Climate Risk Management 11 (2016) 37–52

Contents lists available at ScienceDirect

Climate Risk Management

journal homepage: www.elsevier.com/locate/crm

Past and future climate change in the context of memorable seasonal extremes

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ARTICLE INFO

Article history:
Received 3 October 2015
Revised 11 January 2016
Accepted 19 January 2016
Available online 4 February 2016

Keywords:
Irish climate change projections
Seasonal analogues
North Atlantic storminess
CMIP5
Extreme seasonal weather
Climate change communication

ABSTRACT

It is thought that direct personal experience of extreme weather events could result in greater public engagement and policy response to climate change. Based on this premise, we present a set of future climate scenarios for Ireland communicated in the context of recent, observed extremes. Specifically, we examine the changing likelihood of extreme seasonal conditions in the long-term observational record, and explore how frequently such extremes might occur in a changed Irish climate according to the latest model projections. Over the period (1900–2014) records suggest a greater than 50-fold increase in the likelihood of the warmest recorded summer (1995), whilst the likelihood of the wettest winter (1994/95) and driest summer (1995) has respectively doubled since 1850. The most severe end-of-century climate model projections suggest that summers as *cool* as 1995 may only occur once every ~7 years, whilst winters as wet as 1994/95 and summers as dry as 1995 may increase by factors of ~8 and ~10 respectively. Contrary to previous research, we find no evidence for increased wintertime storminess as the Irish climate warms, but caution that this conclusion may be an artefact of the metric employed. It is hoped that framing future climate scenarios in the context of extremes from living memory will help communicate the scale of the challenge climate change presents, and in so doing bridge the gap between climate scientists and wider society.
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1. Introduction

Despite the considerable body of climate change research produced in recent decades and evidence that decision-makers are actively seeking to improve the uptake of climate risk information, a gap persists between knowledge production and use (NRC, 2009, 2010; Lemos et al., 2012). Among the many challenges is the perception of remote impacts (Moser, 2010), where climate change is regarded as temporally, geographically or socially distant from people's everyday lives (Pidgeon, 2012). This has contributed to a 'psychological distancing' of people from climate change and a consequent lack of public engagement (Spence et al., 2012). It is argued, therefore, that direct personal experience of climate-related weather events may act as a strong 'signal' or 'focusing event' (November et al., 2009; Renn, 2011) around which the otherwise futuristic and abstract

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http://dx.doi.org/10.1016/j.crm.2016.01.004
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nature of climate change may become more tangible, and crucially trigger more substantive public engagement and policy response (Capstick et al., 2015). For example, interview respondents in five flood affected areas of the UK who were directly affected by the series of exceptional deluges during winter 2013/14 exhibited heightened concerns about the impacts of climate change when compared with a national sample of un-impacted respondents (Capstick et al., 2015). With such cases in mind, we assert that Irish climate change projections would be more tangible if grounded in analogues of the recent past.

The Irish climate is projected to warm across all seasons, and it is expected this will be accompanied by an amplified precipitation regime, characterised by wetter winters and drier summers respectively (Sweeney et al., 2008; Gleeson et al., 2013). In addition, the British-Irish Isles (BI) region is expected to experience enhanced wintertime cyclone activity ("storminess"; Gleeson et al., 2013; Zappa et al., 2013a). Recent research suggests that such signals in air temperature and precipitation are already emerging in long-term observational records (McElwain and Sweeney, 2003; Noone et al., 2015), whilst Matthews et al. (2014) reported that the winter of 2013/14 was stormiest in at least 143 years – a season that also experienced above average rainfall at more than half of Irish synoptic stations. The annual air temperature during 2014 was well above the long-term average, being only 0.2 °C below the record set in 2007 (Met Eireann, 2014). While dry summers have been more infrequent of late (Sutton and Dong, 2012; McCarthy et al., 2015), notable deficits in summer rainfall have occurred in living memory, including, for example, the warm and dry summers of 1975/76, 1995 and 2006 (Jones and Conway, 1997; Met Eireann, 2006; Wilby et al., 2015).

Extreme seasonal weather has significant societal implications. Wet and stormy conditions during winter 2013/14 resulted in widespread flooding and coastal inundation. Similarly, hot summers have been associated with increased mortality in Ireland (Pascal et al., 2013), whilst rainfall deficits have impacted the agricultural sector (Stead, 2014). The effects of the latter have the potential to propagate internationally through Ireland's agricultural exports (Hunt et al., 2014). Despite the economic and human costs associated with seasonal extremes being embedded in the public consciousness, communicating to stakeholders the exact scale of the challenge posed by climate change still presents significant difficulties.

Clearly, then, it is of interest to situate observed seasonal extremes within the context of Ireland's possible future climate. Despite extensive research into climate change undertaken for the Island of Ireland (IoI) (e.g. Fealy and Sweeney (2007), Sweeney et al. (2008), Mullan et al. (2012), Gleeson et al. (2013) and Foley et al. (2013)), to date, no study has mapped observed extreme conditions onto projected climates to explore changes in their occurrence. Yet, this kind of information can be particularly useful when communicating the potential impacts of climate change and determining adaptation needs (Sexton and Harris, 2015).

Our aim is therefore to update and complement existing IoI climate projections by exploring the changing likelihood of seasonal extremes – both in the period of observations and future climate scenarios. We first identify the wettest, stormiest winters, and the driest, hottest summers in observational datasets, before assessing how unusual these events are in the long-term context. These extremes are of particular interest given the magnitude of social, environmental and economic impacts they have had previously; additionally they provide a reference for stress testing existing management plans under likely future conditions. We then assess how the likelihoods of these extreme seasons may have already changed during the period of observation, before employing output from a suite of climate model experiments to explore projected future change. We pursue this aim on the premise that such analysis may enable communication of the magnitude of projected changes to a wide range of audiences.

2. Materials and methods

To characterise observed precipitation and temperature extremes we use the average of five long-running Irish temperature series 1900–2014 (Met Eireann, n.d.; A. Murphy, *personal communication*), and the Island of Ireland Precipitation (IIP) series 1850–2010 (Noone et al., 2015). The latter ends in 2010, but winter 2013/14 has already been acknowledged as very wet, and thus potentially of interest in our study of seasonal extremes. We therefore extended the winter (DJF) precipitation series by bridging to 2014 using the $0.25 \times 0.25°$ gridded E-OBS dataset (Haylock et al., 2008). The winter E-OBS time-series was produced by averaging over the domain -10.5 to -5.5 °E and 51.5 to 55.5 °N. For the overlapping period (1950–2014) correlation between E-OBS and IIP is strong (Pearson's $r = 0.95$), so we infer winter IIP precipitation for 2011–2014 by regression-adjusting the E-OBS series (Fig. 1).

To construct a time series of storminess we employ the 20CR reanalysis data (Compo et al., 2011) and use the same spatial domain as Matthews et al. (2014, 2015), who reconstructed wintertime BI storminess (1872–2014) using a cyclone identification routine applied to atmospheric reanalysis products. Whilst desirable because of their explicit classification of cyclones, such techniques are logistically challenging to apply to large climate model ensembles such as the Fifth Coupled Model Intercomparison Project (CMIP5). We therefore sought a simpler metric to define storminess, and, consistent with Benestad and Chen (2006) found that mean seasonal sea-level pressure (MSLP) over the BI was strongly correlated with the storminess metric of Matthews et al. (2014; Fig. 1). Hence, we adopt this simpler metric to quantify DJF storminess. Given concern expressed about the integrity of the early 20CR, we restrict our usage here to the period 1900–2014. As in Matthews et al. (2014) the 20CR data were extended from 2011 to 2014 by regression-adjusting NCEP 1 reanalysis (Kalnay et al., 1996) for the last 4 years. The regression was formulated with 20CR and NCEP MSLP as the independent and dependent variables, respectively. Over the common period (1948–2012) the regression equation had a slope and intercept of 1.41 and 146 hPa, respectively, with a correlation coefficient of 0.97. These regression coefficients were used to adjust

