USE OF A STOCHASTIC WEATHER GENERATOR IN THE DEVELOPMENT OF CLIMATE CHANGE SCENARIOS

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Abstract. Climate change scenarios with a high spatial and temporal resolution are required in the evaluation of the effects of climate change on agricultural potential and agricultural risk. Such scenarios should reproduce changes in mean weather characteristics as well as incorporate the changes in climate variability indicated by the global climate model (GCM) used. Recent work on the sensitivity of crop models and climatic extremes has clearly demonstrated that changes in variability can have more profound effects on crop yield and on the probability of extreme weather events than simple changes in the mean values. The construction of climate change scenarios based on spatial regression downscaling and on the use of a local stochastic weather generator is described. Regression downscaling translated the coarse resolution GCM grid-box predictions of climate change to site-specific values. These values were then used to perturb the parameters of the stochastic weather generator in order to simulate site-specific daily weather data. This approach permits the incorporation of changes in the mean and variability of climate in a consistent and computationally inexpensive way. The stochastic weather generator used in this study, LARS-WG, has been validated across Europe and has been shown to perform well in the simulation of different weather statistics, including those climatic extremes relevant to agriculture. The importance of downscaling and the incorporation of climate variability are demonstrated at two European sites where climate change scenarios were constructed using the UK Met. Office high resolution GCM equilibrium and transient experiments.

1. Introduction

In order to develop scenarios of climate change which are of greatest use in impacts assessment the scenarios should be tailored to their area of application. The first stage in this process is a sensitivity analysis of the impact model in question to changes in the relevant climate variables. Changes in those variables which may result in noticeable changes in the output of the impact model should be incorporated in order to produce realistic climate change scenarios.

In most modelling studies investigating the impact of climate change on crop production changes in only the means of the climate variables have been considered. These changes, derived from global climate models (GCMs), were usually applied to historical weather data to construct scenarios of climate change relevant to agricultural applications (e.g, Kenny et al., 1993; Rosenzweig et al., 1993). Recent work on the sensitivity of crop simulation models to changes in climate variables has clearly shown that changes in climate variability can have a significant effect on crop growth and associated agricultural risk (Semenov and Porter, 1994, 1995;

Climatic Change **35:** 397–414, 1997.

Mearns et al., 1996). Extreme weather events, such as drought or hot or cold spells, can have severe consequences for crops, and the frequency of occurrence of such events has been shown to be better correlated with changes in the variability of climate variables than with changes in the mean values (Katz and Brown, 1992). As crop-growth simulation models incorporate a mixture of non-linear responses of the crop to its environment, it is thus equally important for impact assessments to include changes in climate variability as well as changes in mean climate. Assessments of the impacts of climate change on agricultural production and the appraisal of associated risks to the food supply need to bear the above in mind.

The tools which are most widely used to construct scenarios of climate change for impacts assessment are GCMs (Giorgi and Mearns, 1991; Viner and Hulme, 1994). These complex computer models describe the climatological conditions of the Earth at a finite number of grid points (a grid point model) or by a finite number of mathematical functions (a spectral model). The limiting factor for running GCMs is computational power; a compromise must be reached between the spatial resolution of the model and the computer time required to perform an experiment. Hence, most GCMs tend to have a coarse spatial resolution which leads to approximations in the model representation of meteorological variables at the regional or local scale. These so-called 'sub-grid scale' processes have to be parameterised in the model rather than solved realistically as a function of the fundamental equations. However, despite these limitations, GCMs still provide an opportunity to examine the evolution of climate under a variety of conditions (Gates et al., 1990). There are a number of factors which limit the direct use of their output in scenario development. These include:

1. The ability of the control experiment to adequately simulate the larger-scale features of the present-day climate. This is one of the reasons that the difference between the control and perturbed integrations is used, rather than the raw data from the integrations themselves.
2. The coarse spatial grid-output is on the scale of hundreds of kilometres rather than the tens of kilometres needed for impacts assessment. This coarse resolution also means that sub-grid scale processes, such as precipitation, are not adequately represented and important regional topographic features are also omitted. Hence, although GCMs may be able to simulate large-scale features of climate well, their simulation of regional climate is considerably poorer.

In this study the output from two GCM experiments was combined with a stochastic weather generator, LARS-WG, in order to produce climate change scenarios which were suitable for use in agricultural impact assessment. The requirements of climate change scenarios for agricultural impacts assessment may be summarised as follows:

- scenarios should be site-specific with daily temporal resolution;
- they should include the full set of climate variables required by the impacts model;
- they should include changes in means and climate variability; and
- contain an adequate number of years to permit risk analysis.

This study may be considered in two sections and the results of each are detailed. First, climate change scenarios with high spatial resolution were constructed using regression downscaling to obtain site-specific climate data from the coarse grid-scale GCM data. Second, changes in climate variability were incorporated into the scenarios. In this case, the GCM data were utilised without any downscaling in the absence of a robust method to downscale coarse resolution variability to the site-specific scale. The basic method of producing the climate change scenarios is the same regardless of whether downscaling or climate variability are included. Climate change information, derived from GCMs, was used to perturb the parameters of the stochastic weather generator, LARS-WG, which had previously been calibrated for each site using observed daily climate data. Daily scenario data were then generated from these perturbed parameters. Results are reported for two sites, namely Rothamsted, UK and Seville, Spain.

