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Downscaling general circulation model output: a review of methods and limitations

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Abstract: General circulation models (GCMs) suggest that rising concentrations of greenhouse gases may have significant consequences for the global climate. What is less clear is the extent to which local (subgrid) scale meteorological processes will be affected. So-called 'downscaling' techniques have subsequently emerged as a means of bridging the gap between what climate modellers are currently able to provide and what impact assessors require. This article reviews the present generation of downscaling tools under four main headings: regression methods; weather pattern (circulation)-based approaches; stochastic weather generators; and limited-area climate models. The penultimate section summarizes the results of an international experiment to intercompare several precipitation models used for downscaling. It shows that circulation-based downscaling methods perform well in simulating present observed and model-generated daily precipitation characteristics, but are able to capture only part of the daily precipitation variability changes associated with model-derived changes in climate. The final section examines a number of ongoing challenges to the future development of climate downscaling.

Key words: climate change, downscaling, precipitation, model.

I The rationale for downscaling

> Even if global climate models in the future are run at high resolution there will remain the need to 'downscale' the results from such models to individual sites or localities for impact studies. Downscaling methodologies are still under development and more work needs to be done in intercomparing these methodologies and quantifying the accuracy of such methods (DOE, 1996: 34).

The present generation of general circulation models (GCMs) of the climate system are restricted in their usefulness for many subgrid scale applications by their coarse spatial

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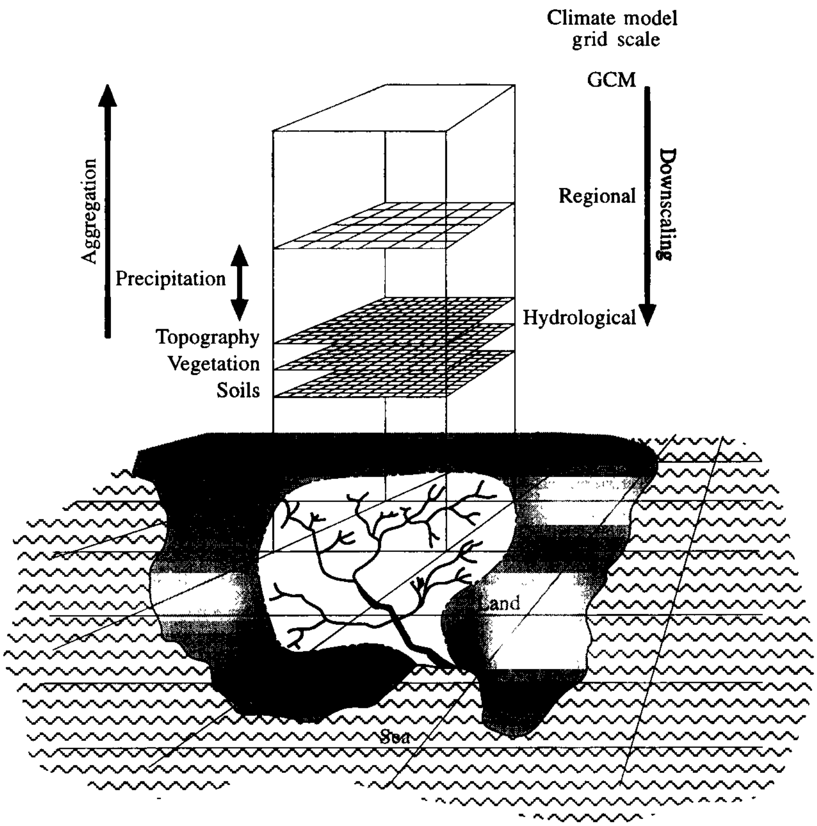

Figure 1 Conceptualization of downscaling and aggregation between atmospheric and hydrologic models
Source: Modified after Hostetler (1994)

and temporal resolution (Wigley *et al.*, 1990; Carter *et al.*, 1994). For example, hydrological models are frequently concerned with small, subcatchment (even hillslope) scale processes, occurring on spatial scales much smaller than those resolved in GCMs (see Figure 1). GCMs deal most proficiently with fluid dynamics at the continental scale and parameterize regional and smaller-scale processes. These scale-related sensitivities and mismatch problems are further exacerbated because they usually involve the most uncertain components of climate models, water vapour and cloud feedback effects (Rind *et al.*, 1992). As Hostetler (1994) has observed, the greatest errors in the parameterizations of *both* GCMs and hydrological models occur on the scale(s) at which climate and terrestrial impact models interface. These mismatch problems, which affect both the temporal and spatial dimensions, have important implications for the credence of impact studies derived by the output of models of climate change, especially as research into potential human-induced modifications to hydrological and ecological cycles is assuming increasing significance.