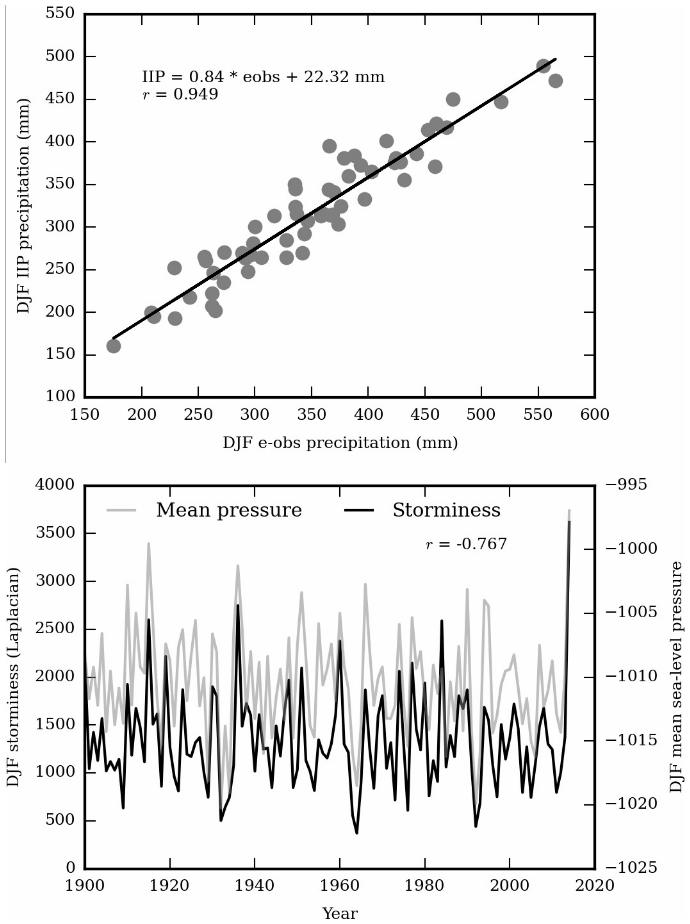

Fig. 1. Top: the relationship between DJF IoI precipitation according to the E-OBS and IIP datasets. Based on the regression function (provided inset, along with associated Pearson's correlation, *r*), E-OBS data 2011–2014 were adjusted to infer IIP precipitation for these years. Bottom: comparison between the DJF storminess metric used by Matthews et al. (2014) and mean sea-level pressure over the BI domain. Note that mean sea-level pressure axis is inverted.

20CR MSLP to NCEP MSLP over the common period, and the record was bridged to 2014 by appending NCEP values for 2013 and 2014.

Projections of Irish climate are taken from the CMIP5 ensemble (Taylor et al., 2012). We use monthly series of surface air temperature, precipitation and MSLP from the "historical" experiment and from Representative Concentration Pathways (RCPs: van Vuuren et al. (2011)) 4.5 and 8.5. Each RCP model run was spliced to its corresponding historical component, as informed by the metadata (Taylor et al., 2010). Time series for the IoI (temperature and precipitation) were generated by averaging across all model grid points between −10.5 to −5.5 °E and 51.5 to 55.5 °N, whereas MSLP was averaged over the BI domain to generate storminess time series. Only model runs with data for the period 1901–2099 were used, resulting in between 67 and 99 series depending on variable and RCP (Table 1). Note that some models include more than one run per RCP, with constituent members differing in terms of either initial conditions or physical parameterization. Including output from a large ensemble provides a more complete sample of uncertainties arising from model structures, parameters, and internally generated climate variability.

We identified seasons with extreme winter precipitation/storminess and summer temperature/precipitation by ranking observed series. The rarity of the most extreme (i.e. top-ranked) seasonal metric was assessed by fitting parametric distributions to the observed record for the period overlapping the historical model runs (1901–2005) and evaluating the cumulative density function. Resulting non-exceedance probabilities were then converted to *z*-scores from the standard normal distribution:

$$z = \phi^{-1}[F(x)]$$

where $F(x)$ is the cumulative distribution function for variable x (e.g. mean winter precipitation) and ϕ^{-1} is the inverse cumulative distribution function (i.e. the percentage-point/quantile function) for the standard normal distribution

Table 1
Details of the number of model runs employed. Abbreviations "Hist", "4.5" and "8.5" refer to historical, RCP 4.5 and RCP 8.5 experiments, respectively.

Modelling group	Model	Temp.			Precip.			MSLP		
		Hist	4.5	8.5	Hist	4.5	8.5	Hist	4.5	8.5
Commonwealth Scientific and Industrial Research Organization (CSIRO) and Bureau of Meteorology (BOM), Australia	ACCESS 1.3	1	1	1	1	1	1	1	1	1
	ACCESS 1.0	1	1	1	1	1	1	1	1	1
Beijing Climate Center, China Meteorological Administration	BCC-CSM1-1	1	1	1	1	1	1	1	1	1
	BCC-CSM1-1-m	1	1	1	1	1	1	1	1	1
College of Global Change and Earth System Science, Beijing Normal University	BNU-ESM	1	1	1	1	1	1	1	1	1
Canadian Centre for Climate Modelling and Analysis	CanESM2	5	5	5	5	5	5	5	5	5
University of Miami – RSMAS	CCSM4	6	6	5	6	6	6	6	6	5
Community Earth System Model Contributors	CESM1-CAM5	4	4	3	3	3	3	3	3	3
Centro Euro-Mediterraneo per I Cambiamenti Climatici	CMCC-CM	1	1	1	1	1	1	1	1	1
	CMCC-CMS	1	1	1	1	1	1	1	1	1
Commonwealth Scientific and Industrial Research Organization in collaboration with Queensland Climate Change Centre of Excellence	CSIRO-Mk3-6-0	10	10	10	10	10	10	10	10	10
EC-EARTH consortium	EC-EARTH	1	1	1	1	1	1	1	1	1
LASG, Institute of Atmospheric Physics, Chinese Academy of Sciences and CESS, Tsinghua University	FGOALS g2	1	1	1	1	1	1	1	1	1
The First Institute of Oceanography, SOA, China	FIO-ESM	3	3	3	3	3	3	3	3	3
NOAA Geophysical Fluid Dynamics Laboratory	GFDL-CM3	1	1	1	1	1	1	1	1	1
	GFDL-ESM2G	1	1	1	1	1	1	1	1	1
	GFDL-ESM2M	1	1	1	1	1	1	1	1	1
NASA Goddard Institute for Space Studies	GISS-E2-H	15	15	3	15	15	3	15	15	3
	GISS-E2-H-CC	1	1	0	1	1	0	1	1	0
	GISS-E2-R	16	16	2	16	16	2	16	16	2
	GISS-E2-R-CC	1	1	0	1	1	0	1	1	0
Met Office Hadley Centre (additional HadGEM2-ES realizations contributed by Instituto Nacional de Pesquisas Espaciais)	HadGEM2-CC	1	1	1	1	1	1	1	1	1
	HadGEM2-ES	4	4	4	4	4	4	4	4	4
Institute for Numerical Mathematics	INM-CM4	1	1	1	1	1	1	1	1	1
Institut Pierre-Simon Laplace	IPSL-CM5A-LR	4	4	4	4	4	4	4	4	4
	IPSL-CM5A-MR	1	1	1	1	1	1	1	1	1
	IPSL-CM5B-LR	1	1	1	1	1	1	1	1	1
Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology	MIROC5	3	3	3	3	3	3	3	3	3
Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies	MIROC-ESM	1	1	1	1	1	1	1	1	1
	MIROC-ESM-CHEM	1	1	1	1	1	1	1	1	1
Max-Planck-Institut für Meteorologie (Max Planck Institute for Meteorology)	MPI-ESM-LR	3	3	3	3	3	3	3	3	3
	MPI-ESM-MR	3	3	1	3	3	1	3	3	1
Meteorological Research Institute	MRI-CGCM3	1	1	1	1	1	1	1	1	1
Norwegian Climate Centre	NorESM1-M	1	1	1	1	1	1	1	1	1
	NorESM1-ME	1	1	1	1	1	1	1	1	1
	Total	99	99	67	98	98	68	98	98	67

(Wilks, 2011). Thus, z indicates the value of the standard normal deviate with a non-exceedance probability equal to x. Conversion to z-scores permits straightforward comparisons between and within series.

To describe seasonal rainfall we select the widely used gamma distribution (e.g. Wilks and Eggleson (1992)). For mean summer temperatures and storminess we select the normal distribution. The former is frequently parameterized in this way (e.g. Schär et al. (2004) and Hansen et al. (2012)) and, along with storminess (mean BI sea level pressure throughout DJF), is theoretically suited to this distribution, as outlined by the central limit theorem (Wilks, 2011). The goodness-of-fit of the normal and gamma distributions for the respective observed variables was assessed via a 5000-trial Monte Carlo simulation following Clauset et al. (2009). This procedure estimates the probability of obtaining a Kolmogorov–Smirnov (KS) test statistic as large as obtained when comparing the data and candidate distribution if the null hypothesis (that the data does indeed follow that distribution) is true.

Where we report return periods for seasonal values in the text, these are defined as the reciprocal of the respective exceedance (non-exceedance) probabilities of the fitted distributions for winter precipitation, storminess and temperature (summer precipitation). Calculated z-scores and return periods are however sensitive to sampling variation. An indication of this sensitivity is provided by a 10,000-realization bootstrap simulation, in which 30-year samples from the respective seasonal observations are randomly selected (with replacement) to fit the distributions.