2. Methodology

LARS-WG and the construction of the scenarios from the GCM data are now described in more detail.

2.1. THE LARS-WG STOCHASTIC WEATHER GENERATOR

Models for the simulation of time-series of a suite of climate variables with certain statistical properties have a long history. The first examples are found in the early 1960s (e.g., Gabriel and Neumann, 1962; Bailey, 1964). Initially models were developed to simulate a single variable, most often daily precipitation for use in hydrological applications. From the beginning of the 1980s models which could generate a whole suite of climate variables, stochastic weather generators, became available (Richardson, 1981; Racsko et al, 1991). Stochastic weather generators may be site-specific, i.e., they generate weather time-series for a single site, or spatial, i.e., they generate weather for a number of locations simultaneously, reflecting the spatial correlation of the different climate variables (Bardossy and Plate, 1991; Hutchinson, 1995). Originally there were two main reasons for the development of stochastic weather generators. The first was the provision of a means of simulating synthetic weather time-series with certain statistical properties which were long enough to be used in an assessment of risk in hydrological or agricultural applications. The observed weather series normally required as input into mathematical models of hydrological processes or simulation models of crop growth are often insufficiently long to allow the estimation of the probability functions of rare events. The second purpose was to provide the means of extending the simulation of weather time-series to unobserved locations. For example, in order to simulate precipitation at an unobserved location the statistical parameters of a weather generator need to be calculated using data from the nearest meteorological stations. These parameters are then interpolated using one or other interpolation techniques (e.g., kriging or thin-plate smoothing splines) and time-series are then generated using the interpolated values of the parameters (Hutchinson, 1995). It is worth noting that a stochastic weather generator is not a predictive tool which can be used in weather forecasting, but is a mean of generating time-series of synthetic weather statistically ‘identical’ to the observations. Of course, it must be borne in mind that statistical ‘identity’ depends on the number of statistics used for the comparison.

New interest in local stochastic weather simulation has arisen as a result of climate change studies. Output from GCMs cannot be used directly as climate change scenarios for the reasons mentioned earlier. The weather generator, however, can serve as a computationally inexpensive tool to produce multiple-year climate change scenarios at the daily timescale which incorporate changes in the mean and climate variability.

In this study the LARS-WG* stochastic weather generator has been used (Racsko et al., 1991; Semenov and Porter, 1994). It generates a suite of climate variables, namely, precipitation, maximum and minimum temperature and solar radiation. Precipitation is considered as the primary variable and the other three variables on a given day are conditioned on whether the day is wet or dry. The simulation of precipitation occurrence is based on distributions of the length of continuous sequences, or series, of wet and dry days. This is different from the approach suggested by Bailey (1964) and re-used by Richardson (1981), which applies a first-order Markov chain to describe the occurrence of wet and dry days. The main limitation of the ‘Markovian’ approach is that the Markov chain has a ‘limited memory’ of rare events and, for example, could fail to simulate accurately long dry series at certain locations (Racsko et al., 1991). This problem was resolved by using the series approach, where the distribution of wet and dry series is derived by accumulating information from the observations. Consideration of long dry series is important in agricultural studies since long droughts significantly affect crop growth and can dramatically decrease yields. Mixed exponential distributions were used to model the dry and wet series so that LARS-WG would be applicable over a wide range of European locations. The amount of rain on wet days was also simulated using a mixed exponential distribution. The distribution of the other weather variables, i.e., maximum and minimum temperature and solar radiation, is based on the current status of the wet or dry series. These variables were considered as stochastic processes with daily means and standard deviations conditioned on the

* The LARS-WG is in a public domain and a version for IBM PC (Windows 95/NT) is available from ftp.lars.bbsrc.ac.uk.

Table I
Description of the European sites

Site	Latitude (°N)	Longitude (°E)	Period of record	Mean annual precipitation (mm)	Mean annual temperature (°C)
Jokioinen, Finland	60.8	23.5	1961–90	582.4	3.6
Rothamsted, UK	51.8	-0.4	1961–90	684.5	9.2
Munich, Germany	48.1	11.6	1951–80	947.5	8.1
Seville, Spain	37.4	-5.9	1975–91	530.1	18.0
Athens, Greece	38.0	23.7	1965–90	367.7	17.6

wet and dry series. The techniques used to analyse the processes are very similar to those presented in Yevjevich (1972) and Richardson (1981). The seasonal cycle of means and standard deviations was removed from the observed record and the residuals approximated by a normal distribution. These residuals were used to analyse a time correlation within each variable. Fourier series were then used to interpolate seasonal means and standard deviations. The simulation of radiation was independent from temperature.

