



Met Éireann

Technical Note No. 63

**To what extent does the large temporal  
variability in Irish precipitation mask  
underlying trends?**

Emily Gleeson, Ciara O'Hara, Séamus Walsh, Sinéad Duffy

Glasnevin Hill, Dublin 9

2015

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**Title:** To what extent does the large temporal variability in Irish precipitation mask underlying trends?

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## **Abstract**

A pertinent question about precipitation trends is how to distinguish a climate change signal from natural variability. This is particularly important for Ireland where, in addition to the high spatial variability, precipitation also has a high level of temporal variability. Future precipitation projections for Ireland are highly uncertain due to conflicting results from climate models. Due to this, using an observation-derived dataset we determined the magnitude of the changes in the spatially-averaged precipitation over Ireland that need to occur, and the length of the record that needs to be available, to separate an externally forced anthropogenic change from changes due to natural variability. We used a 71-year (1942-2012) 1km gridded dataset, derived from precipitation observations over Ireland, to generate a de-trended dataset of annual average precipitation for the country. Using this data, we then created artificial time series of annual precipitation of varying length in terms of years. These datasets had the same underlying natural variability as the original dataset but in addition to this we applied predefined external forcings. We then used statistical testing to determine the minimum length of the time series of annual precipitation and the magnitude of the external forcing required to separate the external trend from the natural variability with statistical confidence. We examined trends in annual, Boreal summer and Boreal winter precipitation using the Mann-Kendall test. For example, in the case of annual precipitation we found that an increase of at least 20% over a period of 30 years (for a monotonically increasing external forcing of 20%) was the minimum needed for the result to be statistically significant at the  $p < 0.1$  level. The number of years required to statistically decouple external from natural forcings increases by a factor of 3 or 4 when the external forcing is applied non-monotonically, and also when the results are considered by season.

## **Keywords**

Irish precipitation, temporal variability, external forcings, climate change, trend analysis, Mann-Kendall.



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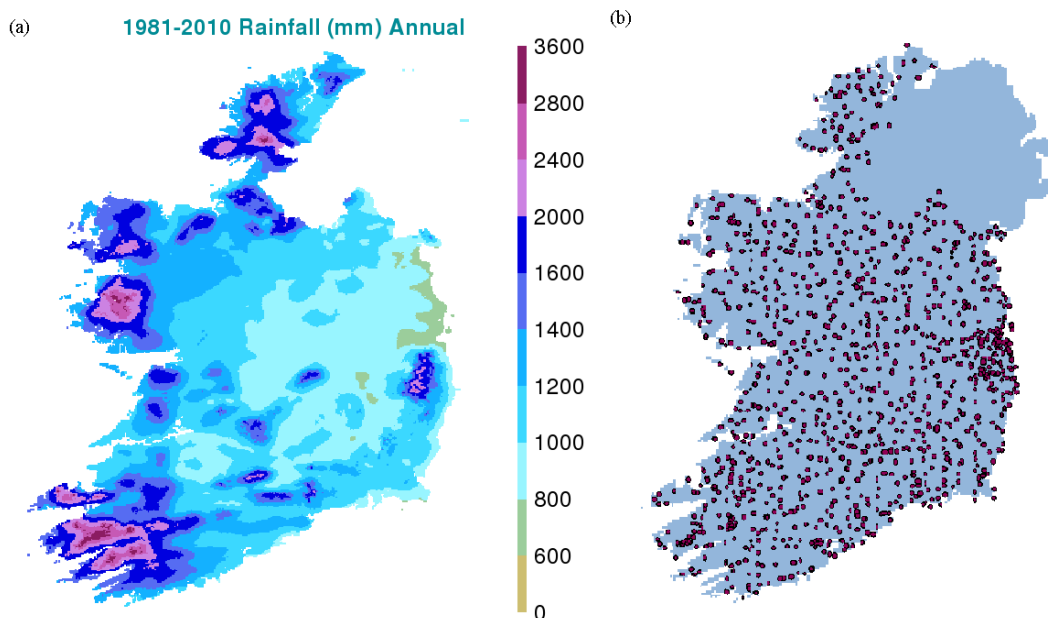


# 1 Introduction

Over the past number of decades, increased surface temperatures have been observed over many parts of the globe (Sánchez-lugo et al., 2012; Morice et al., 2012). These increases have been attributed to anthropogenic forcing (Hegerl et al., 2007; Stott et al., 2010). It is expected that higher temperatures will be accompanied by an amplification of the hydrological cycle (IPCC, 2007; IPCC 2013). Precipitation is the most easily observed component of the hydrological cycle but it is noisy and highly variable and this is particularly true in the case of Ireland. Changes in precipitation may have more important impacts on human and environmental systems than any change in temperature.

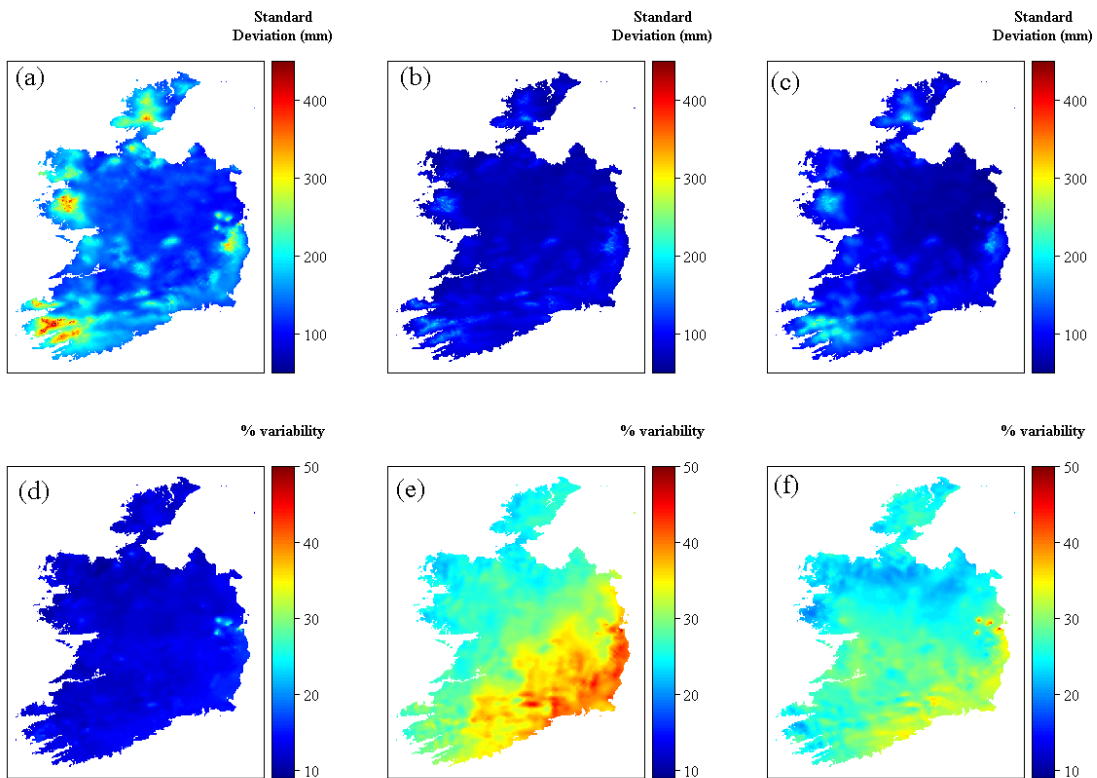
Ireland is located between 5°W and 11°W, and 51°N and 56°N, at the eastern edge of the North Atlantic Ocean, the influence of which dominates its mild climate. The prevailing westerly winds and the local orography largely determine the country's precipitation patterns (Betts, 1990; Sweeney, 2014). Other influences include the North Atlantic sea level pressure, the North Atlantic Drift and large-scale oscillations such as the North Atlantic Oscillation (NAO), the East Atlantic pattern and the Arctic Oscillation (Murphy and Washington, 2001; Hurrell, 1995; Wibig, 1999; Beranová & Huth, 2008).

Ireland's precipitation is very variable both spatially and temporally (Rohan, 1986; Sweeney, 2014) and is characterised by low intensity and long duration events (Fitzgerald, 2007). The national average annual rainfall is 1230mm (Walsh, 2012a) with a west-to-east decrease as shown in the 1981-2010 average annual precipitation in Figure 1(a), where mountainous areas in the west receive over 3000mm annually compared to approximately 750mm in sheltered parts of the east.



**Figure 1:** (a) Mean annual precipitation for Ireland over the period 1981-2012 illustrating the archetypal west-to-east decline. (b) Locations of the stations used in the generation of the 1942-2012 gridded precipitation dataset.

