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Short Communication

Generating downscaled weather data from a suite of climate models for agricultural modelling applications

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ABSTRACT

We describe a generalised downscaling and data generation method that takes the outputs of a General Circulation Model and allows the stochastic generation of daily weather data that are to some extent characteristic of future climatologies. Such data can then be used to drive any agricultural model that requires daily (or otherwise aggregated) weather data. The method uses an amalgamation of unintelligent empirical downscaling, climate typing and weather generation. We outline a web-based software tool (http://gismap.ciat.cgiar.org/MarkSimGCM) to do this for a subset of the climate models and scenario runs carried out for the 2007 Fourth Assessment Report of the Intergovernmental Panel on Climate Change. We briefly assess the tool and comment on its use and limitations.

1. Introduction

The availability of weather data continues to be a serious constraint to undertaking many applied research activities in the realm of agriculture, particularly in developing countries. Because weather is a primary determinant of agricultural production, weather data are needed for many different types of analysis in agricultural science. In addition to the data availability problem, the format in which data are available may be a considerable constraint to their widespread use. Nowhere is this more apparent than in agricultural impacts modelling, particularly in relation to utilising the outputs of climate models to evaluate possible impacts of climate change on crop and livestock production systems over the coming decades. The outputs from General Circulation Models (GCMs), climate models that project into the future, are almost never in a form that can be used directly to drive agricultural models. Considerable processing has to be gone through before such data can be meaningfully used, both for assessing possible impacts and for evaluating adaptation options. This processing generally involves downscaling the outputs from coarse-scaled GCMs to higher spatial and temporal resolutions. Various methods of downscaling exist, each with its own advantages and disadvantages, and each appropriate for different situations (Wilby et al., 2009). Reliable downscaling depends on the availability of reliable historical weather and climate data. Unfortunately, particularly in many developing countries, ground-based observation has declined considerably in the last several decades (Funk et al., 2011). Satellite technology is advancing rapidly and some aspects of weather and climate can be measured this way but such data are a complement to ground-based observation and not a substitute.

Here we describe a generalised downscaling and data generation method, which takes the outputs of a GCM describing a particular future climatology and allows the stochastic generation of a core set of daily weather data that are to some extent characteristic of this future climatology. This builds on previous methods, outlined and applied in Thornton et al. (2006), which utilised data from a suite of climate models used for the Third Assessment Report of the Intergovernmental Panel on Climate Change (IPCC, 2001). These methods have been modified to use outputs from the later generation of climate models utilised in the IPCC's Fourth Assessment Report (IPCC, 2007). The approach is fast and generalisable, and uses a mixture of methods, including simple interpolation (what Wilby et al. (2009) call "unintelligent downscaling"), climate typing and weather generation. Below we describe a web-based tool that uses these methods with a user interface in Google Earth and provides the user with daily weather data for current and future climatologies, which can then be used directly to run some widely-used crop models.

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2. Materials and methods

2.1. Processing the GCM data

Outputs from many GCMs are available in the public domain, notably in the World Climate Research Program's (WCRP's) Coupled Model Intercomparison Project phase 3 (CMIP3) multi-model dataset. This dataset contains model output from 22 of the GCMs used for the Fourth Assessment (AR4; see Table 8.1 in Randall et al., 2007) and for a range of scenarios including the three scenarios reported on in the IPCC's Special Report on Emission Scenarios (SRES) used in the AR4. They are: A2, a high-greenhouse-gas-emission scenario; A1B, a medium-emission scenario; and B1, a low-emissions scenario. The SRES scenarios are described in detail in Nakicenovic et al. (2000).

Model output data are not available for all combinations of GCM and scenario for the basic "core" variables that are needed to drive many crop and pasture models (precipitation, maximum daily temperature and minimum air temperature). From CMIP3 and the Climate and Environmental Retrieval and Archive (CERA) database at the German Climate Research Centre (DKRZ), we found complete data for the three scenarios for a total of six GCMs (Table 1). As other data become available in the future, they can subsequently be included in the software.