Because of these well recognized problems, the International Geosphere–Biosphere Programme (IGBP) and the GEWEX Continental Scale International Project (GCIP) were established with the specific mandate to investigate the complex interactions between the physical and biological components of the planet and their responses to anthropogenic change. A major focus of the BAHC (Biological Aspects of the Hydrologic Cycle) component of IGBP has been the development of tools for generating the high-resolution meteorological inputs required for modelling ecohydrological processes (Bass, 1996). 'Downscaling' approaches have subsequently emerged as a means of interpolating regional-scale atmospheric predictor variables (such as a mean sea-level pressure or vorticity) to station-scale meteorological series (Karl *et al.*, 1990; Wigley *et al.*, 1990; Hay *et al.*, 1991; 1992). Fundamental to the approach is the assumption that relationships can be established between atmospheric processes occurring at disparate temporal and/or spatial scales.

Since the early 1990s, and building on earlier work in meteorology (reviewed, for example, in Wigley *et al.*, 1990) and hydrology (e.g. Richardson, 1981), many such relationships have been identified. Mesoscale weather patterns have been used to model numerous meteorological parameters, such as precipitation occurrence in Washington State (Hughes and Guttorp, 1994); space-time daily rainfall patterns in the Ruhr catchment (Bardossy and Plate, 1992) and eastern Nebraska (Matyasovsky *et al.*, 1993); monthly mean temperature and precipitation in Oregon State (Wigley *et al.*, 1990); extreme precipitation events and drought conditions in the Delaware River basin (Hay *et al.*, 1991); low-frequency precipitation events in the British Isles (Wilby, 1997a); wintertime rainfall in Iberia (von Storch *et al.*, 1993); and estimates of daily pan evaporation rates in southern Louisiana (McCabe and Muller, 1987). Secondary relationships established between circulation patterns and environmental time-series include those encapsulated in studies of flooding in Arizona (Duckstein *et al.*, 1993); low flow-frequency analyses in the River Coln, UK (Wilby *et al.*, 1994); sea-level anomalies in the Japan sea (Maochang *et al.*, 1995) and the Baltic Sea (Heyen *et al.*, 1996); surface water acidification in the east Midlands, UK (Wilby, 1993); and episodic soil loss from the English South Downs (Favis-Mortlock *et al.*, 1991).

This article will review the present generation of downscaling tools and go on to summarize the results of an experiment to intercompare a range of precipitation models used for downscaling. The final section will examine ongoing challenges to the future development of climate downscaling.

II Key approaches

The general limitations, theory and practice of downscaling are well described in the literature (see, for example, Grotch and MacCracken, 1991; von Storch *et al.*, 1993; Wilby, 1994; Kattenberg *et al.*, 1996). For the sake of convenience, downscaling techniques may be described using four categories, namely: regression methods; weather pattern-based approaches; stochastic weather generators; and limited-area modelling. In reality, many downscaling approaches embrace the attributes of more than one of these techniques and therefore tend to be hybrid in nature.

1 Regression methods

Regression methods were among the earliest downscaling approaches. The first article to use this approach specifically in the climate change context was Kim *et al.* (1984); but see also Wigley *et al.* (1990). These approaches generally involve establishing linear or nonlinear relationships between subgrid-scale (e.g. single-site) parameters and coarser-resolution (grid-scale) predictor variables. More sophisticated techniques such as 'expanded downscaling' (Burger, 1996) model mean and short-term variability by linking the covariance of the global circulation with the covariance between local weather variables in a bilinear way. Among regression methods it is also reasonable to include artificial neural network (ANN) approaches since the internal weights of an ANN model emulate nonlinear regression coefficients (Hewitson and Crane, 1992a; 1992b; 1996). Having derived a regression equation or trained an ANN to relate the observed local and regional climates, the equations may then be 'forced' using regional-scale climate data obtained from a GCM operating in either a 'control' or 'perturbed' state. For example, von Storch *et al.* (1993) used a canonical correlation technique to relate winter rainfall in the Iberian Peninsula to sea-level pressure patterns in the North Atlantic. The predicted rainfall for multiple stations was then compared with that derived from the closest GCM grid points. Similarly Wigley *et al.* (1990) regressed site values of temperature and precipitation against spatial area averages of temperature, precipitation, mean sea-level pressure, 700 mb geopotential heights and zonal/meridional components of the circulation predictor variables. Coastal and mountain influences, as well as seasonal atmospheric patterns affecting the northwestern USA, were found to cause significant spatial and temporal variations in model performance.

