted following the terminology of Frame et al. (2017), where SNR > 1 indicates a climate signal emerging from background variability ("familiar"), SNR > 2 indicates "unfamiliar" conditions, and SNR > 3 indicates "unknown" conditions. The direction of the opaque triangles representing each station show the direction of change, while transparent triangles indicate no significant (5% level) relationship with GMST. [Colour figure can be viewed at wileyonlinelibrary.com]

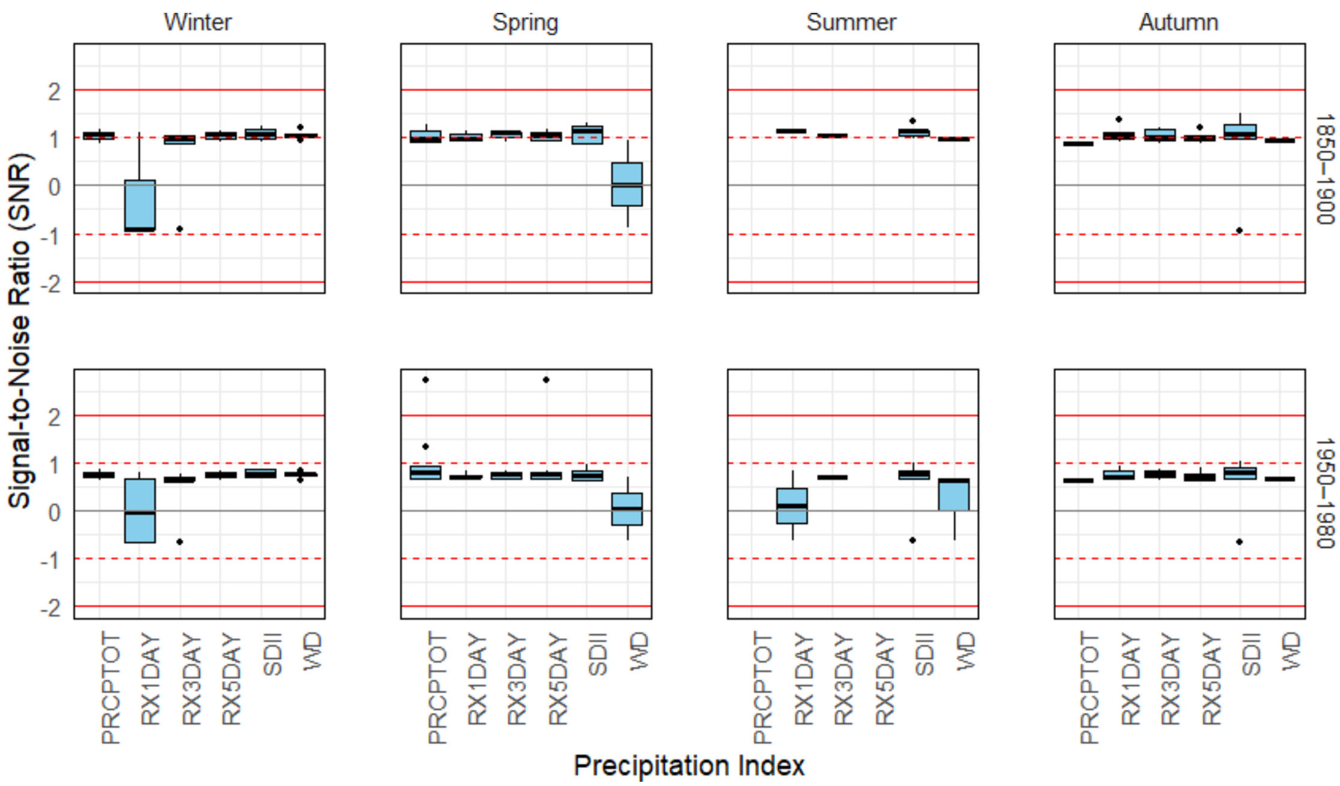

FIGURE 7 | Boxplots of the signal-to-noise ratio for all ETCCDI seasonal indices for the stations with significant (5% level) GMST relationship. The dashed horizontal line represents the threshold for unusual relative to early industrial, while the solid horizontal line represents the threshold for unfamiliar climate. The top row is results relative to 1850–1900 baseline and the bottom row is relative to the 1950–1980 baseline. [Colour figure can be viewed at wileyonlinelibrary.com]