SRES emission scenarios are considerably different in terms of projected changes in temperatures and rainfall for different regions. Table 2 shows the projected mean impacts on global temperature of these different scenarios from the IPCC multi-model ensemble for different time-slices. Although differences between the three scenarios in global warming impacts to 2050 are limited, thereafter these become considerable. Temperature shifts also vary substantially by region. Many GCMs project mean average temperature increases to 2050 for the East Africa region, for example, that are larger than the global mean: for scenario A2, of between about 1.5–2.5 °C. In addition to differences between the emission scenarios used to drive the climate models, the GCMs themselves can vary greatly. It is straightforward to plot rainfall and temperature patterns from different GCMs using the data and tool on the website www.ipcc-data.org, for example. GCMs differ in consistency for regional climate projections, particularly related to precipitation (IPCC, 2007).

The general scheme of the analysis here is as follows. First, we obtained data from the GCMs for five time slices: 1991–2010 (denoted "2000"), 2021–2040 (denoted "2030"), 2041–2060 (denoted "2050"), 2061–2080 (denoted "2070") and 2081–2100 (denoted "2090") for average monthly precipitation and daily maximum (T_{max}) and minimum (T_{min}) air temperatures. Processing of these data resulted in calculated mean monthly climatologies for each time slice and for each variable from the original daily time series produced by each GCM. The mean monthly fields had been interpolated, by the original agencies from whom we obtained the data, from the original resolution of each GCM to 0.5° latitude–longitude using conservative remapping, which preserves the global averages. Second, we calculated monthly climate anomalies (absolute changes) for monthly rainfall, mean daily maximum temperature and mean daily minimum temperature, for each time slice relative to the baseline climatology (1961–1990). The point of origin was designated 1975, being the mid point of the 30-year climate normals.

Third, we fitted a functional relationship to the climate projections for the variables of interest through time, so that we could interpolate the projections to any year. We inspected the responses of the chosen models and found that they were considerably more complicated than those of the third approximation models used in the previous exercise (Thornton et al., 2006). There it was found by stepwise regression that a cubic term was superfluous to describe the projections over time. In the current case, we made a preliminary investigation of the functional forms of the projections using cluster analysis. All pixels from each of the climate models for scenario A1B were clustered for precipitation, T_{max} and T_{min} using the values of the five periods as clustering variates. We used a leader clustering algorithm (Hartigan, 1975) to cope with the volume of data. The threshold was set to produce from 40 to 100 clusters, which were ranked by the number of pixels, and the cluster means were used to inspect the functional form. The first five clusters normally covered 80–90% of the pixels for any given model.

We fitted polynomials through the cluster means by date (constrained through the origin) and this showed that in many cases a quadratic fit over time would have sufficed but in numerous cases only a fourth-order polynomial would suffice. We therefore decided to fit fourth-order polynomials throughout. We made these fits for all models at all scenarios and made another set for the average of the six models. We constructed world maps of the residual surfaces for every time period for each variate and for each model and scenario. Visual inspection of every map showed that deviations from the fitted curves were within expectations for all the models. Finally, we condensed the polynomial coefficients into a data file structure for ready retrieval on a pixel-by-pixel basis (at a resolution of 30 arc-min) for use in subsequent operations: downscaling the anomalies to a higher resolution, and then generating daily weather data that are characteristic, to some extent, of the future climatologies produced, using a stochastic daily weather generator.

2.2. Generating daily data: MarkSim®

MarkSim® is a third-order markov rainfall generator (Jones and Thornton, 1993, 1997, 1999, 2000; Jones et al., 2002), which has been developed over 20 years. It was not designed as a GCM downscaler, but it does now work as such, employing both stochastic downscaling and climate typing.

The basic algorithm of MarkSim is a daily rainfall simulator that uses a third-order markov process to predict the occurrence of a rain day. A third-order model was shown to be necessary for

Table 1
Atmosphere-Ocean General Circulation Models (AOGMCs) used in the work (details from Randall et al., 2007).