To assess systematic changes in z-scores through the observational record, we use a sliding window approach, whereby distributions are fitted to successive 30-year samples. The z-scores for extreme seasons are then recalculated using these updated distributions. Decreases (increases) in the absolute value of z indicate the likelihood of the extreme season was relatively higher (lower) during the respective 30-year window. We also assess trends in the underlying time series using simple least-squares regression (Box, 2002; Hanna et al., 2012). The significance of all trends is calculated using a standard *t*-test, with appropriate adjustment made for autocorrelation in the series, which reduces the effective sample size (cf. Santer et al., 2000).

When assessing future changes in the probability of the extreme seasons, we use the historical component of the model integrations (i.e. 1901–2005) to evaluate $s_{ext} = z^{-1}$, where s_{ext} is the value (of the relevant metric) which yields a *z*-score equal to that achieved by the respective extreme seasons in the observational record. Note that calculation of s_{ext}, involves re-fitting the distributions (gamma and normal) for each variable and model run. In the projected part of the series (2006–2099) we then compute *z* for s_{ext} using distributions again updated using sliding 30-year samples. Changes in *z* between the historical and projected series provide insight into how the likelihood of the extreme seasons may evolve in a changing climate.

For the historical component of the modelled data, the suitability of the normal and gamma distributions to describe the distribution of the respective variables was assessed via the same Monte Carlo technique applied to the observations. To examine whether the suitability of these distribution types changes though time (and particularly throughout the projected RCP experiments), we take the simple approach of calculating the KS statistic for sliding 30-year samples. A systematic increase (decrease) in KS would suggest that the distribution types become progressively less (more) suitable as time progresses.

3. Results

3.1. Observations

Observed series were used to identify the most extreme seasons on record and quantify their rareness (Fig. 2). The suitability of the respective distributions to describe the observations was evaluated via Monte Carlo simulation. For no series could the null hypothesis (that the data were drawn from the candidate distribution) be rejected at the 0.05 level. Thus, we assume that the fitted gamma and normal distributions are suitable to describe the respective variables and can be used to evaluate the rarity of given seasonal conditions.

In terms of dry summers, 1995 stands out as the most exceptional since 1850, registering a *z* value of -2.26. Using the relation $1/p$ to evaluate the return period of such an event (where *p* is the probability of a season at least as extreme for the respective *z* value), we obtain a value of 84 years for this summer. The second and third driest summers occurred in 1913 and 1869, both of which had *z*-scores of −2.20 and estimated return periods of 73 years. For wet winters, the most extreme on record occurred in 1994, with a *z*-score of 2.15 and corresponding return period estimate of 63 years. Ranked second and third were the years 1995 and 1883, registering *z*-scores of 1.96 (return period 40 years) and 1.81 (return period 28 years), respectively. The recent wet winter 2013/14 ranks 7th in the 165-year IIP series, with a respective *z*-score and return period of 1.72 and 23 years.

The hottest summer in the observational record was in 1995, with a *z*-score of 2.84 and return period of 441 years. The summers of 2006 and 1976 – with *z*-scores (return periods) of 2.30 (94 years) and 2.27 (85 years) – were ranked second and third respectively. Our simpler storminess metric concurs with Matthews et al. (2014) which showed 2013/14 was ranked first; the two series also agree about second place (1914/15), but third (1935/36) according to our series was fourth according to Matthews et al. (2014). The stormiest winter has a *z*-score of −3.32 and estimated return period of 2198 years. Storminess in 1915 and 1936 registered *z*-scores of −2.68 and −2.26, with associated return periods of 274 and 84 years respectively.

The return periods quoted should not be overstated because they are sensitive to choice of reference period (and distribution), as demonstrated by the bootstrap simulation results (Table 2). Some of this variation reflects a systematic change in likelihood throughout the observational period (Fig. 3). With the exception of winter storminess, all extreme seasons show signs of increasing likelihood in the record. Using the regression lines in Fig. 3 to smooth shorter-term variations in *z*, the chance of a summer as warm as 1995 shows the largest increase, with a *z*-score of 3.61 (return period of 6415 years) at the beginning of the series (1900–1929), declining to 2.37 (return period of 114 years) for the most recent period assessed (1985–2014). This translates into a 56-fold increase in the likelihood of such a warm summer.

The summer and winter precipitation series exhibit an increasing likelihood of extreme seasons, registering an approximate halving of the return period (i.e. doubling likelihood) when comparing the start (1850–1879) and end (1981–2010 (summer); 1985–2014 (winter)) of the series. Increased likelihood of extremely wet winters and warm summers is significant at the 0.05 level according to the trends in $|z|$ (Fig. 3 and Table 3). For extreme summer precipitation, pronounced low-frequency variability evident in Fig. 3 means that the *p*-value is much larger (and hence not interpreted as significant). The trend analysis also indicates that the likelihood of a winter as stormy as 2013/14 decreased significantly over the period 1900–2014.

Changes in the likelihood of extremes can result from changes to the mean and/or variance of the interannual series being assessed (e.g. Katz and Brown (1992), Schär et al. (2004) and Hansen et al. (2012)), so we investigated trends in the mean and variance of each respective variable (Fig. 4 and Table 3). For means, trends were calculated from annual series with variance assessed using the 30-year running samples shown in Fig. 4. The change in mean summer air temperature is the only trend

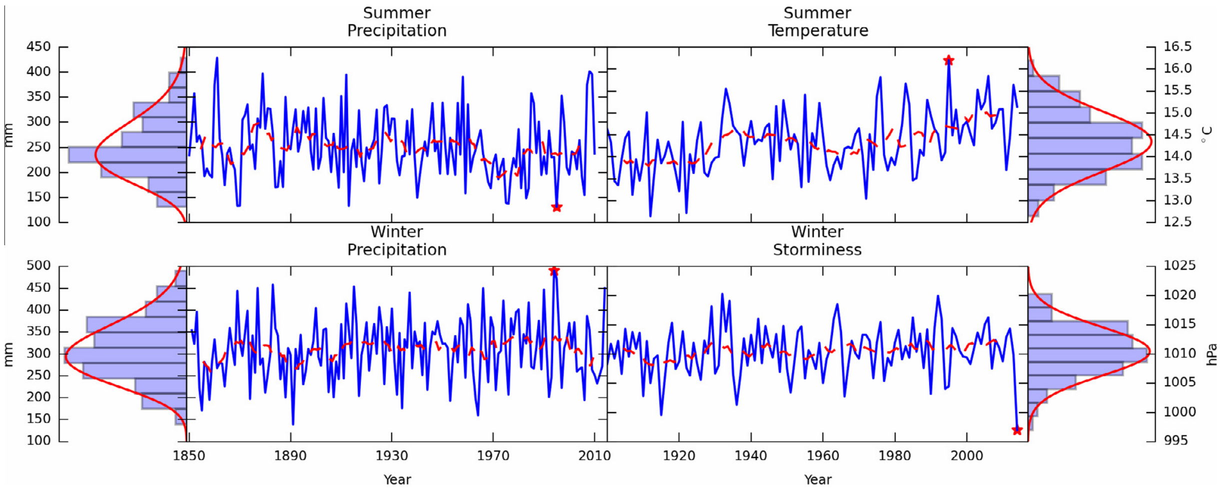

Fig. 2. The line plots provide time series of the respective variables, in which the dotted line is a 10-year (centred) moving average. The seasons classified as most extreme (wettest winter, driest summer, hottest summer, and winter with lowest mean sea-level pressure – the 'stormiest') are highlighted by red stars. Histograms show the distribution of the variables, with fitted gamma (winter/summer precipitation) and normal (winter storminess and summer temperature) distributions overlain (red line). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 2
Results from bootstrap simulation in which 30-year samples from the observational record were randomly selected (with replacement) and normal (JJA temperature and DJF storminess) or gamma (JJA/DJF precipitation) distributions fitted. *z*-scores were then calculated for the most extreme seasons according to these distributions. The process was repeated 10,000 times, with 5th and 95th percentiles evaluated. [1]*z*-scores are arranged according to absolute values, but the signed numbers are displayed here. [2]This field provides the relevant metric when distributions are fit to the entire record (see Section 2for years of observation).