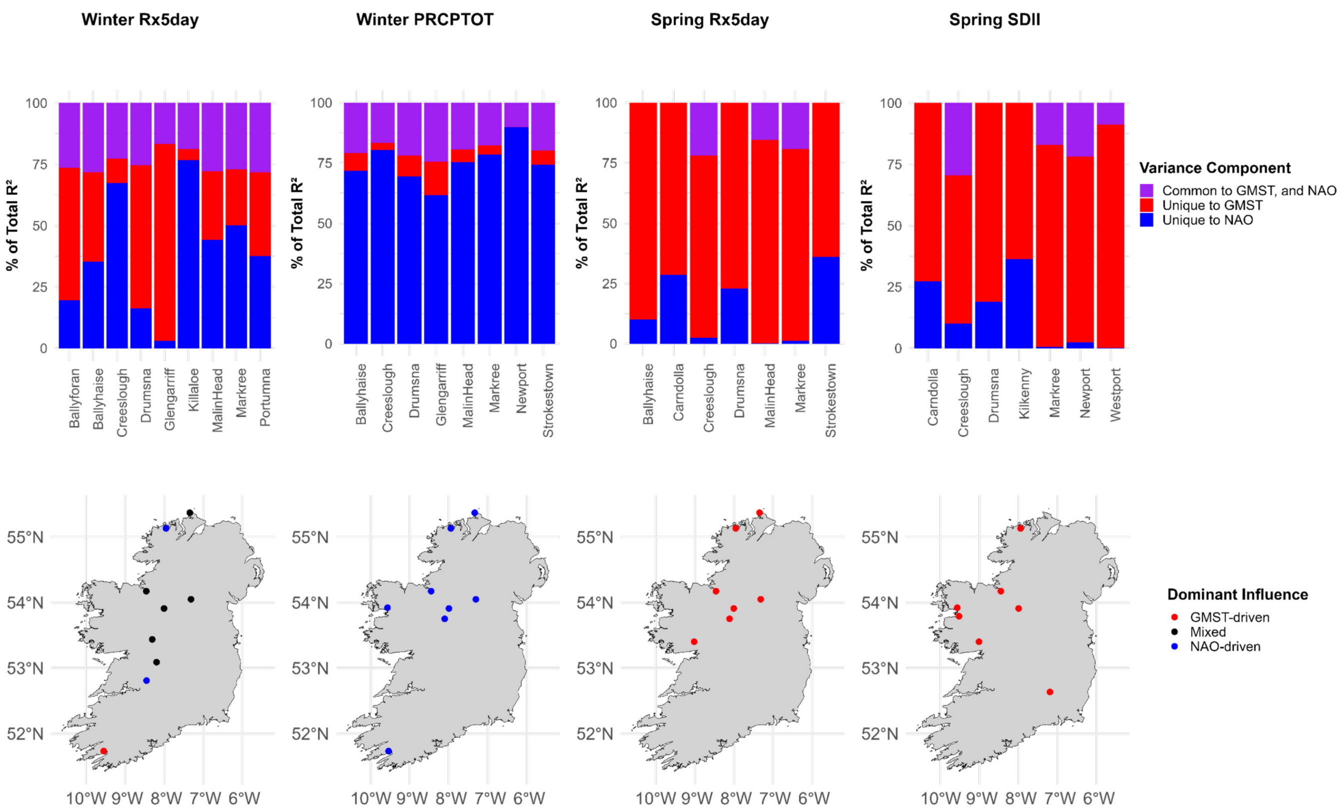

FIGURE 8 | Commonality analysis of variance in winter (Rx5day and PRCPTOT) and spring (Rx5day and SDII) precipitation indices explained by GMST and NAO at stations with significant GMST relationships. The top panel shows the relative contributions of GMST, NAO, and their shared influence on the total explained variance (R^2) at each station, based on commonality analysis. Values represent the percentage of total R^2 attributed to each component. The bottom panel maps the dominant explanatory factor for each station, classified as GMST-driven, NAO-driven, shared variance, or mixed. [Colour figure can be viewed at wileyonlinelibrary.com]

Global mean surface temperature (GMST) is often perceived as an abstract concept for the public (Sutton et al. 2015), whereas local and regional climate variability, which people experience directly through rainfall, floods, or droughts, shapes public perception and adaptation needs. In mid-latitude regions like Ireland, internal variability plays a dominant role in shaping fluctuations in rainfall. This reinforces the importance of quantifying not just the direction of change, but how emerging climate signals compare relative to natural variability. The use of signal-to-noise ratios (SNRs) in this study directly addresses this by evaluating whether observed trends in seasonal rainfall indices are now large enough to exceed the background noise of natural fluctuation.

