RESEARCH ARTICLE

Long-term trends in extreme precipitation indices in Ireland

Ciara Ryan1,2 | Mary Curley2 | Séamus Walsh2 | Conor Murphy1

1Irish Climate Analysis and Research Units, Department of Geography, Maynooth University, Maynooth, Kildare, Ireland
2Climate Services, Research and Applications Division, Met Éireann, Dublin, Ireland

Abstract

Knowledge of long-term changes in climate extremes is vital to better understand climate variability and place present day extreme events in historical context. Analysis of trends in extreme precipitation in Ireland have largely been limited to the second half of the 20th century due to lack of data availability in digital format. Using recently digitized data, this study provides the first assessment of long-term changes in extreme daily precipitation observed at 30 locations across Ireland. Quality control of rescued data is carried out before selected long-term stations are tested for homogeneity using the RHtests software. Details of detected breakpoints and the application of adjustments to daily values are discussed. Eleven extreme precipitation indices are calculated on an annual basis and analysed to determine spatial and temporal trends in the frequency, intensity and magnitude of observed precipitation. The persistence of trends for varying record lengths and for two fixed periods (1910–2019 and 1940–2019) of analysis is assessed for all stations and indices. Results show increases in precipitation intensity, especially notable in the east and southeast of the island. Our findings also show that the contribution of heavy and extreme precipitation events to annual totals is increasing, while there was no persistent trends in annual totals or consecutive wet or dry days.

KEYWORDS

data rescue, Ireland, long-term trends, precipitation extremes

INTRODUCTION

Understanding long-term variability and trends in precipitation is critical for water resource management and assessing potential flood risk. Long-term series of precipitation have been produced for many regions to detect changes in the spatial and temporal variation of this essential climate variable (e.g., Auer et al., 2005; De Jongh et al., 2006; Moberg et al., 2006; Brunet et al., 2014; Ashcroft et al., 2018). In Ireland, previous research has focused on the development and analysis of long-term monthly precipitation series (e.g., Noone et al., 2015; Murphy et al., 2018), while analysis of daily precipitation has largely been limited to the post 1940 period, for which digitized observational and gridded precipitation products are available. Moreover, no previous analysis has assessed long-term changes in precipitation extremes for Ireland using the suite of indices defined by the CCI/CLIVAR/JCOMM Expert Team on Climate Change Detection and Indices (ETCCDI, https://www.wcrp-climate.org/etccdi).
Previous analysis of Irish annual precipitation totals reveals an increase in mean annual precipitation of approximately 5% in 1981–2010, compared with the 30-year period 1961–1990 (Walsh, 2016). In general, larger increases in precipitation amounts are observed in the west of the country. An increase in the frequency of heavy rain days (days with rainfall greater than 10 mm) has been reported at the majority of stations analysed over the period 1961–2010, however, regional variations are evident with occasionally conflicting trends from stations that are geographically relatively close (Walsh and Dwyer, 2012). Sheridan (2001) reported an increase in annual accumulations over the period 1941–1999, particularly in the west of the country, with more notable increases reported since the early 1970s. McElwain and Sweeney (2007) analysed monthly data at Birr and Malin Head from 1890 to 2003 and found significant increases in annual totals at Malin Head with no significant trends detected in the annual precipitation series at Birr. Leahy and Kiely (2011) examined changes in short-duration (~24 hr) precipitation extremes and found strong evidence for increasing trends since the late 1970s, particularly in the west of the country, coinciding with changes in the North Atlantic Oscillation.

Knowledge of changes in extreme precipitation events are a key aspect of monitoring climate change as increases or decreases in the frequency and/or magnitude of extreme precipitation events have high environmental and socio-economic impacts. However, the relative sparseness of long-term digitally available records at appropriate spatial and temporal scales hampers our ability to fully understand changes in precipitation extremes (Brunet and Jones, 2011). The spatial variability of precipitation (particularly daily and sub-daily extremes [Chen et al., 2021]), together with changes in observer practices, gauge location and design, mean that developing reliable, long-term precipitation series is often a challenging task (Wilby et al., 2017). Inconsistencies in long-term data series can arise as a result of changes in measuring techniques, observational and recording practices (e.g., approaches to including snow estimates as part of precipitation totals [Murphy et al., 2019]), objectives and technologies and transfer of data from paper to digital format (Slater et al., 2021). Quality control procedures are crucial to reconcile such inconsistencies and to identify both systematic and non-systematic errors that can confound the detection and interpretation of trends. A well-defined quality control process should be able to flag data errors that could compromise the analysis of natural climate variability, particularly in the study of extreme events (Llabrés-Brustenga et al., 2019). Homogenisation of data to remove spurious non-climatic features from long-term instrumental records is integral to the development of accurate climate data and the assessment of climate variability (Freitas et al., 2013; Vertačnik et al., 2015). While many methods have been developed to evaluate the homogeneity of monthly to annual-resolution climate data, homogenisation of daily data is a highly complex task that is still under development within the research community (Venema et al., 2018).

Recently, Ryan et al. (2020) completed the rescue of 3,616 station years of daily precipitation data (~1.32 million daily values) for stations across Ireland. Details of the data rescue process and dataset development are presented in previous publications (Ryan et al., 2018; Ryan et al., 2020) to provide a fully traceable dataset. The availability of this data now makes it possible to assess changes in daily precipitation extremes back to the early 20th Century. While Ryan et al. (2020) implement basic quality assurance tests, in this article we conduct a more rigorous quality control of rescued data before extracting and homogenizing long-term daily series for stations across Ireland. We then derive indices of annual extremes and assess these for evidence of trends.

The remainder of the article is organized as follows: Section 2 provides a description of the data, the quality control (QC) and homogenisation techniques used to reduce errors in the dataset and methods used to test the direction and magnitude of trends. Section 3 presents the results, while Section 4 provides a discussion of key findings, limitations and directions for future work, before drawing conclusions in Section 5.

## 2 | DATA AND METHODS

### 2.1 | QC of data

The dataset used in this analysis was constructed from recently rescued and digitized historical (pre-1940) daily precipitation data (Ryan et al., 2020) and post 1940 daily precipitation data extracted from Met Éireann's database. The latter contains daily and monthly precipitation records from 1941 onwards, which have previously undergone QC tests, full details of which are provided by Walsh (2016). These include a combination of visual checks, spatial techniques, cross-validation of daily interpolated values, comparison with daily radar accumulations, where available, and an automated system for the re-distribution of cumulative daily values. The pre-1940 dataset comprises daily precipitation data for 114 stations at various locations throughout Ireland for varying time periods (Figure 1).

