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LETTERS

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# The importance of including variability in climate change projections used for adaptation

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**Our understanding of mankind's influence on the climate is largely based on computer simulations[1,2]. Model output is typically averaged over several decades[3] so that the anthropogenic climate change signal stands out from the largely unpredictable 'noise' of climate variability. Similar averaging periods (30-year) are used for regional climate projections[4–6] to inform adaptation. According to two such projections, UKCIP02 (ref. 4) and UKCP09 (ref. 6), the UK will experience 'hotter drier summers and warmer wetter winters'[7,8] in the future. This message is about a typical rather than any individual future season, and these projections should not be compared directly to observed weather as this neglects the sizeable contribution from year-to-year climate variability. Therefore, despite the apparent contradiction with the messages, it is a fallacy to suggest the recent cold UK winters like 2009/2010 disprove human-made climate change[9]. Nevertheless, such claims understandably cause public confusion and doubt[10]. Here we include year-to-year variability to provide projections for individual seasons. This approach has two advantages. First, it allows fair comparisons with recent weather events, for instance showing that recent cold winters are within projected ranges. Second, it allows the projections to be expressed in terms of the extreme hot, cold, wet or dry seasons that impact society, providing a better idea of adaptation needs.**

The need to include the effects of year-to-year climate variability has been shown for an ensemble of climate simulations[11,12], but not for a formal set of probabilistic projections that directly affects adaptation planning. For example, the UKCP09 (ref. 6) projections underpinned the UK's first statutory Climate Change Risk Assessment in 2012. These projections (see Methods) have the added advantage over earlier studies that any conclusions are based on a more comprehensive assessment of key uncertainties. This is because the UKCP09 projections are based on several ensembles (see Supplementary Table 1) of variants of the HadCM3 climate model (about 400 simulations) that explore uncertainties in land, atmosphere and ocean processes, sulphate aerosol chemistry, and the terrestrial carbon cycle, and also use information from an ensemble of international climate models (CMIP3; ref. 13). Observational metrics of model quality are used to constrain the projections by weighting realizations according to their ability to simulate historical mean climate[14] and large-scale temperature trends[15]. Unlike UKCIP02, a Bayesian framework[16] is used to transparently synthesize these data into probability density functions (PDFs), which represent the uncertainties explored by the climate simulations but are conditional on the method and its assumptions, as well as the evidence (model output, observational metrics and expert judgement). For a given emissions scenario, spread in these PDFs (ref. 15) comes from three sources: (i) modelling uncertainty, arising from imperfect understanding and the approximate representation by climate models of processes that determine the forcing associated with the emissions, and the climate response to this; (ii) climate variability on multi-decadal timescales; and (iii) errors in statistical estimates of the climate model responses to changes in forcing[15] (see Methods).

By extending the UKCP09 method[6,14,15] to simulated 1-year averages, we effectively add climate variability on timescales of 1–30 years to form projections for individual seasons (grey plumes in Fig. 1). The PDFs across time can be jointly sampled to generate a set of equally probable realizations. A small sample of these realizations (coloured lines in Fig. 1) show a few possible pathways for the future real climate if it was to experience the prescribed emissions. These reflect a range of plausible climate changes that cannot be ruled out by the observational metrics used to constrain the projections, superimposed by natural variability arising within the climate system. For example, some realizations of summer rainfall have strong drying signals (red), whereas some have a lot of very dry summers but can still produce a few very wet summers (blue). Generally, wet summer and cold winter seasons still exist under climate change, despite the tendency towards milder winters and drier summers covered by the UKCIP02/UKCP09 headline messages.

The impact of adding the year-to-year variability to the 30-year PDFs depends on its size relative to the magnitude of the climate change signal and its associated uncertainty (see Supplementary Fig. 3). In 2000, climate variability dominates the spread for the four variables averaged over England and Wales (hereafter England/Wales), but not for global temperature. The uncertainty increases throughout the twenty-first century for all five variables. For the temperature variables, the growth in spread is due to increasing modelling uncertainty alone. Modelling uncertainty also increases with time for precipitation changes. In winter, further contributions to the growth in total spread during the twenty-first century arise from increases in year-to-year precipitation variability, and in uncertainty associated with timescaling[15], a component of the UKCP09 method (see Methods).

