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Changing probabilities of daily temperature extremes in the UK related to future global warming and changes in climate variability

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ABSTRACT: The impacts of 2 greenhouse gas emissions scenarios (one from the IPCC and one from Greenpeace International) on the occurrence of extreme daily temperature events are considered at several sites in the UK. For each site, a number of probability distributions were tested for goodness-of-fit to 1961-87 observed daily maximum and minimum temperature data using the Kolmogorov-Smirnov test. The parameters of the best-fitting distributions were then perturbed to take into account climate change, both mean and variability. Probabilities of the occurrence of particular temperature threshold events were calculated for both present and future climates. Changes in climate variability were considered in 3 ways: (1) by assuming the present variance stays the same in the future; (2) by imposing standardised percent changes in variance; and (3) by imposing variance changes derived from the UK Meteorological Office high resolution GCM equilibrium climate change experiment. Results presented for 2 contrasting sites illustrate the importance of including changes in variability in climate change studies. Specific results depend on the site and threshold temperature chosen and on the distribution characteristics. However, for example, at Fortrose the 1961-87 mean maximum temperature in July is below 20°C. With increases in global-mean temperature, the probability of this threshold being exceeded increases, although the rate of increase depends on the variance change being considered. The largest rate of increase in probability occurs with a 20% per °C increase in variance. The approach described here has been used in one component of a climate change scenario generator for the UK developed for the UK Ministry of Agriculture, Fisheries and Food.

KEY WORDS: Extreme events · Climate change · Climate variability

INTRODUCTION

Climate, and its variability, are constantly changing. In addition to natural changes, future climate will also be influenced by anthropogenic emissions of greenhouse gases (GHG) and pollutants such as sulphate and other aerosols (Houghton et al. 1992). General Circulation Models (GCMs) are the tools which are now most widely used to generate scenarios of climate change due to anthropogenic emissions for impact assessments (Giorgi & Mearns 1991, Carter et al. 1994). Direct use of output from GCM experiments for the purpose of constructing scenarios relevant for impact assessments is limited, however, by a number of factors. Such experiments often only report changes in the mean values of the climate variables under consideration. In many areas of impact assessment it is the occurrence of extreme climatic events which is most important, e.g. the incidence of killing frost in agriculture (Morison & Butterfield 1990, Unsworth et al. 1993) or intense storm events in hydrology (Wang & Mayer 1994). Information on how the frequency and intensity of these events may change in the future is therefore critical. (In fact, results from GCM experiments can be used to alter both the mean and variability of climate. The selective inclusion by GCMs of processes which control climate variability, however, is often sufficient reason for only changes in the mean to be used.) Furthermore, most climate change scenarios derived from

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GCMs are presented at coarse spatial resolutions — one value for several degrees latitude by longitude representing many hundreds of thousands of square kilometres. For many impact assessments, estimates of site-specific, or local area, changes in climate are needed. Another limitation of using the direct output from GCMs as climate change scenarios is that the changes in climate they simulate cannot be related to prior assumptions about the development of the global economy, GHG and other emissions or land use changes. They refer only to *one* forcing scenario and to *one* climate sensitivity.

In this paper we describe a method for overcoming some of these limitations in relation to scenarios of daily temperature extremes. We consider 2 greenhouse gas emissions projections and the impact these emissions may have on the frequency of extreme daily temperature events at a number of sites in the UK. This requires us to use the results both from a simple 1-dimensional upwelling-diffusion climate model and from a high resolution GCM equilibrium climate change experiment. The method follows that originally suggested in Santer et al. (1990) and further developed and described in Hulme et al. (1994). Here, we extend the method to enable specific consideration of the effects of changes both in mean climate and in climate variability on local minimum and maximum temperature extremes within the UK. We first summarise the approach taken in considering site-specific temperature extremes, before presenting the results of the distribution fitting exercise. The effects of changes in mean climate and in climate variability are then accounted for before, finally, we illustrate an application of the method to 2 contrasting sites within the UK, Fortrose (57.6° N, 4.1° W, 5 m above mean sea level) and Santon Downham (52.5° N, 0.7° E, 24 m above mean sea level). Some discussion both of the limitations and of the value of this approach is presented.

METHODOLOGY

Extreme meteorological events are usually defined as unusual values of observations of certain variables. The term 'extreme events' encompasses both the occurrence of extraordinary values and the exceedence of (or falling below) a particular threshold level (Faragó & Katz 1990). In this paper, estimates are made for a number of UK locations of the probability that an extreme value of maximum or minimum surface air temperature will be higher or lower than a specified threshold, and also of how the probability of such an event will change as a result of GHG-induced global warming.