The first step in the production of daily weather data using a stochastic weather generator was the evaluation of the model parameters for each of the European test-sites (see Table I). Three other sites were used in addition to Rothamsted and Seville in order to ascertain how well LARS-WG performed over a wide range of climatological conditions. Observed daily data were used to calculate the site-specific weather parameters; these parameters were then used by LARS-WG to generate synthetic data. Use of at least twenty years of observed daily data is recommended in order to determine robust statistical parameters. Various statistics were compared in order to ensure that the generator performed well at each location. For all sites except Seville 30 years of observed daily meteorological data were used. Only 17 years of daily weather data were available for Seville. The weather statistics of the observed meteorological data were compared with 30 years of generated data for each site. The following statistics were used in this comparison: monthly mean precipitation amount, standard deviation of monthly precipitation, mean length of the dry series, mean length of the wet series, mean number of wet days, daily mean maximum and mean minimum temperature, standard deviation of daily temperature, mean number of days with maximum temperature greater than 30 °C, mean number of days with minimum temperature less than 0 °C and daily mean radiation.

Some of the results are presented in the Appendix, Tables A-I–IV. Mean daily maximum and minimum temperature, their standard deviations and solar radiation were simulated well by LARS-WG compared to the observations for each site. The statistics of ‘extreme’ temperature, e.g., days with maximum temperature above

30 °C and days with minimum temperature below 0 °C, were also in good agreement with the observed data. Monthly mean precipitation was, however, simulated less accurately. The duration of wet and dry series was simulated relatively well for all sites except Seville. A reason for this may be that the reduced amount of daily data available at this site may have been insufficient to determine robust parameters for LARS-WG. However, extremely long dry periods at Seville at the end of the summer and the beginning of autumn were reproduced by the weather generator. The number of wet days were reproduced well for almost all months at each site. It is apparent that LARS-WG generally performs well in simulating the magnitude and seasonal cycle of the main weather statistics and consequently it was used at all European sites without any additional modifications.

2.2. CONSTRUCTION OF THE CLIMATE CHANGE SCENARIOS

Data from the UK Met. Office high resolution GCM equilibrium (UKHI; Mitchell et al., 1990) and transient (UKTR; Murphy, 1995; Murphy and Mitchell, 1995) experiments were used in the construction of the climate change scenarios. For UKHI, difference fields were calculated between the control and perturbed integrations. However, construction of climate change scenarios from the transient experiment was not so straightforward. One of the problems of UKTR is climate drift in its control integration – there is a noticeable deviation (approximately 1 °C) from the initial ten-year average over the 75-year period of the simulation. How this drift is handled affects the way in which the scenarios are constructed and thus there are a number of different ways of calculating the change fields, each of which makes assumptions about the climate variability and control integration drift (Viner and Hulme, 1993). For our purposes the change fields from UKTR were constructed by calculating the difference between a period in the climate change integration and the corresponding years of the control integration. This definition is appropriate if it is assumed that both the control and climate change integrations exhibit similar drift and long-term variability.

Data from UKTR were available only as decadal time-slices and the last decade, model years 66–75, was selected for use. The global-mean temperature change corresponding to this decade is 1.76 °C. Depending on assumptions concerning future greenhouse gas emissions and climate sensitivity a range of dates as to when this temperature change may occur can be calculated, but a best estimate is towards the middle of the next century. The reader is referred to the latest report from the Intergovernmental Panel on Climate Change (Houghton et al., 1996) for more detailed discussion as to when such changes may occur. In the case of UKHI, the equilibrium global-mean temperature change of 3.5 °C is not expected to occur before the latter years of the next century at the earliest, if at all.

2.2.1. *Scenarios Using Regression Downscaling*

In order to produce scenarios of climate change at the scale required by crop-growth simulation models, it was necessary to 'downscale' the coarse resolution GCM data to specific sites. This procedure involved the development of relationships between the coarse- and local-scale data for the climate variables concerned. There are currently a number of downscaling methodologies in use, including circulation patterns (e.g., Bardossy and Plate, 1991; Matyasovszky et al., 1993; Jones and Conway, 1995) and regression techniques (e.g., Kim et al., 1984; Wigley et al., 1990; Karl et al., 1990; von Storch et al., 1993). Both methods use existing instrumental databases to determine the relationships between large-scale and local climate. Regression techniques develop statistical relationships between local station data and grid-box scale, area-average values of say, temperature and precipitation and other meteorological variables. The circulation pattern approach classifies atmospheric circulation according to type and then determines links between the circulation type, e.g., westerly, and climate variable, for example, precipitation.

There are a number of reservations, however, which need to be considered when using circulation patterns as part of climate change studies, including the problems that some GCMs have in simulating the correct frequencies of weather type and also the observed relationships between particular circulation patterns and temperature and precipitation (see Hulme et al., 1993). Also, the relationships between circulation patterns and, for example, temperature and precipitation, in one area of Europe may not be applicable in another location, so for these reasons it was decided to use the regression approach to downscaling.

At Rothamsted and Seville regression relationships were calculated between local station data (mean temperature and precipitation; i.e., the predictands) and grid-box scale, monthly anomalies of mean sea level pressure (MSLP), the north-south and east-west pressure gradients, temperature and precipitation (i.e., the predictors). The regression relationships were based on anomalies from the long-term mean in order to facilitate the use of the GCM-derived changes in the equations.