The relative roles of climate change and interannual variability become clearer by comparing the 1-year and 30-year PDFs at particular time periods (see Fig. 2). For England/Wales temperature, the warming signal (blue curve) is clear by the 2030s as there is little overlap with zero change. For precipitation changes, the probable sign of the signal by the 2080s is clear for summer and very clear for winter. Generally, studies of the importance of climate change on individual extreme events[17,18] have focused on cases where climate variability reinforces climate change. The addition of year-to-year variability, however, extends both sides of the 30-year PDFs, and it is important not to neglect the seasons where climate variability offsets climate change. As the amplitude of year-to-year variability is large,

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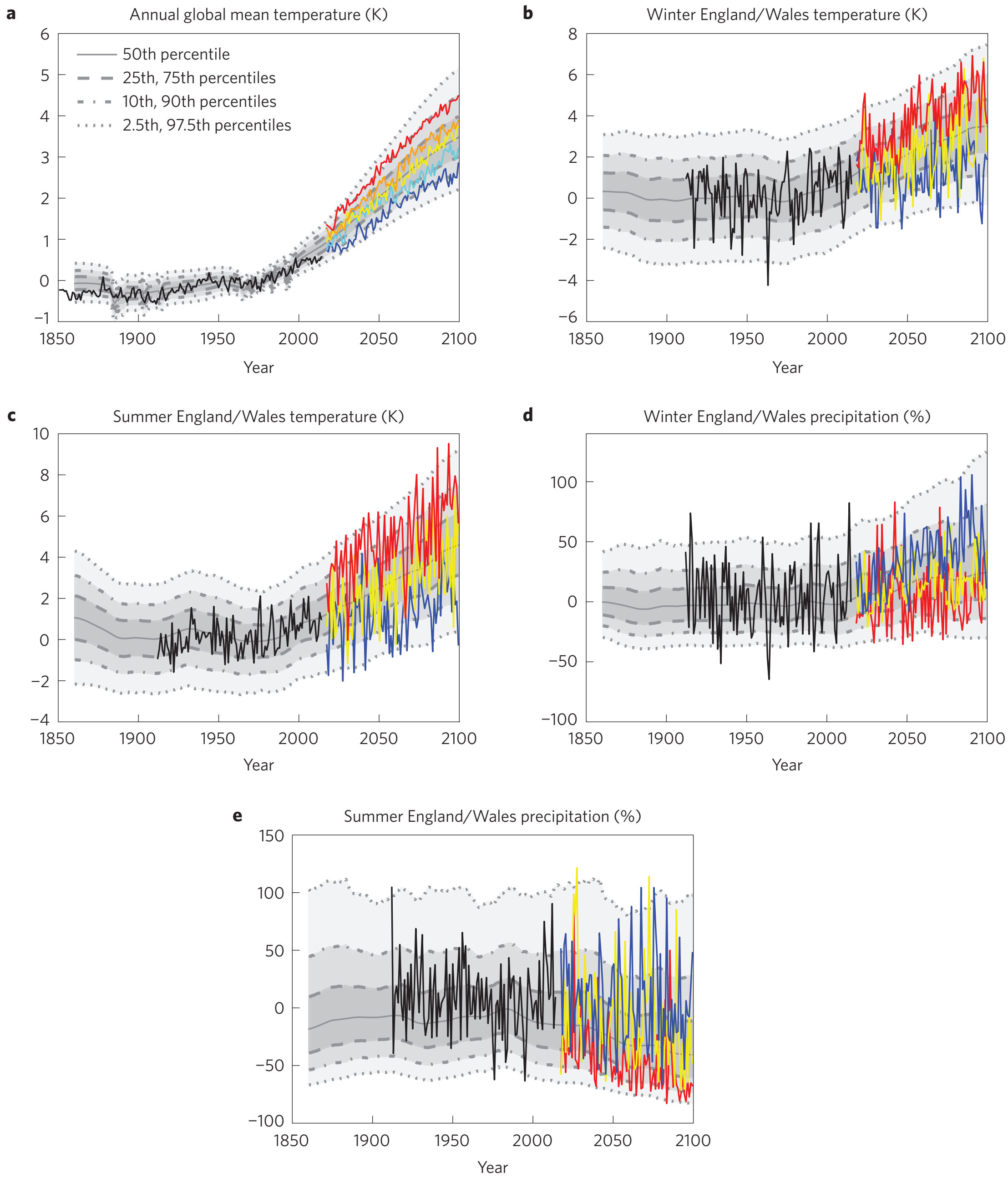


