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Deriving probabilistic based climate scenarios using pattern scaling and statistically downscaled data: A case study application from Ireland

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Abstract
This paper adopts a technique common in the dynamical climate modelling literature, that of pattern scaling, and applies it to previously available statistically downscaled station level data for Ireland for two climatically relevant variables, that of temperature and precipitation. This technique allows for the rapid development of climate scenarios for additional emissions scenarios not previously available from the GCM modelling centres. Having derived the end of century (2080s) change in both these variables for four marker emissions scenarios (A1FI, A2, B2, B1), regional response rates, or the regional rate of warming per °C global warming at each station, were calculated. The estimated ranges in regional responses at each station were then compared to regional response rates for the Irish 'grid box' derived from a larger sample of 14 GCMs, in order to determine if the calculated response rates were illustrative of a wider suite of GCMs. A Monte Carlo (MC) resampling approach was then employed to sample regional response rates for selected stations and for different estimates of future warming. On the basis of the MC approach, probability distribution functions (pdfs) of simulated changes in temperature and precipitation were constructed and compared to the original statistically downscaled data. The methodology and results presented represent a significant contribution to the traditional approach of statistical downscaling through the development of associated likelihoods, rather than just a change in the mean value. While the methodology presented should enable the rapid development of probabilistic based climate projections, based on a limited availability of downscaled climate scenarios, caution needs to be exercised in the interpretation of the results. While they provide a basis for risk or policy assessment, estimates of the level of risk are not independent of the method employed.

Keywords
climate modelling, Ireland, Monte Carlo, pattern scaling, probabilistic scenarios, statistical downscaling, uncertainty

I Introduction

Future projections of anthropogenic climate change arising from increased concentrations of atmospheric CO_2 are subject to a high degree of uncertainty (Jones, 2000). This uncertainty arises largely as a consequence of both aleatory ('unknowable' knowledge) and epistemic or

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systematic ('incomplete' knowledge) uncertainties (Foley, 2010; Hulme and Carter, 1999; Oberkampf et al., 2002). Aleatory uncertainties are considered to be irreducible and result from an inherent indeterminacy of the system being modelled (Hulme and Carter, 1999; Oberkampf et al., 2002). For example, future human behaviour and actions are not predictable, therefore future emissions scenarios must be prescribed on the basis of storylines or indeterminate scenario analysis (Hulme and Carter, 1999), such as the Intergovernmental Panel on Climate Change *Special Report on Emissions Scenarios* (SRES) (Nakicenovic and Swart, 2000). These 'storylines' represent different rates of future world development, based on various scenarios of socio-economic growth, population growth, uptake of energy efficient technologies or continued reliance on fossil fuels and regional versus global development patterns. More recently, an alternative approach, which identifies important radiative characteristics rather than the sequential socio-economic approach of the SRES, has led to the development of the 'next generation' of scenarios (Moss et al., 2010). These scenarios, entitled representative concentration pathways (RCPs), have a larger associated range of atmospheric concentrations being considered compared to the previous SRES.

While any particular scenario may never be realized, and hence no associated probabilities can be attached, they do provide a basis for tentatively exploring potential or plausible future changes in the climate system arising from anthropogenic activities. Epistemic or systematic uncertainties arise primarily from a lack of complete knowledge of the system and are considered to be reducible as our understanding or knowledge of the particular system or environment increases. For example, the envelope of possible values of the sensitivity of the climate system may be narrowed as our understanding of the key climate processes improves. Conversely, it could also be the case that with additional research we could find that we did not previously include a particular process, which could result in the climate sensitivity envelope increasing.

Consequently, future projections of climate will always result in a range of future scenarios being simulated (Hulme and Carter, 1999). If not adequately accounted for, the various sources of uncertainties that exist in the modelling process can result in large uncertainties being associated with the model outcome. This 'cascade of uncertainty' has significant implications, and presents significant challenges, where impacts models (e.g. hydrological, agricultural or economic models), run on the basis of output from a climate model, are subsequently employed to inform strategic decision making. This was further compounded by the fact that, until recently, the use of a single climate scenario or climate trajectory was common in the literature.

While a number of approaches have been developed to address some of the issues that are associated with uncertainties in climate model projections, such as adoption of a 'best guess' framework or taking the mean or median value from a range of scenarios, such 'top-down' or 'predict and provide' approaches are not considered particularly useful for subsequent use in risk analysis, due to an inability to attach probabilities or likelihoods to the selected climate scenario. In addition, without a clear statement on the uncertainties that have, or have not, been incorporated into the research, decision makers need to exercise extreme caution as any subsequent decisions may not encompass the full range of associated risks. Such policy decisions may give rise to maladaptation (over-, under- or inappropriate adaptation). An additional weakness of employing the 'predict and provide' approach in policy formulation is that it tends to dismiss the possibility of local adaptation ('dumb farmer' hypothesis) or only assumes an arbitrary level of adaptation ('clairvoyant farmer') (Dessai and Hulme, 2003). Critically, this approach is predicated on the requirement that climate models provide accurate, reliable and precise 'predictions' of future climate, a requirement which ultimately represents a key limiting factor in the development of robust ('no regrets') adaptation (Dessai et al., 2009).

While climate impact studies that employ the 'predict and provide' approach are abundant in the scientific literature, substantive evidence to support the translation of the scientific outputs from these studies into meaningful adaptation is much less obvious (Wilby and Dessai, 2010; Wilby et al., 2009). As an alternative, sensitivity analyses have been employed to assess the sensitivity, or vulnerability, of a system to incremental changes in climate (e.g. impose an arbitrary ±10%, ±20%, ±30% or ±1°C, ±2°C, ±3°C change on the system being modelled) and constitute a bottom-up approach to informing climate adaptation policy (Dessai and Hulme, 2003). In order to test the sensitivity of a system to changes, a single input is varied while holding all other inputs constant. More recent developments in sensitivity analysis try to account for simultaneous changes in a number of variables and can also take into account uncertainty in inputs (Katz, 2002). Imposed changes may be informed by the output from a climate model or climate models.

However, such bottom-up approaches have been the subject of criticism in the past. While sensitivity analysis could be used to generate response surfaces from which risk thresholds can be identified (e.g. Jones, 2000), such as 'dangerous' climate change, their ability to assess uncertainties in multiple inputs required large computing power (Beven, 2001). Additionally, sensitivity analysis may not necessarily produce consistent and plausible scenarios of future changes (Jones and Mearns, 2003).

Increasingly, the incorporation of probabilities in climate change impact assessments is becoming more widespread. As researchers move from employing single trajectory, top-down approaches towards the use of multiple scenarios from multiple GCMs in climate impact assessments, characterizing uncertainties in the associated scenarios has become increasingly feasible. From a policy development perspective, the identification and communication of uncertainties, and their ranges, may have a useful application in strategic decision making (Burton et al., 2002). For example, if in the case of a regional climate projection of precipitation, a variable which is inherently difficult to simulate reliably, two models produce scenarios with similar magnitude changes but opposite in sign (Giorgi and Francisco, 2000), i.e. 10% increase and 10% decrease in regional precipitation, can a policy maker then assume that there is going to be 0% change (ensemble mean) in precipitation? Adaptation measures required for a 10% increase in precipitation (improved flood defences) are likely to be significantly different to those required for a decrease in precipitation (such as additional reservoir capacity). While such inter-model differences may, or may not, be reduced through increased scientific understanding, the quantification, and subsequent communication, of uncertainties is considered more desirable than assuming a perfect model in adaptation development.

More recently, Prudhomme et al. (2010) and Wilby and Dessai (2010) propose alternative scenario neutral approaches to adaptation which address the sensitivity of adaptation options or pathways to a range of plausible, but uncertain, future climates. Importantly, Wilby and Dessai (2010) also include the potential of non-climatic pressures in influencing a systems response or vulnerability. The scenario neutral approach offers a significant methodological advancement over traditional approaches, through the potential to incorporate probabilistic climate scenarios with existing knowledge of the sensitivity of the system under study, in developing robust or 'no regrets' adaptation. Fundamentally, the scenario neutral approaches as espoused by both Prudhomme et al. (2010) and Wilby and Dessai (2010) argue for the repositioning of climate change information from the start of the climate risk assessment process to further down the risk assessment chain. This approach shifts the requirement for accurate and reliable predictions (i.e. most likely or probable outcome), and arguably an impossible constraint, to one where a range of (uncertain) future projections (i.e. plausible or possible outcomes) are considered for use in assessing the robustness of, rather than developing, different adaptation options or pathways.

Critically, the scientific imperative to further our understanding of the dynamics of the climate system, which seeks to reduce epistemic or systematic uncertainties in climate simulations, remains, but it no longer acts to constrain or supersede the development of robust adaption, a societal imperative. A key benefit to separating the scientific from the societal imperative is that scientific developments (e.g. increased understanding of the systems under study, new scenarios or improved models) can be readily incorporated into the scenario-neutral approach. Additionally, the incorporation of probabilistic based climate distributions into the scenario neutral approach offers the potential to transition from a wholly deterministic based approach to decision making to one which recognizes the inherent, and potentially irreducible, uncertainties required for robust adaptation.

II Challenges for quantifying uncertainties at the regional scale

In spite of their apparent complexity, climate models ultimately represent a simplification of what are complex, and often non-linear, climate processes. Differences in model structure, representation of physical and dynamical processes and parameterization schemes all contribute to differences evident between models, and between models and observations, at the global, regional and grid scales. For example, while most climate models agree that the globally averaged surface temperature will increase as a consequence of increasing atmospheric concentrations of greenhouse gases, significant divergence is evident between models in both the spatial and temporal projections of precipitation. Such differences are most pronounced at the regional scale, with differences not just in the magnitude but also the direction of projected precipitation changes between GCMs.

Due to computational limitations, the typical spatial resolution of many AOGCMs (atmosphere-ocean global climate models) is currently in the order of greater than 100 square kilometres (e.g. model horizontal resolution T63 $\sim$180 km; T159 $\sim$125 km; T106 $\sim$110 km). While this has been demonstrated as adequate to capture low-frequency, large-scale variations in the climate system (e.g. Stephenson and Pavan, 2003), many important processes occur at much smaller spatial scales, such as those processes associated with convective cloud formation and precipitation, and thus are too fine to be resolved in the dynamic modelling process.

As a consequence, a number of techniques have been developed to 'downscale' coarse resolution GCM output to finer spatial and temporal scales. Dynamical regional climate models (RCMs) and empirical statistical downscaling (SD) are the primary means by which regional- or local-scale information is derived from a parent GCM(s). However, the incorporation of an additional downscaling 'layer' to generate high-resolution scenarios will act to both propagate and contribute to uncertainty within the modelling framework (e.g. Dibike et al., 2008; Gachon and Dibike, 2007; Hingray et al., 2007b; Khan et al., 2006; Rowell, 2006), resulting in significant regional variations between downscaled model projections, even when forced with the same GCM and emissions scenario (Haylock et al., 2006). In spite of these shortcomings, employing either dynamical or statistical downscaling has been considered to 'add value' to climate projections, when compared to GCM output at the grid scale (e.g. Fealy and Sweeney, 2007; Feser et al., 2011; Katz, 2002; Rowell, 2006). However, Dessai et al.

(2009) caution against confusing accuracy with precision; while higher-resolution climate projections may represent higher precision than the parent GCM, this should not be confused with increased accuracy of projection. In addition, the notion of added value has been questioned by a number of authors (e.g. Castro et al., 2005; Pielke and Wilby, 2012; Rockel et al., 2008). However, Katz (2002) argues that some downscaling techniques have the potential to be useful, even if they do not offer an improvement over the GCM employed, through enabling uncertainty analysis to be undertaken (e.g. Fowler et al., 2007; Hashmi et al., 2009; Wilby and Harris, 2006).

In recognition of the uncertainties that occur in the modelling framework, a number of methods have been developed that seek to characterize or quantify uncertainty in climate projections at the regional scale. One approach is to employ a number of different GCMs in the development of multi-model ensembles. This typically involves averaging (equal weighting) across a number of climate scenarios or subsequent impact model outputs to produce a mean or averaged ensemble or by selecting the median response. A critique of this approach is that differences in model reliability are not addressed when constructing such climate ensembles. An additional weakness is that it may be inappropriate where significant divergence occurs between models or scenarios. For example, if the resultant ensemble gets the 'right' answer, relative to an observed series, solely due to error cancellation between divergent climate scenarios, it is unlikely that any confidence could be placed in the derived future climate ensembles.

