

BETWIXT
*Built Environment: Weather scenarios for
investigation of Impacts and eXtremes*

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THE CRU DAILY WEATHER GENERATOR

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1. INTRODUCTION

The starting point for climate scenario construction in the Building Knowledge for a Changing Climate (BKCC) programme is the four generic IPCC SRES emissions scenarios and the UKCIP02 scenarios (Hulme *et al.*, 2002) which are the most recent, detailed and reliable climate scenarios for the UK. However, the UKCIP02 scenarios have a number of disadvantages with respect to the requirements of the BKCC programme. The spatial resolution of these scenarios (50 km by 50 km) is still coarser than required for some applications, for example, and they do not provide point-specific information. Some features of the present-day climate, particularly with respect to extreme events such as high temperatures and extreme precipitation, are poorly represented. A number of different approaches could be used to address these disadvantages.

The most appropriate approach, given the lack of point-specific information and concern about reliability, together with the need for self-consistent scenarios for a number of variables (i.e., precipitation, temperature, vapour pressure, relative humidity, wind speed, sunshine duration and reference potential evapotranspiration) is to use the Climatic Research Unit (CRU) daily and hourly weather generators. The CRU daily weather generator is described here. The hourly version will be described in a separate technical briefing note.

A number of different weather generators are available (see Wilks and Wilby, 1999, for a review). The CRU daily weather generator was initially developed by Jones and Salmon (1995). It has been substantially modified as part of the BETWIXT project and it is this modified version that is described here.

Measurements of past meteorological observations at a given site are used to estimate the model parameters, which are then used in a stochastic model to generate streams of daily weather variables (Table 1).

Table 1: Weather variables produced by the daily CRU weather generator.

Primary generated variable:
Precipitation (mm)
Secondary generated variables:
Minimum temperature (degrees C)
Maximum temperature (degrees C)
Vapour pressure (hPa)
Wind speed (ms ⁻¹)
Sunshine duration (hours)
Calculated variables:
Relative humidity (%)
Reference potential evapotranspiration (mm day ⁻¹)

Precipitation is the fundamental, primary variable in the weather generator, from which all the other variables are derived using regression relationships or subsequent direct calculation. Thus it is important that a sufficiently reliable method is used to generate precipitation. Here, a first-order Markov chain model (Richardson, 1981) is used. Once precipitation has been generated (Section 2), the secondary variables (minimum and maximum temperature, vapour pressure, wind speed and sunshine duration) are generated (Section 3). Finally, relative humidity and reference potential evapotranspiration are calculated from the generated variables (Section 4). Note that in the hourly CRU weather generator, wind gust speed is also calculated.

An example of how the CRU daily weather generator is run is presented in Section 5. Detailed information about how the model performs (model validation) and is used to construct climate scenarios will be presented in further technical briefing notes, as outlined in Section 6.

2. GENERATING THE PRIMARY WEATHER GENERATOR VARIABLE - PRECIPITATION

The Markov chain model generates the amount of precipitation (including zero amounts) on any day by sampling at random from a distribution that is determined by the amount of precipitation on the preceding day. Basing the distribution on the previous day's precipitation, makes it a first order model. Using a continuous distribution for precipitation, makes it an infinite state model. The distribution function, also referred to as the transition function (equation 2.1), is the incomplete gamma function (Gregory *et al.*, 1993; Thom, 1958).

$$P(\beta, \gamma; x) = \beta \int_0^x e^{-\beta x} x^{\gamma-1} dx \quad (2.1)$$

Equation 2.1 gives the probability for a given rainfall amount, x , and thus can be used in reverse to calculate the rainfall amount using a number drawn from a random distribution.

The parameters γ and β are calculated by fitting to observed precipitation, and are assumed to depend on the previous day's precipitation and the time of year.

The continuous distribution of observed precipitation amount (including zero amounts) is simulated by a discrete number of bins, whose divisions have to be chosen with some care: too few and the continuous nature of the distribution is lost, but too many and there will not be enough entries in a bin to get reliable fits. Previous work undertaken in the CRU indicates that 12 bins is an appropriate number. Daily data are divided into 24 half-months to allow for seasonal variation. Reliability is also improved by using a sufficiently long training data set – at least 20 years of data are required.

In generating precipitation, the values for γ and β are obtained by interpolating these parameters, for the appropriate half-month, corresponding to the bins nearest to the previous day's generated precipitation amount. The generated precipitation amount is found by using a

random number generator to select a random value of precipitation from the distribution specified by the appropriate values of γ and β .