Ryan et al. (2020) undertook an initial quality assessment of the pre-1940 digitized data. This involved manually cross-checking all flagged observations against the
original record and metadata. At each stage of the transcription process, quality assurance measures were employed to preserve the integrity of the data being rescued. Keying guidelines were developed ensuring conformity to World Meteorological Organization (WMO) standards (WMO, 2016). Monthly totals, extracted from the annual rainfall registers as part of the transcription process, were compared to the derived sum of the daily entries to identify potentially incorrect data entries. The data were double keyed and the entries from different transcribers compared. Where the entries agreed, the value was provisionally accepted as the raw data value. If the values were different, the original record was manually examined to ascertain the true observed value. An examination of errors across all transcriptions revealed a percentage error of <1%. As a final check for transcription errors, the upper and lower 1% of observations (non-zero precipitation) were examined for each individual station record. Values identified as outliers were cross-checked against the original record. Following the application of these initial quality assurance checks the raw data were published to enable users to access the original data (Ryan et al., 2020). Additional QC checks are undertaken here. These can be grouped into four categories: basic integrity tests, tolerance tests, temporal consistency tests and spatial consistency tests. Details of the QC procedures deployed are provided in Table 1. Each test produced a list of values flagged at each station, which were subject to manual inspection. The detection of false positives (e.g., extreme events flagged as outliers) is a common issue in QC assessments, particularly for extremes were intense convective storms can deliver localized high totals. Manual inspection, combined with local/regional knowledge of climatological processes ensured that these important observations were retained.

For the majority of values flagged by the basic integrity tests, the value was adjusted following manual inspection, for example, in cases where zeros were used in place of the missing data indicator or undocumented cumulative totals. Values classified as suspect were accepted if they satisfied each of the following criteria: the value agreed with that recorded on the original record; similar observations were recorded at neighbouring stations; the value was deemed physically reasonable for that station/region/season. Values were rejected and set to missing if they were flagged as suspect and did not satisfy these criteria or if there was evidence reported in the metadata to suggest that the gauge was defective at the time of observation. In total, 59,274 values were flagged and investigated (~4.5% of the data), with slightly less than 1% of the values removed from the quality-controlled version of the dataset used to assess trends. Cumulative daily values which were identified and flagged during the transcription process were redistributed to the respective days on which no observation was recorded. For cumulative values requiring redistribution, a first guess value for days on which no observation was recorded is estimated by means of inverse distance weighted interpolation; the estimated daily amounts are summed and the ratio of this total to the observed cumulative total is calculated; the final estimated daily values are obtained by adjusting the first guess values according to this ratio (Walsh, 2016). No account was taken of potential evaporative losses from cumulative totals over several observational timesteps.

2.2 Deriving long-term station series

The quality controlled pre-1940 rescued data was added to the database containing post 1940 data. For stations with matching station identifiers and locations, the pre-1940 data was joined to the post-1940 data to produce continuous station series. To address gaps in data series, the method developed at Met Éireann by Walsh (2016) which performed well for producing gridded precipitation datasets, was used to infill and extend station series using the rescued data. First, a regression-kriging interpolation
model was used to generate monthly values for all stations in the database. Thus, for stations which had gaps in data, the monthly total was estimated using nearby station data. Next, to generate daily values, inverse distance weighted interpolation was used to disaggregate the monthly interpolated values to provide a complete series of daily values, using the method described in Section 2.1 for cumulative daily values. Finally, stations for analysis were selected. Given the lower station density in the pre-1940 period, only sites with neighbouring station data available were selected when developing long-term series. In total 36 stations were identified based on record length, continuity, completeness and proximity of pre-1940 station locations. The mean record length is 118 years. The longest series length is 146 years for Foulkesmill (Longraigue), the shortest is 91 years for Portumna O.P.W. The selected stations (Table 2) were grouped into two categories as follows:

- Group A stations are those with continuous observations at the same site from start year to end year.

- Group B stations represent those from the post-1940 dataset for which nearby (<15 km) rescued data were available to extend records into the pre-1940 period. B stations were generated using the output of the regression kriging interpolation model.

### 2.3 Homogenisation of derived station series

Relative homogenisation methods (i.e., testing with respect to a homogenous neighbouring station) are
considered more robust than absolute methods, provided station records are sufficiently correlated (Gubler et al., 2017). However, the high spatial variability of daily precipitation make it difficult to find suitable reference series except in the case of parallel measurements (Wang et al., 2010). Moreover, given the sparse spatial density of the station network in the early period (Figure 1), the current homogeneity assessment is restricted to the application of absolute methods. We employ a two-step approach. First, for each station, breakpoints in the monthly series, derived from daily precipitation values, are detected and adjusted using the RHtests software.