**Figure 1 | Projections for individual seasons in response to historical forcings followed by the A1B scenario. a–e**, Data are presented for the five variables (as indicated). Grey shading and lines show percentiles of anomalies in the variables relative to 1961–1990, calculated from 1-year mean PDFs for every year between 1860 and 2100. Coloured lines show three (five for annual global mean temperature) individual realizations of year-to-year variation sampled from the 1-year PDFs so that simulated temporal correlations are captured. Thick black lines show observed annual global and England/Wales temperature and precipitation time series[27,28] up to winter 2014/15. The realizations used in each panel are chosen independently, so the same colours in different plots do not correspond to the same realizations.

the 1-year PDFs show there is still a reasonable chance in the 2030s for a cold or dry winter, or a mild or wet summer (grey shading), the very seasons not covered by the headline messages.

Although it is incorrect to contrast the cold UK winter of 2009/2010 with the message for 'warmer winters'[9], it is fair to compare it with the 1-year PDFs. These PDFs (see Fig. 3a) give a 20% chance by 2020 of having a winter colder than the 1961–1990 average, consistent with CMIP3 predictions that 20–30% of winters over Northern Europe will be colder than average during 2011–2050 (ref. 12). For the 2009/2010 winter in England/Wales which caused the scepticism[9], the probability (using the winter temperature PDF for 2009/2010) is 0.06, which is towards the cold end of the distribution, but is not inconsistent. By considering climate projections on the appropriate timescale, the scope for misinterpreting the 2009/2010 winter in the context of long-term climate change has been removed. In other words, because of climate variability, cold winters do not immediately disappear under climate change, and their occurrence does not contradict the theory or projections. Indeed, the 2009/2010 winter over Europe would have been even colder if it was not for an underlying warming from climate change[19]. The warming signal and its associated uncertainty is projected to increase throughout the twenty-first