The process undertaken is summarised here, but is described in more detail in Barrow et al. (1995; 1996). Observed area-averages corresponding to the grid-box area of UKHI and UKTR were calculated for Rothamsted and Seville for mean temperature and precipitation. Anomalies from the 1961–90 mean were then calculated for each month for each of the five predictor variables. The dataset was split into two time periods, one of which was used to calibrate the regression equations whilst the other was used to verify their performance. Regression relationships were then calculated between the local (i.e., site) and regional (i.e., grid-box) climate. Table II illustrates the performance of the regression models at Seville; results for Rothamsted were reported in Barrow and Semenov (1995) and may also be found in Barrow et al. (1995).

The next step in the procedure was the calculation of the changes in the predictor variables from UKHI and UKTR. At both Rothamsted and Seville some of these changes, particularly mean temperature, were outside of the anomaly ranges

Table II
Performance of the regression model

(a) Calibration of the regression models for Seville based on 1961–1990 observed data. Variance explained (%)

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Temp.	93.8	91.3	84.5	81.9	84.9	90.3	85.4	77.9	94.0	87.4	95.6	97.5
Precip.	82.3	84.6	65.8	81.7	77.3	68.2	20.0	64.8	54.4	67.4	79.4	86.5

(b) Verification of the regression models for Seville using 1951–1960 observed data. Correlation coefficients between observed data and those predicted by the regression models

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Temp.	0.95	0.99	0.82	0.94	0.87	0.87	0.85	0.93	0.97	0.73	0.96	0.98
Precip.	0.91	0.96	0.92	0.97	0.67	0.64	0.0	0.83	0.72	–0.07	0.64	0.89

originally used to calibrate the regression models. Despite this, it was decided to continue the downscaling process, but to add a caveat regarding the confidence placed in the downscaled results because of the combination of poor performance of some of the regression models and of the grid-box changes being outside of the calibration range in some instances. Figure 1 indicates the grid-box and downscaled changes in mean temperature and precipitation at Seville. In the case of mean temperature, site changes are greater than the corresponding areal values in all months except April. Changes in precipitation are not so consistent.

The downscaled changes in mean temperature and precipitation were then used to perturb the parameters of LARS-WG (all other parameters were kept unchanged) and 30 years of daily data were then generated. No changes in variability were included in these scenarios.

2.2.2. *Scenarios Incorporating Climate Variability*

The climate change scenarios incorporating changes in climate variability were constructed without any downscaling of the GCM information for the two sites, Rothamsted and Seville. This was because a robust procedure for downscaling the variability parameters was not available (in the case of LARS-WG these parameters are precipitation intensity, the duration of the wet and dry series and the standard deviation of temperature on wet and dry days). Daily data for the appropriate grid boxes from the control and perturbed integrations of the UKTR experiment were used to calculate changes in precipitation intensity, duration of wet and dry spells and temperature means and variances. These changes were then applied to the LARS-WG parameters previously calculated from the observed daily data at each site. The perturbed parameters were used to generate 30 years of daily data. For comparison, a corresponding scenario without variability was also constructed by