Model name (Date)	Institution	Reference	Resolution	Code
BCCR_BCM2.0 (2005)	Bjerknes Centre for Climate Research (University of Bergen, Norway)	Furevik et al. (2003)	1.9 × 1.9°	BCC
CNRM-CM3 (2004)	Météo-France/Centre National de Recherches Météorologiques, France	Déqué et al. (1994)	1.9 × 1.9°	CNR
CSIRO-Mk3.5 (2005)	Commonwealth Scientific and Industrial Research Organisation (CSIRO) Atmospheric Research, Australia	Gordon et al. (2002)	1.9 × 1.9°	CSI
ECHam5 (2005)	Max Planck Institute for Meteorology, Germany	Roeckner et al. (2003)	1.9 × 1.9°	ECH
INM-CM3_0 (2004)	Institute for Numerical Mathematics, Moscow, Russia	Diansky and Volodin (2002)	4.0 × 5.0°	INM
MIROC3.2 (medres) (2004)	Center for Climate System Research (University of Tokyo), National Institute for Environmental Studies, and Frontier Research Center for Global Change (JAMSTEC), Japan	K-1 Model Developers (2004)	2.8 × 2.8°	MIR
Ensemble average	Average climatology of the above 6 AOGCMs	–	–	AVR

Table 2
Projected mean impacts on global temperatures of three different scenarios.[a]

Scenario	2011–2030	2046–2065	2080–2099
A2 (“high” emissions)	0.64	1.65	3.13
A1B (“medium” emissions)	0.69	1.75	2.65
B1 (“low” emissions)	0.66	1.29	1.79
Committed warming (emissions stabilised at 2000 levels)	0.37	0.47	0.56

[a] Global mean warming from the Intergovernmental Panel on Climate Change (IPCC) multi-model ensemble mean (all climate models) for three periods relative to 1980–1999 for the A2, A1B and B1 emissions scenarios from the IPCC’s Special Report on Emission Scenarios (SRES). Table from Wilby et al. (2009); data source IPCC (2007).

tropical climates, whereas a lower-order model may suffice for temperate climates (Jones and Thornton, 1993). The crux to the efficiency of MarkSim in simulating the actual variance of rainfall observed both in the tropical and temperate regions is its innovative use of resampling of the markov process parameters. To do this, we need the 12 monthly baseline transfer probabilities (i.e., the probability of a wet day following three consecutive dry days), the probability coefficients related to the effect of each of the three previous days and the correlation matrix of the 12 baseline probabilities, all obtained from historical daily rainfall data.

MarkSim therefore works from a large set of parameters; including those for rainstorm size, the set totals 117. To make a globally valid model that does not need recalibration every time it is used, we have constructed a calibration set of over 10,000 stations worldwide. These were clustered into 702 climate clusters using the 36 values of monthly precipitation and monthly maximum and minimum temperatures. Almost all except a few of the calibration stations have more than 10 years of (almost) continuous data. Most stations have 15–20 years of data; a few have 100 years or more. Some of the 117 parameters of the MarkSim model are calculated by regression from the cluster most representative of the climate point to be simulated; the correlation matrix of monthly rainfalls is represented by a mean matrix for the cluster.

MarkSim estimates daily maximum and minimum air temperatures and daily solar radiation values from monthly means of these variables, using the methods originating with Richardson (1981). Monthly solar radiation values are estimated from temperatures, longitude and latitude using the model of Donatelli and Campbell (1997).

MarkSim guarantees that, in the long run, the values used as a starting point for a simulation series will be returned as the average of the simulated series. This is to be expected in a valid weather simulator. If this were all it could do, it would not be judged a good downscaler. When GCM differentials are added to the starting values, not only may the regression values for the coefficients change but they may completely change the climate cluster that is associated with that point. This means that the simulated climate has been shifted to a different type. Thus we have a form of “climate typing”: the type model of the climate can change depending on the GCM differentials, as can the response regressions for the parameters.

This raises a question that we are currently addressing: when does a GCM differential addition take us out of our current cluster space? As yet we do not know. We can calculate just how far any given climate on earth is outside the MarkSim current cluster space, and we have found that about 20% are more than two standard deviations from a calibrated cluster, based on WorldClim, a 1-km interpolated climate grid for the globe (Hijmans et al., 2005). There are two points to make here. First, we can improve the current calibration considerably. We already have a wealth of new data to incorporate in the next MarkSim calibration, and this can be done given appropriate time and resources. Second, we need to look carefully at the climates that are going to occur with global warming. This is problematic: we have reasonably good estimates of future climates from GCMs, but we have no good estimates of future weather. When a GCM differential puts a point out of the range of MarkSim’s simulation clusters then we can only extrapolate from the nearest climate we have now. We can hope that not too many pixels on the earth fall into this situation in the near future; but for more distant future climates, the situation is highly uncertain.