The issue of GCM reliability is likely to have important implications at the regional scale. In an analysis of uncertainty in RCM formulation, Rowell (2006) found that while the RCMs employed (derived from the EU PRUDENCE project; Christensen et al., 2002) contributed a relatively small, but non-negligible, impact on projected seasonal mean climate for the UK, the greatest contribution was found to arise from the parent GCMs. Giorgi and Mearns (2002) demonstrated a procedure for calculating model average, uncertainty range and collective reliability of a range of regional climate projections from ensembles of different AOGCM simulations. The Reliability Ensemble Averaging (REA) method weights GCMs based on individual model performance and criteria for model convergence. This procedure acknowledges that models have different levels of skill associated with modelling different aspect of the climate system and weights models accordingly. However, the use of model convergence as a criterion for model reliability has been subject to critique, as similarities, or a lack of independence, in model structure may result in two or more models producing similar outputs and therefore ascribed a higher weight than a truly independent model.

To address this, Murphy et al. (2004) proposed a Climate Prediction Index (CPI), an objective means of measuring model reliability, which can be used to weight different GCMs according to their relative ability to simulate the observed climate based on broad range of observed variables. This technique has been further refined by Wilby and Harris (2006) for use in impacts assessments. Their method is applied to a narrower suite of GCM outputs relevant to statistical downscaling to produce an Impacts Relevant Climate Prediction Index (IR-CPI). The application by Wilby and Harris (2006) attributes weights to each GCM based on the root-mean-square difference between the standardized modelled and observed climatological means. However, Stainforth et al. (2007) consider the practice of weighting models as 'futile' and argue that it can potentially give rise to misleading assumptions about the reliability of a particular model(s).

An alternative approach to quantifying uncertainties was proposed by Hulme and Carter (1999) who employed a probabilistic framework to examine the uncertainties that affect regional climate change for two locations in the UK. The authors employed a Bayesian Monte Carlo approach to sample from the standardized response of 14 GCM simulations, based on seven GCMs, which they treated as members of a pseudo-ensemble. Their results demonstrated the wide range in the regional response as simulated by the different GCMs. In a similar analysis, New and Hulme (2000) applied a similar approach in a sensitivity analysis of annual river flow to future changes in temperature and precipitation in the UK. While both Hulme and Carter (1999) and New and Hulme (2000) sought to quantify uncertainties at various stages in the modelling framework, they assumed all GCMs were equally skilful.

In an application of the probabilistic framework proposed by Hulme and Carter (1999), a number of authors have undertaken probabilistic based assessments of climate change projections based on scaling the outputs from a number of RCMs with various probability distribution functions of future warming, drawn from a number of GCMs (e.g. Ekström et al., 2007; Hingray et al., 2007a, 2007b). Due to computational limitations, RCMs are constrained to producing climate projections for a limited number of emissions scenarios, most commonly the A2 or B2 scenario, or for specific time periods. To overcome these limitations, a pattern scaling technique, originally postulated by Santer et al. (1990), has developed as a technique which has found widespread use in the climate modelling community (e.g. Hulme et al., 2002; Hulme and Carter, 2000; Kenny et al., 2000; Mitchell et al., 1999). The application of a simple scaling methodology has seen renewed use in recent years due to the widespread availability of regional climate model (RCM) output, based on a limited number of emissions scenarios, through projects as EU PRUDENCE (Christensen et al., 2002) and EU ENSEMBLES (van der Linden and Mitchell, 2009) for Europe, RMIP (Fu et al., 2005) for Asia, CLARIS (Boulanger et al., 2010) for South America, and NARCCAP (Mearns et al., 2009) for North America.

The pattern scaling technique allows for the rapid development of numerous climate scenarios, based on different GCM-emissions scenario combinations which sample a subset of the uncertainty range. For example, if the regional temperature change for the 2070–2099 period, from a particular GCM and emissions scenario, is known, then a normalized ‘response pattern’ can be calculated by dividing by the global mean temperature change for that GCM-emissions combination (ΔT_{A2}). Employing a simple climate model, such as MAGICC, the global mean surface temperature change for the A1 scenario could be calculated for a particular model. Employing the ratio of the global mean surface temperature change for the A1 scenario to the global mean surface temperature change for the A2 scenario ($\langle\Delta T_{A1}/\Delta T_{A2}\rangle$), the projected temperature change for the 2070–2099 period based on the A2 emissions scenario can be rescaled to produce a scaled temperature change for A1 scenario (ΔT_{A1}):

$$\Delta T_{A1} = \left\langle \frac{\Delta T_{A1}}{\Delta T_{A2}} \right\rangle \Delta T_{A2}$$

Fundamentally, this approach is contingent on the assumption that the geographical pattern of change is independent of the forcing, and that the amplitude of response is linearly related to the global mean surface temperature (Ruosteenoja et al., 2003). The assumption of a linear response, proportional to the global mean surface temperature, appears to hold in many cases, particularly for temperature, but less so for precipitation (Mitchell, 2003; Mitchell et al., 1999) as highlighted by Murphy et al. (2004). While the technique can produce a wide range of scenarios, which are useful for examining the range in projected climate response at the regional scale, the resultant scenarios are considered as being equally plausible and have no associated likelihood of occurrence.

Murphy et al. (2004) employed a pattern scaling technique from a single GCM to estimate regional climate uncertainty according to a range of possible changes in averaged global surface temperatures. They show, in one instance, that the pattern scaling approach captured less than 10% of the variance in tropical precipitation and concluded that a single projection from even the most sophisticated GCM will be of limited use for impact assessment. The authors suggest that only multi-model ensembles, sampling as wide a range of model uncertainties as possible, can reliably show the spread of possible regional changes, a finding confirmed by Lopez et al. (2009) and others. Similarly, Ruosteenoja et al. (2007), in a study comparing seasonal based GCM temperature and precipitation projections with RCM output for five European regions derived from the EU PRUDENCE project, employed linear regression to relate the regional GCM response to the global mean temperature simulated by a simple climate model. The resultant 'super-ensemble' was found to be advantageous when only a limited number of experiments were available from an individual GCM (A2 and B2) due to the reduction of random noise within the ensemble.

The use of probabilities is a well-established technique in short- and medium- range weather forecasting where uncertainty in model output is represented by the dispersion of an ensemble (Räisänen and Palmer, 2001). The incorporation of probability distribution functions (pdfs) or cumulative distribution functions (cdfs) in impact assessments is a logical development when dealing with multi-model ensembles from GCMs in order to characterize or quantify uncertainties of future climates at the regional scale. Additionally, Katz (2002) argues that the characterization of uncertainty in the form of probabilities has the added value of 'knowing how little you know' (Katz, 2002, cited in Morgan and Henrion, 1990).

The next section of this paper will outline a methodology to produce probabilistic based regional climate scenarios, based on previously available statistically downscaled data for Ireland, taking into account a number of key uncertainties. The methodology employed is adapted from Hulme and Carter (1999), Jones (2000) and New and Hulme (2000), and applied to two impacts relevant climate variables, that of seasonal mean temperature (°C) and precipitation change (%), for a selection of GCMs. The proposed methodology has previously been applied directly to both GCM and RCM output, but is refined here for application to statistically downscaled data.

III Data and methods

1 Application of a pattern scaling approach to statistically downscaled data for Ireland

Seasonal means of temperature and precipitation were derived for 14 synoptic stations in Ireland for the 2080s (2070–2099) from previously available statistically downscaled daily data (Fealy and Sweeney, 2007, 2008). This data set provides the basis for the remaining analysis. The 30-year period centred on the 2080s was selected as the signal-to-noise ratio is likely to be greatest for this period, compared to early- or mid-century projected changes (Jones, 2000). However, the statistically downscaled data was only available for three GCMs, namely the Canadian Centre for Climate Modelling and Analysis (Canada) version 2.0 (CGCM2), the Commonwealth Scientific and Industrial Research Organization (Australia) Atmospheric Research Mark 2 (CSIRO Mk2) and the Hadley Centre's (United Kingdom) HadCM3, and two emissions scenarios, that of the A2 and B2 (Table 1). These GCMs were selected by the previous authors (Fealy and Sweeney, 2007, 2008) due to their ready availability at the time their study was undertaken and, importantly, the models contributed to the Third Assessment Report (IPCC, 2001) and were widely employed in a range of climate impact studies.

Due to the limited availability of relevant statistically downscaled data for a range of emissions scenarios (e.g. A1FI, B1), a pattern

Table 1. List of GCMs employed in the initial analysis and change in global mean surface temperature (°C) for the A1FI, A2, B2 and B1 emissions scenarios for the 2071–2100 period. Emissions scenarios in italics are those that were available as statistically downscaled projections. The GCMs employed by Fealy and Sweeney (2007, 2008) all participated in the Third Assessment Report (IPCC, 2001). Data from Mitchell et al. (2002).

Model	Institution/Country	Reference	Scenario	ΔT_{global}
CGCM2	CCCma, Canada	Flato et al., 2000	A1FI	4.38
			A2	3.55
			B2	2.46
			B1	2.02
CSIRO Mk2	CSIRO, Australia	Hirst et al., 1996, 2000	A1FI	4.86
			A2	3.94
			B2	3.14
			B1	2.59
HadCM3	UKMO, UK	Gordon et al., 2000	A1FI	4.86
			A2	3.93
			B2	3.07
			B1	2.52

scaling method was employed to generate seasonal mean values for projected changes in temperature and precipitation for the A1FI and B1 emissions scenarios for the three GCMs listed above. In a modification of the pattern scaling methodology, the approach employed here applied the technique to statistically downscaled data as opposed to the more widespread approach which utilizes global or regional climate model output.

The method was applied as follows. The ratio of global mean temperature change (°C) between the individual GCMs and emissions scenarios (Table 1) was employed to scale the statistically downscaled A2 scenario projections for all stations, for both temperature and precipitation for the 2080s, according to the following equation:

$$\Delta T_{A1FI-GCM} = \left\langle \frac{\Delta T_{A1FI-GCM}}{\Delta T_{A2-GCM}} \right\rangle \Delta T_{A2-SD}$$

where ΔT_{A1FI} = projected downscaled change for the A1FI scenario for GCM_i, $\langle \Delta T_{A1FI}/\Delta T_{A2} \rangle$ = ratio of global mean temperature change for GCM_i (Table 1), and ΔT_{A2} = projected downscaled change in temperature for the 2080s period for the A2 scenario from GCM_i.

This method assumes that a linear relationship exists between the downscaled emissions scenarios for the stations (or grids when applied to regional or global climate model data) employed in the analysis. As both the A2 and B2 downscaled scenarios for temperature and precipitation were available, this assumption could be tested by scaling the downscaled A2 scenario, at each station, by the ratio of the A2 and B2 global mean surface temperature change for each GCM, to derive a scaled B2 emissions scenario. If a linear relationship was found to exist between the statistically downscaled B2 and pattern scaled B2 scenario, then the assumption was taken as valid.

Figure 1 illustrates the relationship, on a seasonal basis, between the statistically downscaled and pattern scaled B2 values, for both temperature and precipitation change, by the method outlined above, for the 2080s. While the assumption of a linear (spatial) response was found to be valid between driving emissions scenarios, the slope of the equation was found to vary seasonally. Therefore, seasonal regression equations were derived to account for the difference between the statistically downscaled B2 and pattern scaled B2 projections.