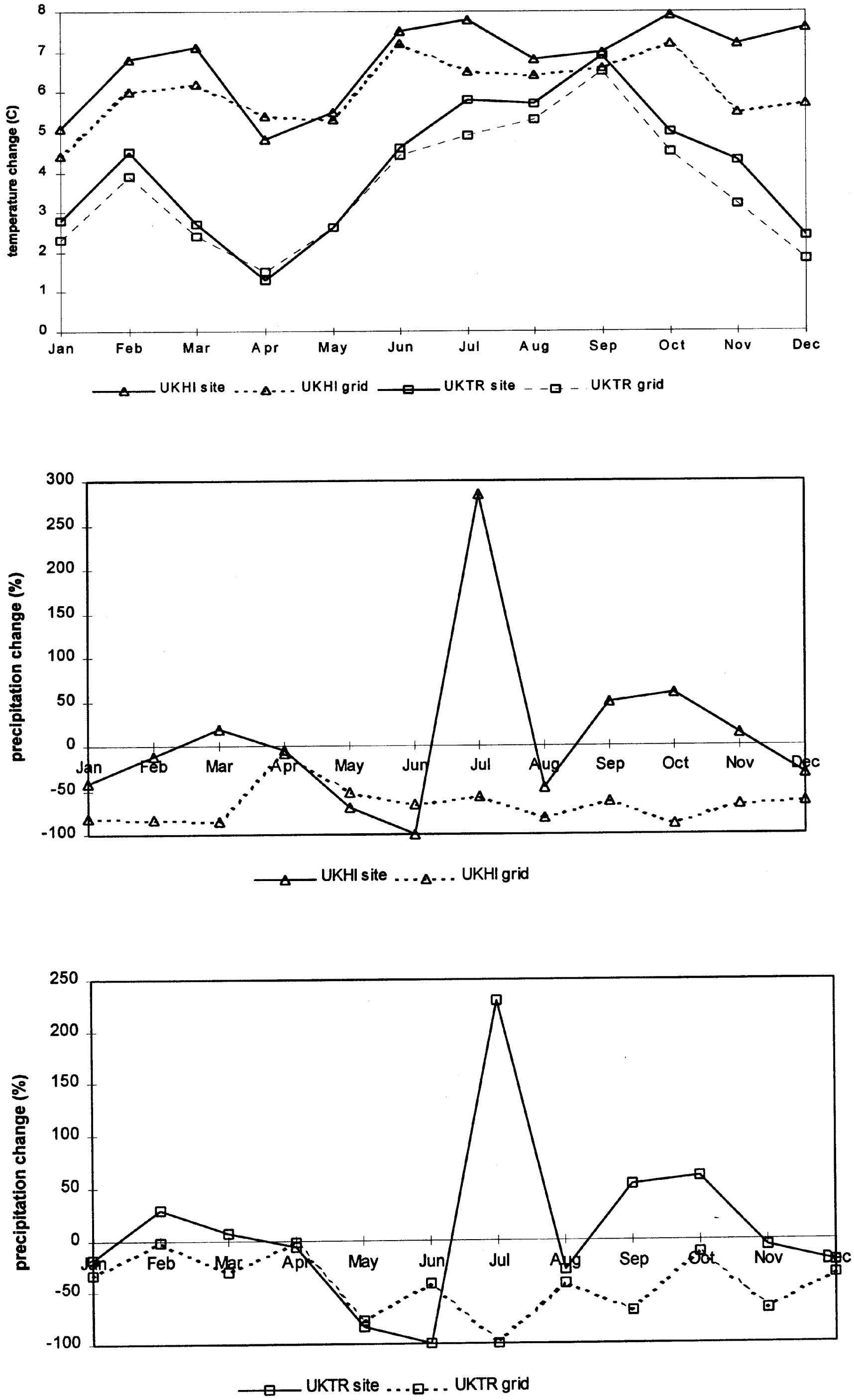

Figure 1. Site (downscaled) and grid box changes at Seville. (a) Mean temperature change (°C) for both UKHI and UKTR; (b) precipitation change (%) for UKHI, and (c) precipitation change (%) for UKTR

applying changes in monthly mean precipitation and monthly mean temperature to the LARS-WG parameters.

The implications and importance of including changes in climate variability in scenarios of climate change was then demonstrated by comparing the effect of scenarios with and without variability on simulated grain yield by using SIRIUS Wheat, a crop-growth simulation model for wheat (Jamieson et al., 1996).

3. Results

3.1. SCENARIOS USING REGRESSION DOWNSCALING

Table III illustrates the effect of downscaling on mean monthly precipitation totals at Rothamsted. If downscaling is not carried out, then both the UKHI and the UKTR scenarios indicate an overall increase in precipitation amount, although there are decreases in precipitation amount in a number of individual months for the UKTR scenario. As a result of downscaling the number of months indicating a decrease in precipitation amount increases for both UKHI and UKTR. In the case of UKHI, however, there is still a general increase in precipitation amount compared to the 'observed' precipitation generated by LARS-WG (indicated in the column entitled 'Base'). For UKTR, on the other hand, downscaling results in a general decrease in precipitation amount. The values marked with asterisk in Table III indicate where the downscaled results have been changed in an opposite direction to those without downscaling when compared with the 'Base' precipitation.

Table IV indicates the effect of downscaling on precipitation amounts at Seville. For both scenarios without downscaling there is a general decrease in precipitation amount. Including downscaling actually results in a general increase in precipitation amount for the UKTR experiment. Although the downscaled UKHI scenario precipitation amounts are less than those of the generated base, they are almost three times greater than for the same scenario without downscaling. Part of the increase in precipitation amount as a result of downscaling is directly attributable to the high July precipitation amounts predicted by the regression model. It is worth noting that the July regression model explained only 20% of the variance in the observed data, and hence these results should be treated with caution. If precipitation is assumed to be zero in this month, precipitation totals for the UKTR experiment are still higher than when downscaling is not included.

3.2. SCENARIOS INCORPORATING CLIMATE VARIABILITY

Incorporation of variability into climate change scenarios should not make any difference to monthly statistics such as, for example, monthly total precipitation or monthly mean temperature. In Table V these means are compared for the UKTR scenarios with and without variability for Seville. There is no significant difference between monthly mean temperatures for the scenarios with and without variability

Table III

Mean monthly precipitation totals (mm) at Rothamsted with and without downscaling. Values marked with an asterisk indicate where downscaling has resulted in a change of the opposite sign compared to the corresponding scenario without downscaling. Changes in variability not included