2.3. Using Marksim

For any location, MarkSim makes use of a climate record. This is independent of the scale of the data but is constant in its form and acceptability to the rest of the MarkSim software. A climate record contains the latitude, longitude and elevation of the location, and monthly values of rainfall, daily average temperature and daily average diurnal temperature variation. It also includes the temporal phase angle, that is, the degree by which the climate record is “rotated” in date. This rotation is done to eliminate timing differences in climate events, such as the seasons in the northern and southern hemispheres, so that analysis can be done on standardised climate data. The climate record is rotated to a standard date, using the 12-point Fast Fourier transform, on the basis of the first phase angle calculated using both rainfall and temperature (Jones, 1987; Jones et al., 2002). In MarkSim, almost all operations are done in rotated date space.

The estimated GCM differential values are added to the rotated record. This is an example of unintelligent downscaling (Wilby et al., 2009); inverse square distance weighting is used over the valid elements of the nearest nine GCM cells. This can be done with a climate database such as WorldClim (Hijmans et al., 2005), although pre-rotated MarkSim datasets are available. WorldClim may be taken to be representative of current climatic conditions (most of the data cover the period 1960–1990). It uses historical weather data from a number of databases. WorldClim uses thin plate smoothing with a fixed lapse rate employing the program ANUSPLIN. The algorithm is described in Hutchinson (1997).

3. Results

A FORTRAN object oriented module was developed to carry out the downscaling outlined above, and this has been linked to a graphical user interface in Google Earth. The module, called MarkSimGCM, is freely available at http://gismap.ciat.cgiar.org/MarkSimGCM/. The user chooses a location (the program will work for any location on land for which WorldClim has underlying climate normals), and then chooses one of the GCMs shown in Table 1 or the ensemble average climatology, one of the three scenarios shown in Table 2, the centre of the time slice to which the generated data will refer, and the number of years of daily weather data required (from 1 to 99). The random number seed for the weather generation can also be set if required, otherwise it is set at random by the system clock on the computer running the application. There is also the option to generate daily data that are representative of current conditions as in WorldClim; in this way, MarkSimGCM operates as an updated version of the CD-based release of MarkSim (Jones et al., 2002).

MarkSimGCM currently produces output in two formats: as annual charts of daily rainfall, maximum and minimum air temperatures and solar radiation; and as annual data files that are fully compatible with the DSSAT (Decision Support System for Agrotechnology Transfer) crop modelling suite (ICASA, 2007). These

Table 3
Comparison of MarkSimGCM simulations with historical data from 73 rainfall stations arranged into 12 Köppen climate classes.

Köppen class[a]	Number of stations	Average precipitation (mm per year)		Variance of annual rainfall		Variance ratio, F	Probability[d] of F	Degrees of freedom (DF)
		MarkSim[b]	Historical data[c]	MarkSim[b]	Historical data[c]			
Af	5	2479	2423	173,672	285,315	1.643	0.131	27
Ah	1	1136	1120	88,101	63,970	1.377	0.118	60
As[e]	9	1380	1373	78,574	65,654	1.197	0.266	48
Aw	10	1275	1217	97,399	131,545	1.351	0.145	52
Bs	12	562	523	22,591	26,057	1.153	0.305	61
Bw	6	268	233	9300	9171	1.014	0.473	69
Cr	1	1680	1673	86,830	149,219	1.719	0.041	34
Cs	3	837	809	39,574	61,482	1.554	0.059	56
Cw	14	767	732	32,489	34,440	1.060	0.419	65
Dc	9	563	557	17,296	12,759	1.356	0.101	99
Do	2	832	788	31,784	16,263	1.954	0.010	51
Eo	1	949	877	47,974	20,272	2.367	0.053	12

[a] See, for example, www.fao.org/sd/EIdirect/climate/EIsp0002.htm for a description of the Köppen system.
[b] From 50 years of simulations.
[c] Calculated from years of the sample data that were complete with 12 months of data with over 25 days of registered rainfall (missing days were compensated).
[d] Calculated using the NAG (1995) library using the degrees of freedom of the MarkSim estimate (49) and the pooled estimate (DF) depending on which way the comparison was made (Fisher and Yates, 1967).
[e] "As" is not a standard Köppen class; it defines a tropical climate where the main rainfall is in the summer months defined by their analogous months in subtropical climes in the same hemisphere (the climatology of the two types is quite different).