As well as this spatial variability, Ireland's precipitation also varies temporally as shown in Figure 2 and Table 1. Figure 2 shows the spatial variation of interannual standard deviation and normalised standard deviation (% variability or interannual standard deviation divided by the mean over the period (Sauro, 2014)) for the 1942-2012 annual, summer and winter periods. In absolute terms, the interannual standard deviation is highest over mountainous regions as expected but the normalised standard deviation reveals a more interesting northwest to southeast pattern in the rainfall variability for summer and winter. Spatial averages of the mean and variability of Irish precipitation are summarised in Table 1.



**Figure 2:** (a) The interannual (b) the interannual JJA (Boreal summer) and (c) the interannual DJF (Boreal winter) standard deviation (mm) in Irish precipitation over the period 1942-2012. (d) The interannual, (e) the JJA (f) the DJF normalised standard deviation (%), a measure of variability, in Irish precipitation over the period 1942-2012, where normalised standard deviation is the standard deviation divided by the mean precipitation over the same period.

	<b>DJF (mm)</b>	<b>MAM (mm)</b>	<b>JJA (mm)</b>	<b>SON (mm)</b>	<b>Annual (mm)</b>
<b>1961-1990 average</b>	350.4	244.8	243.3	347.9	1186.4
<b>1961-1990 stdev</b>	80.1 (22.9%)	60.6 (24.8%)	58.0 (23.8%)	58.2 (16.7%)	108.8 (9.2%)
<b>1981-2010 average</b>	360.4	260.3	266.6	362.1	1246.5
<b>1981-2010 stdev</b>	89.1 (24.7%)	57.2 (22.0%)	76.7 (28.8%)	70.0 (19.3%)	125.3 (10.1%)
<b>1942-2012 average</b>	351.0	241.8	264.7	354.8	1213.3
<b>1942-2012 stdev</b>	78.8 (22.5%)	56.3 (23.3%)	70.4 (26.6%)	67.2 (18.9%)	122.3 (10.1%)

**Table 1:** Spatially averaged precipitation means and standard deviations over the 1961-1990, 1981-2010 and 1942-2012 periods for the Republic of Ireland. Values are also quoted for each Boreal season.

Several studies have been published on precipitation over Ireland and Britain. Most of these have analysed trends in station data or climate model data to discriminate between natural and externally forced changes in precipitation. Here we discuss some of these studies and highlight the differences and potential uses of our new study.

Previous studies on precipitation changes only considered changes where long time series of observed station data were available. McElwain and Sweeney (2003) analysed data from 15 Irish stations up to the year 2000 and drew the general conclusion that northern areas are getting wetter and southern areas slightly drier, in line with outputs from earlier climate models (IPCC, 2001; McGrath & Lynch, 2008). An older study by Jones & Conway (1997) spatially averaged data over Ireland (22 stations including 8 from Northern Ireland). This showed no trend in annual rainfall over the period 1940-1995 but found similar seasonal results to McElwain & Sweeney (2003). However, neither study attempted to conclusively separate natural variability from any externally forced changes, with 10-year moving averages or decadal Gaussian filters used in an attempt to eliminate the natural variability. More recently, comparisons were made between the 1961-1990 and 1981-2010 station long-term averages (LTA) (Walsh, 2012a; Walsh 2012b). This indicated an approximate 6% increase in national average annual rainfall (RoI only) between the two averaging periods ranging from 2-3% in the

east to 8-9% in the west. Most seasons recorded increases, but the south and east recorded decreases in winter. No attempt was made to explain the changes.

An analysis of UK precipitation extremes, derived from Met Office gridded data by Simpson and Jones (2013), found that observed trends in UK precipitation are mostly consistent with projections from climate models. They suggested that the changes in seasonal precipitation totals are likely associated with the NAO and that in recent years it has become harder to determine a detectable anthropogenic influence on UK precipitation than on temperature.

Reconstruction data have also been used as a means of discriminating climate change signals from natural variability. For example, using a 1500-year temperature reconstruction dataset, Hegerl et al. (2007) found that enhanced variability in the past was mainly due to external forcing, in particular from volcanoes, which meant that it could be quantified and hence separated from later greenhouse gas-induced changes. While their area of study included Ireland, the analysis was not split by geographical area nor did it include precipitation. Reconstructed precipitation datasets are scarcer and mostly exist for specific sites or small areas (Hodell et al., 1991; Graumlich, 1993; Casty et al., 2005 among others). However, the European reconstructed precipitation dataset from 1500 to 2000 (Pauling et al., 2006) covers Ireland. No studies have been done using this dataset to separate natural from anthropogenic precipitation changes. However, its relatively coarse resolution (0.5 degrees or ~56km over Ireland) and the fact that it doesn't capture the present day (years 1942-2000 overlap with our 1km dataset – *see Section 2 for further details on this 1km dataset*) mean or variability in precipitation over Ireland restricts its use for the study we proposed.

A popular approach used to discriminate between trends in precipitation due to natural variability and external forcings is the use of climate simulations. The huge importance of the detection and attribution of externally forced climate changes is emphasised by the fact that an entire chapter of IPCC, 2013 is devoted to it (Bindoff et al., 2013). It is thus an important area of further research, in particular for precipitation, which is considered much more uncertain than temperature.

Regarding the use of climate models, common methods include running the models with and without anthropogenic forcings or using the natural variability from a control simulation using pre-industrial greenhouse gas concentrations as a means of separating the anthropogenic signal. The expected anthropogenic fingerprints of change in zonal mean precipitation have been detected in annual and some seasonal data. For example, Zhang et al. (2007) and Noake et al. (2012) used CMIP3 (Coupled Model Intercomparison Project) multi-model data to separate anthropogenically forced zonal mean precipitation changes over land from natural forcings and similarly Polson et al. (2013) and Balan et al. (2012) used CMIP5 multi-model data. However, the detection of regional scale trends is much more difficult though an anthropogenic signal has been detected at high northern latitudes (Min et al., 2008; Polson et al., 2013).

Regional-scale attribution of precipitation change is still problematic and to date there has been no such study carried out for Ireland specifically. Observational uncertainties, in addition to challenges in precipitation modelling, limit confidence in the assessment of changes in precipitation, as the following projections highlight. The results from

Scheff and Frierson (2012) using a suite of 36 global CMIP5 models show some confidence in wetter winters and drier summers for Ireland under the RCP8.5 scenario (van Vuuren et al., 2011) but low confidence in changes for the other seasons. These results for summer are in agreement with the larger CMIP5 ensemble presented in the IPCC AR5 report for the end of the century (Flato et al., 2013) but the results for winter are not statistically significant, showing the large uncertainty that still exists. The relatively low resolution of global climate models hinders their ability to capture local climate details making it necessary to downscale the data to a finer grid. Dynamical downscaling of 25 CMIP3 models to a 25km grid over Europe for the EU ENSEMBLES project (van der Linden et al., 2009) also showed a signal for future drier summers, with greater uncertainty for the other seasons. C4I, an Irish project, further downscaled to a 14km grid over Ireland and the UK (McGrath et al., 2008). This indicated drier summers and springs and wetter winters and autumns, though the trends were not statistically tested. Nevertheless, the models captured the spatial and seasonal observed precipitation patterns of the past climate which gives some confidence in the models (Wang et al., 2006). A 10 model ensemble of EURO-CORDEX data on a 12.5km grid mostly shows a robust increase in annual precipitation over Ireland under RCP8.5 (Jacob et al., 2014). It also shows statistically robust decreases for summer, increases for autumn and winter but no clear signal for spring. A separate study was undertaken by Nolan (2014 under review) and Gleeson et al. (2013), using a mixture of CMIP3 and CMIP5 downscaled simulations under the RCP8.5 emission scenario over Ireland on a 4-7km grid (i.e. the highest resolution regional climate simulation for Ireland). This showed a likely decrease in summer, spring and annual precipitation, a slight decrease in winter with no signal for autumn (Gleeson et al., 2013; Nolan, 2014 under review).

The general uncertainties in climate model simulations of precipitation make quantitative comparisons of model output and observations difficult (Stephens et al., 2010 for global; Nolan, 2014 under review) for Ireland which also limits confidence in the detection and attribution of precipitation changes. The analysis of model simulated precipitation variability for Ireland is smaller than observed variability (Nolan, 2014 under review).

Clearly, with the exception of summer, there is still considerable uncertainty regarding precipitation projections for Ireland and this is one of the main reasons why we chose to use observation-derived data rather than climate model simulations in our approach.