The UK was divided into 9 coherent climatological regions (Fig 1) based on a principal components analysis of the spatial and temporal variations in precipitation, according to work by Wigley & Jones (1987) and updated by Gregory et al. (1991). Within each region a single site, which contained complete records of daily maximum and minimum surface air temperature for the period 1961-87, was selected. The observed daily maximum and minimum temperature data were sorted into monthly subsets (so there were 2 temperature values for each day of each month), and the goodness-of-fit of a number of probability distributions was tested using the Kolmogorov-Smirnov test. It was assumed that the observed records were homogeneous (i.e. no systematic changes in the underlying climatic conditions were occurring during the observational period and that all observations were therefore

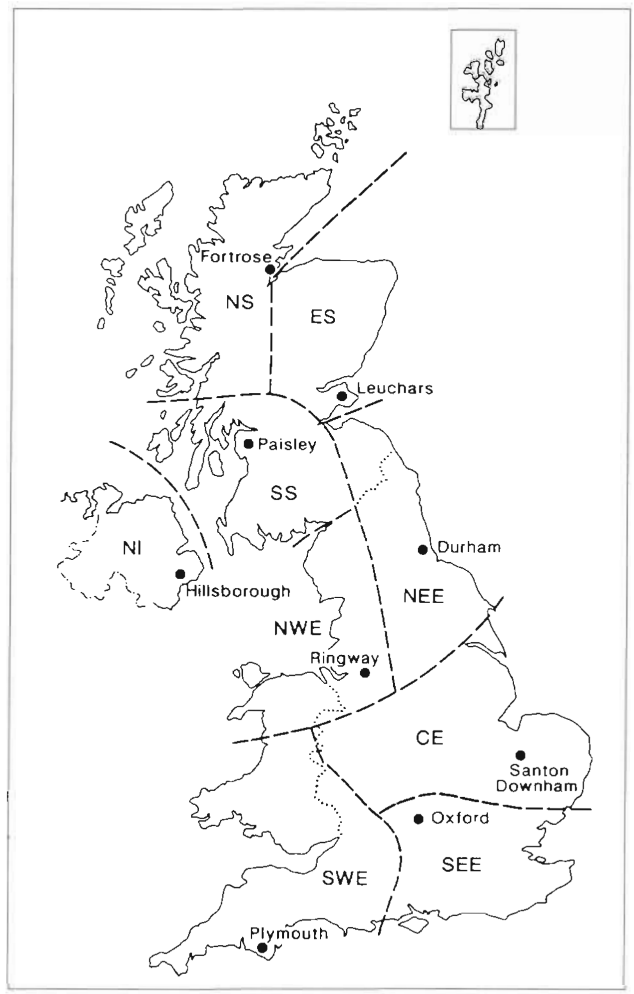

Fig. 1. The 9 coherent climatological regions of the UK (based on PCA of annual precipitation data). Also shown are the individual sites used in the analysis of extreme temperature events

taken from the same statistical population).[1] Probability distributions considered in this analysis included the normal distribution, a number of transformed normal distributions including the log-normal distribution, and the gamma and Gumbel distributions (NERC 1975). The best-fitting distribution was used to calculate the present-day probabilities of exceedence of, or falling below, particular threshold temperatures. Changes to the distribution parameters, reflecting different GHG emissions scenarios, assumptions about the climate sensitivity and changes in climate variability were then applied for various future time horizons to enable estimates of changes in the frequencies of various temperature extremes to be made.

GOODNESS-OF-FIT TESTS — THE KOLMOGOROV-SMIRNOV TEST

Goodness-of-fit tests are designed to test the null hypothesis that some given data are a random sample from a specified probability distribution. The goodness-of-fit of sample data to any kind of probability distribution can be determined using the Kolmogorov-Smirnov (K-S) test. It is advantageous to use this test rather than the χ^2 test since it is not necessary to group the observations into arbitrary categories. For this reason, the K-S test is more sensitive to deviations in the tails of the distributions where frequencies are low (Davis 1986). The K-S test is a nonparametric procedure and thus can be used when the parameters of the sample distribution cannot be completely specified. This test is based on the maximum absolute difference (D_{max}) between the cumulative distribution function (cdf) of the hypothesised distribution and the cdf of the sample. This sample cdf is a step-function which starts at 0 and rises by $1/n$ at each observed value, where n is the sample size. If D_{max} is greater than, or equal to, the critical value (i.e. it is statistically significant) the null hypothesis that the observed data follow the hypothetical model is rejected.

The distribution which was selected as best-fitting the observed data was the one with the smallest maximum difference (D_{max}) value, i.e. the smallest difference between the sample distribution and the hypothesised probability distribution. The critical D_{max} value is largest at the 99% confidence level to ensure that we are correctly rejecting the null hypothesis that the sample data are a good fit to the hypothesised data. Out of the 108 maximum temperature distributions (12 months × 9 sites), we could reject the null hypothesis that the best-fitting distribution described the sample data in only 16 cases at the 99% confidence level. For minimum temperature this number was 9. Comparable values for the 90% confidence level were 48 and 37, respectively. The log-normal distribution occurs most frequently as the distribution best-fitting the observed daily maximum temperature data, implying that, particularly in the summer half-year, the daily maximum temperature data are strongly positively skewed. In winter, however, the normal or square normal distributions provide the better fits. For observed daily minimum temperature the square normal distribution is the most frequent best-fitting distribution throughout the year, implying that these data are generally negatively skewed (see Table 1).

ACCOUNTING FOR THE EFFECTS OF CLIMATE CHANGE

Two GHG and sulphate aerosol emissions scenarios were used to consider climate change effects, namely the Intergovernmental Panel on Climate Change (IPCC) IS92a emissions scenario (Leggett et al. 1992) and the Greenpeace International Fossil Free Energy Future emissions scenario (GI; Boyle 1994). These represent respectively a realistic and an optimistic (the complete phasing out of nuclear power and of fossil fuels by 2010 and 2100 respectively) interpretation of future emissions (cf. Alcamo et al. 1995). The simple climate model MAGICC (Model for the Assessment of Greenhouse Gas Induced Climate Change; Wigley & Raper 1992, Hulme et al. 1995) was used to obtain estimates of global-mean temperature change associated with these emissions scenarios. Fig. 2 shows the MAGICC-derived global-mean temperature changes for both the IS92a and the GI emissions scenarios. The global-mean warming associated with both these scenarios is very similar until 2025, after which the temperature curves diverge. By 2100, the warming associated with the IS92a emissions scenario has reached 2.46°C, compared to 0.95°C for the GI emissions scenario. A central estimate of 2.5°C for the climate sensitivity[2] was used in both cases.