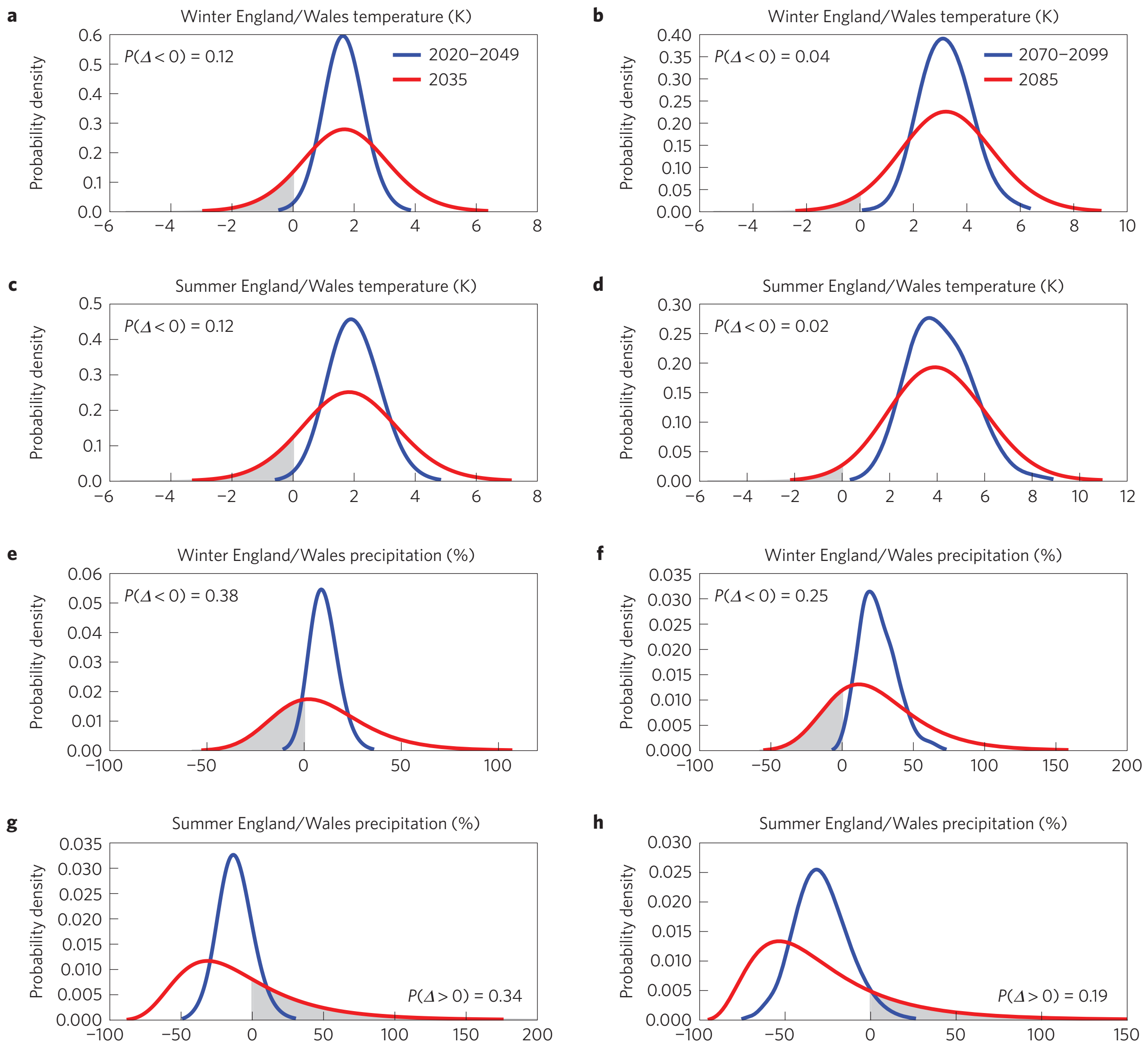


**Figure 2 | Comparison of 1-year PDFs with 30-year PDFs for anomalies in the four England/Wales variables relative to 1961–1990. a–h**, 1-year PDFs (red) and 30-year PDFs (blue) for the four variables indicated for two time periods: 2035 versus 2020–2049 (**a**,**c**,**e**,**g**) and 2085 versus 2070–2099 (**b**,**d**,**f**,**h**). Grey shading to one side of zero highlights the area under the 1-year PDF where variability offsets the climate change signal, and the associated probability is quoted top left or bottom right of each panel.

century, causing the chance of a cold winter to drop steadily to 4% in 2100 (see Fig. 3a), and the chance of England/Wales having a winter as cold as 2009/2010 to drop to 0.6%. Note that although a single number is quoted here and below, this number encompasses the combined uncertainties quantified by the conditional PDF, rather than being for some specific single pathway.

Even if the 2009/2010 winter in England/Wales had appeared well outside the 2.5–97.5th percentiles (as the record 1962/1963 cold winter and 2013/2014 wet winter do), a single observed season outside the projected range could not alone invalidate a probabilistic projection. However, if observed seasonal averages were inconsistent with a PDF over several years, then this would cause concern, indicating potential problems with the projections and some of the scientific understanding built into climate models. Such comparisons between 1-year PDFs and observed seasonal averages are fair. They promote a 'legitimate rather than radical skepticism'[20], allowing people to test and monitor the degree of confidence in the projections that are based on contemporary climate models, which may share common systematic errors[21] and are to an extent dependent on a number of expert choices[22].

One potential problem, which could affect the credibility of the 1-year PDFs and our analysis, arises if there is inadequacy in the climate model's ability to represent the amplitude of year-to-year variability. For the high-frequency (less than 30 years) variance of winter precipitation, the observed value is higher than the sampled value in all but 1.2% of the plausible realizations, showing that the simulated variability during the historical period for winter precipitation is less than observed. Similar tests show that the simulated variability is larger for summer temperature, but reasonably consistent for winter temperature and summer precipitation. The actual impact of this is shown by a simple sensitivity test (red lines in Fig. 3), where variations on timescales below 30 years are re-scaled to that observed. This test shows generally modest effects on these projections, demonstrating that the projections are reasonably robust to errors in the simulation of the amplitude of variability. The most appreciable impact of rescaling the variability occurs for summer England/Wales temperature, providing an example where improved representation of variability in future models may have a significant impact on the projections.