Fixed-period trends are broadly mirrored by SNR values that exceed the emergence threshold in many cases, particularly relative to the early industrial baseline, and are nearing this threshold for the modern reference (1950–1980). Emergence is most pronounced in the west for winter and spring. In winter, the strongest signals occur in PRCPTOT and Rx5day, with significant SNRs also evident in SDII, WD, Rx1day, and Rx3day. Nine stations show statistically significant relationships with GMST in PRCPTOT, and eleven in Rx5day; of these, five and six stations, respectively, are classified as "unusual" relative to the early industrial period. In spring, the strongest emergence appears in SDII and Rx5day, with additional signals in PRCPTOT, Rx1day, and Rx3day. Eight (SDII) and seven (Rx5day) stations exhibit significant relationships with GMST relative to both baselines; with four stations classified as "unusual" in these indices relative to early industrial. Wet day frequency (WD) in spring, however, shows no emergence, suggesting rainfall events are becoming more intense without increasing in frequency, a key marker of warming-driven intensification.

In summer, a localised emergence in rainfall intensity (SDII) is observed in the southeast, with six stations showing significant relationships to GMST. Four of these are classified as unusual relative to early industrial, with several others approaching the emergence threshold against the modern baseline. No other indices show emergence or significant GMST relationships in this season, indicating that warming may be amplifying rainfall intensity without affecting frequency or duration, consistent with Clausius-Clapeyron thermodynamic scaling (Pall et al. 2007). Autumn trends show clear intensification across several intensity-based indices (SDII, Rx1day, and Rx3day). Five southeast stations show significant relationships with GMST. Four stations are classified as unusual in SDII, and three in both Rx1day and Rx3day. However, neither PRCPTOT nor WD show significant relationships with GMST, implying that while rainfall intensity is increasing, the total volume and frequency are not.

Compared to previous emergence studies (Hawkins et al. 2020; Ossó et al. 2022; Murphy, Coen, et al. 2023; Murphy, Kettle, et al. 2023), this analysis finds more robust signals in extreme indices than in seasonal totals, consistent with the high variability (i.e., noise) of precipitation. Notably, Murphy, Coen, et al. (2023) and Murphy, Kettle, et al. (2023) found only one station with seasonal total emergence relative to the early industrial period. In contrast, this study identifies widespread and consistent relationships between extreme indices and GMST. Although some signals remain just below the formal SNR emergence threshold (> 1), the strength and coherence of trends, especially in relation to GMST, suggest that continued warming will likely push many stations beyond the threshold in the near future.

These changes have critical implications for flood risk. Winter and spring exhibit emerging signals in flood-relevant indices in the west, and autumn in the southeast. Rx1day is associated with flash flood potential (Acquaotta et al. 2019), while Rx3day and Rx5day indicate risk of more prolonged flood events. Western Ireland is particularly vulnerable due to its karst geology, which increases susceptibility to groundwater flooding (Morrissey et al. 2020). Moreover, observed increases in rainfall intensity per degree of warming often exceed the Clausius-Clapeyron rate (~6%–7%/°C) (Pall et al. 2007), with many indices showing increases of 12%–27%/°C. These nonlinear intensifications could have substantial implications for fluvial and groundwater flooding (Meresa et al. 2021; Murphy, Coen, et al. 2023; Murphy, Kettle, et al. 2023), agriculture, and water infrastructure planning.

The methodology employed here in which local precipitation changes are scaled relative to GMST has direct relevance for adaptation and mitigation policies. It provides a transparent framework for linking local climate impacts to global warming levels and international policy thresholds, such as the 1.5°C or 2°C targets of the Paris Agreement. However, caution is warranted: GMST provides limited insight into local-scale internal variability, and future local changes may be nonlinear or influenced by compound events (Sutton et al. 2015). While emergence signals in precipitation are typically more muted than those in temperature (Hawkins et al. 2020; Murphy, Coen, et al. 2023; Murphy, Kettle, et al. 2023), the magnitude of percentage increases per °C in rainfall extremes is often greater. Despite wide confidence intervals, likely reflecting the inherent variability of precipitation, these trends indicate additional regional and seasonal dynamics that may intensify risks beyond thermodynamic expectations.