[1]This is a difficult assumption to prove, especially since during this period the concentrations of GHGs were rising in the global atmosphere. At least for the UK, however, little systematic warming or cooling occurred on an annual basis between 1961 and 1987 (Parker et al. 1992). Furthermore, all 9 records were obtained from synoptic stations operated continuously by the UK Meteorological Office and had not been subject to site changes

[2]Climate sensitivity (ΔT_{2x}) is defined as the equilibrium change in global-mean surface air temperature for a doubling of CO_2-equivalent concentrations. IPCC (Houghton et al. 1995) define ΔT_{2x} to range between 1.5 and 4.5°C

Table 1. Frequencies of the probability distributions which best-fit the observed data. (Results from all 9 UK sites have been combined.) Bold values represent the most frequent best-fitting distributions in each month

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
Maximum temperature													
Normal		**5**	2	1						2	**4**	3	17
Square normal	**6**	2	**4**								3	**4**	19
Log normal	2	2	1	**4**	**6**	4	4	2	**7**	**4**		2	38
Root normal	1		2							2	2		7
Cube root normal				1						1			2
Gamma				2									2
Gumbel				1	3	**5**	**5**	**7**	2				23
Minimum temperature													
Normal	1	1	**6**	1		1	1	1		2	**5**	4	23
Square normal	**8**	**6**	3	**8**	**9**	**8**	**6**	**8**	**9**	**7**	1	**5**	78
Log normal							2						2
Root normal		1									3		4
Cube root normal		1											1
Gamma													0
Gumbel													0

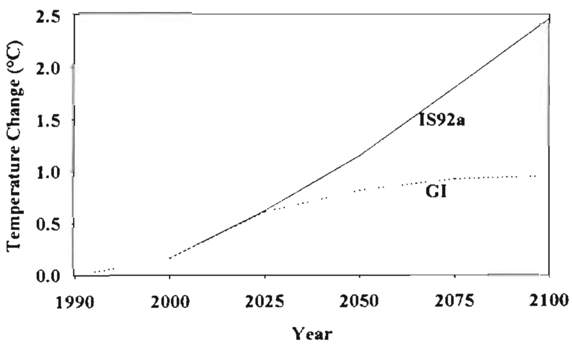

Fig. 2. Global-mean temperature changes (°C) with respect to 1990 for the IS92a and GI emissions scenarios, assuming a climate sensitivity of 2.5°C. Results obtained from the MAGICC model

These results can be used to scale the standardised patterns of climate change derived from GCM experiments (Santer et al. 1990, Hulme et al. 1994). Output from the UK Meteorological Office high resolution GCM equilibrium experiment, UKHI (Mitchell et al. 1990), was interpolated onto a 10' latitude/longitude grid using a Gaussian space-filtering routine and allotting each of the 9 sites to a single grid square. Such interpolation is a very crude form of downscaling, yet since only mean values are being interpolated and only the *changes* between control and perturbed model integrations are being calculated this need not be a spurious technique to use. The UKHI maximum and minimum temperature change fields ($2 \times CO_2 - 1 \times CO_2$) were first standardised with respect to the model's climate sensitivity ($\Delta T_{2x} = 3.5°C$) to obtain patterns of change standardised per degree of global warming. By scaling these standardised change fields with the MAGICC estimates of global-mean temperature change, patterns of change were derived for the 2 GHG emissions scenarios for the years 2000, 2025, 2050, 2075 and 2100. The appropriate grid-square changes were extracted for each site.

In order to examine the impact of the 2 climate change scenarios on the frequency of extreme events, the observed distribution parameters were changed to reflect the scenario changes in maximum and minimum temperature. In each case it was assumed that the probability distributions fitted for the present climate would also describe future maximum and minimum temperatures, although this is not certain. For the normal and all the transformed normal distributions the calculated local temperature change (i.e. the local standardised temperature change multiplied by the global-mean warming) was added to the untransformed mean which was then transformed appropriately to obtain the new distribution mean. This approximation was accurate to less than 0.1°C in all cases except for the square-normal distribution. Here, this approximation resulted in an error greater than 1°C, so a different approach was adopted for this distribution. The observed data were increased in half degree steps up to an increase of 10°C (in order to account for all possible scenario values of temperature increase), the new mean values calculated and a third order polynomial then fitted to the curve of temperature change versus mean value. In all cases the coefficient of determination was greater than 0.99, indicating an almost perfect fit of the curve to the data. The new distribution means were expressed as a function of temperature change and hence could be calculated for any temperature increase up to 10°C.

The gamma distribution mean is defined as $\alpha\beta$, where α is the shape parameter and β is the scale parameter. In order to include the effects of the climate change scenarios considered, the mean of this distribution is increased by the scenario change in temperature. This implies changes to both α and β, which have implications for the variance of this distribution (defined as $\alpha\beta^2$). To perturb the Gumbel distribution to reflect the scenario changes in temperature, the location parameter, α, was increased by the associated temperature change (ΔT) value, whilst the scale parameter, β, was kept constant.