Slight variants of the approach involve regressing the same parameter from a regional to local scale, or across several scales. For example, Carbone and Bramante (1995) regressed spatially averaged monthly maximum and minimum temperatures against the same variables at multiple stations across the southeastern USA. Brown *et al.* (1995) investigated the climatological characteristics of spatial scaling of hourly precipitation by regressing area-average precipitation derived from a nested mesoscale model against the size of the averaging area. Although the log moments of both the model-generated and observed precipitation fields were linearly related to the log scaling factor, a more complex process (such as a random cascade) was considered necessary to describe the overall spatial scaling. Perica and Foufoula-Georgiou (1996) have demonstrated that there is also considerable scope for the development of multifractal approaches to modelling precipitation derived from midlatitude mesoscale convective systems. Foufoula-Georgiou (pers. comm.) has suggested that such systems exhibit fractal properties over the range 4–100 km, implying that, in certain environments, simple log-log scaling relationships may be used to downscale precipitation.

2 Weather pattern approaches

Weather pattern (and circulation) based downscaling methods typically involve statistically relating observed station or area-average meteorological data to a given weather classification scheme, which may be either objectively or subjectively derived (see Yarnal, 1993). Objective and/or automated weather classification procedures include principal components (White *et al.*, 1991), canonical correlation analyses (Gyalistras *et al.*, 1994), fuzzy rules (Bardossy *et al.*, 1995), compositing (Moses *et al.*, 1987), neural networks (Bardossy *et al.*, 1994), correlation-based pattern recognition techniques (Lund, 1963) and analogue procedures (Martin *et al.*, 1997). Examples of subjective circulation typing schemes include the European Grosswetterlagen (Hess and Brezowsky, 1977), the British Isles Lamb Weather Types (Lamb, 1972; Jones *et al.*, 1993) and daily weather types for the Delaware River basin (Hay *et al.*, 1991).

Having selected a classification scheme it is then necessary to condition the local surface variables, such as precipitation, on the corresponding (daily) weather patterns. This is accomplished by deriving conditional probability distributions for observed data such as the probability of a wet day following a wet day or the mean wet-day amount associated with a given atmospheric circulation pattern (see Hughes and Guttorp, 1994). The precipitation series may be further disaggregated by month or season, or by the dominant precipitation mechanism (Wilby *et al.*, 1995). In either case, meteorological time-series may be generated stochastically by applying input sequences of daily weather types to the observed conditional probability distribution functions. The 'forcing' weather pattern series are typically generated using Monte Carlo techniques (Wilby, 1994) or from the pressure fields of GCMs (Matyasovsky *et al.*, 1994). Although the majority of such studies has focused on daily precipitation, series of daily circulation patterns may be used to downscale other variables such as temperature, evaporation and ultraviolet radiation, or multivariate processes such as floods, droughts, acid precipitation, smog, ozone and atmospheric particulates (Bass, 1996).

Regardless of the means of classifying and/or generating new weather pattern series the circulation-based approach to downscaling remains particularly appealing because it is founded on sensible physical linkages between climate on the large scale and weather on the local scale. The statistical and physical dependence of daily precipitation variations on time-series of circulation changes has been demonstrated by numerous authors working in a wide range of climates: for example, Galambosi *et al.* (1996) in Arizona and New Mexico, Wilby *et al.* (1997) in Japan, Bartholy *et al.* (1994) in Hungary and Greece, Wilby (1994) in the UK, and Schubert (1994) in Germany. As well as constructing high-resolution subgrid scale meteorology the weather pattern approach also has considerable potential as a means of validating the internal consistency of GCM control runs (Hulme *et al.*, 1993; McKendry *et al.*, 1995), or as a procedure for removing the synoptic climate signal from environmental data sets (Comrie, 1992).

3 Stochastic weather generators

Stochastic weather generators share many attributes of conventional circulation-based downscaling models, but differ in their means of application to future climate conditions. Richardson's (1981) WGEN model is the most commonly used for climate impact studies: this was originally designed to simulate daily time-series of precipitation amount, maximum and minimum temperature, and solar radiation for the present climate. Rather than being conditioned by circulation patterns, all variables in the Richardson model are simulated conditional on precipitation occurrence. At the heart of all such models are first- or multiple-order Markov renewal processes in which, for each successive day, the precipitation occurrence (and possibly amount) is governed by outcomes on previous days. Models such as WGEN have been adapted for a number of climate change and impact studies (e.g., Wilks, 1992). Mearns *et al.* (1996) used the model to investigate the effect of changes in daily and interannual variability of temperature and precipitation on crop yields in the central Great Plains of the USA. There is also the possibility of spatially distributing WGEN parameters across landscapes, even in complex terrain, by combining interpolation techniques and digital elevation models such as PRISM (Daly *et al.*, 1994).