Our study differs significantly from the studies we have discussed here. It focuses on the temporal rather than the spatial variability and how natural temporal variability can complicate the recognition of long-term externally forced trends. We use spatially averaged annual mean precipitation amounts over the Republic of Ireland (RoI) by averaging a 1km monthly mean 71-year gridded dataset of precipitation for Ireland produced by Met Éireann from observation data. This gives a much better spatial average than the sparse synoptic network of stations that are used in the global and larger-scale observation datasets currently available (e.g. CRU (Harris et al., 2014), E-OBS (Haylock et al., 2008), GPCC (Schneider et al., 2011)). We removed any existing trends from this dataset but retained its natural variability. We then used these data to generate our own artificial annual time series of precipitation to which we added pre-defined external forcing, where external forcing here implies anthropogenic forcing

only. Our goal is also different from other studies. Firstly, we do not consider large latitude bands or wide geographic areas. In addition to being able to attribute a trend to anthropogenic or external forcing other than natural variability, our study investigates the length of a time series of annual precipitation needed and the size of the anthropogenic forcing required, before it becomes possible to separate an externally forced change in precipitation from natural variability.

Section 2 outlines the datasets used in this analysis. In Section 3 we discuss the treatment of the data and statistical testing. The results are given in Section 4, with discussions and conclusions in Section 5.

## 2 Data

71 years of historical Irish (Republic of Ireland only) gridded monthly precipitation data were available for use. These datasets were prepared by Met Éireann from monthly station data archived in their climate database. The number of stations available varies from year to year, but currently consists of approximately 500 stations. At most of these stations precipitation is measured once a day at 0900 UTC, in a standard 5 inch raingauge, but at 25 synoptic stations measurements are accumulations derived from tipping bucket raingauges, and at some remote locations monthly precipitation readings are taken. A map of the precipitation measurement stations in Ireland for the period 1941-2012 is shown in Figure 1(b).

A number of geostatistical methods are used for interpolation of climate data. A comprehensive review is given by Dyras et al. (2005). Perry and Hollis (2005) generated monthly climate grids for a range of parameters for the UK using inverse distance weighted interpolation, Haylock et al. (2008) produced monthly and daily European gridded datasets using thin plated spline and kriging methods, while Zolina et al. (2014) used kriging and grid cell averaging to produce daily grids. Generally these methods involve interpolating fractional anomalies from long term background values. Regression-kriging, (Hengl, 2007), was applied to the Irish rainfall data as a comprehensive robust method which is widely used amongst the climatological community. It combines regression of a dependent variable, which may be normalised, on independent variables such as elevation, latitude, longitude etc., with kriging of the regression residuals. The large scale variability of the target variable is explained by the regression trend, while the residual kriging accounts for the local variability.

Firstly long-term average (LTA) station values and monthly rainfall grids were generated (Walsh, 2012b). Monthly station totals were normalised by dividing by their LTA and a regression model was applied to the normalised rainfall using geophysical parameters (elevation, distance to sea, easting, northing) as independent variables. The regression residuals were interpolated onto a 1km grid by ordinary kriging. The regression trend was then evaluated at each grid point and added to the interpolated residual grid and the final monthly value was obtained by de-normalising. The accuracy of the predictions was estimated using the leave-one-out cross-validation method (LOOCV), where each station value is omitted in turn and its value estimated using the remainder of the dataset. Table 2 shows the average root-mean-square error RMSE for all months and its variation across the data period, and the average normalised RMSE,

RMSEr, that is the RMSE divided by the standard deviation of the data. The RMSEr gives a normalised accuracy of prediction. The RMSEr can be considered satisfactory if it is less than 0.4; in this case the model accounts for more than 85% (R-square=85%) of the variability at the validation points, while values greater than 0.71 account for less than 50% of the variability (Hengl, 2007).

The dataset used in this study are spatial averages of this 1km dataset (over RoI or the area east or west of 8°W). The advantage of using 1km gridded data, as opposed to station data, is that it can provide a mean for the Republic of Ireland which takes high resolution topography into account.

Variation across period 1942-2012				
	Average	Standard Deviation	Minimum	Maximum
RMSE (mm)	13.61	4.48	3.55	31.93
RMSEr	0.35	0.08	0.17	0.7

**Table 2:** Summary of cross validation statistics for the monthly rainfall gridding. The average RMSE for all months in the 71-year period, its variation across the data period and the average normalised RMSE, RMSEr are given. RMSEr is the RMSE divided by the standard deviation of the data.

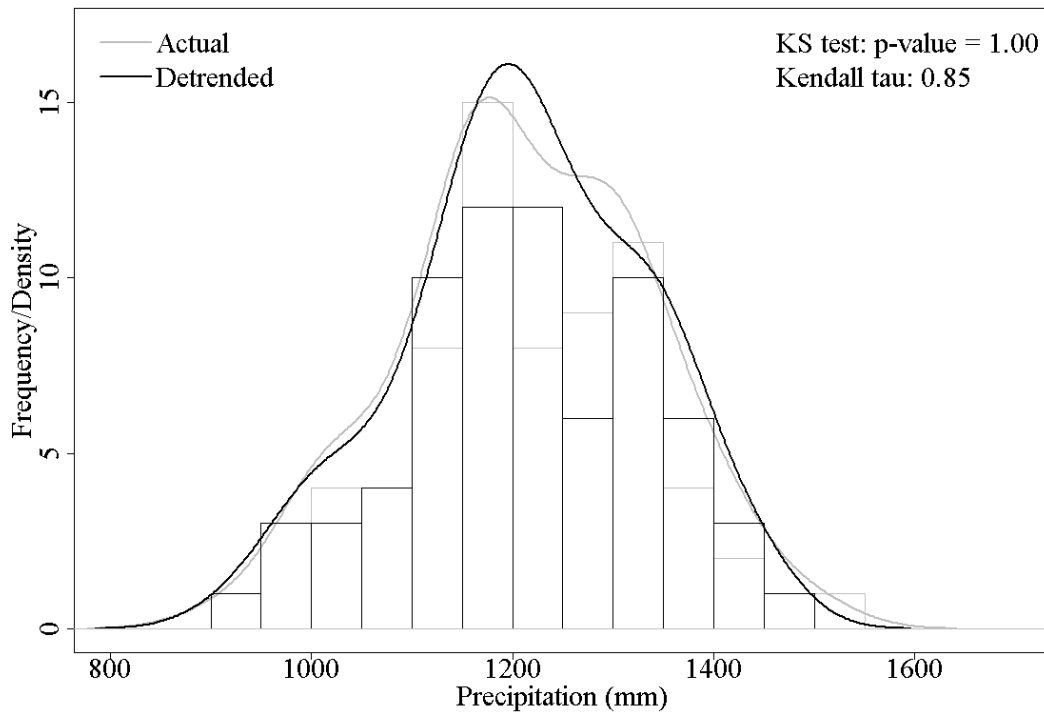
### 3 Methods

The spatially averaged precipitation data over Ireland used in this study were derived from the 71-year 1km gridded observation dataset available for the country. The areal averages considered include the country as a whole and both the eastern (east of 8°W) and western (west of 8°W) areas separately for annual, Boreal summer (June, July, August – JJA) and Boreal winter (December, January, February – DJF) time periods.

We used these data to generate artificial time series of precipitation. Two types of time-series were considered – one where artificial time series (denoted ATS hereafter) of length  $y$  years were generated and the other where the artificially generated time series ATS were appended to the end of the de-trended (*see next paragraph in this section for details on the de-trending*) historical 71-year time series (denoted AH hereafter). It is important to note at this point that we applied increases or decreases to each ATS or the ATS part of AH, but not to the de-trended 71-year historical time series, as a means of mimicking anthropogenic climate change. The details regarding the generation of these data series are outlined later in this section.

As the ultimate goal of the experiments was the discrimination of externally forced anthropogenic changes from natural variability, the 71-year historical dataset was de-trended before use in the experiments. This was necessary because, for example, the Mann-Kendall trend test on the annual data series for the country as a whole returned a p-value of 0.04 indicating a *very likely* (Mastrandrea et al., 2010) increase in precipitation with a magnitude of  $1.58 \pm 1.47$  mm/year ( $p < 0.05$ ) using Sen's slope test.

De-trending, done by subtracting the least-squares fit line from the data (Borchers, 2014), removes trends in a dataset while preserving its underlying variability and magnitude characteristics. A histogram and density plot comparing the original and de-trended annual data for Ireland is shown in Figure 3. The non-significant Kolmogorov-Smirnov (K-S) test (Young, 1977) and non-parametric Kendall tau correlation coefficient (Meals, 2011) of 0.85 provide the necessary statistical evidence that the de-trended dataset contains the same magnitude and variability characteristics as the original dataset. Similarly, the eastern, western, JJA and DJF time series were de-trended.