The frequency of extreme events, however, depends not only on the rate of change of the mean, but also on whether there are changes in other statistical parameters which determine the distribution of the variable, for example, the variance (Wigley 1988). Changes in variance have important implications for the tails of the distribution where the extreme values occur. Katz & Brown (1992) have shown that extreme events are relatively more sensitive to the variability of climate than to its average, and that this sensitivity is relatively greater the more extreme the event. Hence, changes in variability were included in this analysis.

For the normal and transformed normal distributions, changes in variance were simply applied to the distribution variance. However, in the case of the gamma distribution, changing the distribution mean implied a simultaneous change in variance. In order to keep the variance constant, or to change it by a specified amount where required, a variance scaling factor was introduced. This was calculated as in the following example:

Let $\mu_1 = 18.48$, $\alpha_1 = 41.07$ and $\beta_1 = 0.45$. If the mean temperature is increased by 2°C, say, to $\mu_2 = 20.48$, then how do α_2 and β_2 change in a way consistent with a selected variance change? Let the variance scaling factor be denoted by $\Delta\sigma$. The initial observed variance must be multiplied by this factor to obtain the desired variance for the chosen scenario, i.e.

$$\Delta\sigma\alpha_1{\beta_1}^2 = \alpha_2{\beta_2}^2 \Rightarrow \Delta\sigma \times 41.07 \times (0.45)^2 = \alpha_2{\beta_2}^2$$

but, since $\alpha_2 = \dfrac{\mu_2}{\beta_2}$

$$\Delta\sigma\alpha_1{\beta_1}^2 = \mu_2\beta_2 \Rightarrow \Delta\sigma \times 41.07 \times (0.45)^2 = 20.48\beta_2$$

and $\quad \beta_2 = \dfrac{\Delta\sigma\alpha_1{\beta_1}^2}{\mu_2} \Rightarrow$

$\beta_2 = 0.49$ if $\Delta\sigma = 1.2$ (i.e. 20% increase in variance),
or $\beta_2 = 0.32$ if $\Delta\sigma = 0.8$ (i.e. 20% decrease in variance),

and $\alpha_2 = \dfrac{\mu_2}{\beta_2} \Rightarrow$

$\alpha_2 = 41.8$ (for a 20% increase in variance)
or $\alpha_2 = 64.0$ (for a 20% decrease).

For the Gumbel distribution, it was necessary to adjust the scale parameter, β, to account for changes in variance. Once the new variance (σ^2) had been determined, β was calculated from

$$\sigma^2 = \frac{\pi^2\beta^2}{6}$$

and the new mean value then calculated from

$$\mu = \alpha + 0.5772\beta$$

Future climate variability was considered in 3 ways as listed in Tables 3, 4 and 5: (1) the variance was kept the same as that of the original observed record; (2) the variance was changed in accordance with estimates derived from the UKHI experiment; (3) the observed variance was changed arbitrarily, between limits of ± 20% per 1°C of global warming.

For option (2), the variance was calculated from 10 yr of daily UKHI mean temperature data for both the control ($1\times CO_2$) and perturbed ($2\times CO_2$) integrations. Since no daily data from UKHI were available to us for maximum and minimum temperature it was assumed that changes in the mean temperature variance would be the same as, or similar to, those of maximum and minimum temperature. Although changes in mean diurnality are anticipated under conditions of climate change, we have no grounds to suppose that the relative variances of maximum and minimum temperature will alter. For each year of the 2 integrations, the variance was determined for each month, and the monthly values then averaged to obtain the mean monthly variance for each of the 2 GCM integrations. The variance ratio was calculated as:

$$\sigma_r^2 = \frac{\sigma^2_{2\times CO_2}}{\sigma^2_{1\times CO_2}} \tag{1}$$

In order to examine the variance change per degree of global warming, this variance ratio was standardised by dividing by UKHI's climate sensitivity ($\Delta T_{2\times} = 3.5$°C) and then converting the ratio to a percent change:

$$\Delta\sigma^{2*} = 100\left[\frac{(\sigma_r^2 - 1.0)}{\Delta T_{2\times}}\right] \tag{2}$$

Table 2 illustrates the standardised monthly variance change measured in percent for each of the 9 UK sites. The $\Delta\sigma^2$ values were initially calculated at the UKHI resolution (2.5° latitude by 3.75° longitude) and these were interpolated onto the 10' grid as before. The nearest 10' cell to each of the 9 sites was then selected to derive the values shown in Table 2. For all sites there was an increase in variance between May and October, whereas decreases in variance generally occurred in the other months.