| St_id | Station_name                        | Lat.   | Lon.     | Height | Start | End   | Group |
|-------|-------------------------------------|--------|----------|--------|-------|-------|-------|
| 108   | Foulkesmill (Longraigue)            | 52.31056 | −6.76639 | 71     | 1874  | 2019  | A     |
| 175   | Phoenix Park                        | 53.36361 | −6.34972 | 48     | 1881  | 2019  | A     |
| 417   | Inagh (Mt.Callan)                   | 52.84167 | −9.23833 | 122    | 1908  | 2019  | A     |
| 1075  | Roches Point                        | 51.79306 | −8.24444 | 40     | 1883  | 2019  | A     |
| 1275  | Markree                             | 54.175  | −8.45556 | 34     | 1875  | 2019  | A     |
| 1519  | Meelick (Victoria Lock)             | 53.16667 | −8.08056 | 39     | 1910  | 2019  | A     |
| 1529  | Drumsna (Albert Lock)               | 53.91111 | −8.00000 | 45     | 1903  | 2019  | A     |
| 1575  | Malin Head                          | 55.37194 | −7.33917 | 20     | 1885  | 2019  | A     |
| 2375  | Belmullet                           | 54.22750 | −10.00694 | 9     | 1897  | 2019  | A     |
| 1819  | Portumna O.P.W.                     | 53.09167 | −8.19167 | 35     | 1929  | 2019  | A     |
| 1929  | Athlone O.P.W.                      | 53.42222 | −7.94167 | 37     | 1902  | 2019  | A     |
| 2012  | Cashel (Ballinamona)                | 52.51056 | −7.92861 | 80     | 1911  | 2019  | A     |
| 2275  | Valenta Observatory                 | 51.93833 | −10.24083 | 24   | 1875  | 2019  | A     |
| 1812  | Waterford (Tycor)                   | 52.25278 | −7.13056 | 49     | 1890  | 2019  | A     |
| 201   | Glengarriff (Ilacullin)             | 51.73472 | −9.54583 | 7     | 1914  | 2019  | A     |
| 603   | Kenmare (Dereen)                    | 51.76944 | −9.78056 | 24     | 1912  | 2019  | A     |
| 1923  | Glenasmole D.C.W.W.                 | 53.23889 | −6.36667 | 158    | 1900  | 2019  | A     |
| 8212  | Portlaw (Mayfield II)               | 52.29083 | −7.30083 | 8      | 1900  | 2019  | A     |
| 675   | Ballyhaise                          | 54.05139 | −7.30972 | 78     | 1900  | 2019  | B     |
| 706   | Mallow (Hazelwood)                  | 52.19028 | −8.65000 | 94     | 1900  | 2019  | B     |
| 875   | Mullingar                           | 53.53722 | −7.36222 | 101    | 1910  | 2019  | B     |
| 944   | Creeslough (Carrownamaddy)          | 55.13333 | −7.95000 | 88     | 1908  | 2019  | B     |
| 1338  | Omeath                              | 54.08667 | −6.25639 | 12     | 1925  | 2019  | B     |
| 1375  | Dunsany                             | 53.51583 | −6.66000 | 83     | 1900  | 2019  | B     |
| 1475  | Gurteen                             | 53.05306 | −8.00861 | 75     | 1900  | 2019  | B     |
| 2115  | Hacketstown (Voc.Sch.)              | 52.86111 | −6.55278 | 189    | 1918  | 2019  | B     |
| 2528  | Ballyforan (Bord na Mona)           | 53.43972 | −8.30333 | 47     | 1925  | 2019  | B     |
| 4015  | Enniscorthy (Brownswood)            | 52.46306 | −6.56083 | 18     | 1900  | 2019  | B     |
| 4513  | Kilkenny (Lavistown House) II       | 52.63611 | −7.19722 | 58     | 1900  | 2019  | B     |
| 5131  | Kilskeire (Robinstown)              | 53.69278 | −6.96333 | 87     | 1900  | 2019  | B     |
| 6019  | Killaloe Docks                      | 52.81   | −8.44889 | 40     | 1902  | 2019  | B     |
| 6329  | Strokestown (Carrowclogher)         | 53.753  | −8.10800 | 52     | 1908  | 2019  | B     |
| 3310  | Abbeyfeale (Caherlane)              | 52.35194 | −9.28361 | 155    | 1925  | 2019  | B     |
| 1175  | Newport                             | 53.92222 | −9.57222 | 22     | 1910  | 2019  | B     |
| 1433  | Westport (Carrabawn)                | 53.7925 | −9.52722 | 56     | 1909  | 2019  | B     |
| 2227  | Carrndilla                          | 53.40306 | −9.01556 | 24     | 1900  | 2019  | B     |
developed by Wang and Feng (2013) at the Climate Research Division, Atmospheric Science and Technology Directorate, Science and Technology Branch, Environment Canada (http://etccdi.pacificclimate.org/software.shtml). Second, the output from the RHtests software is examined for further breaks by testing the homogeneity of the derived annual indices using the standard normal homogeneity test (SNHT) (Alexandersson, 1986) and the Pettitt test (Pettitt, 1979). This approach supports the selection of series for the analysis of trends.

The RHtests_dlyPrcp software package is specifically designed for homogenisation of daily precipitation data which are non-continuous, non-negative and non-normally distributed. Breakpoints were detected in the monthly log-transformed series using the RHtests software which is based on the penalized maximal t test (Wang et al., 2007) and the penalized maximal F test (Wang, 2008b). These are embedded in a recursive testing algorithm (Wang, 2008a), with the lag-1 autocorrelation of the time series being empirically accounted for. The software facilitates metadata integration by testing both known and unknown breakpoints; hence significant breakpoints (.05 level) were identified using a combination of the statistical methods and station reports.

Specifically, the software was first run to detect all breakpoints that could be significant at the nominal level even without metadata support, referred to as Type-1 breakpoints. Next, a second function was run to detect additional breakpoints (Type-0 breakpoints) which are deemed significant only if supported by reliable metadata. For each station series, the available metadata was investigated to determine whether there was evidence at or near the identified breakpoint dates to support the shifts. Only those Type-0 breakpoints that were supported by metadata, along with all Type-1 changepoints were retained. Type-1 changepoints were also investigated to examine consistency with metadata and other stations in the network.

Before adjusting the daily series, discontinuities in the occurrence frequency of precipitation were investigated. Such discontinuities result from changes in the unit of measurement, measuring precision and observing practices (Wang et al., 2010). For each station series, the series of daily precipitation amounts greater than a given threshold ($P_{th}$) was examined by varying $P_{th}$ over a set of small values that reflect changes in the measuring precision (i.e., 0.2, 0.3 and 0.5 mm). This assessment revealed the presence of discontinuities in the frequency of small measured amounts in the pre-1940 record, most likely related to changes in the unit of measurement (i.e., from imperial to metric). Given that the objective of the present study is to examine trends in indices which require daily precipitation ≥1 mm, adjustments were applied to the series of $P_{th}$ daily precipitation data that was found to be free of frequency discontinuity. This $P_{th}$ varies across station series but does not exceed $P_{th} = 0.5$ mm. It should be noted that all $<P_{th}$ values in the series are left unadjusted, and thus frequency discontinuities remain, affecting values between 0 and $P_{th}$ inclusive.

Where breaks were detected, adjustments were applied to daily station series by means of the quantile mapping (QM) algorithm in the RHtests software (Wang et al., 2010). The algorithm was applied as follows: daily precipitation series (derived from days with non-zero precipitation) were detrended using the linear trend estimated from a multiphase linear regression fit that accounts for the mean shifts at detected breakpoints in the data series (Wang, 2008b; Wang et al., 2010). For each breakpoint to be adjusted, the data in the segment immediately before and after the breakpoint is used to estimate the probability distribution function (PDF). We use all available data in a segment to estimate the PDF, as estimates of the PDF (and hence the QM adjustments) using shorter periods (e.g., <30 years) can contain large sampling uncertainty (Wang et al., 2010). Each segment is divided into $M_q$ quantile categories, and for each quantile, the differences between the means of the two periods is computed. A natural cubic spline is then fitted to the $M_q$ category-mean differences between the segment to be adjusted and the base segment which is then used to estimate the QM adjustments needed to make the data series homogeneous. The choice of the number of quantile categories ($M_q$) used to estimate the spline to derive the QM adjustments was set at $M_q = 4$–16, depending on the length of the shortest segment in a given data series. We use the most recent segment as the base on the assumption that technologies and observational practices generally improve over time. We recognize that the choice of parameters is subjective and may not be optimal for all series, however, the use of detailed metadata to inform decisions increases confidence in the performance of the algorithm, while sensitivity analysis to the choice of different parameters resulted in minor changes to adjustments made.