**Figure 3:** Histogram and density plot of the original and de-trended annual spatially-averaged precipitation data for Ireland. The results of the Kolmogorov-Smirnov (K-S) test and non-parametric Kendall tau correlation coefficient from comparison of the two datasets are included.

Below we outline how the ATS of annual average precipitation over Ireland were generated to which increasing trends were then applied. Increasing trends were also applied to DJF data but decreasing trends to the JJA time series for consistency with CMIP5 and downscaled projections for Ireland's future precipitation (Flato et al., 2013; Jacob et al., 2014; Nolan, 2014 under review). The same techniques were applied for the 3 different areas considered – Ireland as a whole, the area east of 8°W and the area west of 8°W. In the AH experiments, the artificially generated time series (ATS), with applied trends, were appended to the end of the de-trended 1942- 2012 historical time series of Irish precipitation in chronological order.



We firstly focus on the generation of ATS of annual average precipitation for Ireland of length  $y$  years where  $y$  was limited to between 10 and 150 years, depending on the experiment. The selection was done by randomly selecting any  $y$  years from the 71-year de-trended dataset using the standard random selection functions in the R statistics package (Dutang, 2014). We repeated this process 30,000 times, i.e. we generated an ensemble of 30,000 time series of length  $y$ , to take account of possible time series that could arise due to the temporal variability in Ireland's precipitation. 30,000 iterations was deemed sufficient as the results were consistent to within 1% i.e. the proportion of the ensemble returning statistically significant results was consistent to within 1% even if we increased the ensemble size further.

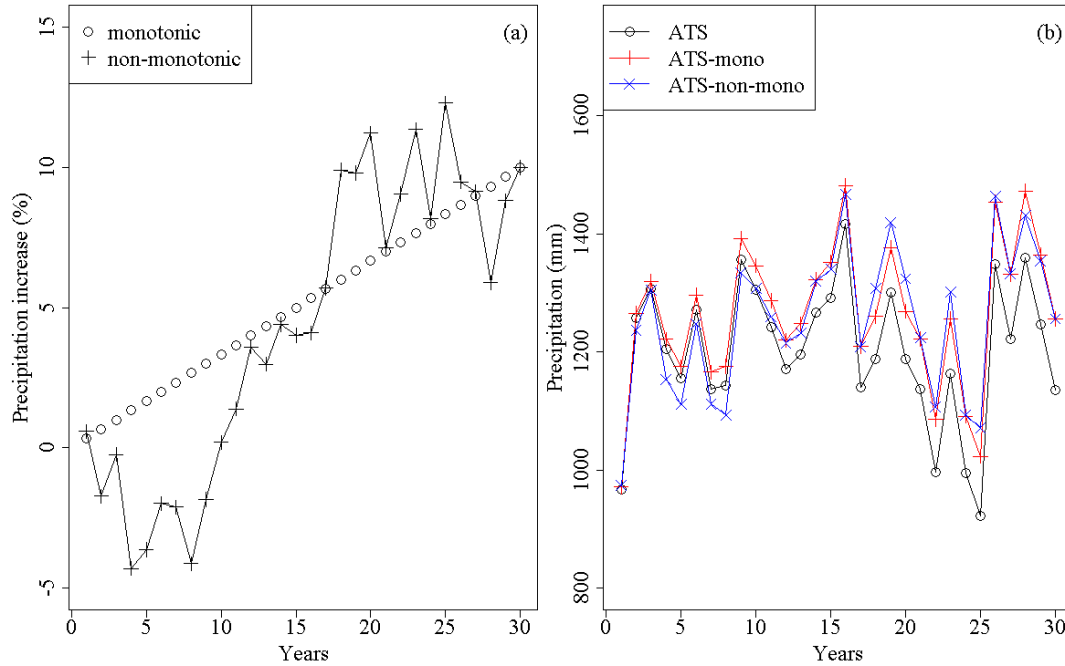
The second step in the process was to apply a forcing, to mimic anthropogenic induced changes, to each of the 30,000 time series of length  $y$  years. This was done by applying increases to each of the  $y$  years in the time series. By year  $y$  a net change of  $x\%$  was applied, where  $x\%$  is the fraction of the 1942-2012 annual mean precipitation over Ireland. In our experiments the forcings were applied linearly monotonically and non-monotonically across the time series. We limited  $x$  to the range 4-20%, as 20% is at the upper end of the changes projected by the latest climate simulations (Flato et al., 2013; Jacob et al., 2014; Nolan, 2014 under review).

For the linearly monotonic case the applied change grew monotonically with each successive year up to the final year  $y$  where the net change was  $x\%$ . In the non-monotonic case where the net result was a positive trend, the forcing applied to each year could be positive or negative and hence was not necessarily always greater than the forcing applied to the previous year. The sign of the forcing was allowed to vary to try to account for the variability of Irish precipitation, since there is no reason to assume that each year in a series would see a positive change in precipitation. The non-monotonic trend was generated randomly but the net forcing was always  $x\%$  by year  $y$ . To try to account for the range of possible non-monotonic trends terminating at  $x\%$  by year  $y$ , the non-monotonic trend applied to each of the 30,000 time series generated for each experiment of length  $y$  years, was also generated randomly. A non-monotonic change is the more realistic scenario, as Irish precipitation is very variable in time, and there are no reasons why we should expect a change to occur monotonically.

Sample time series are illustrated in Figure 4. A linear monotonic trend and non-monotonic trend of 10% by year  $y$  where  $y = 30$  years is shown in Figure 4(a). In Figure 4(b) the effect of both trends on a sample ATS of length  $y$  is shown where ATS-mono is the ATS time series plus the monotonic linearly increasing trend and ATS-non-mono is the ATS time series plus a non-monotonic trend.

There were two main reasons for the experiments using the AH series, which is a combination of the de-trended historical series and ATS. The first is that the de-trended historical part of this time series is similar to a control (pre-industrial) period (Sterl et al., 2012) in climate model simulations. In such simulations greenhouse gas concentrations are held constant, for example at the levels of the year 1850. Therefore, any variability in such data is natural rather than anthropogenic. In our experiments, the anthropogenic forcings are applied to the ATS subsets of the AH data series only. Hence, our AH time series is analogous to a control period in climate simulations followed by an industrial period where known forcings are applied. The second reason

for using AH time series, where the historical section was firstly de-trended, is that it is unknown when (or if) anthropogenically caused changes in precipitation over Ireland occurred. De-trending eliminates this uncertainty. In any comparison study, it is good to have a “before period” – in our case the de-trended historical time series can be considered the “before period” i.e. the period before anthropogenic forcings were in effect.



**Figure 4:** (a) Sample linear monotonic and non-monotonic trends of  $x=10\%$  by year  $y$  where  $y = 30$  years. (b) Sample artificial time series (ATS) of length  $y$  years to which the linear monotonic (ATS-mono) and the non-monotonic trends (ATS-non-mono) were added. It is not possible to discern the trend visually because of the large temporal variability of the underlying dataset.

Finally, we provide a brief outline of the statistical approach taken in this study. The non-parametric two-tailed Mann-Kendall test (Meals et al., 2011; Önöz and Bayazit, 2003; Drápela and Drápelová, 2011; Mondal et al., 2012) was used in the analysis because, despite the nature of the trend being known, variability itself can introduce trends which can occur in either direction. The presence of a trend in the precipitation time series was tested using three confidence levels: 90<sup>th</sup> ( $p < 0.1$ ), 95<sup>th</sup> ( $p < 0.05$ ), and 99<sup>th</sup> ( $p < 0.01$ ); the 90<sup>th</sup> and 95<sup>th</sup> levels are referred to as “very likely” probabilities in IPCC AR5 (Mastrandrea et al., 2010) and the 99<sup>th</sup> level denotes “virtually certain” probabilities. This test checks whether a time-ordered dataset exhibits an increasing or decreasing trend, which may or may not be linear (Frei, 2013), at a predetermined significance level.