To obtain the actual variance change for the site, climate change scenario and year concerned, the local standardised variance change was multiplied by the ap-

Table 2. Percent standardised variance change ($\Delta\sigma^{2*}$) for the 9 UK sites, as derived from the UKHI GCM equilibrium experiment. Bold values indicate a decrease in variance; elsewhere an increase in variance occurs

Month	Fortrose	Leuchars	Paisley	Ringway	Durham	Santon Downham	Oxford	Plymouth	Hillsborough
Jan	**−3**	**−5**	**−6**	**−9**	**−8**	**−8**	**−10**	**−11**	**−9**
Feb	**−1**	**1**	**−3**	**−10**	**−5**	**−10**	**−13**	**−12**	**−8**
Mar	1	1	**−5**	**−12**	**−7**	**−12**	**−15**	**−16**	**−12**
Apr	2	0	**−5**	**−8**	**−6**	**−8**	**−10**	**−11**	**−9**
May	7	7	3	2	3	5	4	6	1
Jun	6	5	2	1	2	3	2	4	1
Jul	5	4	2	5	3	11	13	21	2
Aug	27	26	18	15	17	21	21	28	12
Sep	24	23	15	12	15	19	15	21	10
Oct	5	5	2	3	3	5	4	4	1
Nov	**−8**	**−7**	**−10**	**−7**	**8**	**−5**	**−6**	**−6**	**−10**
Dec	**−7**	**−7**	**−9**	**−7**	**−8**	**−5**	**−6**	**−7**	**−10**

propriate global-mean temperature change. The original distribution variance was then adjusted accordingly.

LOCAL CHANGES

The probabilities of particular threshold temperatures being exceeded were examined at 2 sites, Fortrose and Santon Downham, representing latitudinal extremes within the UK (Fig. 1). Two minimum temperature thresholds, 0 and 10°C, were chosen and one maximum temperature threshold, 20°C. Both the minimum thresholds have agricultural significance: minimum temperatures below 0°C are indicative of air frosts and 10°C is the minimum temperature at which germination of maize for corn or oil will occur (A. Davies, AFRC Institute of Grassland and Environmental Research, Aberystwyth, UK, pers. comm.). The maximum threshold is indicative of warm summer days. Fig. 3a shows the 1961–87 mean daily minimum temperature cycle for Fortrose, with the ±1 standard deviation limits included, and also the cycle with the IS92a warming for 2100 imposed. It can be seen that in summer the warming lies outside the +1 standard deviation limit of current temperature, whereas in winter it is still within this range. However, for Santon Downham (Fig. 3b), by 2100 the warming under IS92a is still within the +1 standard deviation limit, reflecting the larger observed variability of temperature at this location compared to that of Fortrose, and hence perhaps the lesser significance of GHG-induced climate change. The warming associated with the GI emissions scenario by 2100 (0.95°C) is less than half of that of IS92a, and so the perturbed temperature cycle will be well within the +1 standard deviation limit in both locations.

Table 3 shows the probability of January mean minimum temperature being below 0°C at Fortrose and at Santon Downham for both the 1961–87 mean climate and also under the IS92a scenario. The effect of changes in variance is also illustrated.

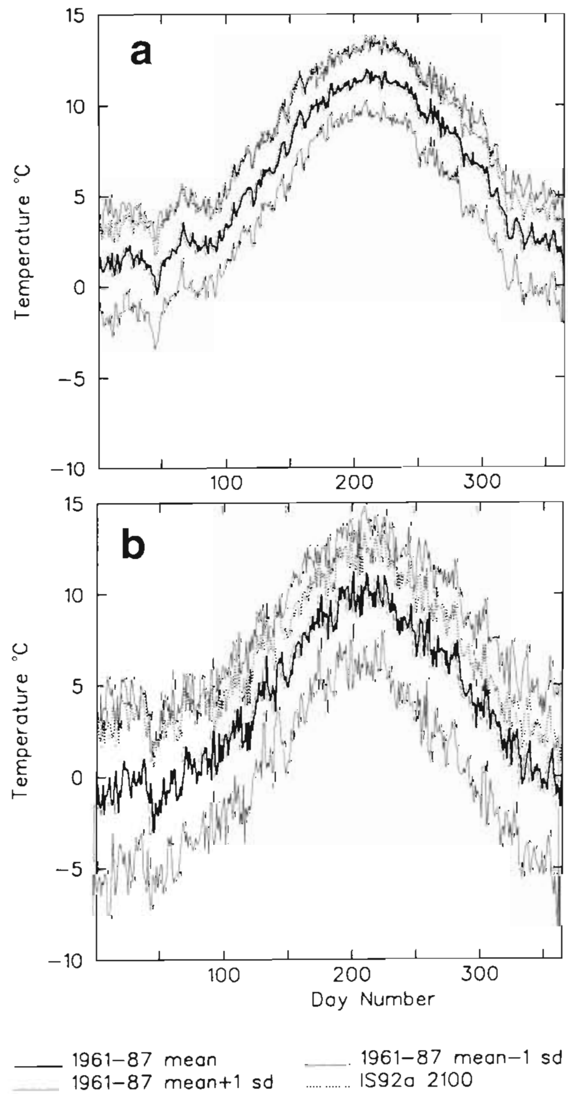

Fig. 3. Mean daily minimum temperature cycle showing ±1 standard deviation limits and GHG-induced warming associated with the IS92a emissions scenario for 2100. (a) Fortrose; (b) Santon Downham

Table 3. Changes in the probability of mean minimum temperature being below 0°C in January assuming the IS92a emissions scenario

Year	IS92a ΔT (°C)	Change in variance Constant	+20%/°C	−20%/°C	UKHI
Fortrose					
1961–87	0.00	0.290	0.290	0.290	0.290
2000	0.17	0.274	0.276	0.271	0.273
2025	0.62	0.234	0.244	0.222	0.232
2050	1.15	0.191	0.210	0.168	0.188
2075	1.80	0.144	0.174	0.107	0.139
2100	2.46	0.106	0.143	0.057	0.099
Santon Downham					
1961–87	0.00	0.517	0.517	0.517	0.517
2000	0.17	0.496	0.496	0.496	0.496
2025	0.62	0.437	0.441	0.430	0.434
2050	1.15	0.367	0.385	0.337	0.357
2075	1.80	0.287	0.325	0.203	0.262
2100	2.46	0.212	0.272	0.059	0.171