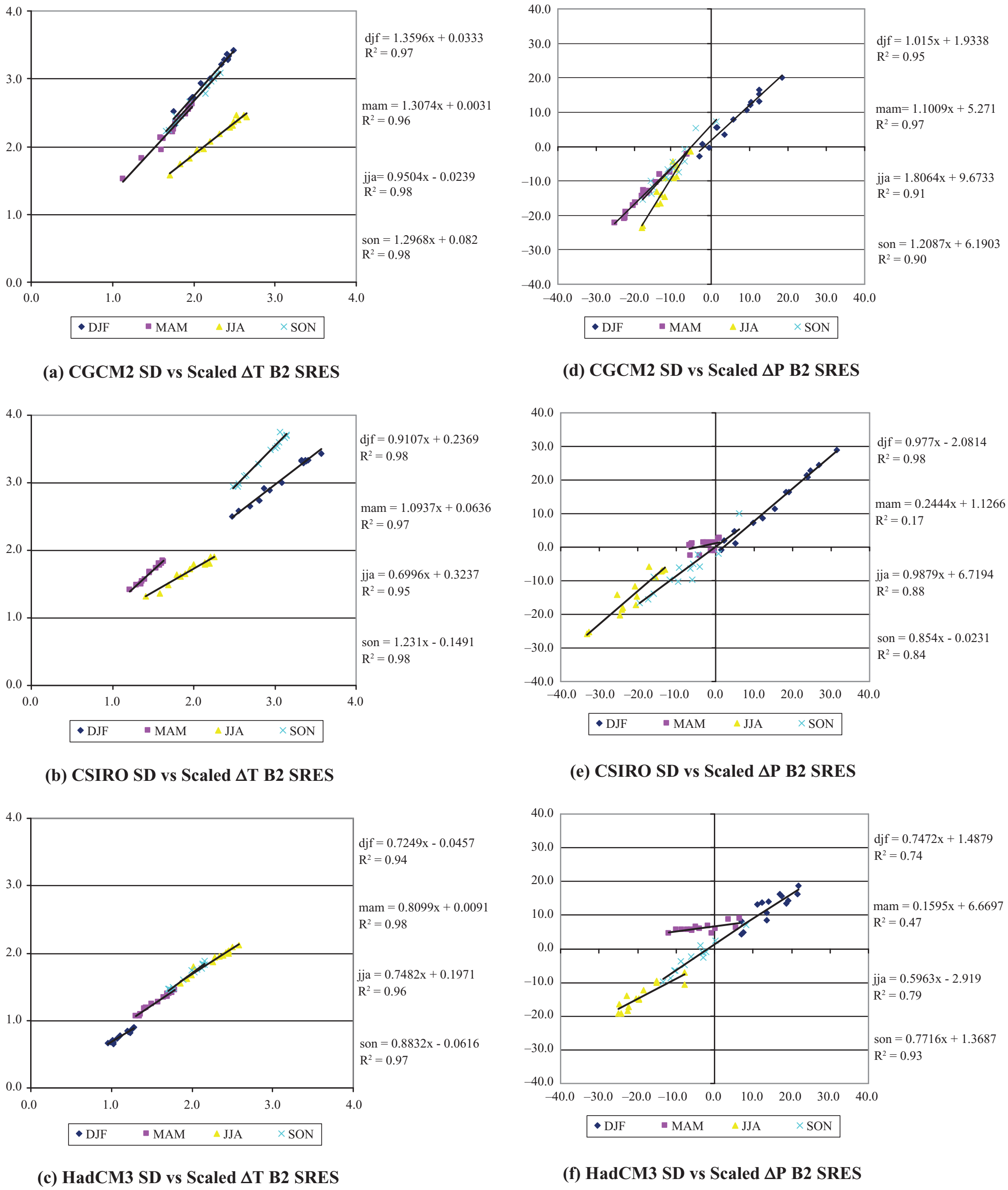

Figure 1. Comparison of statistically downscaled (SD) and scaled B2 temperature (a–c) and precipitation (d–f) based on pattern scaling the statistically downscaled A2 scenario for each GCM. Regression equations and explained variance for each season illustrate the relationship between the statistically downscaled station data and scaled B2 scenarios. These seasonally calculated equations were applied as a correction factor for calculating all scaled scenarios. Scatterplots on the left are in °C, while the scatterplots on the right are % change. (See colour version of this figure online).
Source: Data after Fealy and Sweeney (2007, 2008).

Table 2. GCM scaled temperature change (°C) for selected stations for the 2070–2099 period from three GCMs and the A1FI and B1 emissions scenarios (SRES). Emissions scenarios in italics are those that were available as statistically downscaled projections. The A1FI and B1 scenarios were derived by scaling the statistically downscaled A2 scenario according to the ratio of ΔT from the parent GCM and relevant emissions scenario for each season.

GCM	SRES	Valentia		Malin Head		Casement		Kilkenny	
		ΔT_{DJF}	ΔT_{JJA}	ΔT_{DJF}	ΔT_{JJA}	ΔT_{DJF}	ΔT_{JJA}	ΔT_{DJF}	ΔT_{JJA}
CGCM2	A1FI	5.1	3.6	4.3	3.1	5.9	4.2	5.7	4.5
CGCM2	*A2*	*3.0*	*3.1*	*2.5*	*2.6*	*3.5*	*3.6*	*3.4*	*3.8*
CGCM2	*B2*	*2.9*	*2.0*	*2.3*	*1.7*	*3.3*	*2.4*	*3.2*	*2.4*
CGCM2	B1	2.4	1.6	2.0	1.4	2.8	1.9	2.6	2.0
CSIRO	A1FI	4.4	2.1	3.7	1.9	5.0	2.4	5.0	2.7
CSIRO	*A2*	*3.7*	*2.1*	*3.1*	*1.8*	*4.2*	*2.4*	*4.2*	*2.8*
CSIRO	*B2*	*2.9*	*1.5*	*2.5*	*1.3*	*3.3*	*1.7*	*3.3*	*1.9*
CSIRO	B1	2.4	1.3	2.1	1.1	2.8	1.4	2.8	1.6
HadCM3	A1FI	1.2	2.5	1.1	2.4	1.4	3.1	1.4	3.3
HadCM3	*A2*	*1.4*	*2.5*	*1.2*	*2.4*	*1.6*	*3.1*	*1.6*	*3.3*
HadCM3	*B2*	*0.7*	*1.6*	*0.7*	*1.6*	*0.9*	*2.0*	*0.9*	*2.1*
HadCM3	B1	0.6	1.4	0.5	1.3	0.7	1.7	0.7	1.8

Table 3. Scaled percent change in precipitation (%) for selected stations for the 2070–2099 period from three GCMs and the A1FI and B1 emissions scenarios (SRES). Emissions scenarios in italics are those that were available as statistically downscaled projections. The A1FI and B1 scenarios were derived by scaling the statistically downscaled A2 scenario according to the ratio of ΔT from the parent GCM and relevant emissions scenario for each season.

GCM	SRES	Valentia		Malin Head		Casement		Kilkenny	
		ΔP_{DJF}	ΔP_{JJA}	ΔP_{DJF}	ΔP_{JJA}	ΔP_{DJF}	ΔP_{JJA}	ΔP_{DJF}	ΔP_{JJA}
CGCM2	A1FI	−3.8	−29.2	4.5	−22.3	24.5	−47.7	18.7	−19.4
CGCM2	*A2*	*−4.5*	*−17.4*	*2.0*	*−14.3*	*18.0*	*−25.7*	*13.3*	*−13.0*
CGCM2	*B2*	*−2.8*	*−14.5*	*5.5*	*−4.2*	*13.0*	*−23.0*	*10.7*	*−6.7*
CGCM2	B1	−0.7	−8.3	3.1	−5.1	12.3	−16.8	9.7	−3.7
CSIRO	A1FI	0.1	−24.8	5.5	−13.3	35.1	−31.0	26.6	−19.6
CSIRO	*A2*	*1.8*	*−25.9*	*6.3*	*−16.5*	*30.9*	*−31.0*	*23.8*	*−21.6*
CSIRO	*B2*	*−0.8*	*−17.3*	*4.6*	*−6.7*	*22.7*	*−20.2*	*16.3*	*−5.7*
CSIRO	B1	−0.9	−10.1	2.0	−4.0	17.8	−13.4	13.2	−7.3
HadCM3	A1FI	9.9	−24.3	10.5	−10.1	21.6	−24.6	22.1	−23.9
HadCM3	*A2*	*9.1*	*−29.0*	*9.7*	*−9.8*	*21.8*	*−29.3*	*22.3*	*−28.5*
HadCM3	*B2*	*8.1*	*−18.4*	*4.9*	*−7.0*	*16.3*	*−14.0*	*15.7*	*−17.4*
HadCM3	B1	5.8	−14.0	6.1	−6.7	11.9	−14.1	12.2	−13.8

Having tested the assumption of a linear response pattern, the method was then applied to the statistically downscaled A2 scenarios for all stations and the three GCMs (Table 1) to calculate station level changes for the A1FI and B1 emissions scenarios, based on the respective global temperature response (ΔT_{global}) from the parent GCM. The results from the application of this method are outlined in Table 2, for temperature (°C), and Table 3, for precipitation change

Table 4. Minimum and maximum temperature response (°C)/°C ΔT_{global} for the 14 synoptic stations in Ireland derived from three GCMs and four emissions scenarios, based on the statistically downscaled and scaled station level warming. Stations in italics represent stations referred to in the text.

Temperature (°C)	DJF		MAM		JJA		SON	
	Min	Max	Min	Max	Min	Max	Min	Max
Valentia	*0.23*	*1.19*	*0.38*	*0.93*	*0.44*	*0.86*	*0.48*	*1.01*
Shannon	0.26	1.33	0.44	1.01	0.51	0.99	0.56	1.15
Dublin	0.21	1.02	0.42	0.86	0.47	0.89	0.55	1.17
Malin Head	*0.21*	*0.99*	*0.35*	*0.85*	*0.38*	*0.75*	*0.47*	*0.94*
Roche's Point	0.22	1.10	0.36	0.74	0.49	0.80	0.47	0.97
Belmullet	0.22	1.11	0.37	0.93	0.48	0.83	0.48	1.01
Clones	0.27	1.35	0.46	1.03	0.55	1.03	0.58	1.17
Rosslare	0.22	1.12	0.35	0.62	0.42	0.70	0.48	1.00
Claremorris	0.27	1.36	0.44	1.07	0.56	1.01	0.57	1.18
Mullingar II	0.27	1.36	0.47	1.05	0.54	1.04	0.59	1.21
Kilkenny	*0.28*	*1.31*	*0.46*	*0.99*	*0.56*	*1.08*	*0.60*	*1.27*
Casement	*0.28*	*1.36*	*0.45*	*0.96*	*0.50*	*1.01*	*0.59*	*1.22*
Cork	0.24	1.23	0.40	0.87	0.54	0.94	0.52	1.08
Birr	0.28	1.39	0.46	1.05	0.57	1.06	0.59	1.25

(%), for the selected stations of Valentia, Malin Head, Casement and Kilkenny for the winter (DJF) and summer (JJA) seasons for the 2080s period. These stations were selected as they represent a mix of coastal and interior stations that are dispersed throughout the island and therefore likely to be illustrative of different climatological regimes. The lower temperatures associated with the HadCM3 for the Irish grid box are consistent with previous studies that have employed this model for this region (e.g. Fealy and Sweeney, 2008; Mullan et al., 2012) (Table 2).

2 Derivation of regional response rates

The next stage in the methodology was to calculate regional response rates (i.e. the regional rate of warming per °C global warming) for each station. As a number of GCMs were included in the analysis, the derived regional response rates should represent a sample from the total regional response rate space, which in turn reflect uncertainties in the driving GCMs and emissions scenarios.

Following the method of Hulme and Carter (1999), in order to calculate the regional response rate at each station, the seasonal projected (statistically downscaled and pattern scaled) changes in temperature ($\Delta T_{station}$) and precipitation ($\Delta P_{station}$) for each four selected emissions scenarios were normalized by the parent GCM/emissions scenario combination change in the global mean surface temperature change from Table 1. For example, to calculate the regional response rate for the CGCM2 GCM for the A1FI scenario for winter at Valentia, the projected A1FI $\Delta T_{Valentia}$ of 5.1°C (from Table 2) is normalized by the global ΔT (ΔT_{global}) change from the CGCM2 A1FI of 4.38°C (from Table 1). The resultant normalized value of 1.16°C represents a regional or station response rate of 1.16°C/°C global warming, i.e. for an increase in global mean surface temperature of 1°C, winter seasonal mean temperatures at Valentia are projected to increase by 1.16°C ($\Delta T_{Global} \times \Delta T_{station}$), indicating an above 'average' warming rate at Valentia for that GCM/emissions scenario combination. Minimum and maximum regional response rates

Table 5. Minimum and maximum precipitation response (%)/°C ΔT_{global} for the 14 synoptic stations in Ireland derived from three GCMs and four emissions scenarios, based on the statistically downscaled and scaled station level warming. Stations in italics represent stations referred to in the text.