## 4 Results

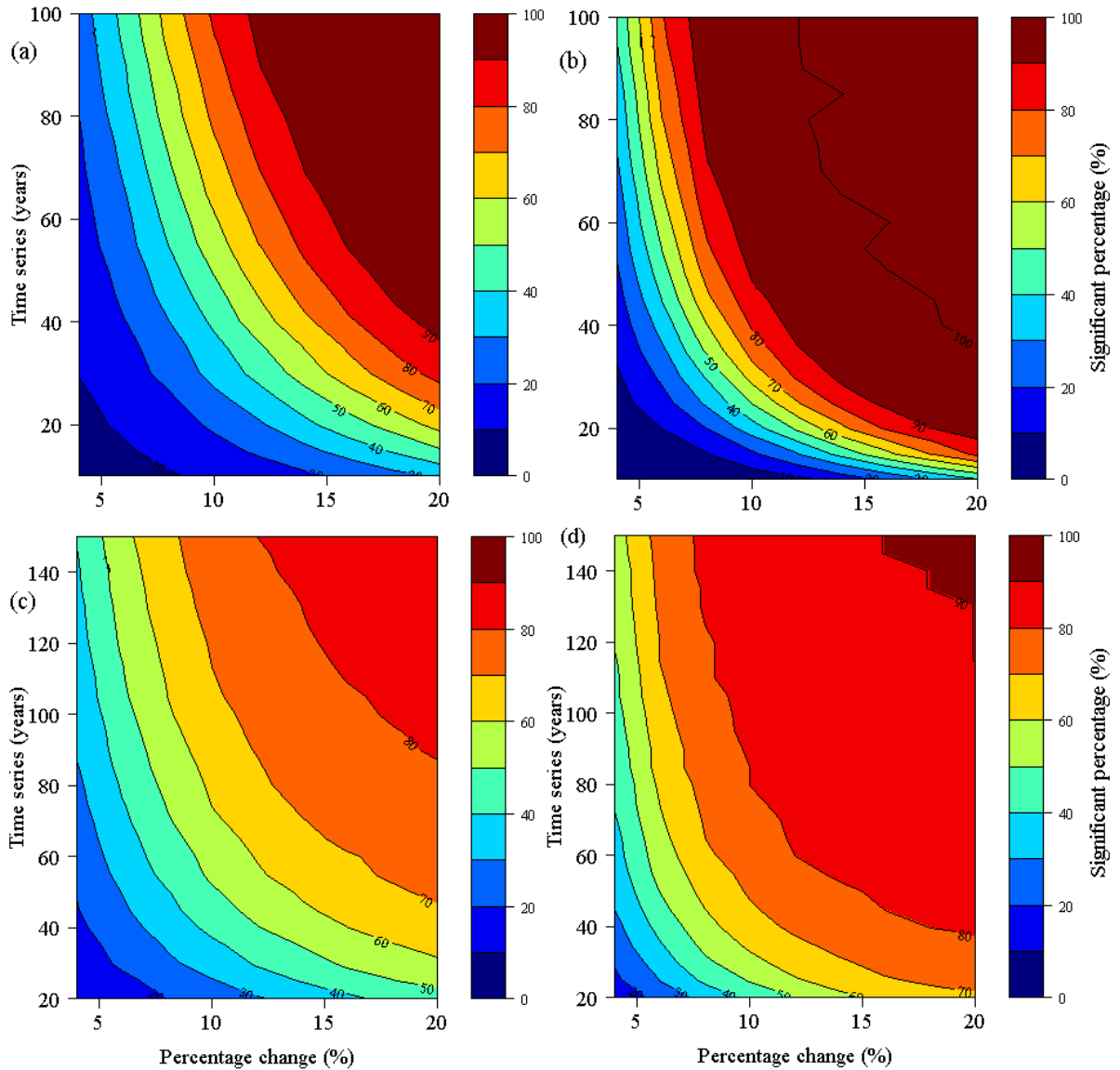
The results section is ordered as follows. The results of the ATS and AH experiments on annually averaged precipitation over Ireland as a whole are covered in section 4.1. The seasonal breakdown (JJA and DJF) of the experiments is included in section 4.2 and in section 4.3 areas east of 8°W and west of 8°W are considered separately.

In the contour figures presented in this section (Figures 5-9), the length of the time series in years,  $y$ , is shown on the  $y$ -axis. Here we mean the part of the time series to which we applied the forcing. The  $x\%$  forcing applied by year  $y$ , either linear monotonically or non-monotonically (to represent anthropogenic forcing), is shown on the  $x$ -axis. The contour lines refer to the percentage of the 30,000 member ensemble of time series generated for the experiment that return statistically significant results for the Mann-Kendall trend test at a given confidence level ( $p < 0.1$ ,  $p < 0.05$  or  $p < 0.1$ ). Although, the contour plots show the full range of percentages (of the 30,000 time series that return statistically significant results for a given confidence level), we have chosen 90% as the cut-off point; all of the results quoted in this section, including the tables, refer to this level of filtering. The 90% level was chosen to provide a rigorous level on which to base our findings. It is not the same as the  $p < 0.1$  confidence interval.

In each experiment the minimum time series length and forcing where 90% of the 30,000 iterations return a statistically significant trend at the relevant confidence level is determined from the corresponding contour plots. For the ATS series the minimum length is  $y$ , while for the AH series the minimum length is  $y+71$ . In the AH plots we have only shown the ATS part of the series i.e. the part to which the forcings were applied. An uncertainty of  $\pm 5$  years was considered most appropriate as the time series length was incremented in steps of 5 years in each experiment. The results are discussed in the following sections.

### **4.1 Annual ATS and AH precipitation time series**

The results of the experiments on the artificial annual time series (ATS and AH) of spatially averaged precipitation over the Republic of Ireland are shown in Figures 5 and 6 for different confidence levels. The interpretation of the axes and contours is as given earlier in this section and in the figure captions. The ATS results for linear monotonic trends of  $x\%$  over  $y$  years are shown in Figure 5(a) at the 95<sup>th</sup> or  $p < 0.05$  confidence level. An increase or forcing of 20% applied incrementally and linearly across a time series of length  $y$  (and reaching 20% by year  $y$ ) is only statistically significant (for at least 90% of the 30,000 ensemble of possible time series used) for  $y$  greater than  $40 \pm 5$  years. As can be seen from Figure 5(a), for smaller  $x\%$ , longer time series ( $y$  years) are required at the same confidence level ( $p < 0.05$  here) as expected.



**Figure 5:** The length of the ATS spatially averaged annual precipitation over Ireland,  $y$  years, is given on the  $y$ -axis. The  $x$ -axis represents the applied forcing,  $x$ , given as a % of the annual mean of the 1942-2012 de-trended spatially averaged historical precipitation dataset for Ireland. The contour levels show the percentage of the 30,000 time series for a given  $x$  and  $y$ , that return statistically significant results at the  $p < 0.05$  confidence level. (a) ATS with linear monotonic trend of  $x\%$  by year  $y$  (b) AH with linear monotonic trend where the time series length is in fact  $y+71$  (c) ATS with non-monotonic trend of  $x\%$  by year  $y$  (d) AH with non-monotonic trend (again time series length is in fact  $y+71$ ).

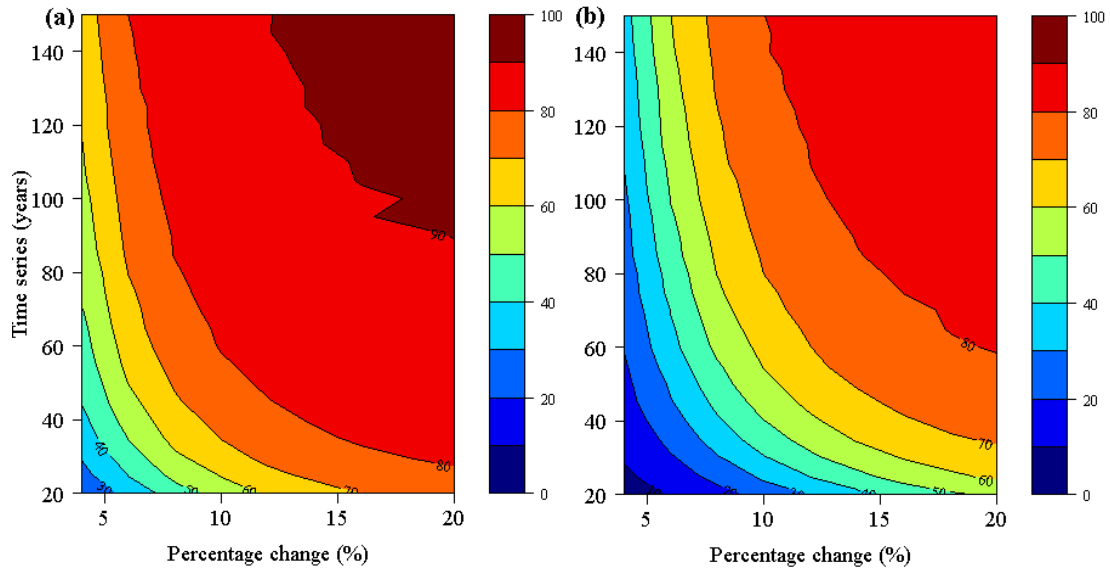
The AH results for the same confidence level ( $p < 0.05$ ) are shown in Figure 5(b). Here the length of the ATS part of this time series (i.e. the artificial series concatenated to the end of the de-trended time series of 1942-2012 historical data) only needs to be  $20 \pm 5$  years (i.e. 20 years + 71) for a 20% increase to be statistically significant. A 10% increase in spatially averaged precipitation requires  $50 \pm 5$  years (in addition to the 71 years of historical data) for the same confidence level.