The effect of changes in variance on the probability of mean minimum temperature being below 0°C in January at both sites is apparent from Table 3. Fig. 4 shows these changes graphically. In all cases, the probability of such an event decreases with increasing temperature, as would be expected. However, it is the rate of change of probability which differs. At Santon Downham the 1961–87 probability of mean minimum temperature being below 0°C in January is almost twice that at Fortrose. The probabilities at Santon Downham also decrease more rapidly with increasing temperature than do those at Fortrose, indicating the larger variance in mean minimum temperature at the former site. If the variance is increased by 20% per °C the rate of decrease in probability is the smallest at both sites. A decrease in variance of 20% per °C results in the largest rate of decrease in probability. Increasing the variance flattens the shape of the probability distribution leading to increases in the area under the distribution tails. Decreasing the variance contracts the distribution shape and so the probability of such an extreme event occurring decreases with increasing temperature more rapidly than if the variance remained constant.

The global-mean temperature change associated with the GI emissions scenario is estimated to be 0.95°C in 2100. This is equivalent to the IS92a global-mean temperature change between the years 2025 and 2050. The decrease in probability of a mean minimum temperature in January being less than 0°C is therefore much smaller under this emissions scenario.

We present similar results for the probability of mean minimum temperature exceeding 10°C in July in Table 4 and Fig. 5. In this case, probabilities are higher at Fortrose, indicating the present higher mean minimum temperature in July at this site compared to Santon Downham. In both cases, Fig. 5 indicates that the largest rate of increase in probability occurs when the variance is decreased by 20% per °C. Increases in variance (the UKHI variance change is an increase in July) result in a slower increase in the probability of mean minimum temperatures being above 10°C.

Finally, we examined the change in the probabilities of higher summer daytime temperatures (Table 5, Fig. 6). It is apparent that although Fortrose has higher minimum temperatures in July compared to Santon Downham, its mean maximum temperatures in this month are not as high (16.5°C at Fortrose compared to 21.4°C at Santon Downham, for 1961–87). Under present climate conditions, the probability of a mean maximum temperature of 20°C being exceeded at Santon Downham is almost 7

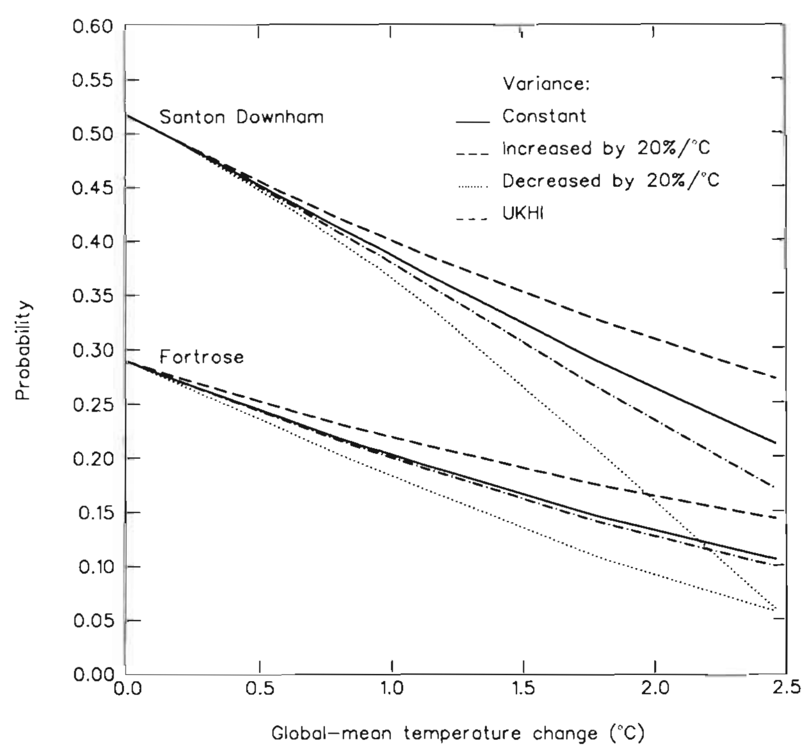

Fig. 4. Effect of changes in variance on the probability of mean minimum temperature being below 0°C in January

Table 4. Changes in the probability of mean minimum temperature being above 10°C in July assuming the IS92a emissions scenario

Year	IS92a ΔT (°C)	Change in variance Constant	+20%/°C	−20%/°C	UKHI
Fortrose					
1961–87	0.00	0.754	0.754	0.754	0.754
2000	0.17	0.776	0.773	0.779	0.776
2025	0.62	0.832	0.821	0.844	0.829
2050	1.15	0.885	0.865	0.907	0.880
2075	1.80	0.932	0.907	0.960	0.925
2100	2.46	0.963	0.936	0.988	0.956
Santon Downham					
1961–87	0.00	0.483	0.483	0.483	0.483
2000	0.17	0.500	0.500	0.500	0.500
2025	0.62	0.545	0.543	0.548	0.544
2050	1.15	0.598	0.590	0.611	0.593
2075	1.80	0.662	0.642	0.696	0.650
2100	2.46	0.722	0.688	0.787	0.701