Metric	[1]*z*-score			Return period (years)		
	[2]Whole period	5th percentile	95th percentile	Whole period	5th percentile	95th percentile
JJA precipitation	−2.26	−1.93	−2.42	84	29	622
DJF precipitation	2.15	2.08	2.60	63	30	502
JJA air temperature	2.84	2.19	2.77	441	60	4436
DJF storminess	−3.32	−3.34	−4.42	2198	202	210,334

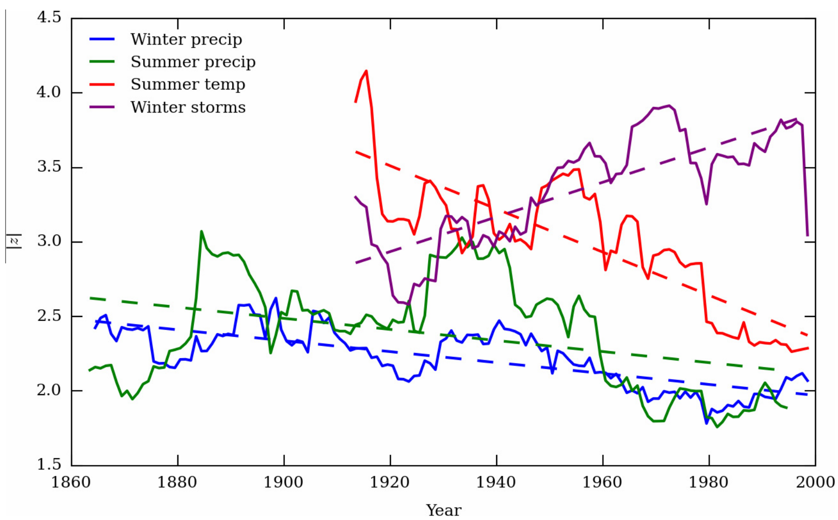

Fig. 3. *z*-scores for top-ranked seasons when distributions (gamma = precipitation; normal = storminess and air temperature) are fitted to sliding 30-year samples. Note that here we plot |*z*|, hence a decrease equates to an increasing likelihood of occurrence. The x-coordinate corresponds to the centre year of the 30-year sample.

that is statistically significant at the 0.05 level, reflecting 0.93 °C warming over the period 1900–2014. For both summer and winter precipitation our analysis finds that trends in the mean have ~20% chance of being drawn from a population with no trend, and highlight that the increase in winter precipitation (+25.7 mm) over the period investigated essentially compensated for the decrease in summer (−25.6 mm). Our analyses also indicate that the trends in mean sea level pressure and variability for all variables are too weak to approach statistical significance at the 0.05 or even 0.10 level.

The variance and mean have increased for wintertime precipitation and summer temperature, so both factors contribute to the increasing likelihood of extreme seasons throughout the observational record (cf. Fig. 5). To explore the relative importance of these factors, we performed two experiments. First, we forced the variability of the respective series to be constant throughout the record (fixed at the variance calculated for the period spanning the whole record), but allowed the mean to vary. Then we reversed the experiment, fixing the mean to that calculated for the entire record, and allowing the variance to change as before. [Note that the variance can be rescaled using $\bar{x}_s + x'_s \frac{\sigma_f}{\sigma_s}$ where x is the variable of interest, the overbar ($\bar{x}_s$) and prime (x'_s) denote the mean and prime, respectively, whilst σ indicates the variance; the subscripts refer to a sample (subscript s) of the full record (subscript f). The mean of a selected sample can similarly be adjusted by adding the difference ($\bar{x}_f - \bar{x}_s$) to each observation].

We used these relations to adjust the variances and means of summer temperature and winter precipitation for the sliding 30-year samples as above. Holding the variance (mean) constant allows us to infer changes in likelihood that would have occurred if only the mean (variance) had changed over the observational period (Fig. 6). For summer air temperature, results underline the much greater importance of changes in the mean in driving the increasing likelihood for such warm summers; enhanced likelihood of wetter winters is to a greater extent the combined consequence of increasing mean winter precipitation and variance, as evidenced by the similar upward trends in likelihood when either the mean or variance is held constant.

3.2. Model projections

The Monte Carlo simulation (Section 2) indicated that the gamma and normal distributions are generally suitable for describing the respective variables in the historical component of the CMIP5 simulations, as the null hypothesis could not be rejected at the 0.05 level in a minimum of 86% (winter precipitation) and maximum of 95% (winter storminess) of the ensemble members. Moreover, visual inspection of the evolving KS-statistics provides little indication that the respective distributions become less suitable through time (Fig. 7). The projected changes in the likelihood of extreme seasons were therefore assessed using these parametric distributions, with results presented in Fig. 8. The historical climate model series do broadly agree with observations regarding the sign of the changes in z-scores over the common period, but appreciable spread is evident between individual model runs while median changes are more modest than observed (Fig. 9). However, on the basis of Fig. 8 we note that for summertime precipitation in particular, low-frequency variability in the observed z-scores is more pronounced than modelled, with running values trending from close to the lowest values observed in the CMIP5 ensemble (pre 1950) to the highest (around 1970). We return to the significance of this modelled low-frequency underdispersion in Section 4.

In the RCP experiments, substantial changes in z are projected for all series except winter storminess (Fig. 8 and Table 4). Particularly dramatic is the very large change in the likelihood of summers as warm as 1995, with a median z-score by the end of the 21st Century less than −1 under RCP 8.5, indicating that, for this period, the likelihood of summer temperatures exceeding those of 1995 would be ~85%. Temperatures as *cool* as 1995 would be expected to occur on average only once in seven years. Thus, for a 30-year period at the end of the 21st Century, 4–5 years out of 30 could be anticipated to be as cool as 1995 (the hottest summer in the observational series) while 25–26 years would be expected to be warmer. This represents an almost 250-fold increase in the likelihood of a summer as warm as 1995 relative to 1901–2005. RCP 4.5 changes are more subtle, but considerable enough to make the summer heat of 1995 close to “normal” by the end of the 21st Century, with a median z-score approaching 0.3.

Summer (dry) and winter (wet) precipitation extremes show similar increases in likelihood over the 21st Century. Under RCP 8.5 the median of model runs indicates that by the end of the century, both summers as dry as 1995 and winters as wet as 1994 are projected to occur approximately one in every 8 years, making these events respectively ~10 and 8 times more

Table 3
Trends in mean and variance based on observed data (given per decade). p-values give the probability that the population the sample is drawn from has a trend of 0. [1]z is dimensionless. [2]We provide the change in mean over the period of observation by multiplying the trend by the number of years of observation (cf. Box, 2002). [3]We provide the trend in the standard deviation.

Metric (years of record; units)	[1]Trend in $\|z\|$	p-value for trend in z-score	Trend in mean	p-value for trend in mean	[2]Δ in mean	[3]Trend in variance	p-value for trend in variance
JJA precipitation (1850–2010; °C)	−0.037	0.697	−1.59	0.203	−25.61	−0.622	0.335
DJF precipitation (1850–2014; mm)	−0.037	0.009	1.58	0.184	25.73	0.535	0.332
JJA air temperature (1900–2014; mm)	−0.145	0.036	0.081	0.000	0.93	0.012	0.372
DJF storminess (1900–2014; hPa)	0.116	0.002	−0.040	0.639	−0.57	−0.012	0.861

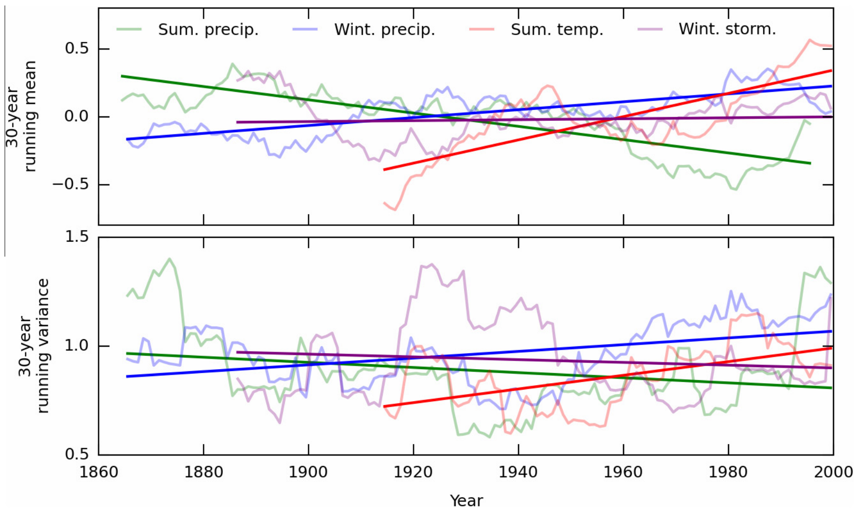

Fig. 4. Running 30-year means (top) and variances (bottom). Prior to calculating running statistics, all variables were standardized by subtracting the mean and dividing by the standard deviation. Darker lines are least-squares trend lines fitted to the smoothed data to indicate the direction of change. Trends in variance discussed in the text and Table 2 are the same as those plotted, but trends in means utilize the raw annual series; smoothed data are only shown here for clarity of illustration.