Following Santo et al. (2014), further tests of the adjusted series were carried out by testing the homogeneity of the derived PRCP/TOT and R5mm (see section 2.4) annual indices using the standard normal absolute homogeneity test (SNHT) and the Pettitt test. The $p$-value of potential breakpoints were plotted to facilitate a relative assessment of breakpoints across all stations. To determine the significance of potential break points, the null hypothesis (no breakpoint detected) was tested against the alternative at the .05 level. As a final assessment, a visual inspection was carried out by plotting the original and the adjusted annual precipitation totals for each series found to be inhomogenous.
2.4 Indices and trend detection

The derived quality controlled, homogenized long-term daily series were assessed for evidence of trends in the characteristics of extreme precipitation. For this purpose, 11 indices defined by the CCI/CLIVAR/JCOMM Expert Team on Climate Change Detection and Indices (ETCCDI, http://cccma.seos.uvic.ca/ETCCDI/) were calculated for each series and investigated for evidence of trends. The selected indices allow examination of changes in intensity, frequency and duration of extreme precipitation events (Alexander et al., 2006). Precipitation indices are summarized in Table 3. For deriving indices, we define a wet day as a day with $\geq 1$ mm precipitation, while the common 30-year base period used to define thresholds for percentile-based indices is 1961–1990.

Indices were derived for two set periods: 1910–2019 and 1940–2019. The 1910–2019 period was selected as the longest common period for which all stations have available records, the shorter 1940–2019 timespan represents the period of available digital records prior to our data rescue efforts. Evidence for monotonic trends was assessed using the Modified Mann–Kendall (MK) test (Hamed and Rao, 1998), a non-parametric rank-based method. The standardized MK test statistic (MKZs) follows the standard normal distribution with a mean of zero and variance of one. A positive (negative) value of MKZs indicates an increasing (decreasing) trend. Statistical significance was evaluated with probability of Type I error set at the 5% significance level. A two-tailed MK test was applied, hence the null hypothesis of no trend (increasing or decreasing) is rejected when $|\text{MKZs}| > 1.96$.

The MK test requires data to be independent (i.e., free from serial correlation) as positive serial correlation increases the likelihood of Type 1 errors or incorrect rejection of a true null hypothesis. Therefore, application of the Modified MK test includes a test to detect positive lag-1 serial correlation at the 5% level using the autocorrelation function (ACF). The existence of trend influences the correct estimate of serial correlation; therefore, original time-series are detrended to form a ‘trend-removed’ residual series before the ACF is applied (Hamed and Rao, 1998).

The magnitude of trend ($\beta$) is estimated using the approach proposed by Theil (1950) and Sen (1968), hereinafter referred to as TSA. To facilitate a relative comparison among different sites, the approach presented by Yue and Hashino (2007) is utilized where the magnitude of trend $\text{TSA}_{\text{rel}}$ (%) for each time-series is expressed as a percentage change over the period of record of $n$ years relative to the mean ($\mu$) for the period, given by:

$$\text{TSA}_{\text{rel}}(\%) = \left( \frac{\beta \times n}{\mu} \right) \times 100$$

| ID   | Indicator name                        | Indicator definitions                                                                 | Units   |
|------|---------------------------------------|--------------------------------------------------------------------------------------|---------|
| RX1day | Max 1-day precipitation amount        | Annual maximum 1-day precipitation                                                  | mm      |
| RX5day | Max 5-day precipitation amount        | Annual maximum consecutive 5-day precipitation                                       | mm      |
| SDII | Simple daily intensity index          | Ratio of annual total precipitation to number of wet days ($\geq 1$ mm)               | mm day$^{-1}$ |
| R5mm | Number of days when precipitation $\geq 5$ mm | Annual count when precipitation $\geq 5$ mm                                           | days    |
| R10mm | Number of heavy precipitation days    | Annual count when precipitation $\geq 10$ mm                                          | days    |
| R20mm | Number of very heavy precipitation days | Annual count when precipitation $\geq 20$ mm                                          | days    |
| CDD  | Consecutive dry days                  | Maximum number of consecutive days when precipitation $<1$ mm                        | days    |
| CWD  | Consecutive wet days                  | Maximum number of consecutive days when precipitation $\geq 1$ mm                    | days    |
| R95pTOT | Very wet days                        | Annual sum of precipitation on days when precipitation exceeds the 95th percentile of daily precipitation in the base period | mm      |
| R99pTOT | Extremely wet days                    | Annual sum of precipitation on days when precipitation exceeds the 99th percentile of daily precipitation in the base period | mm      |
| PRCPTOT | Annual total wet-day precipitation   | Annual total precipitation from days $\geq 1$ mm                                      | mm      |

Note: All indices are calculated annually.
| ID   | Station      | Breakpoint | Reason                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                     |
|------|--------------|------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
For brevity, Tables 6 and 7 present the direction of change and proportion of statistically significant (5% level) trends along with the median magnitude of trend (TSA$_{rel}$ %) and the median number of days per year for the 11 extreme precipitation indices for both fixed periods. Full details of trend statistics calculated for each station and indicator are provided as Supporting Information.

The persistence or dependency of trends on period of record was examined for each station by systematically reducing the start year of analysis from the whole record to a minimum of 30 years following the approach of Murphy et al. (2013), Noone et al. (2015) and Wilby (2006). For each indicator, the MKZs statistic was derived first for the full record for example, 1890–2019, then 1891–2019 and so on until 1990–2019. MKZs values were plotted for each iteration of start years to examine the temporal evolution of trend throughout the period of record. Unlike the fixed period analysis above, the persistence of trends was evaluated for the full record available at each station.

**FIGURE 2** Original (black) and adjusted (red) total annual precipitation for the 16 station series with breakpoints detected and adjusted using RHtests software. Units are millimetres per year [Colour figure can be viewed at wileyonlinelibrary.com]
3 | RESULTS

3.1 | Homogenisation

Following application of the RHtests software, 20 stations were found to be homogenous and did not require adjustment. In total, 22 breaks were detected in 16 of the 36 stations. Multiple breaks were found in five records: three in the Newport series; two each in the Malin Head, Belmullet, Glengarriff and Drumsna series; and a single break point in each of the remaining 11 series. Approximately 80% of detected breakpoints are supported by information contained in the metadata regarding instrument and site changes. Details extracted from metadata for each identified break are presented in Table 4.

To examine the impact of the adjustments on the station series, the original and adjusted annual precipitation totals were plotted for the 16 inhomogeneous series (Figure 2). The magnitude of the adjustments applied to the original data varies across station series and datum as per the QM approach, with larger (smaller) values undergoing a greater (lesser) adjustment. Table 5 provides details of the mean, minimum and maximum annual percentage difference between the original and the adjusted series.

The Pettitt test and the SNHT were applied to the annual series of PRCPTOT and R5mm to detect residual breakpoints following the application of the RHtests software. Across the 36 station series tested, the Pettitt test detected nine significant breakpoints in the PRCPTOT series. Five significant breakpoints were detected in the series of R5mm. The SNHT test detected eleven significant breakpoints in the PRCPTOT series, five of which coincide with breakpoints detected by the Pettitt test. Five significant breakpoints were detected in the R5mm series, four of which were also detected by the Pettitt test. Of the total 30 breakpoints detected in PRCTOT and R5mm by both tests, the timing for 21 are consistent across the network of stations. These occur in the 1970’s and are consistent in timing with a shift to more positive NAO index resulting in stronger mid-latitude westerlies and increased precipitation over Ireland (Kiely, 1999). As would be expected in the presence of widespread natural climate variability, these breakpoints were not detected by Coll et al., 2018 using relative homogeneity methods. Given their consistency in timing across the network and their concurrent timing with a well know shift in the NAO we attribute these break points to natural climate variability.