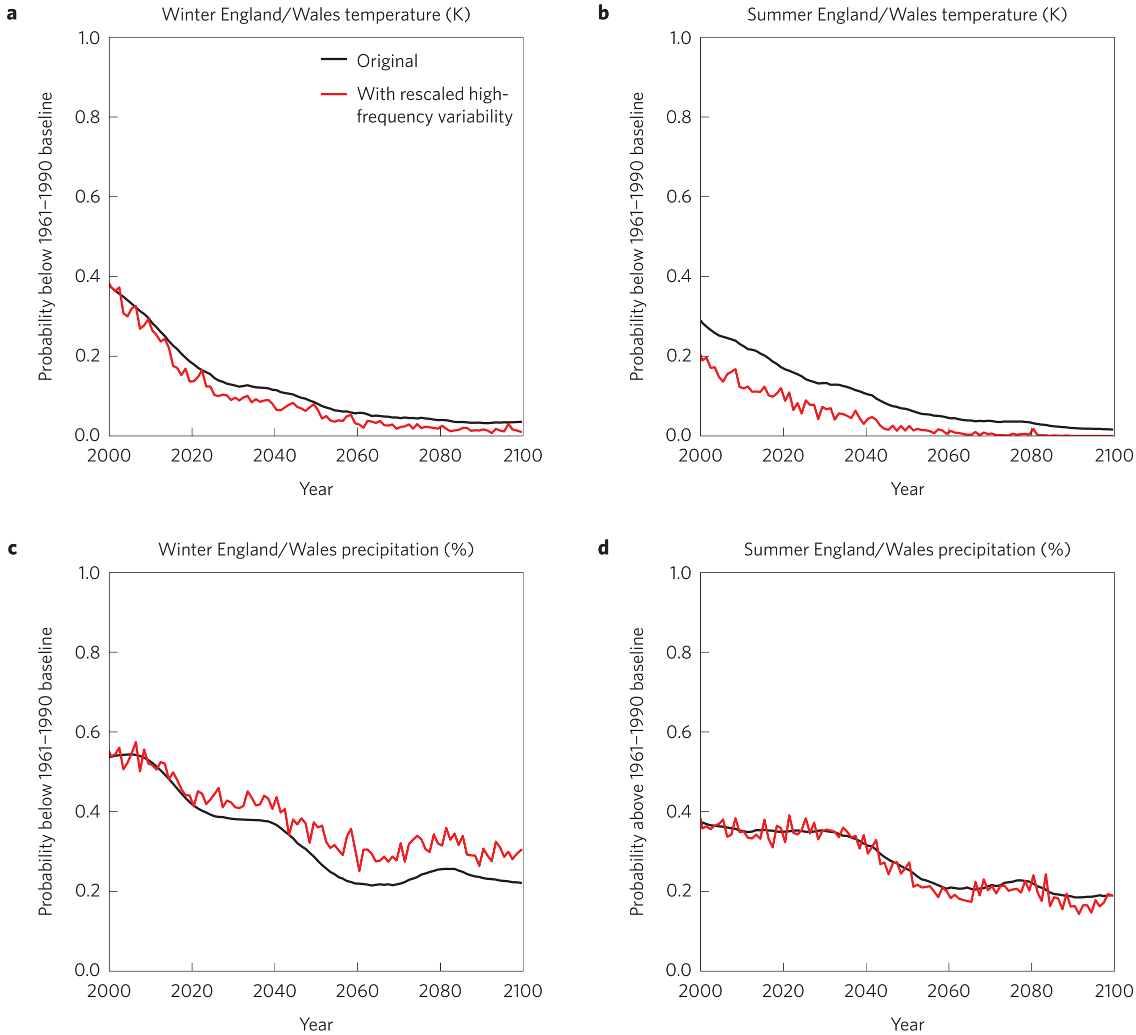


**Figure 3 | Time series of probabilities for seasons that become less likely under climate change. a–d**, Time series of the projected probability that the England/Wales seasonal mean is below the 1961–1990 baseline value (above, in the case of summer precipitation). The black lines are estimated from the conditional (see text) 1-year cumulative PDFs (so the values at 2035 and 2085 equal the areas of the grey shading in Fig. 2). The red lines are based on sampled realizations (and hence noisier), where high-frequency variations below 30-year timescales have been re-scaled so that the high-frequency variance equals the observed value. The red lines are estimated as the fraction of sampled realizations that are above zero for summer precipitation and less than zero for the other variables at each time point. The legend in **a** applies to all panels.