times that of Fortrose. With increases in global-mean temperature, these probabilities increase, although the rate of increase again depends on the variance change being considered. At Santon Downham, the rate of increase in probability is greatest when the variance is decreased by 20% per °C and smallest when the variance is increased by 20% per °C. At Fortrose, however, the smallest rate of increase in probability is obtained with a 20% per °C decrease in variance and the largest increases in probability occur with a 20% per °C increase in variance. At this site, the mean maximum temperature in July is below the 20°C threshold value. Increasing the variance increases the probability of this threshold being exceeded (the tails of the distribution are extended), whereas decreasing the variance implies that it is less likely that this threshold value will be exceeded (the tails of the distribution are contracted). At Santon Downham, however, the mean maximum temperature in July already exceeds the 20°C threshold being considered. If the variance is increased, the tails of the distribution are extended and it becomes more likely that lower temperatures may occur. Hence, the probability of the 20°C threshold being exceeded decreases with an increase in variance. Decreases in variance, however, result in the tails of the distribution being contracted. This has a greater effect at the lower end of the distribution and so the probability of the threshold being exceeded increases. In this example, the impact of changes in variance depends on the position of the distribution mean in relation to the threshold value.

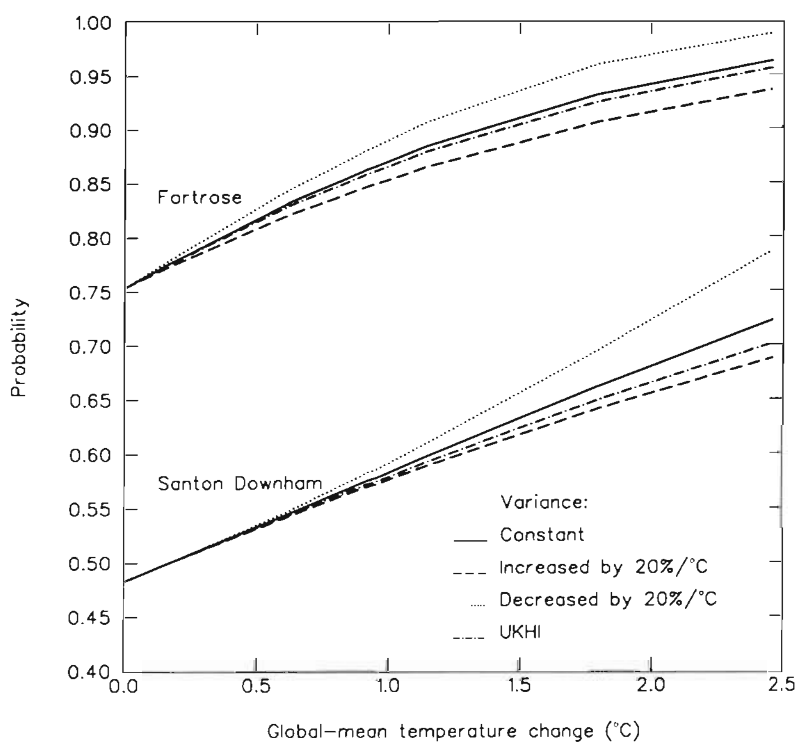

Fig. 5. Effect of changes in variance on the probability of mean minimum temperature being above 10°C in July

DISCUSSION AND CONCLUSIONS

The work presented here forms part of a project to investigate future changes in transient climate and climate extremes in the UK, funded by the UK Ministry of Agriculture, Fisheries and Food. This project involved the development of an interactive desktop computer model, SPECTRE (Spatial and Point Estimates of Climate change due to TRansient Emissions), which allows the construction of scenarios of future changes in mean climate over the UK from GCMs, including the impact of climate change on temperature extremes of relevance to agriculture. Although the project was concerned mainly with agricultural impacts, the same methodology can be used to generate scenarios of relevance for other impact areas, e.g. the energy sector. This would be achieved simply by selecting a threshold minimum or maximum temperature which is relevant to the impact area under consider-

Table 5. Changes in the probability of mean maximum temperature being above 20°C in July assuming the IS92a emissions scenario

Year	IS92a ΔT (°C)	Change in variance Constant	+20%/°C	-20%/°C	UKHI
Fortrose					
1961–87	0.00	0.094	0.094	0.094	0.094
2000	0.17	0.107	0.110	0.104	0.108
2025	0.62	0.134	0.144	0.122	0.136
2050	1.15	0.170	0.189	0.147	0.175
2075	1.80	0.222	0.249	0.185	0.230
2100	2.46	0.283	0.312	0.234	0.291
Santon Downham					
1961–87	0.00	0.654	0.654	0.654	0.654
2000	0.17	0.665	0.663	0.668	0.664
2025	0.62	0.703	0.694	0.714	0.698
2050	1.15	0.745	0.726	0.769	0.734
2075	1.80	0.791	0.760	0.836	0.773
2100	2.46	0.832	0.790	0.898	0.807

ation, e.g. maximum temperatures above 27°C for the application of air conditioning (Hulme et al. 1993).

We recognise that there are a number of limitations associated with this method relating both to the construction of the climate change scenarios and to assumptions associated with the probability distributions. These include the following:

– Site-specific changes in temperature have been obtained by simple interpolation of the coarse-scale GCM output, rather than by a more sophisticated downscaling procedure.