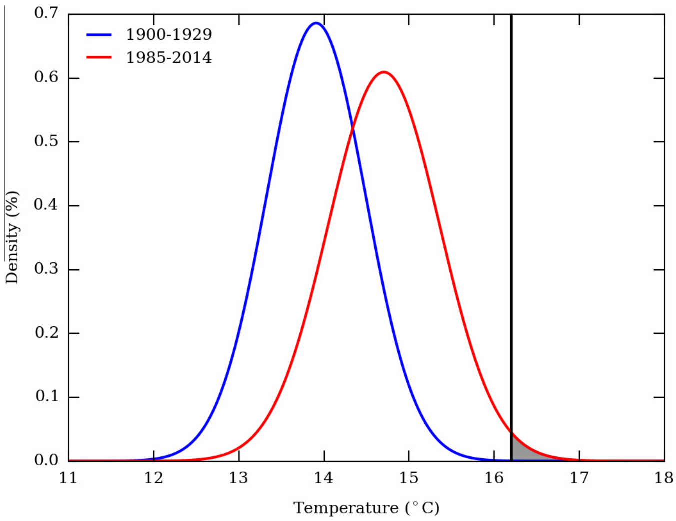

Fig. 5. Fitted normal probability density functions for 30-year mean summer air temperature samples taken from the beginning and end of the observed record. The area under each curve integrates to 100%. The vertical line highlights summer temperature in 1995. Note that more of the distribution extends beyond this limit for the recent 30-year sample. This results from a shifting of the mean to the right, as well as a broader distribution (i.e. larger variance).

likely than during the historical period (Section 2). Unsurprisingly, these changes are more muted under RCP 4.5. By the end of the century median *z*-scores of −1.92 and 1.56 are found for summer and winter precipitation, corresponding to return periods of 36 and 17 years, respectively. Projections of our storminess metric give no suggestion of increasing likelihood for extreme seasonal conditions.

Although the median changes in seasonal precipitation and summer temperature are substantial, we emphasize that the projected uncertainty is large enough for the reference *z*-scores to lie within the 90% ensemble confidence intervals for precipitation (summer and winter) under RCP 4.5 (Table 4). For RCP 8.5, the reference *z*-score for summer precipitation remains above the 5th percentile (i.e. the ensemble indicates more than 5% chance that summers as dry as 1995 will be *less* likely by the end of the 21st Century). By contrast, there is more than a 95% chance that summers as hot as 1995 and winters as wet as 1994 will be more likely by the end of the 21st Century under RCP 8.5 (Table 4).

To explain variability in likelihood in more detail, we assessed the evolving means and variances of the projected series (Figs. 10 and 11), with changes relative to the 1961–1990 period reported in Table 4 for consistency with previous studies. The median increase (decrease) in winter (summer) precipitation by the end of the 21st Century is 16.8% (−18.6%) under RCP

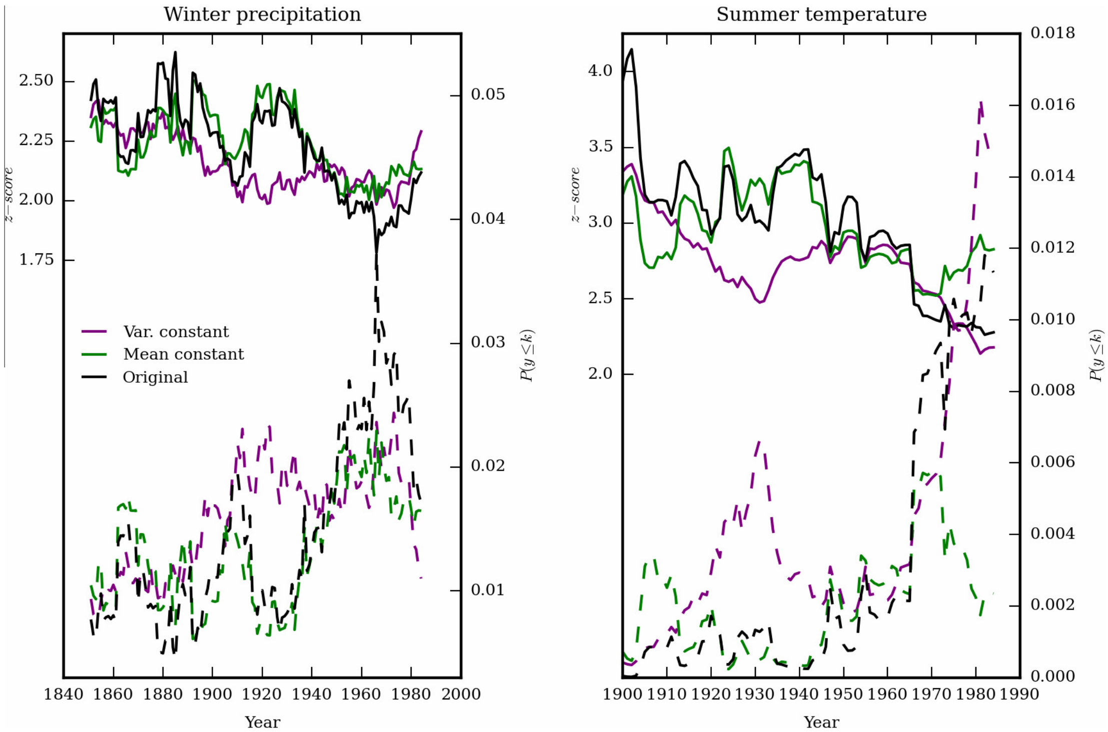

Fig. 6. Time-evolving *z*-scores (solid lines, left axes) and corresponding p-values (dotted lines, right axes) for the top-ranked seasons, when distributions are fitted to sliding 30-year samples. Each line corresponds to a different experiment, in which the mean or variance is held constant, whilst the other is allowed to evolve; the 'original' series is the same as plotted in Fig. 3.

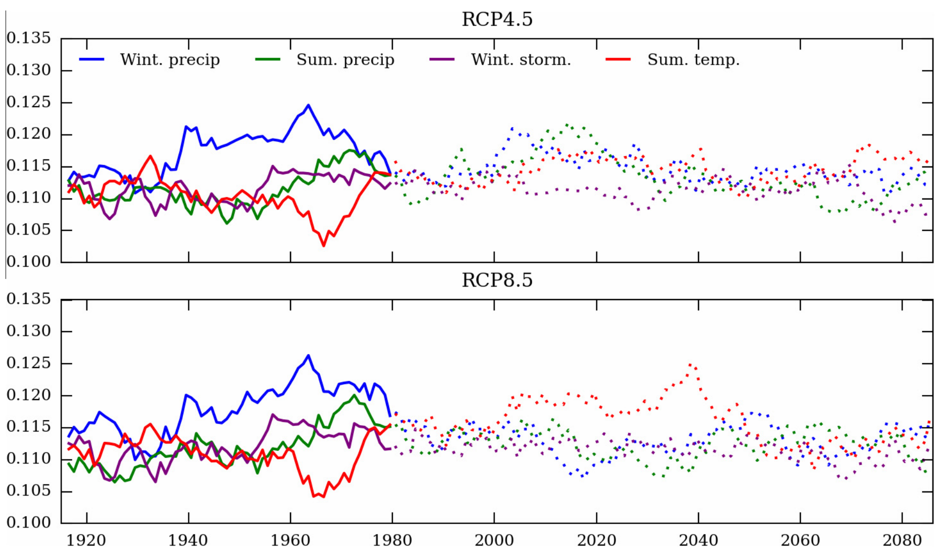

Fig. 7. Ensemble mean values of the Kolmogorov–Smirnov test statistic (KS) for 30-year samples for the RCP experiments. Note that the historical (projected) components of the respective series are plotted with solid (dotted) lines.