The confusion around the 2009/2010 cold UK winter arose from an apparent contradiction with the message based on the 30-year PDFs. Before seeing how the 1-year PDFs might alter the headline messages in such cases, we consider instances of seasonal extremes that are consistent with a warming climate signal (see Fig. 4). The 1-year projections show over the twenty-first century substantially increased risk of these. The probability of a summer that was considered very hot historically (occurring once every 20 years) rises to 0.9 by 2100. The probability in 2100 for very mild winters is 0.74, whereas for very dry summers and very wet winters, it is 0.4 and 0.32, respectively. The use of 1961–1990 to define a baseline extreme season follows UKCP09. However, as users might want to consider alternative reference periods[23], the 1-year samples have an advantage over the UKCP09 PDFs, as they can be readily re-centred to different baseline periods. In Fig. 4c, for example, the choice of the more recent period 1981–2010, which for winter precipitation had more extreme seasons than 1961–1990, gives a modest reduction in the increased future risk.

These projections suggest new headline messages are possible, that are robust to the sampling of the main uncertainties, choice of baseline, or amplitude of simulated variability. For winter temperature this could be 'Over England and Wales, we expect an increasing chance of warmer winters, with fewer colder ones'. We suggest this summary would have reduced the chances for confusion with the 2009/2010 UK winter, in contrast to the original message. Recent wet summers experienced by England/Wales are a good example of the benefit of 1-year projections (Fig. 3d) as they show for 2000–2030 there is still a 35–40% chance of getting a wetter than average summer. Indeed, throughout the twenty-first century, there is an 18% dropping to 10% chance of having a 'very wet' summer (20% above the 1961–1990 average) (not shown). For summer precipitation, a suitable description of the projections might be 'Over England and Wales, we expect an increasing chance of dry summers, but only a modest reduction in the chance of very wet summers'. These new messages convey the sense of the overall climate change signal while factoring in the role played by the interannual variability. A planner using the 1-year PDFs for adaptation will have information on both wet and dry summers, whereas someone using the 30-year projections might only focus on 'drier summers'. In this sense, the wider 1-year PDFs highlight the adaptation challenge more effectively than the 30-year PDFs. They also present the projections in terms of the probability of extreme seasons, which people