3. SECONDARY GENERATED VARIABLES – MINIMUM AND MAXIMUM TEMPERATURE, VAPOUR PRESSURE, WIND SPEED AND SUNSHINE DURATION

Mean temperature, diurnal temperature range, vapour pressure, wind speed and sunshine duration are derived through first order auto-regressive processes (Mearns *et al.*, 1984). Minimum and maximum temperatures are then derived from the mean temperature and diurnal temperature range. For reasons of simplicity, all variables are normalised to a mean of unity and a standard deviation of one. Using the observed data, the regression weights are calculated by fitting the appropriate equation (i.e., 3.1, 3.2, 3.3 or 3.4) for the appropriate transition and variable.

3.1 Mean temperature and diurnal temperature range

As for precipitation, the data are divided up into half-monthly blocks so that any seasonal variation of the regression weights can be allowed for. In addition, data for the following four transition types are treated separately (including normalisation, see above):

<i>Transition</i>	<i>Yesterday</i>	<i>Today</i>
DD	Dry	Dry
WW	Wet	Wet
DW	Dry	Wet
WD	Wet	Dry

This is a necessity, as the correlation of temperature between successive DD days, say, is distinctly different from successive WW days.

DD and WW

$$X_i = aX_{i-1} + \varepsilon \quad (3.1)$$

DW

$$X_i = aX_{i-1} + dP_i + \varepsilon \quad (3.2)$$

WD

$$X_i = aX_{i-1} + dP_{i-1} + \varepsilon \quad (3.3)$$

where the X_i s are mean temperature or diurnal temperature range for the different transitions, and a and d are the regression weights. The random element ε is the product of a number chosen at random from a normal distribution, scaled to ensure that the overall standard deviation of the generated series is unity.

3.2. Vapour pressure, wind speed and sunshine duration

For vapour pressure, wind speed and sunshine duration

$$X_i = aX_{i-1} + bT_i + cR_i + dP_i + \varepsilon \quad (3.4)$$

where X_i is vapour pressure, wind speed or sunshine duration, T_i is mean temperature, R_i is diurnal temperature range and P_i is mean precipitation and a , b , c and d are the regression weights. The random element ε is again the product of a number chosen at random from a normal distribution, scaled to ensure that the overall standard deviation of the generated series is unity.

4. CALCULATED VARIABLES – RELATIVE HUMIDITY AND REFERENCE POTENTIAL EVAPOTRANSPIRATION

4.1 Relative humidity

Relative humidity (rh) is calculated from vapour pressure (VP) using equation 4.1. Saturated vapour pressure (VP_s), which is required in equation 4.1, is calculated using the Magnus equation 4.2:

$$rh = \frac{VP}{VP_s} \quad (4.1)$$

$$vp_s = 6.107e^{\frac{17.38t}{239+t}} \quad (4.2)$$

where t is mean temperature.

4.2 Reference potential evapotranspiration

Many methods are available for the calculation of potential evapotranspiration, some of which have large and complex input data requirements. For BETWIXT purposes, a relatively simple method which can be calculated from the CRU daily weather generator outputs is required. A suitable method is the grass reference potential evapotranspiration (ET_o) calculated using the FAO (Food and Agricultural Organization) Penman-Monteith method (Allen *et al.*, 1994). The CRU and University of Newcastle have experience of using this method for the construction of climate change scenarios in the EU funded SWURVE (Sustainable Water: Uncertainty, Risk and Vulnerability in Europe) project (<http://www.ncl.ac.uk/swurve/>). The choice of this method in the SWURVE project was based on an inter-comparison of different formulations to estimate potential evapotranspiration for European environments completed during the earlier EU-funded WRINCLE (Water Resources: Influence of Climate change in Europe) project (<http://www.ncl.ac.uk/wringle/>).

Following the method of Allen *et al.* (1994), as implemented in the SWURVE project, ET_o is calculated using equation 4.3

$$ET_o = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T + 273.16} U_2 (e_a - e_d)}{\Delta + \gamma(1 + 0.34U_2)}$$

(4.3)

where:

ET_o	is reference crop evapotranspiration [mm day ⁻¹]
R_n	is net radiation at crop surface [MJ m ⁻² d ⁻¹]
G	is soil heat flux [MJ m ⁻² d ⁻¹]
T	is average temperature at 2 m height [°C]
U_2	is windspeed measured at 2 m height [m s ⁻¹]
$(e_a - e_d)$	is vapour pressure deficit for measurement at 2 m height [kPa]
Δ	is slope vapour pressure curve [kPa °C ⁻¹]
γ	is psychrometric constant [kPa °C ⁻¹]
900	is coefficient for the reference crop [kJ ⁻¹ kg K d ⁻¹], Allen <i>et al.</i> (1994)
0.34	is wind coefficient for the reference crop [s m ⁻¹], Allen <i>et al.</i> (1994)