8.5, and 9% (−4%) for RCP 4.5. The equivalent summer temperature changes are 3.1 °C (RCP 8.5) and 1.9 °C (RCP 4.5). These changes are similar in magnitude to those found by Fealy and Sweeney (2007), who reported summer precipitation decreases of −20 % and winter increases of 15% under the A2 SRES scenario (representing a high emissions forcing). Uncertainty in summer precipitation is, however, large in our ensemble, with no change within the 90% confidence interval under both RCPs (Table 4). The temperature changes here also concur with Sweeney et al. (2008), who concluded that a summer

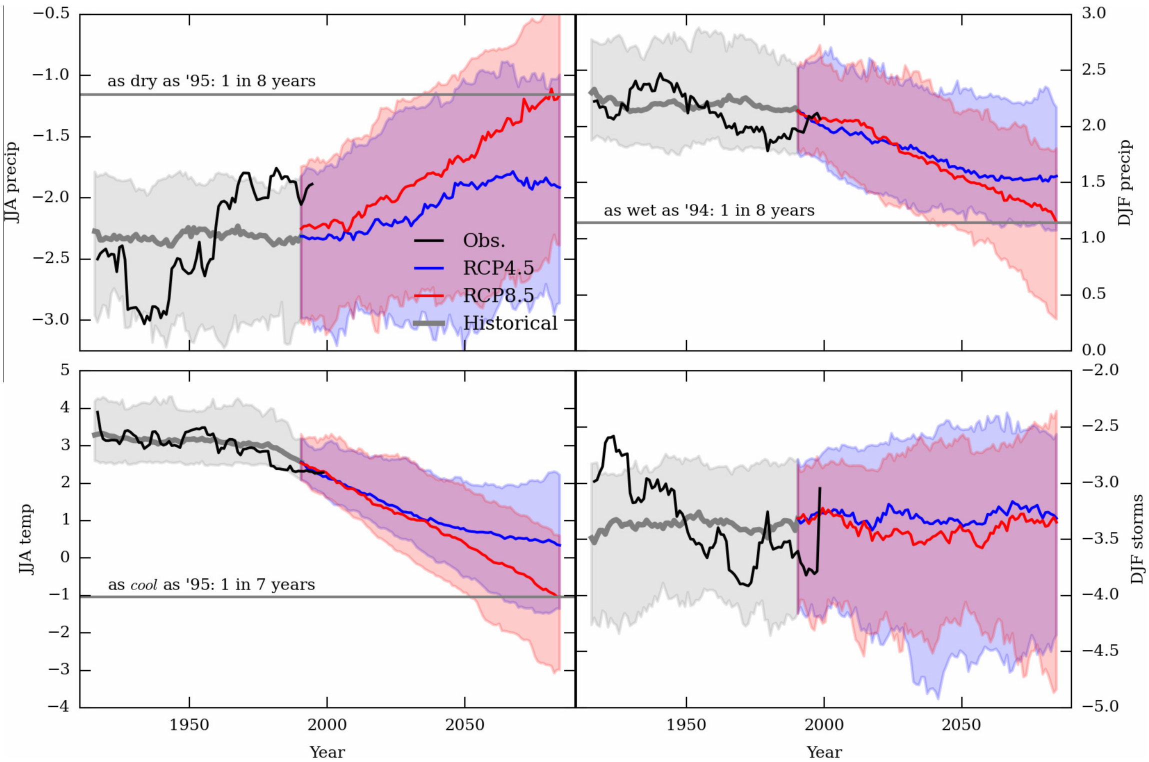

Fig. 8. Evolution of z-scores in the historical and RCP experiment calculated for centred, 30-year sliding windows. The shaded region of the CMIP5 ensemble spans 5–95th percentiles, whilst the solid lines provide the median. The discontinuity between the historical and RCP 8.5 medians is because only a subset of historical model runs continues to RCP 8.5. Note that the observed series are also displayed in each panel and the different scaling on the respective y-axes.

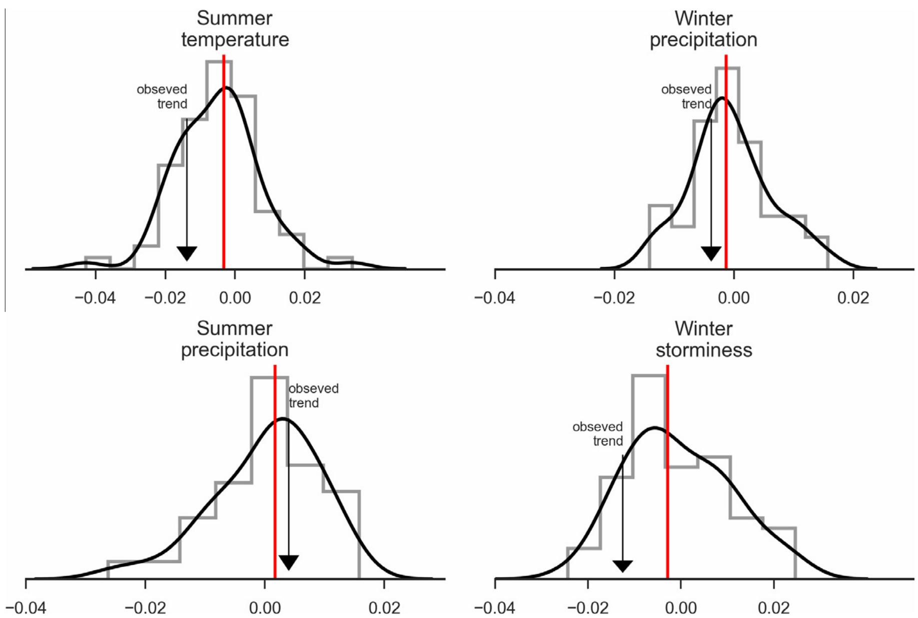

Fig. 9. Least-squares trends in z-scores (per year) during the historical CMIP5 experiments (1901–2005). The black line is the kernel density estimate, providing a smoothed illustration of the density summarised in the underlying histogram (grey outline). The red line highlights the median of this distribution whilst the arrow indicates the gradient of the trend lines plotted in Fig. 3. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 4
Summary of CMIP 5 projections for the end of the 21st century (2070–2099).[1]We provide the *z*-score of the most extreme season on record in brackets for convenience. [2]Units of the change in mean are °C for air temperature and % for all other variables. [3]Changes in variance are given as %. Note that for comparison to previous studies, all changes in mean and variance are referenced to the 1961–1990 period in the historical experiment.

	[1]Metric	*z*-score			[2]Δ Mean			[3]Δ Variance		
		Median	5th %-tile	95th%-tile	Median	5th %-tile	95th%-tile	Median	5th %-tile	95th%-tile
RCP 4.5	JJA precipitation ($z = -2.26$)	−1.92	−2.86	−0.99	−4.02	−22.97	8.65	101.02	59.56	179.51
	DJF precipitation ($z = 2.14$)	1.56	1.07	2.17	8.97	3.32	16.32	120.85	71.18	205.72
	JJA air temperature ($z = 2.83$)	0.34	−1.36	2.22	1.87	0.35	2.95	124.40	67.86	270.80
	DJF storminess ($z = -3.32$)	−3.31	−4.35	−2.56	−0.01	−0.13	0.16	101.15	58.61	161.46
RCP 8.5	JJA precipitation ($z = -2.26$)	−1.16	−2.39	−0.35	−18.56	−34.88	5.39	99.05	58.98	168.09
	DJF precipitation ($z = 2.14$)	1.14	0.28	1.80	16.84	4.43	30.79	148.53	76.30	254.88
	JJA air temperature ($z = 2.83$)	−1.03	−2.99	0.60	3.08	1.46	5.14	208.62	100.01	449.38
	DJF storminess ($z = -3.32$)	−3.35	−4.84	−2.36	0.02	−0.21	0.29	105.73	56.17	175.50

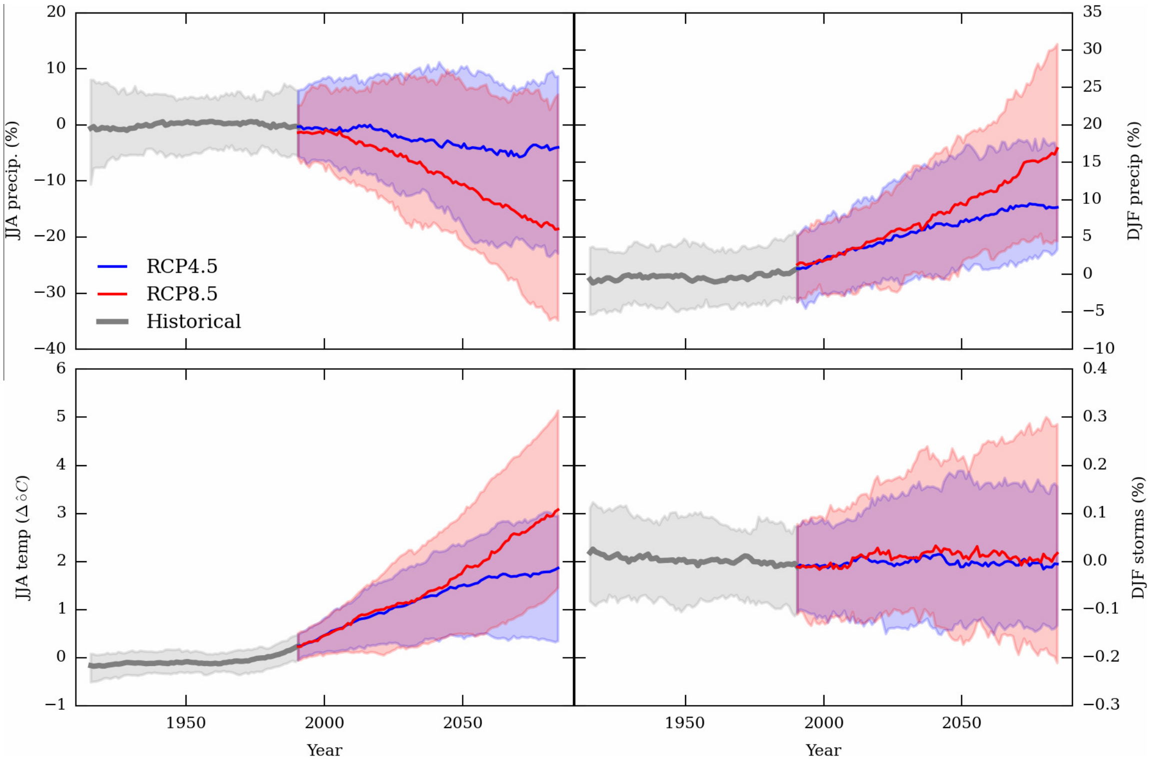

Fig. 10. Centred 30-year running means of the respective variables, expressed as anomalies from 1901–2005. See Fig. 8 caption for further details.

temperature increase of 3 °C was projected by 2080 under the same A2 scenario. Mean winter sea level pressure shows no change under either RCP according to our assessment.