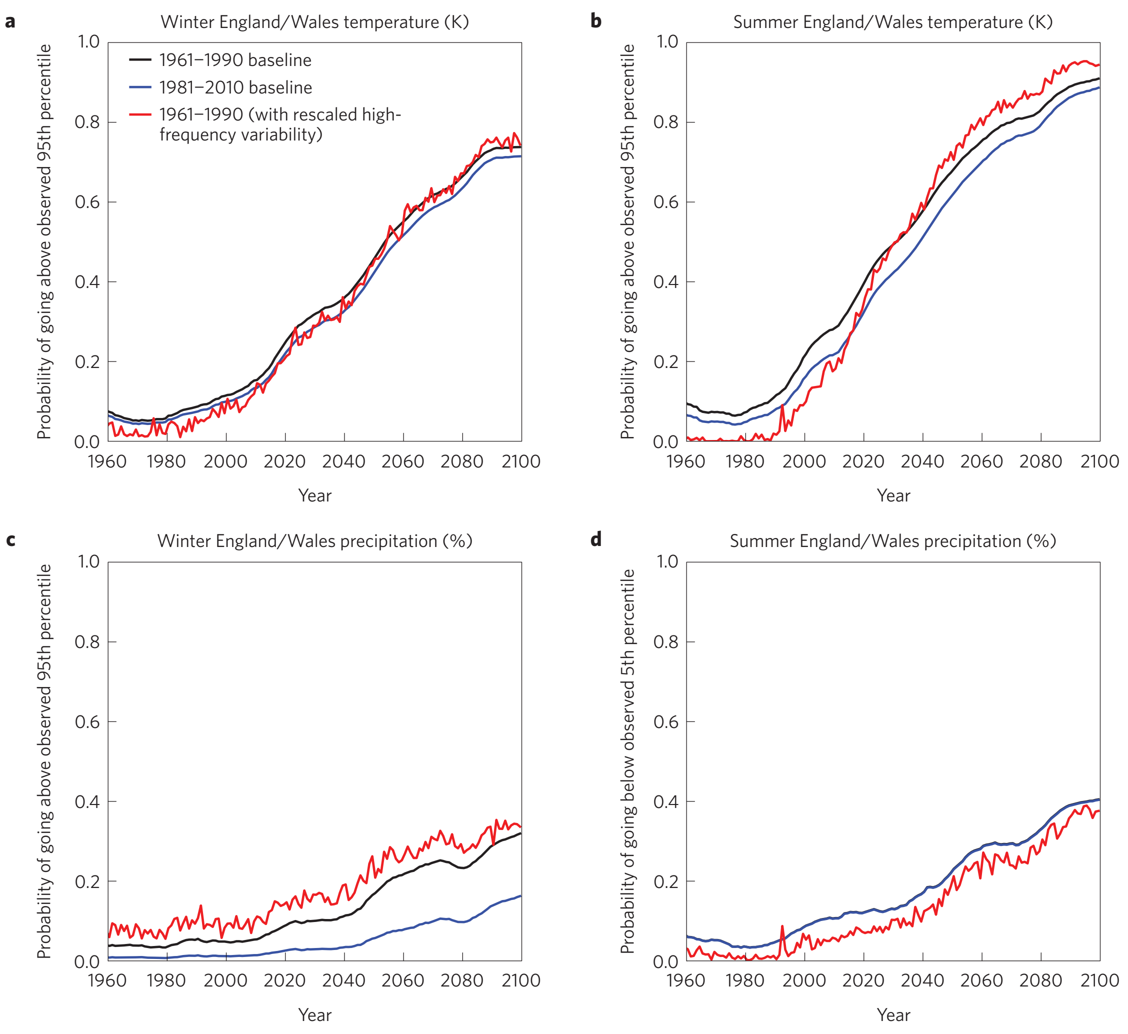


**Figure 4 | Time series of probabilities for extreme seasons that become more likely under climate change. a–d**, Probability of exceeding the 95th percentile of the observed baseline distribution for England/Wales summer and winter temperature and winter precipitation, or going below the 5th percentile for summer precipitation. The black and blue lines use the conditional (see text) 1-year cumulative PDFs, but for two different baseline periods (for summer precipitation, the blue and black lines coincide, because the observed 95th percentiles in the two baseline periods happen to be the same). The red lines are based on sampled realizations with adjusted variance as in Fig. 3, and are estimated as the fraction of realizations that exceed (go below) the 95th (5th) percentile of the observed 1961–1990 distribution at each time point. The legend in **a** applies to all panels.

can more easily relate to their experience, and to weather events that have major impacts, for example, very hot summers or wet seasons linked with heatwaves and flooding, respectively.

The 2009/2010 winter over Europe was characterized by a very high frequency of anticyclonic blocking events[19]. Ideally, the climate projections would be expressed in terms of changes in frequency and intensity of such weather regimes that really impact society, for example, heatwaves, droughts, cold spells and sustained periods of precipitation. This would make them even more relevant to people, giving a clearer idea about the future types of weather that society might experience. To enable this requires the climate model to sufficiently represent the key phenomena that drive the extreme weather events, such as the jet stream, storm tracks, tropical cyclones, anticyclonic blocks, convective storms, stratosphere–troposphere interactions, and teleconnections to tropical SSTs. The climate models used for UKCP09 projections are limited in this respect, so we have only extended the 30-year PDFs by including variability down to the seasonal timescale, as this was found to be adequately simulated (empirically correcting the amplitude in variability did not significantly affect the results in Figs 3 and 4). Enhanced resolution in climate models has already shown improved representation of stratosphere–troposphere interactions[24] and blocking[25], and with further development of climate models using improved process metrics[26], we would expect one day to be able to produce climate projections with this greater level of detail.

## Methods

Methods and any associated references are available in the online version of the paper.