Six stations were identified as having potential remaining discontinuities and were subsequently excluded from further analysis. These stations are Abbeyfeale (st3310), Carndolla (st2227), Westport (st1433), Creeslough (st944), Drumsna (st1529) and Kenmare (st603). The Drumsna gauge is known to have underestimated precipitation prior to 1942 when a new gauge was installed. A comparison of precipitation totals from both gauges over a 13-month period revealed that the new gauge reported 154% of the old gauge. The Drumsna series was corrected for a breakpoint detected in 1942, however, remaining discontinuities are evident in the adjusted series. The other five stations are located in the

| Station_id | Station_name | Mean (%) | Min (%) | Max (%) |
|------------|--------------|----------|---------|---------|
| 201        | Glengarriff  | 7.4      | 4.8     | 11.5    |
| 675        | Ballyhaise   | 8.4      | 0.1     | 9.6     |
| 706        | Mallow_HW    | 2.7      | 0.2     | 4.4     |
| 944        | Creeslough   | −11.3    | −12.5   | 1.3     |
| 1175       | Newport      | 10.2     | 5.9     | 17.8    |
| 1275       | Markree      | 18.4     | 1.9     | 21.2    |
| 1338       | Omeath       | 14       | 3.5     | 16.4    |
| 1519       | Meelick      | 11.2     | 3       | 12.5    |
| 1529       | Drumsna      | 24.4     | 4.5     | 38.9    |
| 1575       | Malin Head   | 17.2     | 8       | 26.6    |
| 1812       | Tycor        | 12.8     | 2.1     | 13.9    |
| 1929       | Athlone      | 16.8     | 15.4    | 18.4    |
| 2275       | Valentia     | 8.8      | 5.5     | 9.3     |
| 2375       | Belmullet    | 11.7     | −9.9    | 25.6    |
| 2528       | Ballyforan   | 11.6     | 2.3     | 13.1    |
| 6019       | Killaloe     | 8.4      | 3.7     | 9.1     |
west and the northwest of the country where station density is lowest in the pre-1940 period. The Creeslough series was corrected for a breakpoint detected in 1928, however, a visual assessment of the annual series following adjustment suggests the presence of a remaining shift in the early 1960's that was not detected by RHtests. No breakpoints were detected by RHtests in the series for Abbeyfeale, Carndolla, Kenmare and Westport. However, a visual inspection of the original annual time series, the annual PRCPTOT and the R5mm time series for individual stations as well as a comparison of the series across all stations revealed large trends and potential breakpoints that were not detected by RHtests in testing the monthly series.

Following the removal of these six stations, the Pettitt test detected four significant breakpoints in the annual PRCPTOT and one significant breakpoint in the annual series of R5mm when applied to the remaining 30 station series. Figure 3 displays the p-values of potential breakpoints for the Pettitt and SNHT tests. For the Pettitt test, all five breakpoints were detected in the period 1976–1979 and are consistent with the timing of other non-significant break points across the network. The SNHT detected six significant breakpoints in the annual PRCPTOT series and one significant breakpoint in the annual R5mm series. Two of these were detected in the period 1977–1978. In the absence of evidence for widespread changes in measurement practices, the timing of these breakpoints suggest that a genuine climatic process was identified as inhomogeneities in the majority of series. A shift in the North Atlantic Oscillation (NAO) to a predominantly positive phase since the mid-1970s is noted in Irish precipitation records around this time (Kiely, 1999). The remaining breakpoints were detected in 2007 at Strokestown (Carrowclogher) and Inagh (Mt. Callan) and in the years 1987 and 1910 at Ballyhaise and Glenasmole, respectively. Only the break point at Glenasmole in 1910 occurs at a time when no other stations show non-significant breakpoints. It was noted during the QC process that the occurrence of heavy precipitation during December 2010 at Glenasmole resulted in large monthly and annual totals. The values were investigated and accepted based on consistency with observations recorded at neighbouring stations. Such large values can introduce spurious breakpoints in the time series. Moreover, this breakpoint is detected in both the PRCPTOT and R5mm series by the SNHT but is not

**FIGURE 3** p-values of potential breakpoints detected in the annual series of PRCPTOT (top) and R5mm (bottom) indices using the Pettitt test and the standard normal homogeneity test (SNHT). Red dashed line indicates significance at the .05 level [Colour figure can be viewed at wileyonlinelibrary.com]
detected by the Pettitt test in either series. Previous studies (e.g., Ducre-Robitaille et al., 2003; Toreti et al., 2011) have reported increases in SNHT false break detection at the beginning and the end of the series. Given the presence of this breakpoint at the beginning of the series we retain it for examining trends.

### 3.2 Fixed period trend analysis

Trends were assessed for the network of 30 homogenized daily precipitation series for two fixed periods: 1910–2019 (Table 6; Figure 4) and 1940–2019 (Table 7; Figure 5). For both periods, increasing trends in extreme precipitation indices are more prevalent than decreasing, with the exception of consecutive dry days (CDD) and consecutive wet days (CWD) in the period 1910–2019 and CDD in the period 1940–2019.

The percentage of stations reporting increasing trends in Rx1day and Rx5day is consistent over both periods of analysis. However, there is a marked increase in the number of stations reporting statistically significant increases in Rx5day in the period 1910–2019. Of the stations reporting decreasing trends none are found to be statistically significant. There is a shift in the direction of trends at both Valentia and Glengarriff located in the southwest from a negative trend in the direction of trends at both Valentia and Glengarriff to be statistically significant. There is a shift in the stations reporting decreasing trends none are found to be statistically significant. Large variations in trend magnitude exist across the network. Largest trends found for Rx5day with a median increase across all stations of 6.06% over the period 1910–2019, increasing to 8.35% for 1940–2019. For the latter, the 95% confidence interval in trend magnitude across the network spans −6.81 to 23.77%. Largest trends are evident in the midlands for the period 1910–2019, extending to the southeast for the 1940–2019 period of analysis.

The percentage contribution from wet days (R95pTOT) and very wet days (R99pTOT) to total precipitation is also dominated by increasing trends. In the period 1910–2019, 83.3% of stations show increasing trends, 13.3% significant, with 76.7% of stations showing increasing trends in R99pTOT of which 16.7% are significant. For both periods, R95pTOT has the largest median increase in trend magnitude (TSArel ~14%) across all stations. Again, there is large variability in trend magnitude across stations. For the period 1910–2019, for instance, R95pTOT shows a median increase of 5.07% across the network, with the 95% confidence intervals ranging from −5.07 to 61.87%. Largest trends in both periods are found in the midlands and the east and southeast of the island. Significant trends reported in R95pTOT and R99pTOT at Foulkesmill (Longraigue), Portlaw (Mayfield II) and Cashel (Ballinamona) over the shorter period of analysis (1940–2019) are not observed in the longer record (1910–2019), while the longer record shows significant trends at Inagh (Mt. Callan) and Mullingar. The record for Markree station, situated in the northwest, shows the opposite. For R95pTOT, positive trends are reported in both periods of record with significant trends observed in the 1940–2019 period. For R99pTOT, negative trends are observed in both periods of record with significant trends observed in the 1940–2019 period.