As outlined in the Introduction, a linear monotonically increasing incremental trend is not a realistic representation of possible changes in precipitation over time due to the large number of factors that affect precipitation. The results for non-monotonic increases to annual precipitation time series at the  $p < 0.05$  confidence level are shown in Figure 5 (c) and (d). As expected, the number of years required before a trend could be considered statistically significant at the same confidence level, increased considerably. For an increase or forcing of 20% a time series longer than 150 years is required in the ATS case or  $115 \pm 5$  years (i.e.  $115 \pm 5$  years +71) in the AH case. Note that simulations of length greater than 150 years (or 71+150 years in the AH experiments) were not carried out due to computational resource limitations.

Non-monotonic AH test results for the lower confidence level of  $p < 0.1$  (Figure 6(a)) and the higher level of  $p < 0.01$  (Figure 6(b)) are illustrated in Figure 6. For  $p < 0.01$  and an increase or forcing of 20%, more than 150 years was required for the results to be statistically significant. For  $p < 0.1$ ,  $80 \pm 5$  years was required (in each case the number of years does not include the 71 year historical time appended to the time series). A summary of these results, along with others from subsequent sections are summarised in Table 3 where forcings of 20% were applied. Annual and seasonal results are presented for the  $p < 0.1$  (90<sup>th</sup>),  $p < 0.05$  (95<sup>th</sup>) and  $p < 0.01$  (99<sup>th</sup>) confidence levels. The forcings are applied both linearly monotonically and non-monotonically and in all cases the numbers quoted refer to where at least 90% of the 30,000 ensemble members in the particular test return statistically significant results at the relevant level.

<b>Linear monotonic</b>	<b>Annual ATS (years) <math>\pm 5</math> years</b>	<b>Annual AH (years) <math>\pm 5</math> years</b>	<b>JJA ATS (years) <math>\pm 5</math> years</b>	<b>JJA AH (years) <math>\pm 5</math> years</b>	<b>DJF ATS (years) <math>\pm 5</math> years</b>	<b>DJF AH (years) <math>\pm 5</math> years</b>
<b>p&lt;0.1</b>	30	15	140	45	130	60
<b>p&lt;0.05</b>	40	20	>150	60	>150	70
<b>p&lt;0.01</b>	55	25	>150	100	>150	105
<b>Non- monotonic</b>	<b>Annual ATS (years) <math>\pm 5</math> years</b>	<b>Annual AH (years) <math>\pm 5</math> years</b>	<b>JJA ATS (years) <math>\pm 5</math> years</b>	<b>JJA AH (years) <math>\pm 5</math> years</b>	<b>DJF ATS (years) <math>\pm 5</math> years</b>	<b>DJF AH (years) <math>\pm 5</math> years</b>
<b>p&lt;0.1</b>	>150	80	>150	>150	>150	>150
<b>p&lt;0.05</b>	>150	115	>150	>150	>150	>150
<b>p&lt;0.01</b>	>150	>150	>150	>150	>150	>150

**Table 3:** A summary of the test results where a 20% forcing (linear monotonic and non-monotonic) was applied to annual, JJA and DJF ATS and AH time where the overall forcing was +20% by the end of the annual and DJF time series but -20% for JJA. The values quoted in this table are the minimum number of years required, for at least 90% of the 30,000 ensemble members used for each time series length to return statically significant results at the confidence level  $p$  given in the left most column of the table. Hence, these values represent the minimum number of years required to separate an external trend from the natural variability with statistical confidence. In the AH columns the values refer to the number of years succeeding the 71-year historical section of the time series.



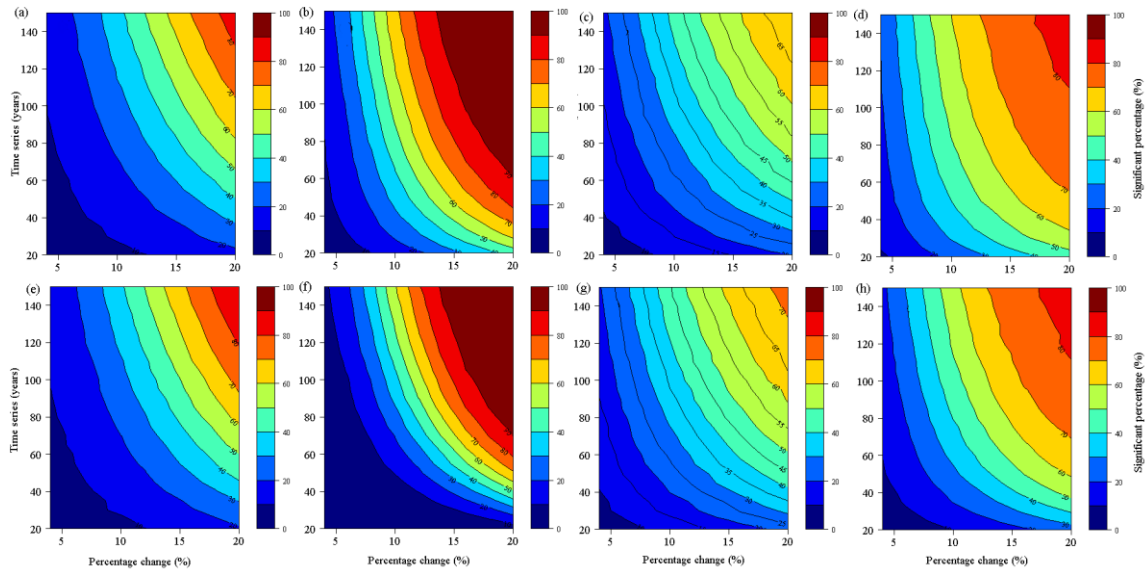
**Figure 6:** The length of the AH spatially averaged annual precipitation over Ireland is  $y+71$  years where the varying  $y$  is given on the  $y$ -axis. The  $x$ -axis represents the applied forcing,  $x$ , given as a % of the annual mean of the 1942-2012 de-trended spatially averaged historical precipitation dataset for Ireland. The contour levels show the percentage of the 30,000 time series for a given  $x$  and  $y$ , that return statistically significant results at a given confidence level. AH with a non-monotonic trend of  $x\%$  by year  $y$  for (a)  $p < 0.1$  and (b)  $p < 0.01$  confidence levels.

#### 4.2 JJA and DJF ATS and AH precipitation time series

As shown in Figure 2, the relative standard deviation or % variability of summer and winter precipitation over Ireland exceeds the interannual % variability. This is also reflected in the results by season shown in Figure 7 (longer time series are needed for trends to become statically significant) where the forcings applied to the summer or JJA data were negative and positive forcings were applied to the DJF data.

For example, we can see from Figure 7 (a) that a 20% linear monotonic decrease in precipitation, applied decrementally across the JJA ATS time series only becomes statistically significant at the  $p < 0.05$  levels after more than 150 years. In the more realistic AH case (Figure 7 (b)) this reduces to  $60 \pm 5$  years, where 60 denotes 131 years in total, 60 years to which forcings were applied along with the 71 years of de-trended historical JJA data.