	Base	Without downscaling		With downscaling	
		UKHI	UKTR	UKHI	UKTR
Jan	64.8	105.6	72.7	83.4	60.3*
Feb	55.1	82.1	71.3	78.0	68.9
Mar	50.9	74.2	52.3	72.4	55.1
Apr	44.9	54.3	38.6	54.3	39.5
May	57.9	52.7	62.9	33.5	53.9*
Jun	62.9	65.5	65.5	59.5*	61.9*
Jul	53.5	51.9	47.6	52.3	48.1
Aug	60.0	83.5	40.4	55.7*	24.5
Sep	56.9	61.2	43.0	58.7	39.5
Oct	69.6	85.0	77.6	79.5	73.7
Nov	56.4	56.6	76.2	56.0*	81.5
Dec	69.9	98.1	78.4	102.1	79.2

Table IV

Mean monthly precipitation totals (mm) at Seville with and without downscaling. Values marked with an asterisk indicate where downscaling has resulted in a change of the opposite sign compared to the corresponding scenario without downscaling. Changes in variability not included

	Base	Without downscaling		With downscaling	
		UKHI	UKTR	UKI	UKTR
Jan	84.9	15.8	56.7	48.1	68.8
Feb	62.3	10.7	61.4	54.9	80.4*
Mar	51.6	7.9	35.5	61.6*	55.2*
Apr	41.8	38.3	41.1	39.7	39.0
May	36.5	17.4	7.8	11.0	5.7
Jun	13.2	4.5	7.6	0.0	0.0
Jul	5.5	2.3	0.0	21.0*	18.0*
Aug	4.0	0.7	2.3	2.1	2.8
Sep	11.4	4.3	3.6	17.1*	17.4*
Oct	51.0	6.0	44.8	81.3*	81.3*
Nov	71.1	24.1	23.4	80.2*	66.0
Dec	63.2	23.6	41.5	42.9	76.9*

for all months. Results from a t-test indicate that precipitation totals were significantly different for four months out of seven during the vegetation period for winter wheat (January–July). The differences in the totals are most probably due to the way in which the scenarios were constructed, rather than to the weather generator (see Barrow et al., 1996). For three of these months (May, June and July) precipitation for both scenarios was so low that it did not make a big difference to total precipitation over the vegetation period, 184 mm and 210 mm with and without variability, respectively, compared to 496 mm for the base climate. For the base climate the grain yield simulated by SIRIUS Wheat was 5.6 t/ha and its coefficient of variation (CV) was 0.24 (Table VI). According to the UKTR scenario without variability, the grain yield does not change much (5.2 t/ha) and the CV remains about the same (0.23). If changes in climate variability are considered the results are very different. The grain yield drops to 3.9 t/ha and the CV almost doubles to 0.48. The reason for this is not the total amount of precipitation, but the change in precipitation distribution over the vegetation period and the prolonged dry spells. The probability of producing yields less than 3.5 t/ha is almost 50% for the UKTR scenario with variability and only about 10% for the UKTR scenario without variability or for the baseline climate (Figure 2). The high probability of obtaining low grain yields may make wheat an economically unsuitable crop in Spain under this climate change scenario. A detailed comparison of five wheat models (AFRCWHEAT2, CERES, NWHEAT, SIRIUS and SOILN), including model sensitivity to changes in means and variances of weather variables and model performances for a set of climate change scenarios, are presented in Wolf et al. (1996) and Semenov et al. (1996).

4. Conclusions

A stochastic weather generator has been used in this climate change study as a computationally inexpensive tool to construct site-specific climate change scenarios which incorporate changes in climate means and climate variability, as indicated by two UK Met. Office GCM experiments, UKHI and UKTR, and which are suitable for agricultural impacts assessment. Site-specific scenarios were produced using regression downscaling techniques, whilst scenarios incorporating changes in variability used only the GCM grid-box changes. The daily time-series for both types of scenario were produced by the LARS-WG stochastic weather generator which had been previously calibrated for a number of European sites. The GCM-derived changes were then applied to the parameters of the weather generator for each site and 30 years of daily data generated. This study has demonstrated that the different methods of scenario construction produce significantly different climate change scenarios which, in the case of Seville, imply quite different conclusions concerning the suitability of wheat cultivation in this area of Spain as a result of climate change.

Table V

Mean monthly total precipitation (mm) and maximum temperature (°C) at Seville, Spain, for the UKTR scenario without downscaling. Values marked with an asterisk indicate where the hypothesis of equal monthly means was rejected with 95% confidence level

	Without variability		With variability	
	Precip.	Temp.	Precip.	Temp.
Jan	55.5	12.0	34.4*	11.9
Feb	64.5	15.5	60.6	15.6
Mar	34.6	15.6	23.7	15.7
Apr	40.6	17.0	38.4	17.3
May	7.8	21.7	15.0*	21.9
Jun	7.5	28.6	3.0*	28.0
Jul	0.0	31.6	9.2*	31.5
Aug	2.3	32.5	0.3*	32.5
Sep	3.5	31.2	0.7*	31.6
Oct	48.8	24.0	30.3	24.4
Nov	23.6	17.2	3.5*	16.9
Dec	43.1	12.2	20.4*	12.0