These findings are broadly consistent with IPCC AR6 conclusions, which project increased precipitation intensity in a warming world. However, this study challenges some prevailing narratives. As stated by the IPCC (2023), the contrast in precipitation between wet and dry seasons is projected to increase. Updated high-resolution, multi-model climate projections for Ireland (Nolan 2025), building on earlier ensemble simulations (Nolan and Flanagan 2020), project similar seasonal changes. Yet observational data show no strong drying trend in summer and instead reveal intensification in the southeast. Similarly, while winter increases are projected and observed in the west, this study highlights non-significant decreases in the south and east, contrary to climate model projections. Results here reveal stronger spring intensification than models suggest. Autumn changes are also more prominent in observations than projected, particularly for intensity indices in the southeast.

Interannual variability associated with the NAO plays a significant role in winter precipitation emergence patterns. In winter, precipitation totals have been shown to be strongly correlated with the winter NAO index (Murphy et al. 2018). Commonality analysis here reveals that GMST and NAO jointly explain variability at western stations in winter PRCPTOT and Rx5day. This suggests that natural modes of variability like the NAO may not be independent noise but rather embedded within a warming climate signal, complicating the separation of anthropogenic and natural drivers in attribution studies. It is important to note that there are other modes of internal variability that influence Ireland's rainfall that have not been considered. For instance, McCarthy et al. (2015) and Sutton and Dong (2012) demonstrate the strong relationship between variability in the Atlantic Multidecadal Oscillation (AMO) and summer precipitation totals in Ireland. Future work could more directly explore how internal variability, such as NAO or AMO phase shifts, interact with anthropogenic warming to modulate extreme rainfall.

There is also potential to expand the current framework using multivariate emergence analysis (e.g., King et al. 2024), which captures compound climate risks. Coupled changes in temperature and precipitation can amplify impacts (Zscheischler et al. 2018), and co-emergence of variables has been shown to enhance signal detectability (Mahony and Cannon 2018; King et al. 2024). Future work could also compare observed linear trends to pattern-scaled model projections (e.g., Osborn et al. 2016) for more robust attribution.

This study demonstrates the value of integrating fixed-period trend analysis, monthly persistence testing, and emergence diagnostics to assess how rainfall extremes in Ireland are responding to climate change. The findings reinforce the need for regionally and seasonally tailored adaptation strategies. Western Ireland will need to manage increasing multi-day rainfall extremes, while the southeast faces growing challenges related to rainfall intensity. Robust national adaptation planning must account for these spatial and seasonal differences to remain resilient under future climate conditions. This work builds on and depends critically on efforts to rescue and quality-control long-term observational records (Noone et al. 2016; Ryan et al. 2018, 2021, 2022). Continued investment in data curation is essential to ensure that future assessments can effectively monitor and respond to ongoing climate changes.

5 | Conclusion

This study provides robust evidence that seasonal rainfall extremes in Ireland have intensified over the period 1930–2019. Crucially, climate change impacts are not solely defined by the magnitude of change, but by how these changes compare to the natural variability society has historically experienced. This analysis demonstrates that statistically unusual changes in precipitation have already emerged relative to the early industrial baseline and are nearing this threshold for the modern reference (1950–1980). Emergence is most pronounced in the west during winter and spring, and in the southeast during summer and autumn. While detecting emergence in precipitation is inherently more challenging due to high natural variability, the results reveal clear signals in several indices, with many stations showing strong relationships with global mean surface temperature (GMST), underscoring the role of anthropogenic warming. Although some signals remain just below the formal SNR emergence threshold (> 1), the strength and coherence of trends, especially in relation to GMST, suggest that continued warming will likely move many stations beyond the threshold in the coming years. Results also highlight the critical role of internal variability, particularly the North Atlantic Oscillation (NAO), in modulating winter extremes. Although the NAO plays a dominant modulating role in winter precipitation extremes, the presence of significant GMST relationships in the SNR analysis indicates that these are still robust climate change signals. Commonality analysis reveals that GMST and NAO jointly explain variability at western stations in winter, suggesting that internal variability is partially embedded within the forced climate change response, rather than acting as independent noise. In contrast, spring signals are less influenced by NAO and more clearly attributable to global warming. These results carry substantial implications for flood risk management, infrastructure design, and adaptation planning. Moreover, the findings challenge projected narratives of widespread summer drying, highlighting the value of high-resolution, observation-based assessments. As climate change progresses, continued investment in data curation and advanced analytical approaches will be critical. Regionally tailored strategies will be essential to address the evolving risks associated with increasingly intense and seasonally variable rainfall extremes across Ireland.

Author Contributions

Saoirse Fordham: writing – original draft, investigation, conceptualization, methodology, validation, visualization, formal analysis. **Conor Murphy:** supervised the study and reviewed and edited the manuscript.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Data S1:** Supporting Information.