Precipitation (%)	DJF		MAM		JJA		SON	
	Min	Max	Min	Max	Min	Max	Min	Max
Valentia	*−1.28*	*2.64*	*−5.89*	*2.34*	*−7.38*	*−3.91*	*−6.33*	*−2.32*
Shannon	0.66	4.43	−10.22	2.66	−7.72	−4.43	−4.09	−0.24
Dublin	5.59	10.01	−6.59	2.28	−11.07	−5.34	−4.73	−1.20
Malin Head	*0.57*	*2.47*	*−9.24*	*2.94*	*−5.09*	*−1.53*	*−1.62*	*2.20*
Roche's Point	1.37	4.42	−2.78	2.20	−10.58	−4.83	−7.41	−2.81
Belmullet	−0.93	2.32	−6.77	2.44	−4.49	−1.80	−2.83	0.00
Clones	4.42	7.64	−9.08	2.98	−6.55	−2.26	−3.96	−0.17
Rosslare	2.35	4.89	−5.45	2.03	−8.07	−2.37	−4.56	−1.99
Claremorris	3.51	5.84	−7.38	2.87	−4.88	0.81	−4.59	−0.19
Mullingar II	4.20	7.58	−9.12	2.61	−8.26	−3.73	0.53	3.70
Kilkenny	*3.76*	*6.05*	*−8.01*	*2.39*	*−7.25*	*−1.82*	*−6.16*	*−2.10*
Casement	*4.45*	*7.85*	*−7.21*	*2.35*	*−10.89*	*−4.55*	*−3.40*	*−0.81*
Cork	−0.22	4.27	−4.40	2.13	−7.92	−1.81	−6.44	−1.38
Birr	5.07	8.57	−8.26	2.56	−8.24	−3.78	−2.82	0.29

for the 14 synoptic stations for both temperature and precipitation are shown in Tables 4 and 5. These values reflect the minimum and maximum values from the three GCMs and four emissions scenarios.

The derived regional response rates were assumed to be illustrative of the likely total range in regional response rates if a wider range of GCMs had been included. To assess this contention, data from 17 GCMs (Table 6), all of which contributed to the Fourth Assessment Report (IPCC, 2007), were employed to derive regional response rates for the model grid box(es) representing Ireland. Differences in ΔT (°C) between specific models and emissions scenarios identified in Table 1 and Table 7 are attributed to availability of different experimental runs of the model (e.g. ΔT (°C) for some emissions scenarios in Table 1 were calculated using MAGICC). Additionally, the reported ΔT_{global} (°C) in Table 1 represent the period 2071–2100, while the statistically downscaled data cover the period 2070–2099. These differences are considered to have a negligible impact on the findings highlighted here. As the GCM data existed on differing resolutions, the data from each GCM was regridded to a common resolution of 3.75° × 3.75° employing a simple spatial interpolation procedure, consistent with the resolution of the GCMs employed above. Monthly data for both temperature and precipitation rate for both the 1961–1990 (20C3M) and 2070–2099 periods was then extracted from the resultant grid cell representing Ireland for the three available emissions scenarios, namely, the A1B, A2 and B2 (Table 7). Seasonal mean values for temperature and precipitation were then calculated to determine the projected change in these variables between the control (20C3M) and future (2070–2099) scenario runs for the three emissions scenarios. On the basis of this derived data, regional response rates were calculated, as above, for the grid box representing Ireland for each of the 17 GCMs and three scenarios.

While a direct comparison between GCM grid box, representing Ireland, and point scale (station level) regional response rates is not feasible, regional response ranges derived from a selection of the GCMs for the Irish grid box are

Table 6. List of the GCMs employed to calculate the regional response rates for the Irish grid box. All models were regridded to a common resolution of 3.75° × 3.75° to enable comparisons between models. The GCMs listed were employed in the Fourth Assessment Report (IPCC, 2007) (Data from the IPCC Data Distribution Centre; http://www.ipcc-data.org).

Sn	Model (GCM)	Modelling group	Spatial resolution (Lon*Lat)	No of cells	Equilibrium climate sensitivity (°C)	Transient climate response (°C)
1	BCCR-BCM2.0	Bjerknes Centre for Climate Research (Norway)	Gaussian – 128 × 64	2	–	–
2	CCSM3	National Centre for Atmospheric Research (USA)	Gaussian 256 × 128	9	2.7	1.5
3	CGCM3.1 (T47)	Canadian Centre for Climate Modelling and Analysis (Canada)	Gaussian 96 × 48	1	3.4	1.9
4	CSIRO-Mk3.0	CSIRO Atmospheric Research (Australia)	Gaussian 192 x 96	4	3.1	1.4
5	CNRM-CM3	Météo-France/Centre National de Recherches Météorologiques (France)	Gaussian 128 × 64	2	n.a.	1.6
6	ECHAM5/MPI-OM	Max Planck Institute for Meteorology (Germany)	Gaussian 192 × 96	4	3.4	2.2
7	ECHO-G	Meteorological Institute of the University of Bonn/ KMA meteorological inst., and M & D group (Germany/Korea)	Gaussian 96 × 48	1	3.2	1.7
8	GFDL-CM2.0	Geophysical Fluid Dynamics Laboratory (USA)	Regular 144 × 90	3	2.9	1.6
9	GFDL-CM2.1	Geophysical Fluid Dynamics Laboratory (USA)	Regular 144 × 90	3	3.4	1.5
10	GISS-ER	NASA/Goddard Institute for Space Studies (USA)	Regular 72 × 46	1	2.7	1.5
11	UKMO-HadCM3	UK Met. Office (UK)	Regular 96 × 73	2	3.3	2.0
12	UKMO-HadGEM1	UK Met. Office (UK)	Regular 192 × 145	6	4.4	1.9
13	INM-CM3.0	Institute for Numerical Mathematics (Russia)	Regular 72 × 45	1	2.1	1.6
14	IPSL-CM4	Institute Pierre Simon Laplace (France)	Regular 96 × 72	2	4.4	2.1
15	MIROC3.2 (medres)	National Institute for Environmental Studies, and Frontier Research Centre for Global Change (Japan)	Gaussian 128 × 64	2	4	2.1
16	MRI-CGCM2.3.2	Meteorological Research Institute (Japan)	Gaussian 128 × 64	2	3.2	2.2
17	PCM	National Centre for Atmospheric Research (USA)	Gaussian 128 × 64	2	2.1	1.3

Table 7. Change in global ΔT (°C) associated with each of the 17 GCMs outlined in Table 6 for the three available SRES (A1B, A2, B1) for the 2070–2099 period (data from the IPCC Data Distribution Centre; http://www.ipcc-data.org). Blank cells indicate that data were not available for that particular GCM/emissions scenario combination. Differences are evident in ΔT in selected models from Table 1. These differences are attributed to variant runs or experiments undertaken by the specific modelling centres and the method employed (MAGICC) to scale the GCM data in Table 1.

Sn	Model (GCM)	CERA (Acronym)	A1B	A2	B1
1	BCCR-BCM2.0	BCM2	2.99	3.38	1.98
2	CCSM3	NCCCSM	3.38	4.30	2.11
3	CGCM3.1 (T47)	CGMR	2.85		
4	CSIRO-Mk3.0	CSMK3	2.20	2.89	1.29
5	CNRM-CM3	CNCM3	3.06	3.77	2.03
6	ECHAM5/MPI-OM	MPEH5	3.61	3.74	2.58
7	ECHO-G	ECHOG	3.01	3.26	
8	GFDL-CM2.0	GFCM20	3.22	3.44	2.39
9	GFDL-CM2.1	GFCM21	2.80	3.21	1.94
10	GISS-ER	GIER	2.23	2.73	1.62
11	UKMO-HadCM3	HADCM3	3.40	3.81	2.42
12	UKMO-HadGEM1	HADGEM	4.20	2.78	
13	INM-CM3.0	INCM3	3.12	3.74	2.46
14	IPSL-CM4	IPCM4	3.42	3.85	2.60
15	MIROC3.2 (medres)	MIMR	3.57	3.90	2.52
16	MRI-CGCM2.3.2	MRCGCM	2.56	2.84	1.87
17	PCM	NCPCM		2.85	

Table 8. Temperature (°C) and precipitation (%) response ranges (minimum and maximum) for the 2070–2099 period for the land area grid boxes (Ireland) encompassing Ireland derived from 14 GCMs (Ireland), excluding those models employed previously, and the minimum and maximum response rates derived from the 14 synoptic stations (Stations) derived from three GCMs. For comparative purposes, response rates are shown for the two emissions scenarios in common, namely the A2 and B1.

	Variable	DJF	MAM	JJA	SON
Ireland (14 GCMs)	Temperature	0.28 – 0.95	0.28 – 0.98	0.15 – 1.26	0.08 – 1.42
	Precipitation	–0.7 – +12.7	–20.8 – –5.6	–30.9 – –12.1	–3.97 – +6.9
Stations (3 GCMs)	Temperature	0.21 – 1.39	0.35 – 1.05	0.44 – 1.08	0.47 – 1.27
	Precipitation	–1.3 – +10.0	–10.2 – +2.9	–10.6 – +0.81	–7.3 – +3.7

shown in Table 8 for illustrative purposes. To assess if the original three GCMs employed in the pattern scaling approach above, namely CGCM2, CSIRO Mk2 and HadCM3, were a representative sample of the likely response rates if a larger sample of GCMs had been included, these three GCMs were excluded from the results presented in Table 8. Additionally, only regional response rates for the A2 and B1 emissions scenarios, in common between both the selected 14 GCMs (Ireland) and the station level data (Stations), are shown. Broadly, the minimum and maximum response rates calculated for temperature for both the Irish grid box (Ireland), based on 14 GCMs, and synoptic stations (Stations), based in the statistically downscaled and pattern scaled data (3 GCMs), are comparable, while the minimum response rates for precipitation tend to deviate more significantly (Table 8). The largest differences are associated with the minimum response rates for precipitation in Spring (MAM) and Summer (JJA), of –20.8%/°C and –30.9%/°C for the Irish grid box and –10.2%/°C and –10.6%/°C for the synoptic stations, respectively. The difference in values between the regional response rates calculated at the grid box and point scale can perhaps in part be explained by the difference in scale, but also by the recognized inability of GCMs to reliably simulate this variable at grid/regional scales. This finding also highlights the significant divergence evident between GCMs in projecting precipitation which gives rise to much larger projected precipitation changes relative to the statistically downscaled values.

On the basis of a comparison based on the values outlined in Table 8, the regional response rates at each station were taken to be representative of the likely regional response rates if a larger number of GCMs had been included in the statistical downscaling of Fealy and Sweeney (2007, 2008), taking into consideration the difference in spatial scales and GCM lineage. However, to confirm this, statistically downscaled data from a wider range of GCMs would be required. At a minimum, the regional response rates calculated at the station level capture a significant portion of the uncertainty space identified from the larger suite of 14 ‘independent’ GCMs.

3 Deriving probabilistic based seasonal scenarios

In order to generate probability distribution functions (pdfs) of changes in temperature and precipitation for individual synoptic stations, which take into account some of the key uncertainties, including emissions (through the incorporation of four marker scenarios) and GCM uncertainty (through the derived regional response rates), a Monte Carlo (MC) sampling technique was employed to sample from the minimum and maximum ranges in regional response rates for both temperature (Table 4) and precipitation (Table 5) for the four selected synoptic stations and for different estimates of future warming as represented by ΔT_{global}. The two estimates of ΔT_{global} were as follows:

1. ΔT in global mean surface temperature change (2070–2099) from the three global climate models employed in the statistical downscaling approach employed by Fealy and Sweeney (2007, 2008) (Table 1 – range in ΔT_{global} from 2.02 to 4.86°C representing the range in warming associated with the three GCMs and four emissions scenarios employed) (Method I);
2. ΔT in global mean surface temperature change (2070–2099) from the 17 global climate models from Table 7. For consistency, the available minimum and maximum range in ΔT_{global} (ΔT_{global} range of 1.29 to 4.3°C) was taken from the A2 and B1 scenarios (Table 7) as values for these emissions scenarios were also available for the station level regional response rates, derived from the statistically downscaled and pattern scaled approach described previously (derived from Table 3) (Method II).

In addition, the ΔT in global mean surface temperature change (2070–2099) from a combination of GCM and emissions scenarios (Table 1 and Table 7) were employed in conjunction with the regional response rates from one station, Casement Aerodrome, located on the east coast of the island of Ireland, to highlight differences between the four marker emissions scenarios of A1FI, A2, B2 and B1.

As the range in values could not be assumed to be drawn from a specific distribution, a uniform prior (i.e. ascribes an equal probability to all values) was ascribed to both the regional response rates at the station level and the range in ΔT_{global} derived from the GCMs. For all methods, the MC simulation was set to produce 10,000 replications or samples.