5. RUNNING THE CRU DAILY WEATHER GENERATOR

A suitably long (i.e., at least 20 year) daily time series of observed meteorological data must be available in order to calibrate or train the weather generator for each location, i.e., in order to calculate the weather generator parameters for each site. For BETWIXT, 10 such sites have been identified in consultation with BKCC partners. These sites include Ringway (Manchester Airport, 53.35 N 2.28 W, elevation 69 m), which has daily data for the period 1961-1995. The Ringway data were obtained from the British Atmospheric Data Centre and are available for use by academic BKCC partners from the BETWIXT web site. They are used here as an example of running the CRU daily weather generator.

The results shown in Figure 1 were obtained using 12 precipitation bins and a minimum precipitation cutoff of 1.0 mm (i.e., any day with less than 1 mm of observed or generated precipitation is defined as a dry day). The weather generator is stochastic, which means that, once the parameters have been calculated, it can be run for any length of time. The Figure 1 results are for a 35 year period, but a period of 100 or even 1000 years could be used if desired. A different sequence of random numbers is produced each time the weather generator is run, hence different daily time series are produced each time. Thus it is important to use output from multiple runs when validating performance, for example. The Figure 1 weather generator results are averaged over 1000 35-year long simulations. Although the model was calibrated for the 35-year period 1961-1995, its stochastic nature means that there is no day-by-day or year-by-year correspondence between the observed and simulated time series.

Figure 1 shows the observed (blue) and simulated (red) proportion of dry days (upper panel) and mean daily precipitation (lower panel) for each half-month for Ringway. The mean of the 1000 weather generator simulations is shown in each case, together with the plus/minus two standard deviation range calculated across the 1000 simulations. In all half-months, the observed value lies within the simulated range, indicating the good performance of the weather generator with respect to these two statistics.