The principal issue involving the application of WGEN or other stochastic weather generators to future climates has been the method of adjusting the parameters in a physically realistic and internally consistent way. Katz (1996) demonstrated, using daily observations at Denver, Colorado, that when the WGEN parameters are varied, certain unanticipated effects can be produced. For example, modifying the probability of daily precipitation occurrence changed not only the mean daily temperature but also its variance and autocorrelation in possibly unrealistic ways. One solution to such a problem is to clarify the distinction between conditional and unconditional statistical parameters.

Gregory *et al.* (1993) have suggested an alternative use of Markov models for interpreting the results obtained from GCM experiments. By calibrating and then comparing the stochastic model parameters derived from observed series and GCM control runs it is possible to validate a GCM. Similarly, by comparing the parameters obtained from control and perturbed climate data, climate change-related changes in these parameters could be evaluated. Alternatively, in order to assess the stability of such parameters, Wilby (1994) calibrated a stochastic weather generator for stations in the UK using two synoptically contrasting periods. These scenarios were then used to synthesize proxy data sets representing climates with extreme dry- to dry-day and wet to wet-day persistence.

4 Limited-area climate models

Given the limitations of GCM grid-point predictions for regional climate change impact studies, the final downscaling option is to embed a higher-resolution limited-area climate model (LAM) within the GCM, using the GCM to define the (time-varying) boundary conditions (Giorgi, 1990; Mearns *et al.*, 1995). Although LAMs can produce climatologies for 20–50 km horizontal grid spacing and 100–1000 m vertical resolution there are several acknowledged limitations of the approach. LAMs still require considerable computing resources and are as expensive to run as a global GCM. Furthermore, they are somewhat inflexible in the sense that the computational demands apply each time that the model is transferred to a different region. Above all, the LAM is completely dependent upon the veracity of the GCM grid-point data that are used to drive the boundary conditions of the region – a problem that applies also to circulation-driven downscaling methods.

Nonetheless, LAMs have the ability to simulate smaller-scale atmospheric features such as orographic precipitation (e.g., Segal *et al.*, 1994) and may ultimately provide atmospheric data for impact assessments that reflect the natural heterogeneity of the climate at regional scales (Hostetler, 1994). Furthermore, Pielke *et al.* (1991) have demonstrated that the high spatial heterogeneity of small-scale atmospheric and biological processes does affect regional climates, and that these effects potentially have strong feedbacks to the global climate. Zeng and Pielke (1995), for example, used extensive numerical simulations with the Colorado State University model to demonstrate that small-scale topographic influences on mesoscale sensible heat, moisture and momentum fluxes can be larger than, and have a different vertical structure from, the turbulent fluxes of a typical GCM grid box. Mearns *et al.* (1995) concluded that errors in the frequency and intensity fields of daily precipitation produced by the NCAR Community Climate Model and NCAR/Penn State mesoscale model (MM4) were due to inadequate representation of topography, even with a horizontal resolution of 60 km.

Since different methods have different strengths and weaknesses, this has prompted some commentators to advocate closer integration of stochastic, empirical and dynamic (LAM) downscaling methods (Hostetler, 1994; Bass, 1996). Accordingly, Frey-Buness *et al.* (1995) combined a weather-typing approach with a mesoscale model of the Alpine region in Europe. By obtaining conditional probabilities for a particular mesoscale event associated with each weather type it was then possible to obtain downscaled climatologies for winter and summer under $1 \times CO_2$ or $2 \times CO_2$ conditions using ECHAM3 GCM output (Cubasch *et al.*, 1992). In another study, Kelly *et al.* (1988) obtained high-resolution weather forecasts by downscaling data from an operational synoptic-scale numerical weather prediction model using a digital elevation model (DEM). Vertical lapse rates – which are a function of the time of day and prevailing synoptic conditions – were used to translate upper-atmosphere variable fields to the land surface. The DEM and objective analysis were then used to downscale the surface representation to a 1 km grid.

III A comparison of statistical downscaling methods

Given the range of downscaling techniques, there is clearly a need to compare methods using standard data sets and model performance criteria. Furthermore, it is important to provide the impacts community with clear measures of model capability and reliability, particularly with regard to the realistic simulation of *daily* precipitation occurrence, persistence and amounts (see, for example, Arnell, 1996). With these aspirations in mind Wilby *et al.* (1996b) recently conducted an analysis of several downscaling techniques applied to six contrasting regions in the USA (Figure 2 and Table 1), for annual and seasonal (DJF, MAM, JJA, SON) periods.