### Table 6: Direction of change and proportion of statistically significant (5% level) trends for 1910–2019 fixed period extreme precipitation indices

| Indicator | Stat. | Positive (sig.) % | Negative (sig.) % | Stat. | Magnitude (CI) % | Stat. | No. of days year⁻¹ (CI) |
|-----------|-------|------------------|------------------|-------|-----------------|-------|------------------------|
| CDD       | MKZs  | 53.3 (3.3)       | 46.7 (0.0)       | TSAref| (−16.82,17.41)  | TSA   | (−0.03,0.03)           |
| CWD       | MKZs  | 43.3 (10)        | 56.7 (13.3)      | TSAref| (−19.01,15.08)  | TSA   | (−0.02,0.02)           |
| PRCPTOT   | MKZs  | 76.7 (13.3)      | 23.3 (0.0)       | TSA   | (−6.25,11.39)   | TSA   | NA                     |
| R95pTOT   | MKZs  | 83.3 (13.3)      | 16.7 (0.0)       | TSAref| 13.72 (−9.3,37.29) | TSA   | NA                     |
| R99pTOT   | MKZs  | 76.7 (16.7)      | 23.3 (0.0)       | TSA   | 5.07 (−10.2,61.87)| TSA   | NA                     |
| Rx1day    | MKZs  | 73.3 (6.7)       | 26.7 (0.0)       | TSAref| 3.64 (−11.27,19.41)| TSA   | NA                     |
| Rx5day    | MKZs  | 83.3 (26.7)      | 16.7 (0.0)       | TSA   | 6.06 (−6.96,19.23)| TSA   | NA                     |
| SDII      | MKZs  | 73.3 (40)        | 26.7 (3.3)       | TSAref| 3.84 (−2.02,9.75) | TSA   | NA                     |
| R5mm      | MKZs  | 66.7 (13.3)      | 33.3 (0.0)       | TSA   | (−8.47,11.64)   | TSA   | (−0.05,0.08)           |
| R10mm     | MKZs  | 83.3 (10)        | 16.7 (0.0)       | TSA   | 6.22 (−6.46,20.54)| TSA   | 0.02 (−0.02,0.06)      |
| R20mm     | MKZs  | 83.3 (10)        | 16.7 (0.0)       | TSAref| 0.38 (32.5)     | TSA   | (0.0,0.02)             |

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 with confidence intervals given by the lower/upper bounds. Number of days is the medium numbers of days per year across all stations with confidence intervals given by the lower/upper bounds.
CDD reveals little change, with only one significant trend reported in either period. Overall, there is a relatively even split between increasing and decreasing trends in both periods. Figures 4 and 5 indicate that decreasing trends in CDD tend to be more prevalent in the south and southwest, while increasing trends tend to be more prevalent in the midland region. In the period 1910–2019, 43.3% of stations report increases (10% significant).
and 56.7% of stations report decreases (13.3% significant) in CWD. However, there is shift in the direction of trends reported in the period 1940–2019, with 70% of stations reporting increasing trends in CWD, 20% of which are significant. The shift in direction of trend is most prevalent in the southwest of the country. Median trend in number of days per year across all stations reveals no change in either fixed period for both CDD and CWD.

Increasing trends in indices measuring precipitation threshold frequency are reported in both periods of analysis for all three indicators that is, R5mm, R10mm and R20mm, however, the magnitude of trends are small (see Tables). The number of stations reporting increasing trends in R5mm decreases slightly in the period 1910–2019. Increasing trends in R5mm are observed at stations in the north and northwest, namely Malin Head, Belmullet and Newport which are significant over the longer period of record, whereas stations in the southwest show significant trends in the shorter period which are not observed in the period 1910–2019. The number of stations showing increasing trends in R10mm remains stable over both periods, however, a higher number of stations report significant increases over the period 1940–2019. There is an increase in the number of stations reporting increasing trends in R20mm for the period 1910–2019 compared to the period 1940–2019. The largest trends in R20mm in both periods of analysis are observed in the south and southeast of the country. No stations report statistically significant decreases in the frequency of precipitation events ≥5 mm, ≥10 mm or ≥20 mm in either of the fixed periods assessed.

Both the number of stations reporting increasing trends and the median magnitude of change in intensity (SDII) is relatively consistent over the two periods of analysis, however, there is a slight increase in the number of stations reporting statistically significant increases over the period 1910–2019. These significant increasing trends in SDII are most notable in the east and southeast of the country. The magnitude of trends in intensity are also very consistent across both study periods. For the period 1910–2019 the median magnitude of change in SDII across the network is 3.84%, with the 95% confidence interval ranging from –2.02 to 9.75%.

The number of stations reporting statistically significant increases in total annual wet-day (≥1 mm) precipitation (PRCPTOT) more than doubles in the period 1940–2019 compared to the period 1910–2019. There is also a shift in the direction of trend in some stations in the southeast over the shorter period of analysis. No significant decreases are reported in either period analysed. A slight decrease is noted in the median magnitude of change reported in the period 1910–2019 compared to the period 1940–2019.

### 3.3 Persistence of trends over full period of record

While the previous section highlights the predominance of increasing trends in daily precipitation indices, the dependence of results on the two different periods of record was also noted. In this section, we assess the robustness of trends for different start dates over the full

### Table 7: Direction of change and proportion of statistically significant (5% level) trends for 1940–2019 fixed period extreme precipitation indices