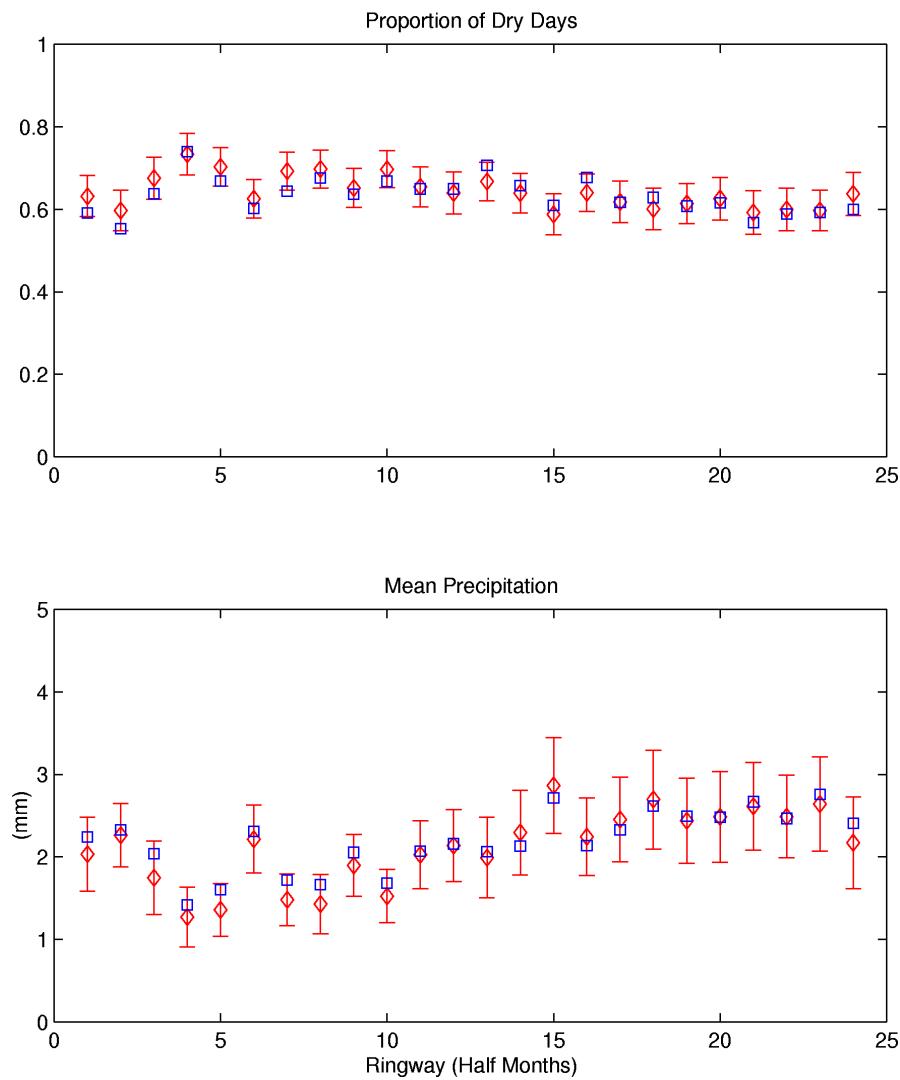


Figure 1: Observed (blue) and simulated (red) proportion of dry days (top panel) and mean daily precipitation (lower panel) for each half month at Ringway based on a 35 year period. Observed values are the mean for the period 1961-1995. The simulated values are the mean of 1000 weather generator runs (red triangles). The red lines and bars show the variability of the 1000 series (plotted as plus/minus two standard deviations around the mean).

6. CONCLUDING REMARKS

The CRU daily weather generator is able to provide daily time series for the weather variables listed in Table 1 for specific UK sites, such as Ringway, which have sufficient (i.e., at least 20 years) of observed data for the primary and secondary generated variables.

The example results in Figure 1 indicate that the weather generator performs well with respect to these two precipitation statistics (proportion of dry days and mean precipitation amount) for Ringway. However, more extensive validation (including investigation of the ability to

reproduce extreme events, such as high precipitation events, and the other generated weather variables) is required before this daily weather generator can be used to construct climate change scenarios for use in the BKCC programme. The results of these validation studies will be described in another BETWIXT technical briefing note. Yet another briefing note, will describe how the weather generator parameters are perturbed in order to construct climate scenarios which are consistent with the UKCIP02 scenarios. The latter note will also demonstrate how the CRU daily weather generator can be run using precipitation output from the University of Newcastle GNSRP model (Burton *et al.*, 2004) as the primary variable, in order to obtain secondary and calculated variables (Table 1) that are fully consistent on a day-by-day basis with the GNSRP generated precipitation.

REFERENCES

Allen, R. G., Smith, M., Pereira, L. S. and Perrier, A., 1994: 'An update for the calculation of reference evapotranspiration'. *ICID Bulletin*, **43**, 35-92.

Burton, A., Kilsby, C.G., Moaven-Hashemi, A. and O'Connell, P.E., 2004: *Neyman-Scott Rectangular Pulses Rainfall Simulation System*, BETWIXT Technical Briefing Note 2.

Gregory, J.M., Wigley, T.M.L. and Jones, P.D., 1993: 'Application of Markov models to area-average daily precipitation series and interannual variability in seasonal totals', *Climate Dynamics*, **8**, 299-310.

Hulme, M., Jenkins, G.J., Lu, X., Turnpenny, J.R., Mitchell, T.D., Jones, R.G., Lowe, J., Murphy, J.M., Hassell, D., Boorman, P., McDonald, R. and Hill, S., 2002: *Climate Change Scenarios for the United Kingdom: The UKCIP02 Scientific Report*, Tyndall Centre for Climate Change Research, School of Environmental Sciences, University of East Anglia, Norwich, UK. 120pp.

Jones, P.D. and Salmon, M., 1995: *Development and Integration of a Stochastic Weather Generator into a Crop Growth Model for European Agriculture*, MARS Project, Final Report to Institute of Remote Sensing Applications, Agricultural Information Systems (ISPRA), Contract No. 5631-93-12, ED ISP GB.

Mearns, L.O., Katz R.W. and Schneider, S.H., 1984: 'Extreme high-temperature events: changes in their probabilities with changes in mean temperature', *Journal of Climate and Applied Meteorology*, **23**, 1601-1613.

Richardson, C.W., 1981: 'Stochastic simulation of daily precipitation, temperature, and solar radiation', *Water Resources Research*, **17**, 182-190.

Thom, H.A.S., 1958: 'A note on the gamma distribution', *Monthly Weather Review*, **86**, 117-122.

Wilks, D.S. and Wilby, R.L., 1999: 'The weather generation game: a review of stochastic weather models', *Progress in Physical Geography*, **23**, 329-357.