The Monte Carlo sampling technique was applied as follows. The regional response range (minimum and maximum values) for winter temperature at Valentia for the 2080s is 0.23–1.19 (°C/°C ΔT_{global}) (Table 4). The MC analysis was set to generate 10,000 randomly sampled values from this range, based on a uniform prior. A parallel set of 10,000 randomly sampled values was generated based on the ΔT in global mean surface temperature change from the three global climate models (2.02 to 4.86°C) outlined in Table 1, again based on a uniform prior. The resultant pdfs were then generated based on the combination of the two uniform distributions (i.e. $\Delta T_{global} \times \Delta T_{station}$).

IV Results

Tables 9 and 10 show the results for each of the two different measures of changes in global ΔT (Methods I and II) with the regional response rates at the selected synoptic stations of Valentia, Malin Head, Kilkenny and Casement. The results from Methods I and II are also compared to the ensemble of the statistically downscaled A2 and B2 emissions scenario calculated by Fealy and Sweeney (2007, 2008) employing the IR-CPI (after Wilby and Harris, 2006) (Table 11).

Probability distribution functions for changes in temperature and precipitation, at each station and season, based on Method I are shown in Figures 2 and 3, for the 2080s. Projected changes in both temperature and precipitation are shown to display a considerable spread in values. For example, winter temperature at Casement suggests an increase from 0.6 to 6.6°C by the 2080s (2070–2099) period. In fact, winter temperatures at all stations show a greater spread than in all other seasons. Temperature displays a consistent direction of change for all seasons, in spite of the differences in magnitudes. For precipitation, differences in both direction and magnitude are projected, with equal likelihood, at all stations for spring. Winter precipitation at Valentia and autumn precipitation at Malin Head also display different directions of change with equal likelihoods. Results from the statistical downscaled ensemble (Table 11), while comparable to the mean changes projected by Method I, take no account of uncertainties or the fact that a projected change could differ in direction. Importantly, the pdfs indicate a clear direction of change for precipitation for some seasons, namely summer and autumn, independent of GCM and emissions scenario.

Figures 4 and 5 illustrate the derived pdfs for temperature and precipitation change based on Method II, which employed an estimate of global surface temperatures (1.29 to 4.3°C) from a range of 17 GCMs (Table 7) rather than from just three GCMs originally employed by Fealy and Sweeney (2007, 2008) (Table 1). As only two emissions scenarios were in common between both the 17 GCMs and the station level regional response rates, namely the A2 and B1, the resultant pdfs tend to display a smaller range in values when compared to Method I, which included four emissions scenarios (A1FI, A2, B2, B1). Similarly, seasonal mean projected changes are slightly lower for Method II. In spite of this, the projected seasonal mean changes in temperature and precipitation at the four stations are comparable. Similar to Method I, Method II indicates that projected changes in precipitation are likely to differ in both direction and magnitude, particularly in spring, reflecting large inter-GCM model uncertainties in this variable at the regional/station level scale.

In a comparison of projected mean changes in temperature and precipitation by the 2080s between the original statistically downscaled ensemble data from Fealy and Sweeney (2007, 2008) and the combined pattern scaling and MC methods employed here, the probabilistic approach (Method I) indicates equivalent or

Table 9. Method I. Seasonal mean change in temperature (°C) and precipitation (%) for Valentia, Malin Head, Kilkenny and Casement for the 2080s. Also shown are values for minimum (min), maximum (max), median (med) and quartiles (Q1 = 1st quartile; Q3 = 3rd quartile).

Method I		Temperature						Precipitation					
Station	Season	Mean	Min	Q1	Med	Q3	Max	Mean	Min	Q1	Med	Q3	Max
Valentia	DJF	2.4	0.5	1.5	2.3	3.2	5.8	2.3	–6.2	–1.0	2.2	5.4	12.8
	MAM	2.3	0.8	1.7	2.1	2.8	4.5	–6.1	–28.5	–12.4	–5.7	0.9	11.3
	JJA	2.2	0.9	1.7	2.2	2.7	4.2	–19.4	–35.8	–23.4	–18.8	–14.9	–8.0
	SON	2.6	1.0	1.9	2.5	3.1	4.9	–14.9	–30.7	–18.5	–14.0	–10.7	–4.7
Malin Head	DJF	2.1	0.4	1.3	1.9	2.7	4.8	5.2	1.2	3.4	4.9	6.8	12.0
	MAM	2.1	0.7	1.5	2.0	2.5	4.1	–10.9	–44.8	–20.2	–10.2	–0.4	14.1
	JJA	1.9	0.8	1.5	1.9	2.4	3.6	–11.4	–24.7	–14.5	–10.7	–7.8	–3.1
	SON	2.4	1.0	1.9	2.3	2.9	4.6	1.0	–7.9	–2.2	0.9	4.0	10.7
Kilkenny	DJF	2.7	0.6	1.7	2.6	3.6	6.4	16.9	7.6	13.1	16.6	20.2	29.4
	MAM	2.5	0.9	1.9	2.4	3.0	4.8	–9.7	–38.9	–17.6	–9.2	–0.7	11.5
	JJA	2.8	1.1	2.2	2.7	3.4	5.2	–15.6	–35.2	–20.0	–14.6	–10.3	–3.7
	SON	3.2	1.2	2.4	3.1	3.9	6.2	–14.2	–29.9	–17.8	–13.4	–10.1	–4.3
Casement	DJF	2.8	0.6	1.8	2.7	3.7	6.6	21.2	9.0	16.4	20.6	25.4	38.1
	MAM	2.4	0.9	1.8	2.3	2.9	4.7	–8.3	–34.8	–15.6	–7.8	–0.1	11.4
	JJA	2.6	1.0	2.0	2.5	3.2	4.9	–26.6	–52.7	–32.7	–25.2	–19.7	–9.2
	SON	3.1	1.2	2.4	3.0	3.8	5.9	–7.2	–16.5	–9.4	–6.8	–4.7	–1.7

Table 10. Method II. Seasonal mean change in temperature (°C) and precipitation (%) for Valentia, Malin Head, Kilkenny and Casement for the 2080s. Also shown are values for minimum (min), maximum (max), median (med) and quartiles (Q1 = 1st quartile; Q3 = 3rd quartile).

Method II		Temperature						Precipitation					
Station	Season	Mean	Min	Q1	Med	Q3	Max	Mean	Min	Q1	Med	Q3	Max
Valentia	DJF	1.5	0.1	1.0	1.5	2.0	4.1	1.5	–4.4	–0.6	1.4	3.4	9.8
	MAM	1.4	0.2	1.1	1.4	1.7	3.3	–3.8	–19.8	–8.0	–3.7	0.6	8.3
	JJA	1.4	0.2	1.1	1.4	1.6	3.2	–12.1	–25.7	–14.2	–11.9	–9.8	–1.6
	SON	1.6	0.3	1.3	1.6	1.9	3.6	–9.3	–22.3	–11.4	–9.0	–6.9	–0.9
Malin Head	DJF	1.3	0.2	0.8	1.2	1.7	3.4	3.3	0.3	2.2	3.2	4.2	8.3
	MAM	1.3	0.2	1.0	1.3	1.6	2.8	–6.8	–30.6	–13.0	–6.6	–0.3	9.8
	JJA	1.2	0.2	1.0	1.2	1.4	2.7	–7.1	–17.5	–9.0	–6.9	–5.0	–1.3
	SON	1.5	0.2	1.2	1.5	1.8	3.3	0.6	–5.3	–1.4	0.6	2.6	7.4
Kilkenny	DJF	1.7	0.2	1.1	1.6	2.2	4.6	10.5	1.8	8.8	10.4	12.1	21.8
	MAM	1.6	0.2	1.2	1.5	1.9	3.7	–6.1	–27.2	–11.3	–5.9	–0.5	8.4
	JJA	1.8	0.3	1.4	1.7	2.1	3.9	–9.7	–27.4	–12.5	–9.4	–6.6	–1.1
	SON	2.0	0.3	1.6	2.0	2.4	4.9	–8.9	–23.7	–11.0	–8.6	–6.5	–1.3
Casement	DJF	1.8	0.2	1.1	1.7	2.3	4.7	13.2	2.1	10.9	13.0	15.4	26.8
	MAM	1.5	0.2	1.2	1.5	1.8	3.4	–5.2	–24.0	–10.0	–5.0	–0.1	7.6
	JJA	1.6	0.3	1.3	1.6	1.9	3.4	–16.6	–39.2	–20.1	–16.2	–12.7	–1.8
	SON	1.9	0.3	1.5	1.9	2.3	4.1	–4.5	–12.4	–5.8	–4.4	–3.0	–0.5

Table 11. Comparison of projected mean temperature (°C) and precipitation (%) change in the statistically downscaled ensemble (SD-Ens) for selected stations, based on the A2 and B2 emissions scenarios, calculated by Fealy and Sweeney (2007, 2008) employing the IR-CPI approach (after Wilby and Harris, 2006), the mean change calculated from the probability distribution functions (Method I) employing the broader range of emissions scenarios (A1FI, A2 B2, B1) and for the probability distribution functions derived from the 17 GCMs and station level regional response rates for the A2 and B1 emissions scenarios (Method II). All values are for the 2080s (2070–2099) period.

		Temperature			Precipitation		
Station	Season	SD-Ens	Method I	Method II	SD-Ens	Method I	Method II
Valentia	DJF	2.0	2.4	1.9	3.5	2.3	1.5
	MAM	1.9	2.3	1.8	−9.8	−6.1	−5.0
	JJA	2.1	2.2	1.9	−25.6	−19.4	−15.9
	SON	2.4	2.6	2.1	−16.0	−14.9	−12.1
Malin Head	DJF	1.7	2.1	1.7	5.8	5.2	4.2
	MAM	1.7	2.1	1.7	−11.1	−10.9	−8.9
	JJA	1.9	1.9	1.7	−13.1	−11.4	−8.0
	SON	2.3	2.4	2.0	0.1	1.0	−0.7
Kilkenny	DJF	2.3	2.7	2.2	16.9	16.9	13.7
	MAM	2.1	2.5	2.0	−12.7	−9.7	−8.0
	JJA	2.7	2.8	2.4	−25.8	−15.6	−12.6
	SON	3.0	3.2	2.6	−16.7	−14.2	−11.6
Casement	DJF	2.3	2.8	2.3	19.2	21.2	17.6
	MAM	2.1	2.4	1.7	−9.7	−8.3	−6.8
	JJA	2.6	2.6	2.2	−31.8	−26.6	−18.9
	SON	2.9	3.1	2.5	−10.5	−7.2	−6.1

greater warming for all seasons at the selected stations. For projected changes in precipitation, Method I indicates more conservative changes, mainly lower projected decreases, for nearly all stations and seasons when compared to the statistically downscaled ensemble results. Such small differences between both approaches are not unexpected, as fundamentally both methods rely on the same parent GCMs (Table 1).

Method II, which employed only two emissions scenarios, the A2 and B1, but a larger number of GCMs, indicates much more conservative projected mean changes in temperature and precipitation by the 2080s for the selected stations in all seasons. The lower projected values, when compared to the statistically downscaled ensemble method (SD-Ens) or Method I approach can be readily explained by the difference in ΔT_{global} between the various approaches. The SD-Ens and Method I employ the same parent GCMs (ΔT_{global} ranges from 2.02 to 4.86°C), while for Method II, in spite of employing more GCMs with a larger range in ΔT_{global} (1.29 to 4.3°C), the minimum and maximum values are lower than those employed by the other two approaches, highlighting the contribution of emissions scenario uncertainty.