Table VI

The effect of climate variability on crop yield and its coefficient of variation (CV), as simulated by SIRIUS Wheat, for UKTR scenario at Seville, Spain. Total precipitation and cumulative mean temperature were calculated for the winter wheat vegetation period from January to July

	Base	UKTR	UKTR with variability
Grain yield, t/ha	5.6	5.2	3.9
CV of yield	0.24	0.23	0.48
Total precipitation, January–July, mm	296	210	184
Cum. Temperature, January–July, °C	3630	4293	4323

The disadvantage of using regression downscaling is that it is rather data intensive; observed data from several sites are required in order to calculate observed areal means and anomalies. Construction of site-specific scenarios of climate change may be aided by the current development of Regional Climate and High Resolution Limited Area Models (RegCMs and HRLAMs, respectively). This methodology has been recently developed for climate change studies (Dickinson et al., 1989; Giorgi, 1990). The basic idea of the approach is to run a RegCM with a high grid resolution (approximately 50km) but only over a limited area of interest. The RegCM is a physically-based model nested into the GCM and is able to repro-

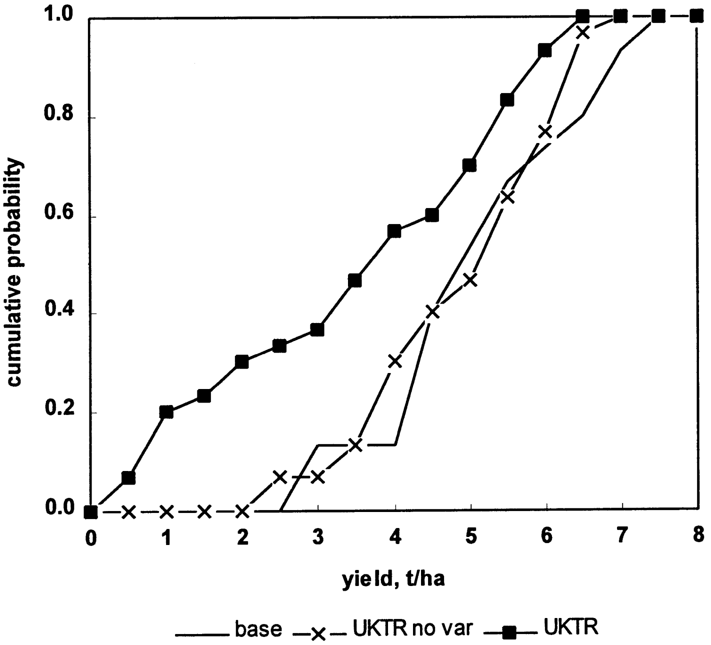

Figure 2. Cumulative probability functions of grain yield as simulated by SIRIUS Wheat for the base climate and for the UKTR scenarios with and without changes in climatic variability.

duce regional climate in more detail than the GCM itself. However, recent work on the validation of a RegCM has shown that there may be still large differences between model output and observed weather statistics, especially in the case of climate variability (Mearns et al., 1995a,b). This means that the construction of local climate change scenarios from these models may be as problematic as from GCMs. Hence, the need for local stochastic weather generators in climate change studies will remain in the near future.

Acknowledgements

The UK Met. Office GCM data were provided by the Climate Impacts LINK Project (Department of the Environment Contract PECD 7/12/96) on behalf of the UK Met. Office. The authors would like to thank Pete Jamieson for his assistance with SIRIUS Wheat. Many thanks also to Mike Hulme and two referees, Linda Mearns and Hans von Storch, for their valuable comments. This work was funded by the Commission of the European Communities' Environment Programme (Contract EV5V-CT93-0294). Elaine Barrow was also partially funded by a grant from the University of East Anglia. IACR Long Ashton receives grant-aided support from the Biotechnology and Biological Sciences Research Council in the UK.

Appendix

Table A-I
Comparison of observed (Obs) and generated (Gen) monthly mean precipitation (total, mm)

	Rothamsted		Jokioinen		Seville		Athens		Munich	
	Obs	Gen	Obs	Gen	Obs	Gen	Obs	Gen	Obs	Gen
Jan	62.8	64.8	35.8	33.1	60.9	84.9	40.7	47.3	52.1	58.6
Feb	53.4	55.1	24.4	23.7	79.5	62.3	47.7	47.9	54.5	52.7
Mar	50.3	50.9	25.3	34.7	46.4	51.6	44.7	48.7	53.4	59.0
Apr	48.0	44.9	31.5	25.7	53.4	41.8	30.3	26.9	72.5	71.6
May	52.2	57.9	35.2	37.4	20.9	36.5	15.9	16.3	99.3	108.9
Jun	56.6	62.9	46.5	51.6	14.2	13.2	9.8	11.1	135.0	132.9
Jul	53.4	53.5	79.9	66.2	3.5	5.5	4.4	11.1	128.7	136.0
Aug	62.6	60.0	83.0	77.2	6.2	4.0	5.3	6.8	112.3	107.9
Sep	60.9	56.9	65.2	77.7	17.0	11.4	10.2	10.0	73.1	78.0
Oct	57.2	69.6	58.3	72.8	57.5	51.0	45.3	30.9	57.6	45.6
Nov	72.4	56.4	55.3	52.9	90.4	71.1	47.8	46.8	57.3	55.6
Dec	69.0	69.9	42.0	42.4	80.3	63.2	65.7	65.2	51.9	55.5