Three broad categories of downscaling model were considered: two artificial neural network approaches (ANN1 and ANN2); two stochastic rainfall simulation models

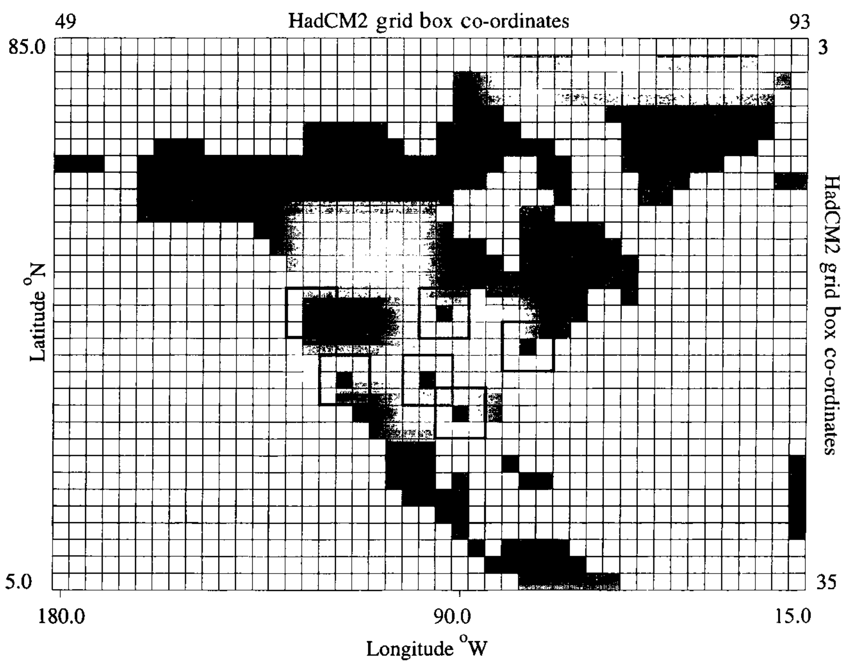

Figure 2 Location of the six North America study regions with respect to the grid of the Hadley Centre coupled ocean–atmosphere model
Source: Modified after Climate Impacts LINK Project (Department of the Environment, UK)

Table 1 Downscaling study regions

HadCM2 grid box	Latitude	Longitude	Location
1792	45° N	123.75° W	Salem, OR
1800	45° N	93.75° W	Minneapolis, MN
1997	40° N	75° W	Philadelphia, PA
2082	37.5° N	116.25° W	Yucca Mountain, NV
2183	35° N	97.5° W	Oklahoma, OK
2281	32.5° N	90° W	Jackson, MS

(WGEN and SPEL); and two methods based on vorticity (airflow) indices, the binned vorticity method (CRU) and the semi-stochastic airflow method (UD). Detailed descriptions of all the models may be found in Wilby *et al.* (1996b) or individually in the references provided in Table 2. Of the two ANN approaches, ANN2 was selected for detailed comparison with other models because its inclusion of temperature as a predictor variable was considered to make it a more comprehensive alternative.

The models were applied to single sites and five-site area averages for areas surrounding six 'target' grid boxes from the Hadley Centre coupled ocean-atmosphere climate model grid (HadCM2; Mitchell *et al.*, 1995; Johns *et al.*, 1997; Mitchell and Johns, 1997). In addition to the downscaling model, single grid-box area-average daily precipitation data from HadCM2 were also considered for each of the six 'target' regions (see Figure 2). Two periods were sampled from the HadCM2 'SUL' (combined CO_2 and sulphate aerosol forcing) experiment, periods approximating the present (1980–99 in model years) and a century into the future (2080–99).

The downscaling models were calibrated using daily precipitation data (from single sites or averaged over a number of sites) and (with the exception of WGEN and SPEL) atmospheric circulation data obtained from the National Centers for Environmental Protection (NCEP) reanalysis (Kalnay *et al.*, 1996). The two stochastic models, WGEN and SPEL, were calibrated using all data for 1979–95. The other models were calibrated over 1979–87 and validated using data for 1988–95.

Except for WGEN and SPEL, the downscaling models were then forced using the same predictor variables (i.e., geopotential heights, temperature and vorticity) taken from the HadCM2 SUL experiment for the present and future climate. To quantify comparisons between different models, between observed and simulated data over the validation period, and between present-day and future climate, 14 diagnostic statistics were considered: the mean, median, standard deviation and 95th-percentile of the wet-day amounts; the (conditional) probabilities of dry-dry (Pdd) and wet-wet (Pww) day occurrences; the (unconditional) probability of a wet-day (Pw); the mean, standard deviation and 90th-percentile of wet- and dry-spell durations; and the standard deviation of monthly precipitation totals.