| Indicator | Stat. | Positive (sig.) % | Negative (sig.) % | Stat. | Magnitude (CI) % | Stat. | No. of days-year⁻¹ (CI) |
|-----------|-------|------------------|------------------|-------|-----------------|-------|----------------------|
| CDD       | MKZs  | 40 (0.0)         | 60 (0.0)         | TSA   | 0 (−21.13,18.48)| TSA   | 0 (−0.05,0.04)      |
| CWD       | MKZs  | 70 (20)          | 30 (0.0)         | TSA   | 0 (−11.05,26.25)| TSA   | 0 (−0.02,0.04)      |
| PRCPTOT   | MKZs  | 76.7 (30)        | 23.3 (0.0)       | TSA   | 6.4 (−3.94,16.53)| TSA   | NA                   |
| R95pTOT   | MKZs  | 76.7 (20)        | 23.3 (0.0)       | TSA   | 13.61 (−17.05,44.69)| TSA   | NA                   |
| R99pTOT   | MKZs  | 73.3 (13.3)      | 26.7 (0.0)       | TSA   | 0 (−30.89,66.84)| TSA   | NA                   |
| Rx5day    | MKZs  | 66.7 (3.3)       | 33.3 (0.0)       | TSA   | 6.02 (−11.71,24.22)| TSA   | NA                   |
| SDII      | MKZs  | 73.3 (30)        | 26.7 (3.3)       | TSA   | 3.78 (−3.8,10.88)| TSA   | NA                   |
| R5mm      | MKZs  | 73.3 (13.3)      | 26.7 (0.0)       | TSA   | 5.34 (−6.64,15.82)| TSA   | 0.05 (−0.06,0.14)   |
| R10mm     | MKZs  | 83.3 (20)        | 16.7 (0.0)       | TSA   | 6.09 (−9.76,22.79)| TSA   | 0.02 (−0.03,0.09)   |
| R20mm     | MKZs  | 73.3 (10)        | 26.7 (0.0)       | TSA   | 0 (0.41,0.04)   | TSA   | 0 (0.03)            |

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 with confidence intervals given by the lower/upper bounds. Number of days is the medium numbers of days per year across all stations with confidence intervals given by the lower/upper bounds.
period of record for all 30 stations and indices. Plotting the MKZs for all stations/indices (see Figure 6) also allows inspection of trends in individual stations relative to the pattern of change across the network, potentially identifying stations with trends that depart from the pattern of the wider network. From Figure 6 both A and B category series show consistent trend persistence, except for a small number of series for specific indices.
(see below), indicating the robustness of the infilling procedures used.

CDD shows a lack of statistically significant trends for all stations across the network for varying start years. Similarly, the majority of stations show no significant trends for varying start years for the CWD index. However, for some stations there is evidence that tests commencing before the 1900s show significant increasing trends, together with tests commencing between 1950 and 1970. Significant decreasing trends in CWD are evident for other stations for tests commencing in the early decades of the 1900s. However, these are not persistent for varying start dates. Two stations show trends in CWD that depart from the general pattern of trends across the
network (both B category series). For tests commencing prior to 1950, Strokestown (Carrowclogher) shows large and significant increasing trends (e.g., MKZs > 4 for tests commencing in 1910). Kilskyre (Robinstown) shows large and significant decreasing trends for tests commencing after 1960. These results suggest remaining inhomogeneities at these stations affecting trends in CWD.

PRCPTOT shows a predominance of increasing trends across the full period of record for the majority of stations. Notably, there is greater variation in trend direction and magnitude for tests commencing prior to the 1900s. Persistently significant increasing trends are evident for stations/tests commencing prior to the 1970s. For tests commencing after the 1970s, the vast majority of stations show non-significant trends. The Markree series shows a notable deviation for the general pattern of trends in PRCPTOT for tests commencing before 1900, which raises suspicion about the quality of the early part of this A category series. Similarly, the Tycor series (A category) shows significant decreasing trends for tests commencing prior to 1905.

SDII shows the largest variation in trend magnitude and direction across the network of stations, with different stations showing persistent significant increasing and decreasing trends for tests commencing throughout the record. R95pTOT and R99pTOT are dominated by increasing trends for different start years, with persistent significant increasing trends evident for some stations for tests commencing since the 1930s. Only a small number of stations show weak, non-significant decreasing trends in these indices. Both R5mm and R10mm show a predominance of increasing trends for most stations for different test periods. For tests commencing post 1970 there is a tendency for non-significant trends. For stations with records extending prior to 1900 there is greater variation across stations in trend tests commencing in the late 1800s. For R10mm Markree and Newport station series show significant increasing and decreasing trends, respectively, for tests commencing prior to 1890. While the number of stations available for comparison decreases at this time, the trends appear larger than those at other stations. Trends in Rx1day and Rx5day precipitation show coherence across the network for varying start dates. On the whole, trends in Rx5day tend to be persistently positive for the majority of stations, irrespective of start date.

4 | DISCUSSION

This study derived quality controlled long-term daily precipitation series for 36 stations across Ireland by leveraging data rescue efforts to extend existing digital records available from 1940. The average series length is 118 years, with some stations dating back to 1870s. Following quality control and homogenisation, trends in precipitation extremes from annual ETCCDI indices were examined for 30 stations. Results indicate the predominance of increasing trends across the network. However, the direction, magnitude and significance of trends is dependent on the period of analysis, emphasizing the importance of the long records developed here. The analysis of trend persistence for varying start years indicates the influential role of low frequency variability on trend results. Of particular influence may have been the shift to more prevalent positive NAO conditions around the late 1970s and a greater predominance of westerly airflow (e.g., Hurrell, 1995; Kiely, 1999; Murphy et al., 2013). Concurrent changes are most evident for the CWD, PRCPTOT, R5mm and R10mm indices.

Most previous assessments of precipitation in Ireland have been limited to the post-1940 record and have not undertaken assessment of ETCCDI indices (e.g., Sheridan, 2001; Walsh and Dwyer, 2012) making direct comparison difficult. Assessments undertaken for longer records have focused on seasonal and annual totals (e.g., Butler et al., 1998; McElwain and Sweeney, 2007; Noone et al., 2015). These studies have drawn attention to the increase in annual totals, particularly for stations on the western seaboard. Our results show that of the indices examined here, PRCPTOT is most sensitive to the influence of low frequency variability and period assessed. We find the greatest magnitude of trends for indices measuring the contribution of heavy precipitation events to annual totals (i.e., R95pTOT and R99pTOT), particularly in the south and south east of the island. The largest number of significant increasing trends is reported for intensity (SDII), also in the east and south of the island, which suggests a different driving mechanism for changes in extremes for this region.

A crucial step in assessing trends is the quality assurance of available data to ensure derived results are not an artefact of measurement practice or data processing. It is widely accepted that the reliability and accuracy of homogenisation procedures generally decrease with the increasing temporal resolution of homogenisation (Venema et al., 2012). The task is further complicated for early records as station density typically decreases with time (Hollis et al., 2019). Therefore, homogenisation of daily data is considered to be a much more challenging problem than homogenisation at monthly or annual scales (Coll et al., 2018). Relatively few homogenisation algorithms include methods for the homogenisation of daily climate series and those that do for example, MASH (Szentimrey, 1999, 2014) and ACMANT (Domonkos, 2015) tackle the homogenisation of daily precipitation
data based on a procedure in accordance with the multiplicative (or cumulative) model that is assumed for monthly data. Moreover, the theoretical minimum number of well-correlated reference stations needed for the application of relative homogenisation methods as recommended by the World Meteorological Organization is three, with at least four reference stations required to obtain good results in more complex situations (WMO, 2020). Obviously, this is challenging for records that extend into the 1800s, given decreasing network density.