The projections indicate essentially stationary variance for mean winter sea-level pressure and summer precipitation throughout the 21st Century, but this does not extend to summer air temperature and winter precipitation, where median increases in the variance of 109% and 49%, respectively, are suggested by the end of the 21st Century. Only in the case of summer air temperature under RCP 8.5 does zero change in the variance fall outside the 90% confidence region (Table 4). The concurrent increases in variance and mean would both contribute to enhanced likelihood of extremely warm summers and wet winters. As with our assessment of observations, we explored the relative importance of these mean and variance changes by repeating the 30-year sliding-window analysis for the projections to assess changes in the associated *z*-values, whilst alternately holding these moments (mean and variance) constant at their historical values (see Section 3.1). Evidently, it is again changes in the mean that drive the enhanced projected likelihood of extremely warm summers. This dominance is less clear for winter precipitation, but changes in variance are still of secondary importance (Fig. 12).

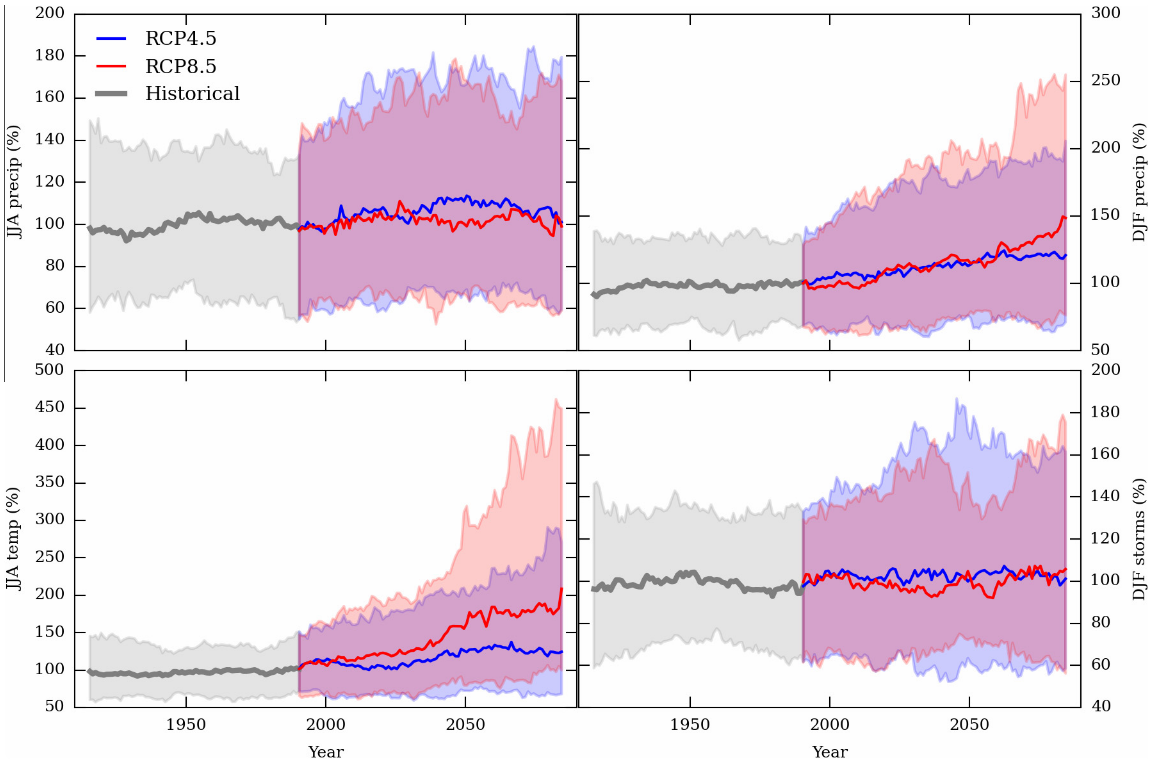

Fig. 11. Centred 30-year running variances for the respective variables. Units are given as percent of 1901–2005 variance. See Fig. 8 caption for further details.

4. Discussion and conclusion

Over the period spanned by observational records the likelihood of extremely wet winters and hot summers increased significantly. These changes were driven mainly by a trend towards wetter mean winters and warmer mean summers, with smaller contributions from increasing year-to-year variation in these variables. At the most extreme, the likelihood of a summer as warm as 1995 has increased by a factor of more than 50 over the observational period. Whilst such changes are dramatic, similarly large increases in the probability of extremely warm seasons have been reported elsewhere (Schär et al., 2004; Hansen et al., 2012). These changes should not be taken lightly, as an increase in the occurrence of extremely warm summers may have significant consequences for society (cf. Subak et al., 2000), not least for human health. Research has shown, for example, that despite the temperate IoI climate mortality rates in Ireland are temperature-dependent (Goodman et al., 2004; Gleeson et al., 2013; Pascal et al., 2013), whilst Pascal et al. (2013) specifically highlighted the excess mortality during the summer of 1995. Although we only considered changes in the mean summer temperature here, and not the occurrence of heatwaves, we note that previous IoI studies observed the frequency of hot days to increase in line with mean summer temperatures (McElwain and Sweeney, 2003). This scaling is anticipated to continue in future (Fealy and Sweeney, 2008; Mullan et al., 2012; Gleeson et al., 2013). Thus, the possibility of summer temperatures as warm as 1995 occurring almost 50% and 90% of the time by the end of the 21st Century according to RCP 4.5 and 8.5, respectively, must be of concern. Moreover, there could be enhanced warming with coincident episodes of poor air quality in urban areas (Wilby, 2008).

Climate model projections of increases in the likelihood of extremely dry summers and wet winters – continuing trends suggested by the long-term observations – also imply significant challenges for water resource management. Historically, high winter rainfall totals have resulted in widespread flooding throughout the British-Irish Isles (Wilby and Quinn, 2013; Muchan et al., 2015), and hydrological modelling suggests that projected changes in seasonal precipitation for the IoI effects corresponding changes in the annual flow regime, thus likely resulting in increased winter flood risk and summer drought (Charlton et al., 2006; Steele-Dunne et al., 2008; Bastola et al., 2012). Relative to changes in summer air temperature, however, projected changes in extremely wet winters and dry summers are more subtle, and the probability of seasons like those witnessed in 1994/1995 may still be relatively low by the end of the 21st Century, particularly if aggressive cuts in greenhouse gas emissions lead to a trajectory more consistent with RCP 4.5.