DSSAT files can be downloaded as a zip file by the user, if required, and used directly to run any of the crop models in the DSSAT.

While MarkSim itself has been extensively tested (see Jones and Thornton, 1993; Jones and Thornton, 1997), here we ran a comparison of MarkSimGCM simulations with historical data from 73 rainfall stations covering a range of different rainfall regimes, in terms of the average annual rainfall and the variance of annual rainfall. For each station, a MarkSimGCM run was carried out for current climate to produce 50 years of simulated data, and the annual mean and variance were calculated. Each station was classified according to the Köppen classification and simulated means and variances were pooled within each class. Results are shown in Table 3. MarkSim either underestimates or overestimates the annual rainfall variance by a small amount over much of the range tested, but mostly insignificantly. However, significant, systematic variation does appear to happen in the colder climates (D and E) where MarkSim consistently overestimates variance. Although MarkSim was developed for the tropics, this does warrant further study. This testing also highlighted another issue: two of the test stations, Morropan, Peru (latitude 5.18°S, longitude 79.98°W) and Guayaquil, Ecuador (latitude 2.15°S, longitude 79.88°W), lie on the western coast of South America in an area considerably affected by the El Niño-Southern Oscillation (ENSO) effect. MarkSim simulates their average rainfall reasonably accurately, but it is not currently able to simulate accurately an ENSO effect that produced an annual rainfall almost ten times the long-term average twice during the period for which we have measured data (data not shown). Whether MarkSim can be adapted to simulate such extreme rainfall variances is an interesting question. However, we now have more than 44,000 stations of rainfall data waiting to be incorporated into MarkSim version 2, compared with the 9200 stations that are in the version tested here.

The data produced by MarkSimGCM can, with care, be used in many ways. We have used them to identify areas of sub-Saharan Africa in which cereal cropping may become increasingly risky in the future, where the increased probabilities of failed seasons may mean that people will need to shift from cropping and increase their dependence on livestock (Jones and Thornton, 2009). We have used similar methods to assess possible changes in yields of maize and beans in East Africa, using the bean and maize models in the DSSAT (Thornton et al., 2009). Recently, we have used these data in a study to identify "hotspots" of climate change and food insecurity to target research activities in the tropics on adaptation, mitigation and risk management (Ericksen et al., 2011).

4. Discussion and conclusions

All downscaling activity is affected by considerable uncertainties of different types. First, even from the GCMs themselves, it is clear that present and future predictability of climate variability and climate change is not the same everywhere and that gaps in knowledge of basic climatology are revealed by a lack of agreement between climate models in some regions (Wilby, 2007). While confidence in projected patterns of warming and sea level rise is higher now, confidence is less in projections of the numbers of tropical storms and of regional patterns of rainfall over large areas of Africa, south Asia and Latin America. This highlights the importance of using different scenarios and different models to assess likely climate changes and their impacts. Second, our understanding is limited of what the local-level impacts of climate change are likely to be, which means that evaluating the adequacy of different downscaling techniques is difficult. Third, a significant gap lies between the information that we currently have at seasonal time scales and the information we have at longer time scales: information about what is likely over the next 3–20 years, critical for many types of planning, is still largely missing (Washington et al., 2006).

Despite these uncertainties, MarkSimGCM can provide weather data for possible future climatologies that agricultural impact modellers can use with care. We are currently in the process of increasing the number of formats in which output data can be exported, and a stand-alone version of the software is being developed that can be called from scripts or other computer programs, to facilitate the generation of weather data for large numbers of grid cells, if required. We also plan to adapt the software to include CMIP5 datasets (model runs being undertaken for the IPCC's Fifth Assessment report, scheduled for release in September 2013), as these become available. As noted in Section 2.2, the power of MarkSim and MarkSimGCM could be considerably increased by the addition of large numbers of additional calibration stations. This might lead to more information being extractable from downscaled GCM data on the nature of the variability of weather that is associated with different climate clusters. Without this, the lack of information on future weather variability associated with future climatologies is likely to remain a stumbling block to comprehensive impact assessment studies. In the meantime, MarkSim GCM provides a straightforward way of investigating some of the potential impacts of changes in climatology on agricultural systems in the coming decades.

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