The following comparisons are reported here: between different downscaling models applied at the single-site level and calibrated using observed data; between different downscaling models applied to area-average observed precipitation data; and between different climate-model time periods for different downscaling models.

In the first two cases, we compared the validation performances of the different models. As an index of overall performance of each downscaling method, we calculated the root mean square error (RMSE) between the simulated value of each diagnostic

Table 2 Notations for precipitation models used in the comparison exercise

Notation	Description	References
HadCM2	Hadley Centre coupled ocean–atmosphere model forced by combined CO_2 and sulfate aerosol forcing. Two 20-year periods were selected: present climate (1980–99) and a perturbed, future climate (2080–99)	Mitchell *et al.* (1995), Johns *et al.* (1997), Mitchell and Johns (1997)
ANN1	Artificial neural network calibrated against observed single-site and area-average precipitation, and forced using daily 700 and 500 hpa heights obtained from the two HadCM2 periods	Hewitson and Crane (1992a; 1992b; 1994; 1996)
ANN2	Artificial neural network calibrated against observed single-site and area-average precipitation, and forced using daily 700 and 500 hpa heights and temperatures obtained from the two HadCM2 periods	Hewitson and Crane (1992a; 1992b;1994; 1996)
WGEN	First-order, two-state Markov process of daily rain-fall occurrence. Wet-day precipitation amounts are modelled using gamma distributions. Downscaled future precipitation was produced by perturbing WGEN parameters in proportion to the changes in model parameters calibrated using the HadCM2 present and future data	Richardson (1981), Wilks (1989; 1992), Gregory *et al.* (1993), Wilby *et al.* (1996b)
SPEL	An alternating negative binomial recurrence process for wet- and dry-spell lengths. Wet-day precipitation amounts are modelled using gamma distributions. Downscaled future precipitation was produced by perturbing SPEL parameters in proportion to the changes in model parameters calibrated using the HadCM2 present and future data	Wilby *et al.* (1996b)
CRU	Binned vorticity method of resampling observed daily rainfall sets. Downscaled precipitation is modelled by sampling rainfall occurrence and amounts from discrete vorticity classes. Only the distribution of daily vorticity values is assumed to change between the present and future climate	Conway *et al.* (1996), Conway and Jones (1996; in press)
UD	Semi-stochastic precipitation occurrence and intensity drived by vorticity. Downscaled precipitation is modelled using nonlinear empirical relationships between wet-day occurrence/persistence/mean amounts and vorticity. Only the distribution of daily vorticity values is assumed to change between the present and future climate	Conway *et al.* (1996), Wilby *et al.* (1996a; 1996b)

statistic and its observed value over 1988–95, summed over all sites. The models were tested using all data (as opposed to seasonal subsets, i.e., DJF, MAM, JJA, SON) in order to maximize the number of available rain days, particularly at the arid sites of Yucca Mt and Oklahoma, and to minimize the effect of missing data on model validation results. The validation of annual as opposed to seasonal models was also considered to be a more rigorous test of the models' integrity. Note that the validation exercise allowed an assessment of the performance of ANN2 relative to CRU relative to UD, and of WGEN relative to SPEL. It does not, however, allow a like-with-like comparison between the ANN2, CRU and UD approaches and WGEN or SPEL, because the latter two models were calibrated and assessed over the full 1979–95 data periods (see below).

In the second case, we included the HadCM2 present-day data in the comparison, comparing its diagnostic statistics with the observed area-average statistics for 1979–95. This provides a crude validation of the HadCM2 simulation for the six study regions, which is reported in more detail elsewhere (Wigley *et al.*, 1997). It is not a strict validation because the 1980–99 HadCM2 SUL results correspond only very roughly to the 'real-world' 1980–99 and 1979–95 periods (see Wigley *et al.*, 1997), and because the model results used are for a single grid box while the observed area-average data span up to nine grid boxes.

In the third case, we first determined the climate model changes for each diagnostic statistic directly from the model outputs for present and future climate. To quantify these changes nondimensionally, we expressed them as percentages. For each statistic this gave 24 values (six regions by four seasons). As an overall index of the model-generated change in each diagnostic statistic, we used the mean of the absolute percentage changes. We then drove the ANN2, CRU and UD models (as recalibrated using the full observed data set, 1979–95) with present-day and future climate model output, and assessed the changes in the various diagnostic statistics as for the directly calculated GCM results. Finally, we determined changes using the WGEN and SPEL models calibrated using the grid-point HadCM2 output. (For most statistics, since the earlier analyses demonstrated WGEN and SPEL models are able to simulate observed and climate model data well, any assessment of change using WGEN and SPEL should agree well with the direct climate model results.)