Figure 6 illustrates boxplots of the application of the methods outlined above to just one synoptic station, that of Casement Aerodrome, a station located on the east coast of Ireland, to illustrate the range in GCM derived projections both within and between individual emissions scenarios for seasonal mean temperature. Figure 7 shows the same, but for seasonal mean precipitation. While all GCM and emissions scenarios indicate that warming is likely to occur at Casement Aerodrome by the end of the

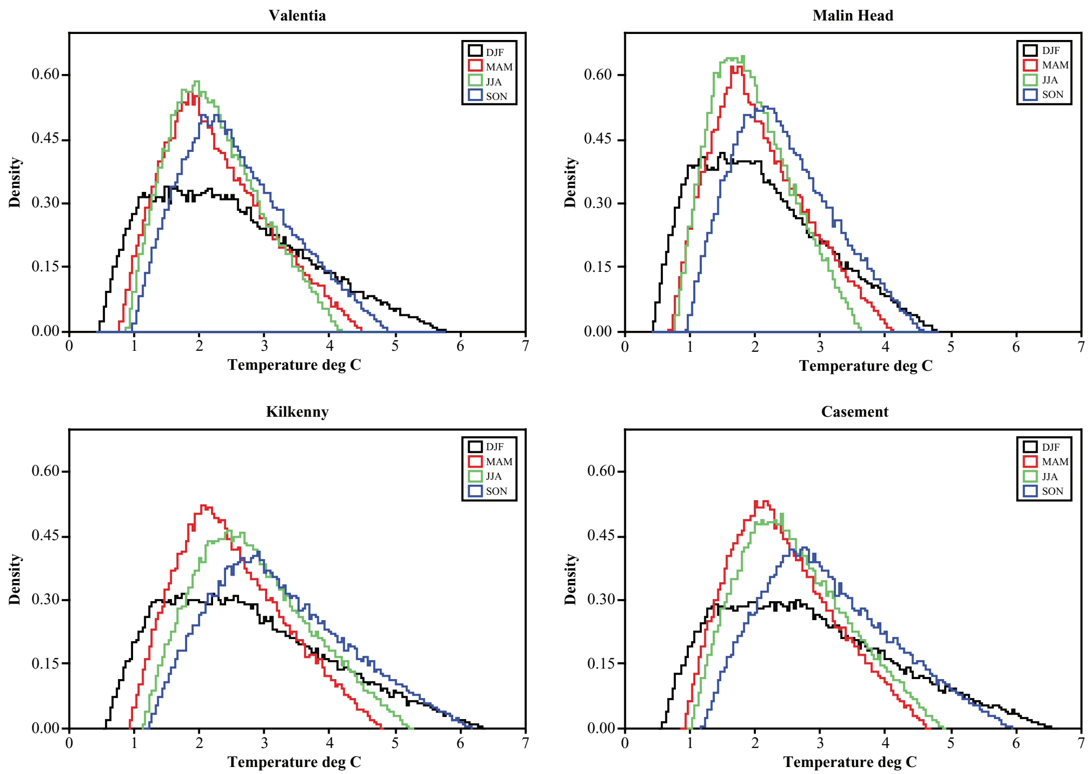

Figure 2. Method I. Probability distribution functions of projected change in seasonal mean temperature (°C) for Valentia, Malin Head, Kilkenny and Casement for the 2070–2099 period, assuming a uniform distribution for ΔT_{global} from three GCMs (Table 1) and the regional response rates. (See colour version of this figure online).

present century, the magnitude of the projected changes vary according to GCM and emissions scenario. The largest range in projected change in mean temperature for any one emissions scenario is projected for the A1FI scenario during the winter season (1.3–6.5°C). When the four emissions scenarios are considered, the range increases to 0.3–6.5°C for winter. The season with the smallest projected range in mean temperature, when all emissions scenarios are considered, is summer (0.6–4.6°C).

For precipitation, as with Methods I and II, the largest changes are projected to occur in winter (+6 to +35%) and summer (–53.0 to –6.0%). From Figure 7, the projected direction of change in mean precipitation at Casement Aerodrome is consistent between emissions scenarios. However, for spring, when the full range in projections is considered, both the direction and magnitude of change (–32.0 to +6.0) are found to differ between GCMs and emissions scenarios. These findings highlight the difficulty with any approach that requires GCM models to provide accurate and reliable 'predictions' (such as the 'predict and provide' approach) and also, the likely challenges associated with the single trajectory approach, which until recently, has been common practice within the impacts community.

V Discussion and Conclusions

Kass and Raftery (1995) suggest that 'any approach that selects a single model and then makes inference conditionally on that model ignores the uncertainty involved in model selection, which can be a big part of overall

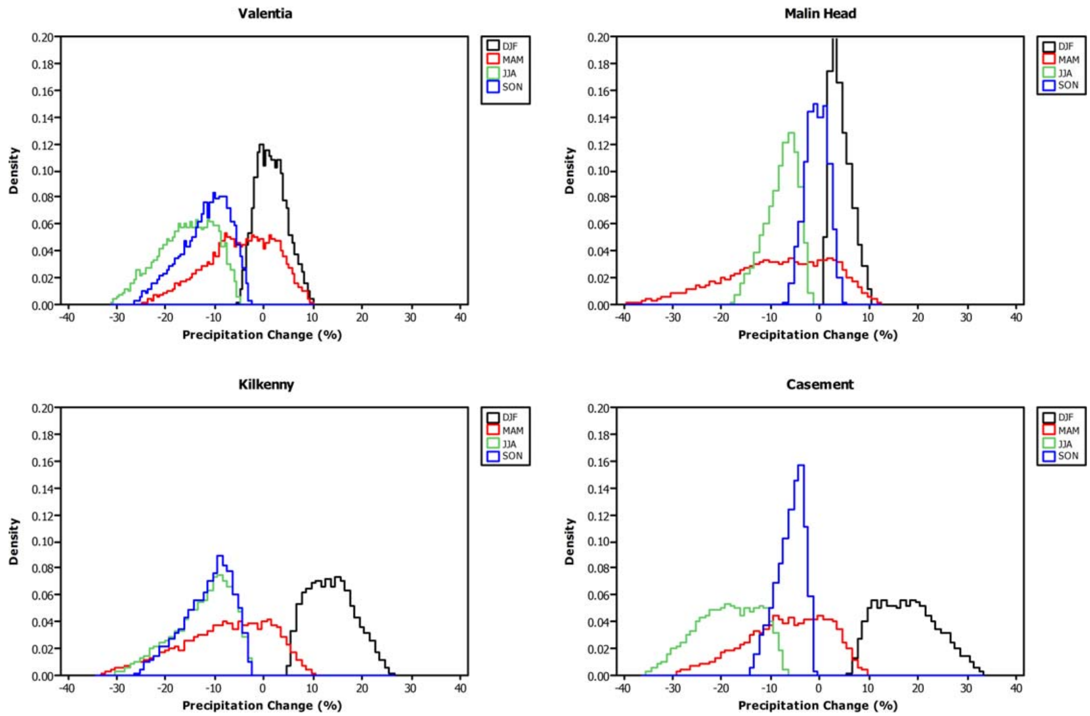

Figure 3. Method I. Probability distribution functions of projected change in seasonal precipitation (%) for Valentia, Malin Head, Kilkenny and Casement for the 2070-2099 period, assuming a uniform distribution for ΔT_{global} from three GCMs (Table 1) and the regional response rates. (See colour version of this figure online).

uncertainty', and 'this leads to underestimation of the uncertainty about quantities of interest, sometimes to a dramatic extent' (Kass and Raftery 1995: 784). Yet, in spite of this early acknowledgement, the climate modelling and impacts community continued to produce and employ single trajectory climate scenarios for use in impact assessments which sought to inform policy making ('predict and provide'). While there was a valid historical reason for such, arising from the limited number of centres who were undertaking global climate modelling due to the computational resources required and associated expense of running such model simulations, the implications for the policy community were significant. GCMs have been found to produce such divergent scenarios at the regional scale that it is difficult, if not impossible, to develop appropriate adaptation strategies (Stakhiv, 1998) based on one or a few global climate models. Hulme and Carter (1999) consider the practice of employing a limited number of climate scenarios as 'dangerous', as such an approach only reflects a partial assessment of the associated risk involved. Modelling the climate system will always result in a range of possible futures being projected, even when forced with the same emissions scenario (Hulme and Carter, 1999).

While a number of techniques have developed in order to account for model differences, an inability to produce probabilistic based projections has proved a limiting factor in enabling the potential risk of climate change impacts in key sectors to be quantified, and potentially hindered the subsequent development of suitable policy responses to reduce or mitigate such impacts. More recently, this topic has received

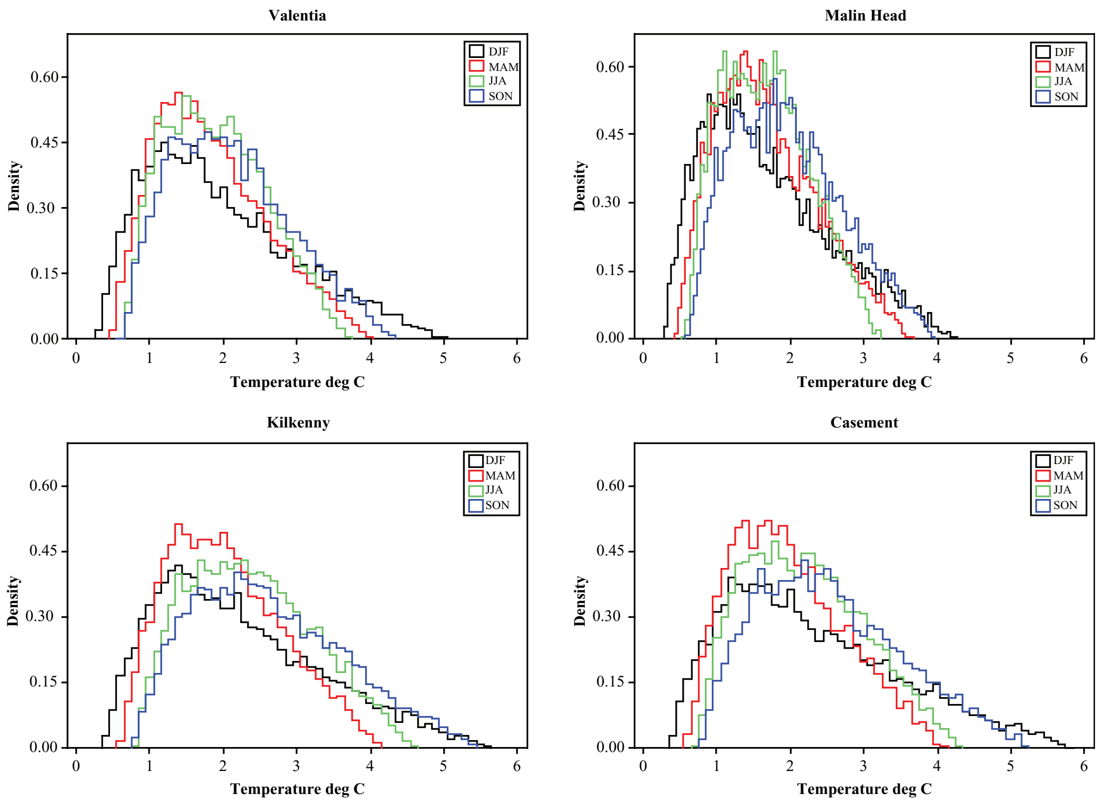

Figure 4. Method II. Probability distribution functions of projected change in seasonal mean temperature (°C) for Valentia, Malin Head, Kilkenny and Casement for the 2070–2099 period, employing uniform priors for ΔT_{global} from the 17 GCMs and station level regional response rates. Probability distributions functions are for the A2 and B1 emissions scenarios. (See colour version of this figure online).

much attention in the literature, with divergent attitudes and opinions towards the most suitable approach to employ. In spite of such divergence in attitudes, the discussion is a necessary one. Some exciting developments have also emerged, through the perturbed physics experiments (PPEs) (Murphy et al., 2004) and large-scale experiments such as Climateprediction.net, which included a significant participation of non-climate scientists and the public at large in providing distributed computer resources for climate modelling at the global scale. More recently, the development of scenario-neutral approaches (e.g. Prudhomme et al., 2010; Wilby and Dessai, 2010) represents a significant and important contribution to the debate.