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## Author contributions

D.M.H.S. and G.R.H. both conceived the method. D.M.H.S. coded up the solution by modifying the original code of G.R.H. and D.M.H.S. which was used to produce UKCP09. D.M.H.S. drafted the initial version of the manuscript and Supplementary Information and made the plots. Both authors discussed the results and implications, and commented on the manuscript at all stages.

## Additional information

Supplementary information is available in the online version of the paper. Reprints and permissions information is available online at www.nature.com/reprints. Correspondence and requests for materials should be addressed to D.M.H.S.

## Competing financial interests

The authors declare no competing financial interests.

## Methods

The method used here to make our probabilistic climate projections[14,15] consists of two stages and is based on the six ensembles outlined in Supplementary Table 1. The first stage[14] uses a Bayesian framework[16] to predict, at the resolution of the global climate model, the distribution of equilibrium response to doubled $CO_2$ levels. The method combines information from: a perturbed parameter ensemble (PPE; ensemble 1 in Supplementary Table 1), where ensemble members are based on a standard version of the HadCM3 climate model but differ in the values of the model parameters that control atmosphere and land-surface processes; multimodel ensembles of other international climate models[13]; and observations. Expert judgement is also included, for example, in specifying prior distributions for uncertain model parameters, and in the choice of observations. The Bayesian method requires a more robust sampling of the set of parameter combinations than provided by the PPE. This is done by building an emulator, a statistical model trained on the emergent properties of the PPE, which can be used to predict the recent mean climate and the equilibrium response to a doubling of $CO_2$ for any combination of parameter values, not just those sampled by the PPE. The Bayesian framework allows the projections to be constrained by a set of multiannual mean observations by weighting different model variants according to their ability to simulate aspects of historical mean climate. The framework recognizes that climate models are imperfect, and combines information from the emulator and the multimodel ensemble to specify and include structural modelling uncertainty in the land/atmosphere component of the climate model in the predicted probabilities.

The second stage uses a timescaling approach[15] to provide probabilistic projections for regional climate change for different time periods during the twenty-first century by combining information from the probabilistic projections from stage one with GCM ensembles that explore uncertainties in the time-dependent response to historical forcings and projected future emissions (Ensembles 2–6). The time-dependent regional response is emulated by assuming a linear variation with global annual mean temperature change, the latter being predicted by a simple climate model (SCM). The timescaling is done for each sampled parameter combination; the PDFs of equilibrium response to doubled $CO_2$ concentrations from stage one are sampled jointly to provide the climate feedbacks required to drive the SCM, and the normalized response per unit degree of global temperature change. The SCM is comprised of an energy balance model for prediction of land and ocean temperature change driven by changes in greenhouse gas, aerosol, solar and volcanic forcing, with a one-dimensional diffusion–advection equation for vertical ocean heat transport, and a simple carbon cycle model. By varying SCM parameters, global uncertainties in aerosol forcing, ocean heat uptake and carbon cycle feedbacks are accounted for. Parameters of these Earth System components of the SCM are calibrated to reproduce the response of the transient perturbed physics (Ensembles 3-6) and multimodel ensemble simulations, and then sampled along with the atmospheric parameters during scaling to provide projections for regional change. The sampled projections are then reweighted, based on the likelihood that they correctly replicate observed historical changes in surface temperature, and combined to provide time-dependent PDFs to the end of the twenty-first century for the A1B emissions scenario[29]. We note that UKCP09 had an additional third stage, not used here, to convert GCM-resolution PDFs produced from the first two stages to PDFs at 25 km.

For each model variant it is also possible to generate a realization by sampling error associated with the timescaling (see Supplementary Information) and adding it to the emulated climate change signal. Furthermore, a set of equally probable realizations is used here. This is generated by sampling with replacement 1,000 model variants 2,000 times according to their likelihood weight, taking the emulated climate change for these 2,000 model variants, and adding sampled 'noise' from the timescaling.

In this study we show climate projections for annual global mean temperature and four climate variables over the three grid boxes that represent England and Wales, for two timescales: 30 years and one year. For the 1-year PDFs, we make a minor modification to the second stage described above to account for the short-term signal from volcanic eruptions (see Supplementary Figs 1 and 2 and related discussion).

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