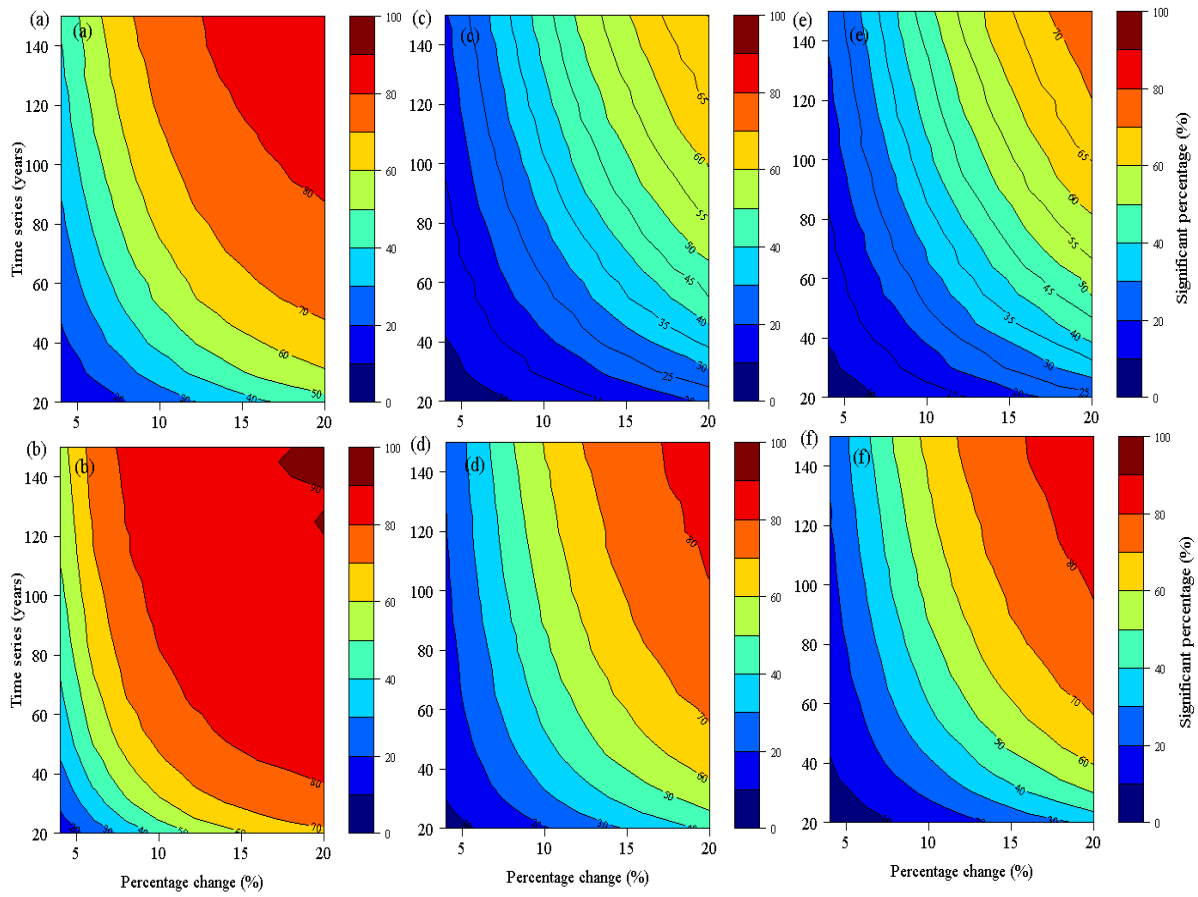
Similarly a 20% forced increase in DJF precipitation takes  $>150$  years and  $70 \pm 5$  years in the ATS and AH linear monotonic cases respectively (Figure 7 (e) and (f)). For the non-monotonic ATS and AH summer and winter cases (Figure 7 (c), (d), (g), (h)) it takes greater than 150 years for the trends to be statistically significant for a 20% decrease or increase respectively for each confidence interval considered. These seasonal results, where forcings of 20% were applied, are summarised in Table 3 for  $p < 0.1$  (90th),  $p < 0.05$  (95th) and  $p < 0.01$  (99th) confidence levels.



**Figure 7:** The length of the time series of spatially averaged JJA or DJF precipitation over Ireland,  $y$  years (or  $y+71$  for the AH cases), is given on the  $y$ -axis. The  $x$ -axis represents the applied forcing,  $x$ , given as a % of the mean of the JJA or DJF 1941-2012 de-trended spatially averaged historical precipitation dataset for Ireland. The contour levels show the percentage of the 30,000 time series for a given  $x$  and  $y$ , that return statistically significant results at the  $p<0.05$  confidence level. (a) ATS with linear monotonic trend of  $x\%$  by year  $y$  for JJA (b) AH with linear monotonic trend where the time series length is in fact  $y+71$  for JJA (c) ATS with non-monotonic trend of  $x\%$  by year  $y$  for JJA (d) AH with non-monotonic trend (again time series length is in fact  $y+71$ ) for JJA. (e) to (h) similar to (a) to (d) but DJF.  $x$  is negative for JJA but positive for DJF.

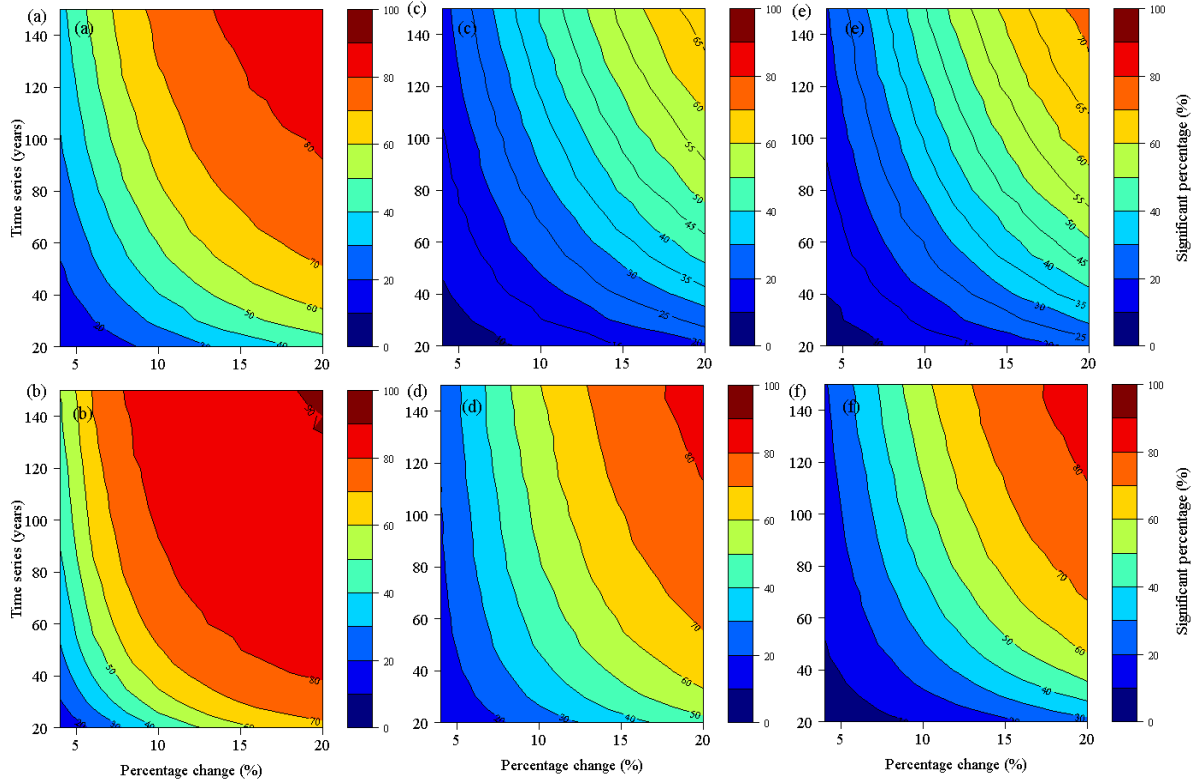
### 4.3 East of $8^{\circ}W$ and west of $8^{\circ}W$ ATS and AH annual precipitation time series

The final suite of tests involved splitting the country into two areas: east of  $8^{\circ}W$  and west of  $8^{\circ}W$ . Non-monotonic forcings were only considered and annual, JJA and DJF time periods were investigated. For the ATS annual time series (both east and west of  $8^{\circ}W$ ), and a non-monotonic forcing of 20% by the end of the time series, more than 150 years are required for the trend to be statistically significant for  $p<0.05$  (Figures 8(a) and 9(a)). Under similar conditions but for the AH time series this reduces to  $120 \pm 5$  years for the west and  $125 \pm 5$  years for the east (+71 years of historical data) for the trend to be statistically significant for  $p<0.05$  (Figures 8(b) and 9(b)). As before significant results by season take longer to detect (i.e. require longer time series):  $> 150$  years in all cases (Figure 8 (c) to (f) and Figure 9 (c) to (f)). These east/west results, where forcings of 20% were applied, are summarised in Table 4 for  $p<0.1$  (90th),  $p<0.05$  (95th) and  $p<0.01$  (99th) confidence levels.