The generation of multiple scenarios from different GCMs has received much focus within the statistical downscaling community, largely due to the ease in implementation of statistically based downscaling approaches. However, traditional statistical downscaling approaches do not explicitly account for the uncertainties that accrue in the modelling process. Intercomparison of dynamically based downscaled scenarios has also become feasible through European Union funded projects such as PRUDENCE and ENSEMBLES, which focused on producing outputs from multiple GCM-RCM combinations for a common domain over Europe. The availability of such data from a number of RCMs has greatly contributed to the development of probabilistic

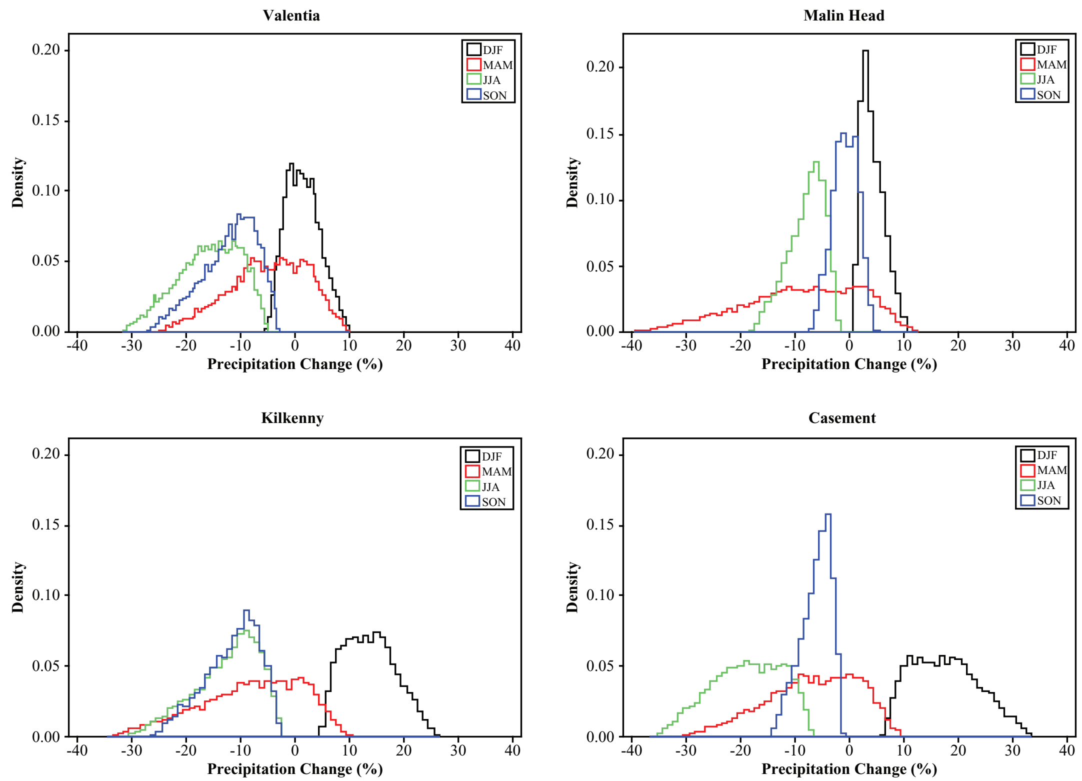

Figure 5. Method II. Probability distribution functions of projected change in seasonal mean precipitation (%) for Valentia, Malin Head, Kilkenny and Casement for the 2070–2099 period, employing uniform priors for ΔT_{global} from the 17 GCMs and station level regional response rates. Probability distributions functions are for the A2 and B1 emissions scenarios. (See colour version of this figure online).

based approaches at the required scale for policy assessment and decision making, based on dynamical regional climate models.

The application of techniques as outlined in this paper seeks to contribute to methodological developments in the field of statistical downscaling through the generation of probability distribution functions, accounting for key uncertainties from emissions scenarios to the GCMs employed, and perhaps represents a significant addition to the traditional techniques employed in statistical downscaling. Additionally, the ability to include alternative, or (previously) unavailable, emissions scenarios (i.e. A1FI and B1) through pattern scaling allows for a broader range of plausible futures to be included in any subsequent analysis.

While the projected mean changes in temperature and precipitation, based on the probabilistic approach, were found to be comparable to the ensemble mean directly derived from the statistically downscaled data, the probability distribution functions indicated a wide range in the distribution of the projected changes. Projections of temperature were found to be consistent in the direction and magnitude of change; however, results for precipitation were found to vary in both direction and magnitude in particular seasons. While the probabilistic based mean seasonal projected changes in precipitation was found to be more conservative than that of the ensemble mean from the statistical downscaling approach, the range in projected changes was found to vary. Therefore, the development of probabilistic

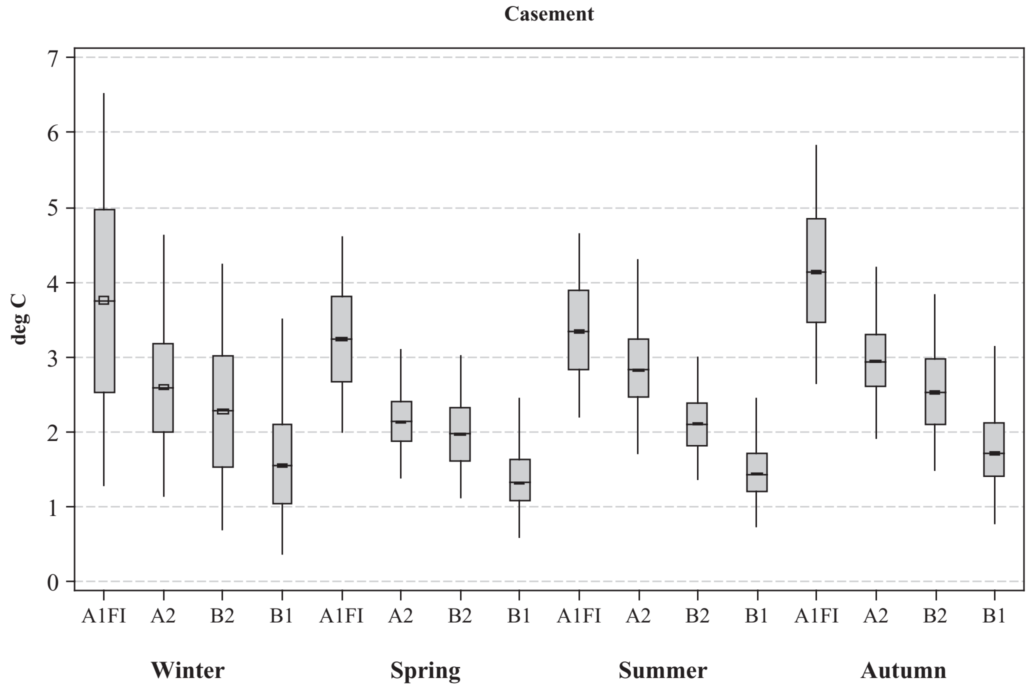

Figure 6. Boxplots of the projected changes in seasonal mean temperature (°C) for the synoptic station at Casement Aerodrome for four emissions scenarios: A1FI (3 × GCMs), A2 (17 × GCMs), B2 (3 × GCMs) and B1 (17 × GCMs). GCM data taken from Table 1 (3 × GCMs) and Table 7 (17 × GCMs). The first (Q1) and third (Q3) quartiles are denoted by the boxes and the median (Q2) by the centre line. Whiskers represent the minimum and maximum data points within 1.5 box heights from the bottom/top of the box.

scenarios provides a valuable assessment of variables/seasons where the associated uncertainties may require alternative policy options to be more rigorously assessed. For example, uncertainty associated with projected precipitation changes at all stations during the spring months by the 2080s, which results in both increased and decreased precipitation being modelled with equal likelihood, is highlighted as a case in point. From a policy perspective, these findings are particularly relevant for sectors dependent on water supply and availability that seek to develop robust adaptation options. Under the traditional approach to impact assessment, such uncertainty may be viewed as a justification to adopt a 'wait and see' approach to adaptation on the basis of not having an optimal solution, while the alternative scenario-neutral approach can readily accommodate such uncertain climate information, with the ultimate aim of developing robust adaptation options which are insensitive to uncertainties. Importantly, the approach also has the potential to highlight seasons/locations where climate information simply cannot address the needs of the policy community (e.g. seasons/locations where an equal likelihood of both positive and negative changes are suggested).

However, a significant weakness in this approach is that no strict quantification of uncertainty in predictor selection in the statistical downscaling procedure employed by Fealy and Sweeney (2007, 2008) is accounted for. This source of uncertainty is likely to be greatest in cases where a number of optimum predictor sets may exist, but the resultant downscaled

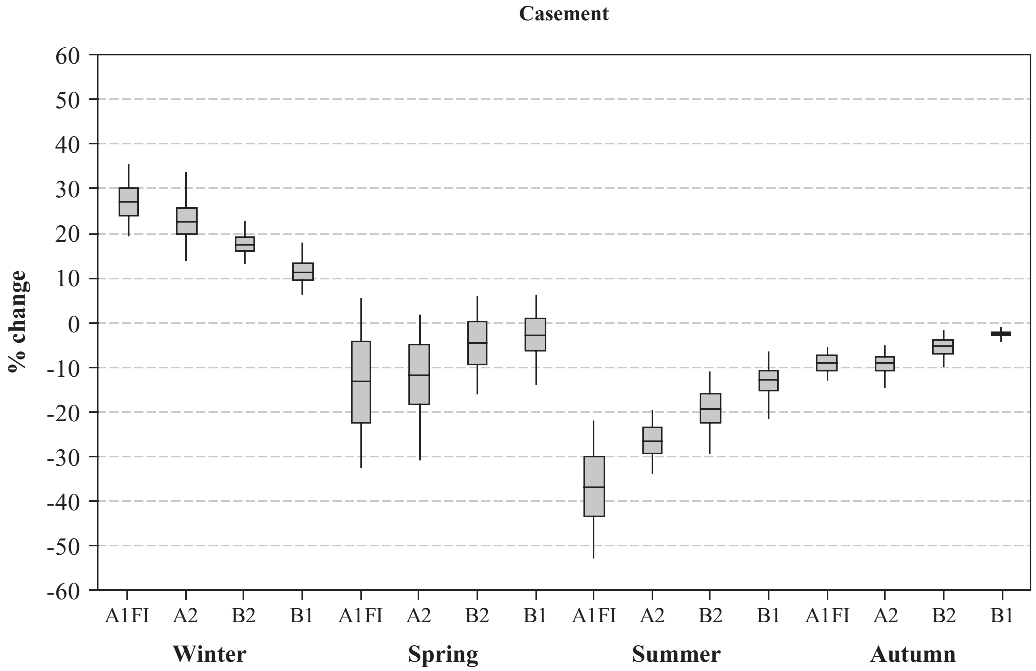

Figure 7. Boxplots of the projected changes in seasonal mean precipitation (%) for the synoptic station at Casement Aerodrome for four emissions scenarios: A1FI (3 × GCMs), A2 (17 × GCMs), B2 (3 × GCMs) and B1 (17 × GCMs). GCM data taken from Table 1 (3 × GCMs) and Table 7 (17 × GCMs). The first (Q1) and third (Q3) quartiles are denoted by the boxes and the median (Q2) by the centre line. Whiskers represent the minimum and maximum data points within 1.5 box heights from the bottom/top of the box.

scenarios produce divergent responses. Such a situation can arise when candidate predictors which have a large sensitivity to warming, such as relative humidity and temperature, contribute separately to two equally optimum sets of predictors. While both sets of predictors may provide a similar level of explanation in the validation of the downscaled data, the future projected change in the desired variable will largely be determined by the sensitivity of the selected predictor set. However, this is a recognized weakness in statistical downscaling and, generally, the selection of the optimum predictor set seeks to avoid the use of overly sensitive candidate predictors in the selection criteria.

In addition, the ability of the GCM to simulate candidate predictors employed in the statistical downscaling approach will also contribute to the uncertainty. This source of uncertainty arises due to sub grid scale processes and model parameterizations within the parent GCM. Dibike et al. (2008), in an analysis of uncertainty in statistically downscaled temperature and precipitation in northern Canada, suggests that the regression based downscaling approach employed in their analysis was able to reproduce the climate regime over highly heterogeneous terrain when driven by 'accurate' GCM predictors. Such findings indicate that the regression based approach may not contribute as much uncertainty to the cascade as the GCM employed. Similar conclusions have been arrived at for downscaled output employing regional climate models.

The method outlined here is also considered to be sensitive to choice of GCMs employed, in that the contribution of an individual model which projects a change in the statistically downscaled temperature or precipitation, opposite in sign to all available GCMs, is considered to have equal weight in the uniform distribution ascribed as a prior to the regional response rate. While attributing a non-uniform distribution as a prior to the regional response rates is difficult to ascertain objectively, weighting the contribution of projected changes from each GCM is one alternative. Determining the relevant criteria, such as convergence of model output (Giorgi and Mearns, 2002), to derive the weights, however, requires careful consideration.

In spite of these shortcomings, the proposed method represents a technique by which probabilistic based climate scenarios can be rapidly developed, even with limited availability of downscaled data. The outcome of this research can readily be employed within the scenario neutral framework approach which has the ultimate aim of ensuring adaptation that is robust to future changes in the climate system, whatever it may bring. Nevertheless, a note of caution is still required: information derived from probabilistic based climate assessments is not independent of the methodology employed (e.g. New et al., 2007). In addition, the contribution of full end-to-end probabilistic based climate impact assessments to the decision making process remains largely untested with the exception of one or two peer-reviewed studies (Wilby et al., 2009).