Our study represents a relatively rare attempt to detect and correct inhomogeneities in daily precipitation data for long-term records spanning more than a century. We employed the RHtests homogenisation software as it provides one of the few methodologies for the detection and adjustments of breaks in daily precipitation data without the use of a reference series. Moreover, the use of absolute tests avoids issues of circularity where neighbouring stations were used to fill missing data prior to homogenisation. Reeves et al. (2007) found that two-phase regression methods, as implemented in the RHtests software, had a comparable level of performance to methods such as the standard normal homogeneity test (SNHT), with the performance of the algorithm dependant on the parameters defined by the user. In total, 22 breaks were identified by RHtests software in 16 of the 36 stations, with approximately 80% of detected breakpoints supported by metadata relating to instrument and site changes and were adjusted using QM. However, subsequent assessment of residual breakpoints in PRCPTOT and R5mm using the Pettitt and SHNT tests resulted in six stations being excluded from the analysis of trends. For four of these stations (Abbeyfeale, Carndolla, Kenmare and Westport) no significant breakpoints were detected by RHtests, despite the fact that potential breakpoints documented in metadata were manually entered and tested.

For Drumnsa station, two significant residual breakpoints were detected; the first in 1917 had no associated metadata but was also detected in a previous study by Noone et al. (2015) using HOMER (Homogenisation Software in R) software. The second breakpoint detected in 1942 corresponds to the installation of a new gauge at the time. While this break was detected by RHtests and corrected, discontinuities evident in the adjusted series suggest that the adjustment applied was too modest. The final station to be excluded was Cressleagh. This series was corrected for a breakpoint detected in 1928, however, a visual assessment of the annual series following adjustment suggests the presence of a remaining shift in the early 1960's that was not detected by RHtests. Given these uncertainties surrounding break detection and correction we suggest that other studies also examine output from RHtests algorithms for residual breaks, as was also done by Santo et al. (2014) in their assessment of Portuguese seasonal extremes.

While the nature of the network analysed required the use of absolute homogeneity tests, our analysis built in assessments of residual breakpoints and trend tests that leverage information from across the network, thereby building confidence in our results. For instance, the plotting of p-values for residual breaks across series (Figure 3) allowed comparison of the timing of potential break points across the network, helping to isolate breaks unlikely to be associated with climate variability. Furthermore, the assessment of trend persistence following Noone et al. (2015), Murphy et al. (2013) and Wilby (2006) aided the visual detection of stations for which the behaviour of trends through the record deviated significantly from other stations. In this regard, cautionary flags were raised for trend in some stations/indices where remaining inhomogeneities may exist, particularly in early records. These include Strokestown, Markree and Newport, especially for trends in CWD, PRCPTOT and R5mm.

There is much scope for further work to build on the dataset and results presented. Future work will assess changes in seasonal and monthly extremes across the derived network. This will be important for furthering understanding of drivers of changes in precipitation extremes. Given the trends in intensity and the contribution of heavy rainfall events to annual totals in the south and east of the island, regression of local indices onto global mean surface temperature akin to Hawkins et al. (2020) would facilitate examination of the emergence of an anthropogenic climate change signal. Noone et al. (2015) presented a long-term monthly precipitation network for the island of Ireland. Future updates of that network should include monthly totals for the additional stations developed here. While this work has improved understanding of the changing nature of extreme precipitation on the Island of Ireland, it would not have been possible without concerted efforts at data rescue. While significant progress has been made in making pre-1940 daily precipitation available for scientific scrutiny through the PhD research of the lead author (Ryan et al. 2018; Ryan et al., 2020), much data remains to be rescued and digitized for Ireland. Ongoing data rescue initiatives at Met Éireann could be directed at filling the spatial gaps in this network and improving the density of data from early stations to both assist with understanding the spatial distribution of changes and to open the possibilities for deploying relative homogenisation methods. There is also the potential to develop gridded monthly products back to at least the start of the 20th Century (Hollis et al., 2019). While we chose to infill missing data prior to
homogenisation, future work might also investigate the sensitivity of results to infilling pre or post homogenisation and/or distance thresholds used to identify neighbouring stations for infilling (especially in upland locations). Lastly, given the uncertainties associated with homogenisation of daily data, future work should also evaluate the findings presented here using other homogenisation software packages and changepoint detection methods (e.g., PELT [Killick et al., 2012]). Insights from initiatives such as the European Research Area for Climate Services (ERA4CS) INDECIS project that are assessing approaches to homogenisation of daily data will be critical in this regard.

Finally, with increasing concerns about the impacts of climate change, understanding changes in the characteristics of precipitation is increasingly important given that climate extremes often exhibit different behaviours than changes in average conditions. The UN Intergovernmental Panel on Climate Change (IPCC) Fifth Annual Assessment Report (AR5) states that over most of the mid-latitude land masses, extreme precipitation events are very likely to be more intense and more frequent in a warmer world (IPCC, 2014). Trenberth (2011) estimate a 7% increase in water vapour content for every 1°C rise in temperature. Our findings are largely consistent with expected changes in daily precipitation extremes in a warming world. The overall tendency of increasing trends observed here suggest that heavy or extreme precipitation events are contributing significantly more to annual precipitation totals in Ireland, while precipitation is becoming more intense, particularly in the east and southeast of the country. However, potential changes in North Atlantic atmospheric circulation patterns will also have a direct impact on future precipitation, with changes in the frequency and intensity of Atlantic depressions and their associated weather fronts and convective activity important factors for extreme precipitation (Matthews et al., 2015). Therefore, it is important to further investigate the driving mechanisms behind the trends reported. Other studies of extreme rainfall changes in the region reveal complex driving mechanisms (e.g., Maraun et al., 2011; Lenderink and Fowler, 2017; Brown, 2018).

5 | CONCLUSION

This study examines trends in annual precipitation for Ireland using the ETCCDI indices for a newly developed long-term daily precipitation network. Stations within the network have an average record length of 118 years, with some stations dating back to the 1870s. Our results show the predominance of increasing trends across the island, the growing contribution of heavy precipitation events to annual totals and increases in precipitation intensity, especially in the east and southeast of the island. While results are consistent with expectations in a warming world, the influence of low frequency variability is substantial. Understanding variability and change in long-term climate is dependent on data rescue activities and approaches to homogenisation of daily data. While approaches to undertake the latter are still in their infancy, this work shows the benefits of combining existing techniques to increase confidence in the derived series.

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AUTHOR CONTRIBUTIONS

Mary Curley: Conceptualization; methodology; project administration; supervision; validation; writing – review and editing. Séamus Walsh: Methodology; project administration; software; writing – review and editing. Conor Murphy: Conceptualization; investigation; methodology; project administration; resources; supervision; writing – original draft; writing – review and editing.

ORCID

Ciara Ryan https://orcid.org/0000-0001-6281-5123
Mary Curley https://orcid.org/0000-0002-6209-8221
Conor Murphy https://orcid.org/0000-0003-4891-2650

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