**Figure 8:** The length of the time series of spatially averaged precipitation over Ireland but west of  $8^{\circ}\text{W}$ ,  $y$  years (or  $y+71$  for the AH cases), is given on the  $y$ -axis. The  $x$ -axis represents the applied forcing,  $x$ , given as a % of the mean of the 1942-2012 de-trended spatially averaged historical precipitation dataset for Ireland but again west of  $8\text{W}$ . The contour levels show the percentage of the 30,000 time series for a given  $x$  and  $y$ , that return statistically significant results at the  $p < 0.05$  confidence level. (a) ATS annual time series (b) AH annual (c) ATS JJA (d) AH JJA (e) ATS DJF (f) AH DJF.  $x$  is negative for JJA but positive for DJF.





**Figure 9:** The length of the time series of spatially averaged precipitation over Ireland but east of 8°W,  $x$  years (or  $x+71$  for the AH cases), is given on the y-axis. The x-axis represents the applied forcing,  $y$ , given as a % of the mean of the 1941-2012 de-trended spatially averaged historical precipitation dataset for Ireland but again east of 8W. The contour levels show the percentage of the 30,000 time series for a given  $x$  and  $y$ , that return statistically significant results at the  $p < 0.05$  confidence level. (a) ATS annual time series (b) AH annual (c) ATS JJA (d) AH JJA (e) ATS DJF (f) AH DJF.  $x$  is negative for JJA but positive for DJF.

East	Annual ATS (years) ± 5 years	Annual AH (years) ± 5 years	JJA ATS (years) ± 5 years	JJA AH (years) ± 5 years	DJF ATS (years) ± 5 years	DJF AH (years) ± 5 years
<b>p &lt; 0.1</b>	>150	85	>150	>150	>150	>150
<b>p &lt; 0.05</b>	>150	125	>150	>150	>150	>150
<b>p &lt; 0.01</b>	>150	>150	>150	>150	>150	>150
West	Annual ATS (years) ± 5 years	Annual AH (years) ± 5 years	JJA ATS (years) ± 5 years	JJA AH (years) ± 5 years	DJF ATS (years) ± 5 years	DJF AH (years) ± 5 years
<b>p &lt; 0.1</b>	>150	80	>150	>150	>150	>150
<b>p &lt; 0.05</b>	>150	120	>150	>150	>150	>150
<b>p &lt; 0.01</b>	>150	>150	>150	>150	>150	>150

**Table 4:** This table is similar to table 3 except the results are for the area of Ireland east of 8°W (denoted East in the table) and west of 8°W (denoted west in the table), and all of the results refer to non-monotonic increases/decreases. See table 3 for further information

## 5 Discussion/Conclusion

Precipitation over Ireland is highly variable, both spatially and temporally. Changes in amounts or variability may have more important effects on humans and environmental systems than temperature changes. Attributing changes in precipitation to anthropogenic forcing rather than natural variability is therefore an important area of study. To date, only limited studies related to this topic exist for Ireland, and in these studies no attempt was made to explain the changes in precipitation (e.g. McElwain & Sweeney, 2003; Walsh, 2012a; Walsh 2012b).

Studies using CMIP3 and CMIP5 multi-model climate simulation ensembles have also been used for this purpose. However, regional-scale attribution of precipitation change is still problematic and to date no such study has been carried out for Ireland specifically. The CMIP3 and CMIP5 multi-model global simulations, as well as various regional downscaled ensembles, highlight the large uncertainty in precipitation projections for Ireland (Zhang et al., 2007; Noake et al., 2012; Polson et al., 2013; Balan et al., 2012). While studies suggest decreases in Boreal summer precipitation for Ireland, there is still considerable uncertainty regarding the other seasons. This limits confidence in detection and attribution of precipitation changes for Ireland and is one of the main reasons why we chose to use observation-derived data.

We have used spatially averaged annual mean precipitation amounts over the Republic of Ireland (RoI) by averaging a 1km monthly mean 71-year gridded dataset of precipitation for Ireland produced by Met Éireann from its observation data. This gives a much better spatial average than the sparse synoptic network of stations used in the global and larger scale observation datasets currently available.

We examined the temporal rather than the spatial variability of precipitation over Ireland and how natural temporal variability can act to mask long-term externally forced trends. We removed any existing trends from this 71-year dataset but retained its natural variability. We then used this data to generate an artificial annual time series (ATS) of precipitation to which we added pre-defined external forcing, where external forcing here implies anthropogenic forcing only. In addition to being able to attribute a trend to external forcing rather than natural variability, our study investigated the length of a time series of annual precipitation needed and the size of the external forcing required, before it becomes possible to separate an externally forced change in precipitation from natural variability with high statistical confidence ( $p < 0.1$  or higher).

We considered both artificial time series (ATS) and artificial time series appended to the end of the de-trended 71-year time series (AH) for 3 areas - the country as a whole (RoI), east of  $8^{\circ}\text{W}$  and west of  $8^{\circ}\text{W}$ , separated for annual, JJA and DJF time periods. We applied the external forcing both linearly monotonically and non-monotonically to capture the easiest (linear monotonic) and most difficult detection scenarios. Changes in precipitation amounts (positive or negative) of up to 20% were considered as this is the upper limit of the range predicted by the latest climate simulations. Time series of up to 150 years were used (limited by computational resources). For each experiment (ATS, AH, season, area) a 30,000 member ensemble was generated using the de-trended past data. Results for which 90% of these were statistically significant (Mann Kendall trend test) at a particular confidence level ( $p < 0.1$ ,  $p < 0.05$ ,  $p < 0.1$ ) were considered.

As expected, the Mann-Kendall trend tests return statistically significant results more readily for longer time series ( $y$ ) and larger applied percentages of anthropogenic change ( $x$ ). In addition, for the AH time series the trends are statically significant after fewer years,  $y$ , but note that the true time series length in the AH experiments is  $y+71$  as  $y$  only denotes the number of years over which the forcing is applied.

In the case of the dataset covering the whole country (RoI), at the  $p<0.05$  confidence level our results show that an ATS of at least  $40\pm 5$  years is required for a 20% forced (anthropogenic) linear monotonic increase in annual precipitation to be statistically attributed to its anthropogenic origin rather than natural variability. The same experiment using AH time series requires a shorter ATS time period of  $20\pm 5$  years but the full AH time series is actually  $71+(20\pm 5)$  years in length. Higher/lower significant levels ( $p<0.01$ ,  $p<0.1$ ) required longer/shorter time series and smaller forcings are also more difficult to detect (Figure 5).

The linear monotonic trend is more readily detectable than the non-monotonic trends because in the non-monotonic cases the applied forcings can vary in sign from year-to-year, while the net percentage forcing of  $x\%$  is applied by the final year,  $y$ , in the time series. A different non-monotonic trend was applied randomly to each of the 30,000 ensemble members in each experiment. Non-monotonic changes are more realistic, as Irish precipitation is highly variable in time, and there are no reasons why we should expect a change to occur monotonically.

For the non-monotonic case (at the  $p<0.05$  confidence level) our results show that an ATS of  $>150$  years is required for a net 20% forced increase (anthropogenic) in annual precipitation to be statistically attributed to its anthropogenic origin rather than natural variability and  $115\pm 5$  (i.e.  $71+(115\pm 5)$  years) for the AH case. At the  $p<0.1$  level this reduces to  $80\pm 5$  (i.e.  $71+(80\pm 5)$  years). Other variations of trends are possible (though not tested here) including a non-linear monotonic trend. It would also be possible to change the length of the de-trended historical time series appended to the ATS to try and ascertain how long a data series is required, prior to applying an external forcing, for the forcing to be detectable. Detections by season were harder to achieve, requiring more than 150 years for non-monotonic trends to be statistically significant even at the  $p<0.1$  level and 40-60 years for linear monotonic AH time series. This is due to the higher interannual variability of JJA and DJF precipitation compared to on an annual time scale (Figure 2 and Table 1). Similarly, considering areas east and west of  $8^\circ\text{W}$  separately, because of the large west-to-east decrease in average annual precipitation (as shown in Figure 1(a)), makes detection more difficult. Again, more than 150 years are needed to detect trends by season or 80-90 years at the  $p<0.1$  level for AH data series.

This is the first detection and attribution study of its kind for Ireland. Future possibilities include carrying out the calculations on the 1km grid to include both spatial and temporal variability. A new climate reanalysis study is currently in progress for Ireland using the mesoscale HARMONIE model (HiRLAM Aladin Research for Mesoscale Operational Numerical Weather Prediction in Euromed) (Seity et al., 2011; Brousseau, et al., 2011) on a 2.5km grid covering the period 1980 to the present day with future plans to extend the reanalysis to the entire twentieth century. Such a dataset would be of extreme value in a precipitation detection and attribution study.

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