Figures 3(a) and (b) show selected model validation results using the across-site and season RMSEs between model and observed diagnostic statistic values, for single sites and area averages, respectively. For ANN2, CRU and UD, the comparison is between pairs of downscaled and observed diagnostics for the 1988–95 validation period. For the two airflow models (CRU and UD) the diagnostic statistic values used were the means over 100 stochastic simulations, whereas for ANN2 only one climate realization was used to calculate the diagnostics. For WGEN and SPEL 1979–95 data were used, and the expected values of the diagnostics were calculated either using multiple stochastic simulations or, where possible, analytical methods.

The validation tests revealed, as one would expect a priori, that the WGEN and SPEL methods were superior to all other methods for the majority of diagnostics. This result arises because only calibration data were derived for these methods, and because some diagnostics in the WGEN and SPEL methods are constrained to match the original data values perfectly. A notable weakness of both these stochastic models was their inability to capture the standard deviation of monthly rainfall totals (i.e., lower-frequency variations). This is a well-known result for WGEN (see, e.g., Gregory *et al.*, 1993).

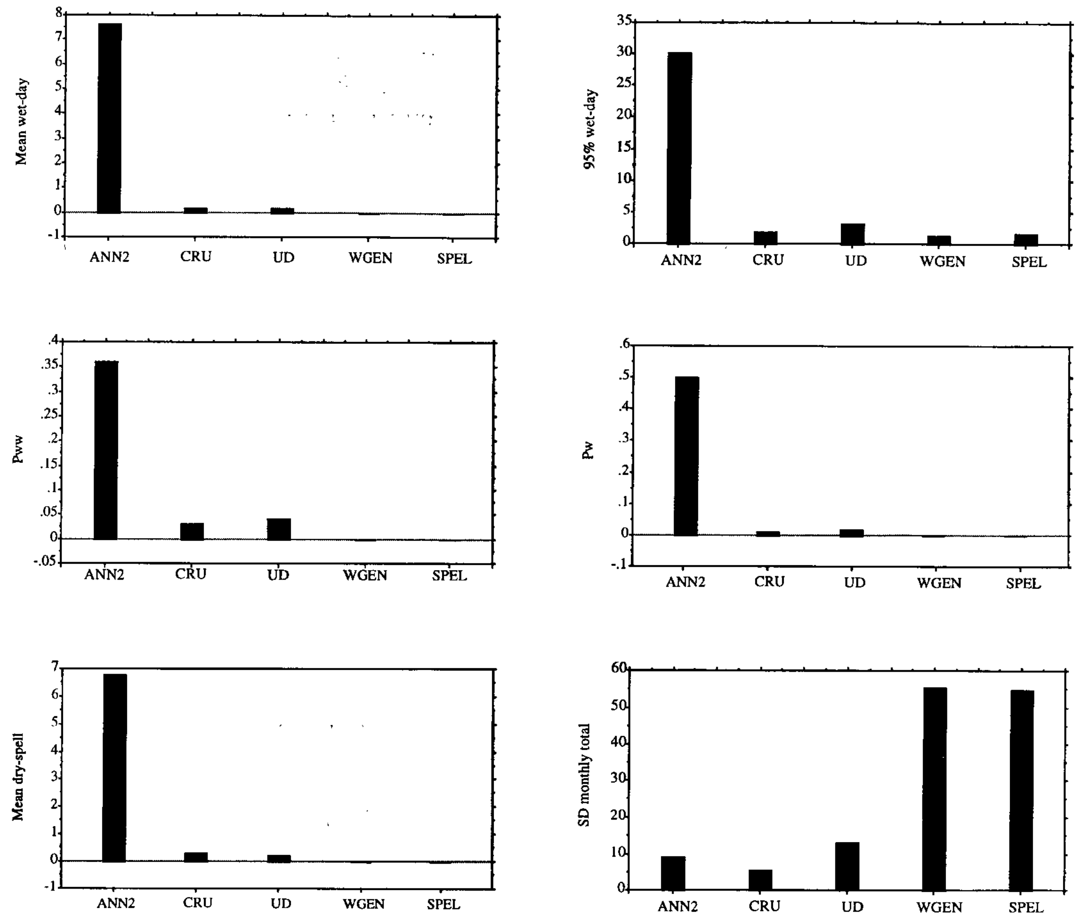

Figure 3a Selected root mean square error (RMSE) validation results from annual downscaling models at single sites: mean wet-day amount (mm); 95th-percentile wet-day amount (mm); conditional wet- to wet-day probability (Pww); unconditional wet-day probability (Pw); mean dry-spell length (days); standard deviation of monthly precipitation totals (mm)
Source: Wilby *et al.* (1996b)

Both vorticity-based methods performed well and were consistently better than the ANN method, partly because of the latter model's tendency to overestimate the frequency of 'trace' wet days. The UD method performed slightly better than the CRU method for area-average precipitation, and slightly worse for the single-site precipitation diagnostics. The UD method was generally more successful than the CRU method for wet-day occurrence modelling, but less skillful for the wet-day amount distributions.