In light of the results in Section 3.2 it is also important to note the limited ability of the CMIP5 models in capturing low-frequency variability in summertime precipitation. McCarthy et al. (2015) detailed the important role the Atlantic

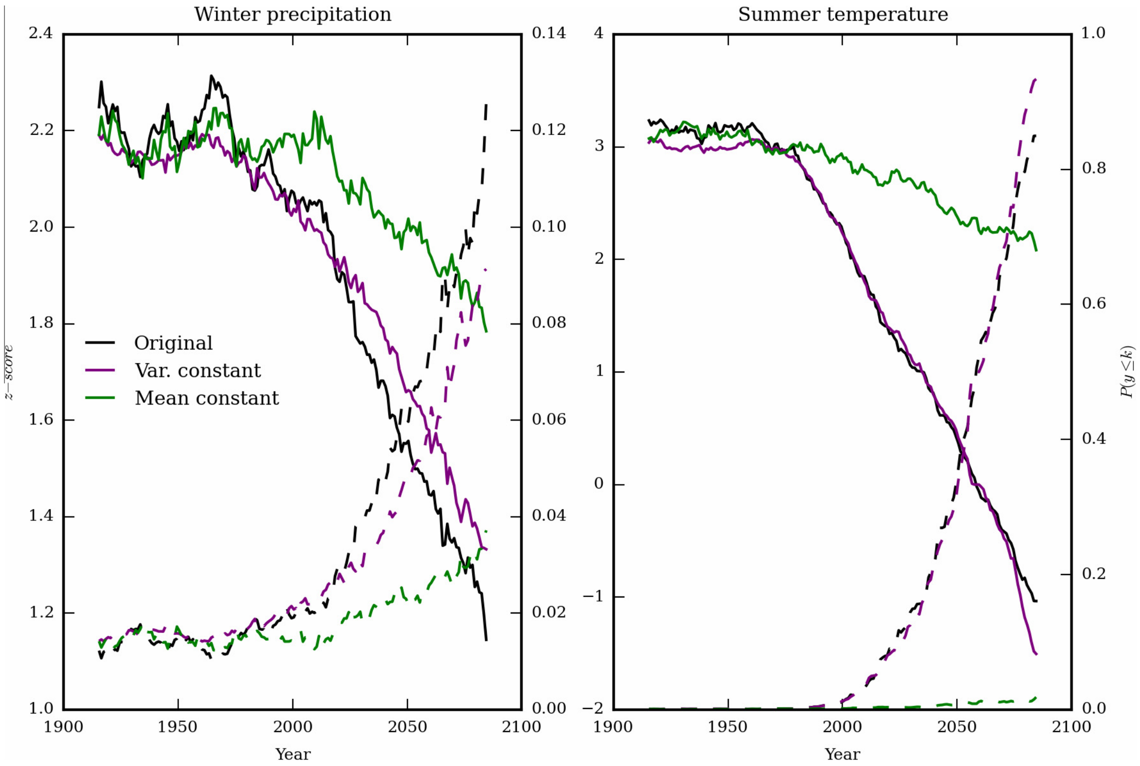

Fig. 12. Time-evolving *z*-scores (solid lines, left axes) and corresponding *p*-values (dotted lines, right axes) for the top-ranked seasons, when distributions are fitted to sliding 30-year samples in the historical and RCP 8.5 experiments. Each line corresponds to a different experiment, in which the mean or variance is held constant, whilst the other is allowed to evolve; the 'original' series is the same as the median plotted in Fig. 8.

Multidecadal Oscillation (AMO) in sea-surface temperatures (SSTs) plays in determining IoI precipitation during this season, yet it is known that the CMIP5 ensemble captures the atmospheric fingerprint of the AMO poorly (Ruiz-Barradas et al., 2013). Thus, we highlight that the future projections detailed here are unlikely to represent decadal-scale fluctuations in precipitation that may be driven by SST variability. As a consequence, even if the CMIP5 ensemble realistically resolves the IoI climate change signal for a given RCP, substantial low-frequency deviations in summertime precipitation – not evident in the constituent CMIP5 model runs – may be possible. We therefore emphasise that summertime CMIP5 precipitation projections are likely underdispersed, and this should be kept in mind if leveraging these data for adaptation planning.

Model projections gave no suggestion of an increase in the probability of the stormiest winter on record, with conditions like those experienced during 2013/14 remaining highly unlikely even until the end of the 21st century. This somewhat conflicts with previous research using the CMIP5 ensemble, as Lehmann et al. (2014) found evidence for increasing 21st Century eddy kinetic energy over the BI region, whilst Zappa et al. (2013a) used a cyclone-tracking algorithm to infer that the number of both cyclones and "strong" cyclones would increase over the same region and period. Whilst the CMIP5 models are known to have difficulty simulating a realistic North Atlantic storm track, these projected changes are robust to biases (Zappa et al., 2013a,b). We note, however, that our results are not directly comparable with these assessments as we employed a larger number of model runs than either study, and used a very different metric to infer "storminess". We suggest that the latter is the most likely reason for this discrepancy. In selecting seasonal mean sea level pressure, our measure of storm activity is simple, but correlates well with the more sophisticated definition of Matthews et al. (2014); it also correctly identifies the occurrence of more prominent stormy seasons (Section 2). However, measures which emphasise individual synoptic features (as in Lehmann et al. (2014) and Zappa et al. (2013a)) will be more sensitive to changes in the characteristics of extra-tropical cyclones. In cases where storms are compensated by more frequent episodes of higher pressure, our integrated measure of synoptic activity will not detect changes in the occurrence or severity of storm events. However, at present this explanation for discrepancy between storminess metrics remains conjecture and we suggest that this be explored further in future research examining in detail the projected changes in synoptic atmospheric circulation affecting IoI.

In the context of atmospheric dynamics, we highlight here the possibility that the extreme seasonal conditions projected to increase in likelihood may in the future be synoptically dissimilar to their historical analogues. For example, historically warm summers in the IoI region have often been characterised by dry conditions typical of anticyclonic circulation (cf. Jones et al., 1999), but future warm summers may not necessarily be driven by the same atmospheric circulation: warming can be expected across weather types, so the same high temperatures may in the future be realised under other circulation regimes. Practically, this means that future summers as warm as observed extremes may be very different regarding other meteorological quantities (e.g. wind speed/direction, humidity and air quality). The same principle extends to seasonal precipitation extremes, given that regional precipitation intensity is projected to increase (Gleeson et al., 2013; Zappa et al., 2013a). Future winters as wet as the historical extremes, for example, may therefore require fewer days of rainfall to attain these totals. In summary, we highlight the possibility that future realisations of historically extreme conditions should not be assumed to experience weather similar to the analogues used herein.

It is also important to emphasise that for all variables, the results presented here provide only a first-order assessment of the changing likelihood of extreme conditions. Our analysis draws upon a large number of model runs from CMIP5 giving equal weight to all constituent series regardless of their physical realism (Liepert and Lo, 2013) or ability to capture the past IoI climate. We also note that output from CMIP5 is spatially coarse, and as a result will not capture important features of the IoI climate that may be important in determining the changing likelihood of extreme seasons. For example, the complex influence of topography on rainfall generating processes will be poorly represented at this scale (Fealy and Sweeney, 2007; Sweeney, 2014). We have also not attempted to resolve spatial variability in projected climate changes across the island. However, given the modest spatial scale of the IoI relative to the synoptic systems which define its weather, we assert that this simplification is defendable. Indeed, previous spatially disaggregated projections of IoI for temperature and precipitation have shown relatively modest variability across the island (Sweeney et al., 2008).

We suggest that future research should be tasked with updating the analogues as new extreme seasons emerge, thus ensuring contemporary events are leveraged appropriately to aid in climate change communication. To this end, we highlight that at the time of writing (January, 2016), the BI-region has experienced an exceptionally wet December, and if such conditions persist, the winter of 2016 could be a candidate for this treatment. We also note the opportunity of extending our analyses by scaling the changing likelihood of extreme seasons to changes in mean global temperature (cf. Seneviratne et al., 2016), thus permitting more tangible illustration of the regional climate impacts associated with given greenhouse gas emission trajectories.

In summary, our findings suggest that IoI climate has experienced a substantial change in the occurrence of extreme seasonal temperatures and rainfall that, in the earlier half of the 20th century, would have been considered highly exceptional. The observed increase in likelihood is consistent with projected future changes in the IoI climate, and our study indicates that such events are likely to become less the exception and more the norm as further warming is experienced. This is most apparent in the almost 250-fold (RCP 8.5; relative to 1901–2005) increase in the likelihood of a summer as warm as 1995 – the warmest currently on record.

In light of this, our preparedness to reduce emissions and plan appropriately is critical for determining the range of unavoidable impacts we are likely to experience. However, despite its significance, communicating the exact scale of the challenge climate change poses has, to date, proved difficult. We hope that by contextualising such changes relative to observed extremes, our analysis will prove useful in this regard as it provides more tangible reference points for a wide range of audiences. Such references may provide insight into how physical systems, as currently configured, may respond to future change, and hence what actions will be required to ensure appropriate mitigation and adaptation. Thus, it is hoped that our results will reduce 'psychological distancing' from the reality of climate change, whilst enhancing the accessibility of climate risk information.

5. Data availability

The processed monthly CMIP5 data employed in the analysis can be accessed by FTP from ftp.nas1.nuim.ie. Anonymous login is not presently supported, so please contact the corresponding author to be granted access.

Acknowledgements

We thank Met Eireann for access to the long-term temperature series, and acknowledge support for the Twentieth Century Reanalysis Project provided by the U.S. Department of Energy, Office of Science Innovative and Novel Computational Impact on Theory and Experiment (DOE INCITE) program, and Office of Biological and Environmental Research (BER), and by the National Oceanic and Atmospheric Administration Climate Program Office. TM, CB and CM acknowledge funding provided by the Irish Environmental Protection Agency under project 2014-CCRP-MS.16. The authors also extend thanks to two anonymous reviewers whose comments improved this work considerably.

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