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References

Beven KJ (2001) *Rainfall-Runoff Modelling: The Primer*. Chichester: Wiley.

Boulanger J-P, Brasseur G, Carril A, et al. (2010) The European CLARIS Project: A Europe-South America network for climate change assessment and impact studies. *Climatic Change* 98(3–4): 307–329.

Burton I, Huq S, Lim B, Pilifosova O, and Schipper EL (2002) From impacts assessment to adaptation priorities: The shaping of adaptation policy. *Climate Policy* 2(2/3): 145–159.

Castro CL, Pielke RA, Sr, and Leoncini G (2005) Dynamical downscaling: Assessment of value retained and added using the Regional Atmospheric Modeling System (RAMS). *Journal of Geophysical Research* 110: D05108.

Christensen JH, Carter TR, and Giorgi F (2002) PRUDENCE employs new methods to assess European climate change. *EOS* 83(13): 147.

Dessai S and Hulme M (2003) Does climate policy need probabilities? Tyndall Centre Working Paper No. 34. Norwich: Tyndall Centre for Climate Change Research.

Dessai S, Hulme M, Lempert R, and Pielke R (2009) Climate prediction: A limit to adaptation. In: Adger N, Lorenzoni I, and O'Brien K (eds) *Adapting to Climate Change: Thresholds, Values, Governance*. Cambridge: Cambridge University Press, 64–78.

Dibike YB, Gachon P, St-Hilaire A, et al. (2008) Uncertainty analysis of statistically downscaled temperature and precipitation regimes in northern Canada. *Theoretical and Applied Climatology* 91(1–4): 149–170.

Ekström M, Hingray B, Mezghani A, and Jones PD (2007) Regional climate model data used within the SWURVE project – 2: Addressing uncertainty in regional climate model data for five European case study areas. *Hydrology and Earth System Sciences* 11(3): 1085–1096.

Fealy R and Sweeney J (2007) Statistical downscaling of precipitation for a selection of sites in Ireland employing a generalised linear modelling approach. *International Journal of Climatology* 27(15): 2083–2094.

Fealy R and Sweeney J (2008) Statistical downscaling of temperature, radiation and potential evapotranspiration to produce a multiple GCM ensemble mean for a selection of sites in Ireland. *Irish Geography* 41(1): 1–27.

Feser F, Rockel B, von Storch H, et al. (2011) Regional climate models add value to global model data: A review and selected examples. *Bulletin of the American Meteorological Society* 92: 1181–1192.

Flato GM, Boer GJ, Lee WG, et al. (2000) The Canadian Centre for Climate Modelling and Analysis global coupled model and its climate. *Climate Dynamics* 16: 451–467.

Foley AM (2010) Uncertainty in regional climate modelling: A review. *Progress in Physical Geography* 34(5): 647–670.

Fowler HJ, Blenkinsop S, and Tebaldi C (2007) Linking climate change modelling to impacts studies: Recent advances in downscaling techniques for hydrological modelling. *International Journal of Climatology* 27(12): 1547–1578.

Fu C, Wang S, Xiong Z, et al. (2005) Regional climate model intercomparison project for Asia. *Bulletin of the American Meteorological Society* 86: 257–266.

Gachon P and Dibike YB (2007) Temperature change signals in northern Canada: Convergence of statistical downscaling results using two driving GCMs. *International Journal of Climatology* 27(12): 1623–1641.

Giorgi F and Francisco R (2000) Evaluating uncertainties in the prediction of regional climate change. *Geophysical Research Letters* 27: 1295–1298.

Giorgi F and Mearns LO (2002) Calculation of average, uncertainty range, and reliability of regional climate changes from AOGCM simulations via the 'Reliability Ensemble Averaging' (REA) Method. *Journal of Climate* 15: 1141–1158.

Gordon C, Cooper C, Senior CA, et al. (2000) The simulation of SST, sea ice extents and ocean heat transports in a version of the Hadley Centre coupled model without flux adjustments. *Climate Dynamics* 16(2/3): 147–168.

Hashmi MZ, Shamseldin AY, and Melville BW (2009) Statistical downscaling of precipitation: State-of-the-art and application of bayesian multi-model approach for uncertainty assessment. *Hydrology and Earth Systems Sciences Discussions* 6: 6535–6579.

Haylock MR, Cawley GC, Harpham C, et al. (2006) Downscaling heavy precipitation over the United Kingdom: A comparison of dynamical and statistical methods and their future scenarios. *International Journal of Climatology* 26(10): 1397–1415.

Hingray B, Mezghani A, and Buishand TA (2007a) Development of probability distributions for regional climate change from uncertain global mean warming and an uncertain scaling relationship. *Hydrology and Earth System Sciences* 11(3): 1097–1114.

Hingray B, Mouhous N, Mezghani A, et al. (2007b) Accounting for global-mean warming and scaling uncertainties in climate change impact studies: Application to a regulated lake system. *Hydrology and Earth System Sciences* 11(3): 1207–1226.

Hirst AC, Gordon HB, and O'Farrell SP (1996) Global warming in a coupled climate model including oceanic eddy-induced advection. *Geophysical Research Letters* 23: 3361–3364.

Hirst AC, O'Farrell SP, and Gordon HB (2000) Comparison of a coupled ocean-atmosphere model with and without oceanic eddy-induced advection. 1. Ocean spin-up and control integrations. *Journal of Climate* 13(1): 139–163.

Hulme M and Carter TR (1999) Representing uncertainty in climate change scenarios and impact studies. In: Carter T, Hulme M, and Viner D (eds) *Representing Uncertainty in Climate Change Scenarios and Impact Studies*, Proceedings of the ECLAT-2 Helsinki Workshop, 14–16 April, 1999. Norwich: Climatic Research Unit, 11–37.

Hulme M and Carter TR (2000) The changing climate of Europe. In: Parry ML (ed.) *Assessment of the Potential Effects of Climate Change in Europe*. Report of the ACACIA Concerted Action. Norwich: University of East Anglia.

Hulme M, Jenkins GJ, Lu X, et al. (2002) *Climate Change Scenarios for the United Kingdom: The UKCIP02 Scientific Report*. Tyndall Centre for Climate Change Research. Norwich: School of Environmental Sciences, University of East Anglia.

Intergovernmental Panel on Climate Change (IPCC) (2001) *Climate Change 2001: The Scientific Basis*. Contribution of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change (IPCC). Cambridge: Cambridge University Press.

Intergovernmental Panel on Climate Change (IPCC) (2007) *Climate Change 2007: The Physical Science Basis*. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge: Cambridge University Press.

Jones RN (2000) Analysing the risk of climate change using an irrigation demand model. *Climate Research* 14: 89–100.

Jones RN and Mearns LO (2003) Assessing future climate risks. In: Lim B, Carter I, and al Huq S (eds) *Adaptation*

Policy Framework. Technical Paper 5. New York: United Nations Development Programme, 119–114.

Kass RE and Raftery AE (1995) Bayes factors. *Journal of American Statistical Association* 90: 773–795.

Katz RW (2002) Techniques for estimating uncertainty in climate change scenarios and impact studies. *Climate Research* 20: 167–185.

Kenny GJ, Warrick RA, Campbell BD, et al. (2000) Investigating climate change impacts and thresholds: An application of the CLIMPACTS integrated assessment model for New Zealand agriculture. *Climatic Change* 46(1/2): 91–113.

Khan MS, Coulibaly P, and Dibike Y (2006) Uncertainty analysis of statistical downscaling methods using Canadian Global Climate Model predictors. *Hydrological Processes* 20: 3085–3104.

Lopez A, Fung F, New M, et al. (2009) From climate model ensembles to climate change impacts: A case study of water resource management in the South West of England. *Water Resources Research* 45: W08419.

Mearns LO, Gutowski WJ, Jones R, et al. (2009) A regional climate change assessment program for North America. *EOS* 90(36): 311–312.

Mitchell JFB, Johns TC, Eagles M, et al. (1999) Towards the construction of climate change scenarios. *Climatic Change* 41: 547–581.

Mitchell TD (2003) Pattern scaling: An examination of the accuracy of the technique for describing future climates. *Climatic Change* 60: 217–242.

Mitchell TD, Hulme M, and New M (2002) Climate data for political areas. *Area* 34: 109–112.

Morgan G and Henrion M (1990) *Uncertainty: A Guide to Dealing with Uncertainty in Quantitative Risk and Policy Analysis*. Cambridge: Cambridge University Press.

Moss RH, Edmonds JA, Hibbard KA, et al. (2010) The next generation of scenarios for climate change research and assessment. *Nature* 463: 747–756.

Mullan DJ, Favis-Mortlock DT, and Fealy R (2012) Modelling the impacts of climate change on future rates of soil erosion: Addressing key limitations. *Agricultural and Forest Meteorology* 156: 18–30.

Murphy J, Sexton D, Barnett D, et al. (2004) Quantification of modelling uncertainties in a large ensemble of climate change simulations *Nature* 430: 768–772.

Nakicenovic N and Swart R (eds) (2000) *Special Report on Emissions Scenarios*. A Special Report of Working Group III of the Intergovernmental Panel on Climate Change. Cambridge: Cambridge University Press.

New M and Hulme M (2000) Representing uncertainty in climate change scenarios: A Monte-Carlo approach. *Integrated Assessment* 1: 203–213.

New M, Lopez A, Dessai S, and Wilby R (2007) Challenges in using probabilistic climate change information for impact assessments: An example from the water sector. *Philosophical Transactions of the Royal Society A* 365: 2117–2131.

Oberkampf WL, DeLand SM, Rutherford BM, et al. (2002) Error and uncertainty in modelling and simulation. *Reliability Engineering and System Safety* 75: 333–357.

Pielke RA Sr, and Wilby RL (2012) Regional climate downscaling – what's the point? *EOS* 93(5): 52–53.

Prudhomme C, Wilby RL, Crooks S, et al. (2010) Scenario-neutral approach to climate change impact studies: Application to flood risk. *Journal of Hydrology* 390: 198–209.

Räisänen J and Palmer TN (2001) A probability and decision-model analysis of a multimodel ensemble of climate change simulations *Journal of Climate* 14: 3212–3226.

Rockel B, Castro CL, Pielke RA Sr, et al. (2008) Dynamical downscaling: Assessment of model system dependent retained and added variability for two different regional climate models. *Journal of Geophysical Research* 113: D21107.

Rowell DP (2006) A demonstration of the uncertainty in projections of UK climate change resulting from regional model formulation. *Climatic Change* 79(3): 243–257.

Ruosteenoja K, Carter TR, Jylhä K, and Tuomenvirta H (2003) *Future Climate in World Regions: An Intercomparison of Model-Based Projections for the New IPCC Emissions Scenarios*. Helsinki: The Finnish Environment, Finnish Environment Institute.

Ruosteenoja K, Tuomenvirta H, and Jylhä K (2007) GCM-based regional temperature and precipitation change estimates for Europe under four SRES scenarios applying a super-ensemble pattern-scaling method. *Climatic Change* 81: 193–208.

Santer BD, Wigley TML, Schlesinger ME, and Mitchell JFB (1990) Developing climate scenarios from equilibrium GCM results. Report 47. Hamburg: Max-Planck-Institut-für-Meteorologie.

Stainforth DA, Allen MR, Tredger ER, and Smith LA (2007) Confidence, uncertainty and decision-support relevance in climate predictions. *Philosophical Transactions of the Royal Society, A* 365: 2145–2161.

Stakhiv EZ (1998) Policy implications of climate change impacts on water resources management. *Water Policy* 1: 159–175.

Stephenson DB and Pavan V (2003) The North Atlantic Oscillation in coupled climate models: A CMIP1 evaluation. *Climate Dynamics* 20: 381–399.

van der Linden P and Mitchell JFB (eds) (2009) ENSEMBLES: Climate change and its impacts: Summary of research and results from the ENSEMBLES Project. Exeter: UK Met Office.

Wilby RL and Dessai S (2010) Robust adaptation to climate change. *Weather* 65: 180–185.

Wilby RL and Harris I (2006) A framework for assessing uncertainties in climate change impacts: Low flow scenarios for the River Thames. *Water Resources Research* 42: W02419.

Wilby RL, Troni J, Biot Y, et al. (2009) A review of climate risk information for adaptation and development planning. *International Journal of Climatology* 29(9): 1193–1215.