– Only a single GCM has been used. Climate change scenarios will differ depending on the GCM employed. Although inter-model changes in mean temperature may not be that different (compared to precipitation, for example), changes in temperature variability may differ widely. This would have implications for the probability estimates described here.

– The major assumption that has been made in this work is that the form of the probability distribution, calculated from observed daily data, remains the same in the future, although the shape and scale parameters of the distributions obviously change. Until longer daily time series are available from GCMs for analysis this may be the best approach available.

– Furthermore, we have had to assume that future changes in minimum and maximum temperature variance are the same as for mean temperature.

– A final reason why the changes described here should be viewed as merely provisional scenarios is that although the emissions scenarios, and hence global-mean radiative forcing, used to generate *global-mean* temperature changes include the effects of sulphate aerosols, the GCM experiment used to estimate the *pattern* of temperature change over the UK did not. It is now suspected that recent and future GHG warming over large parts of Europe has been partly (or largely) offset by regional cooling associated with sulphate aerosols (Taylor & Penner 1994). Incorporating such effects into scenarios such as those described here must await further experiments using GCMs with aerosols included.

The work described here illustrates how important it is to account for changes in future climate variability affecting the probability of particular threshold temperature events occurring, as well as changes in the mean values of climate variables. This type of information will be of value in future crop breeding programmes by helping in the development of new cultivars which are well adapted to future cli-

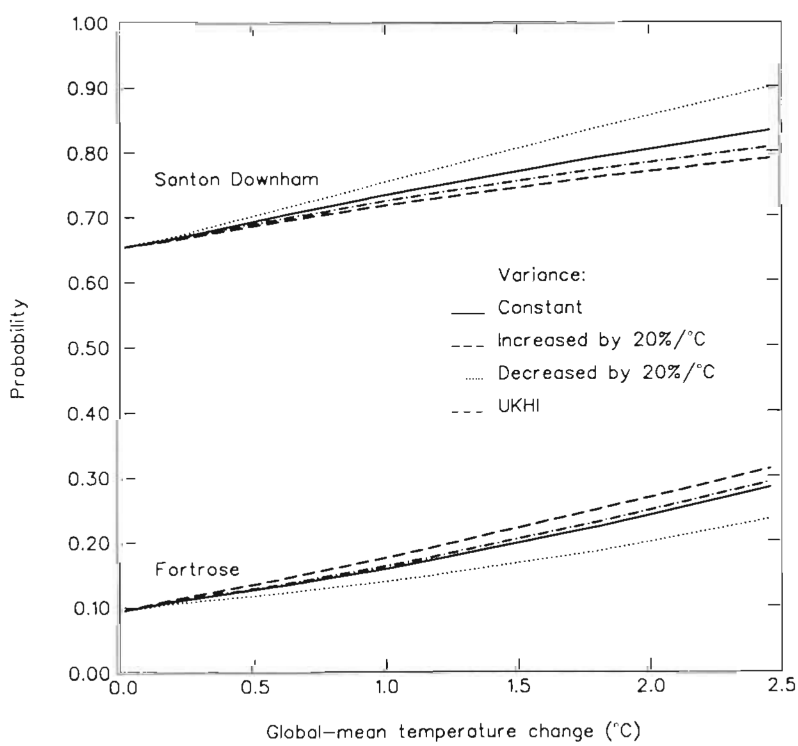

Fig. 6. Effect of changes in variance on the probability of mean maximum temperature exceeding 20°C in July

mate. The agricultural application of such information is illustrated in the following example.

At Fortrose by 2100 under the IS92a emissions scenario, a mean minimum temperature of 10°C is almost always exceeded during June, July, August and September (Fig. 3a). There is also no risk of frost over these months. Hence, crops which require a minimum temperature of 10°C for germination or emergence could be planted in late May to early June around 2100 with a high certainty that this minimum temperature will be exceeded. This is about one month earlier than could be achieved currently at Fortrose. One such crop is grain maize, which also needs a 10°C minimum temperature for maturation. By 2100, the mean growing season for this crop is extended by 7 wk under the IS92a scenario. Although the minimum temperature regime at Fortrose is sufficient for growth of this crop, the optimum temperatures for growth, however, are between 21 and 30°C (A. Davies pers. comm.). Under the current climate, a mean maximum temperature of 20°C is unlikely to occur before June or after September. This mean maximum temperature is likely to be exceeded most often in July, but only on 3 days of the month. By 2100 under the IS92a scenario, the period of occurrence of mean maximum temperatures exceeding 20°C increases to be between April and October, but the number of days on which this temperature is likely to be exceeded in July only increases to 9. Hence, although grain maize could be grown at this latitude it would probably not achieve maturity over the growing season because of the time required to reach the thermal requirements for each developmental stage.

At Santon Downham, there is currently a slight risk of frost even in July and August (Fig. 3b). This risk only disappears for July between 2025 and 2050 and for August between 2050 and 2075 under the IS92a scenario. Under the GI scenario, the frost risk only disappears for July between 2050 and 2075. By 2100 under IS92a the probability of a minimum temperature above 10°C is 0.72 in July compared to the 1961–87 mean of 0.48 (Table 4). However, maximum temperatures in July at Santon Downham reach higher values than at Fortrose. Under IS92a, the probability of a 20°C maximum temperature being exceeded is 0.83 by 2100 (compared to 0.65 for 1961–87; Table 5). Hence, crops with a minimum temperature requirement of 10°C will probably ripen faster than at Fortrose, although germination may not be as successful.

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