Table A-II
Comparison of observed (Obs) and generated (Gen) mean dry series length (days)

	Rothamsted		Jokioinen		Seville		Athens		Munich	
	Obs	Gen	Obs	Gen	Obs	Gen	Obs	Gen	Obs	Gen
Jan	2.3	2.9	3.0	3.3	7.0	5.8	4.8	5.3	3.2	3.0
Feb	2.9	3.0	3.2	3.8	4.1	6.7	5.0	6.8	3.2	3.6
Mar	3.7	3.3	4.2	3.4	7.1	6.1	5.8	6.2	4.1	4.7
Apr	3.2	3.6	3.7	4.6	5.3	7.7	6.4	7.4	3.3	4.5
May	3.1	3.6	4.8	4.8	10.0	8.6	7.7	10.5	3.0	3.0
Jun	3.9	3.4	3.9	4.6	13.5	12.0	11.4	14.7	2.5	3.1
Jul	3.6	4.5	3.4	4.2	33.4	29.9	33.9	20.2	2.6	3.1
Aug	3.6	3.8	3.3	3.2	66.6	47.6	45.5	26.7	3.0	2.9
Sep	3.3	3.7	2.8	3.6	25.1	37.6	16.6	40.7	3.4	3.8
Oct	3.6	4.3	3.0	3.0	11.9	31.0	16.3	26.8	4.7	5.1
Nov	3.1	3.4	2.8	2.5	7.6	9.0	8.1	14.0	5.0	5.9
Dec	2.6	3.1	2.6	3.0	7.6	7.7	5.2	8.9	3.1	4.6

Table A-III
Comparison of observed (Obs) and generated (Gen) mean daily maximum temperature (°C)

	Rothamsted		Jokioinen		Seville		Athens		Munich	
	Obs	Gen	Obs	Gen	Obs	Gen	Obs	Gen	Obs	Gen
Jan	5.6	5.1	–4.6	–4.4	15.5	15.1	12.9	12.8	1.4	1.8
Feb	6.0	6.6	–4.3	–5.0	16.3	17.0	13.9	14.1	3.3	3.5
Mar	9.1	9.3	0.4	0.1	20.1	19.2	16.0	16.5	8.0	8.9
Apr	12.0	12.4	6.6	7.8	21.5	22.2	20.2	20.4	12.6	13.2
May	15.8	15.5	14.7	14.2	26.4	26.4	25.3	25.4	17.2	16.5
Jun	19.1	18.7	19.5	19.1	31.5	30.6	29.8	29.8	20.5	20.8
Jul	20.6	20.3	20.7	21.3	35.2	34.5	32.5	32.7	22.5	22.5
Aug	20.4	20.4	19.0	19.0	35.1	35.2	32.1	32.3	22.0	21.6
Sep	17.9	18.2	13.4	13.4	32.3	31.8	28.9	27.9	19.0	18.1
Oct	14.0	13.8	7.6	7.0	25.6	26.0	23.1	23.5	13.3	13.1
Nov	9.0	9.3	1.7	1.6	19.7	19.8	18.3	18.0	6.7	7.2
Dec	6.6	6.6	–2.2	–2.7	16.1	16.1	14.7	14.6	2.5	3.2

Table A-IV
Comparison of observed (Obs) and generated (Gen) mean number of days with $T_{\mathrm{min}} < 0$ °C

	Rothamsted		Jokioinen		Seville		Athens		Munich	
	Obs	Gen	Obs	Gen	Obs	Gen	Obs	Gen	Obs	Gen
Jan	13.7	18.8	29.2	30.8	3.1	3.9	0.8	0.6	25.6	28.4
Feb	12.7	14.4	26.9	27.5	1.7	1.2	0.4	0.6	21.5	24.0
Mar	9.4	9.8	28.2	30.3	0.0	0.1	0.3	0.3	17.0	19.3
Apr	3.5	4.2	20.6	23.0	0.0	0.1	0.0	0.0	7.0	8.7
May	0.4	0.5	6.6	5.3	0.0	0.0	0.0	0.0	0.7	0.8
Jun	0.0	0.0	0.5	0.4	0.0	0.0	0.0	0.0	0.0	0.0
Jul	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Aug	0.0	0.0	0.3	0.3	0.0	0.0	0.0	0.0	0.0	0.0
Sep	0.0	0.1	3.9	3.8	0.0	0.0	0.0	0.0	0.1	0.3
Oct	0.8	0.8	11.3	14.7	0.0	0.0	0.0	0.0	4.9	4.5
Nov	6.0	6.9	20.2	26.0	0.4	0.6	0.0	0.0	14.1	18.6
Dec	11.0	16.8	27.6	30.2	2.9	3.6	0.1	0.2	23.2	26.4

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(Received 11 November 1996; in revised form 23 September 1996)