From Figure 3(b) the performances of the GCM and downscaling methods in simulating present-day conditions at the grid-box level may be compared. When considering all 14 diagnostics, HadCM2 was superior to (i.e., had lower RMSE values than) the ANN model for 12/14 diagnostics, the CRU model for 4/14 diagnostics, the UD model for 3/14 diagnostics and the WGEN/SPEL models on one occasion (*viz.* in simulating monthly timescale variability). The GCM produced superior realizations of

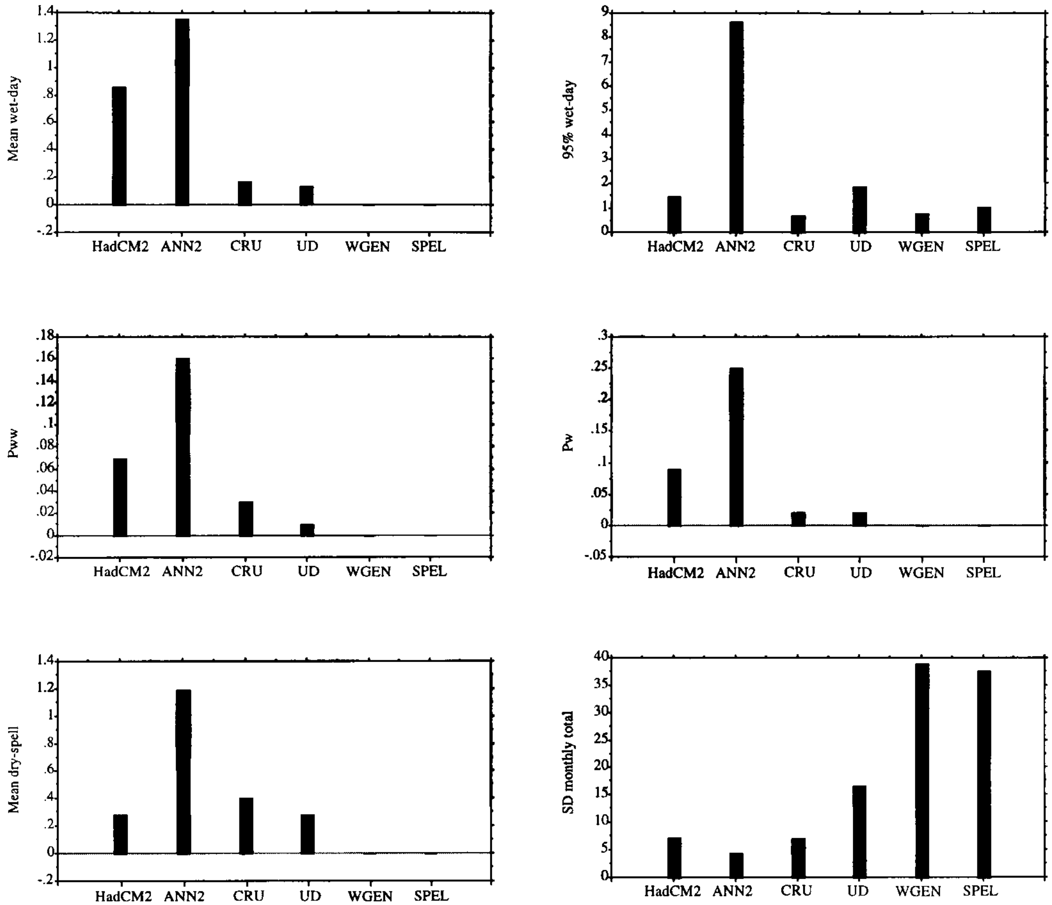

Figure 3b Selected root mean square error (RMSE) validation results from annual downscaling models for grid-box area averages: mean wet-day amount (mm): 95th-percentile wet-day amount (mm); conditional wet- to wet-day probability (Pww); unconditional wet-day probability (Pw); mean dry-spell length (days); standard deviation of monthly precipitation totals (mm)
Source: Wilby *et al.* (1996b)

dry-spell occurrence and persistence compared with the CRU model, and better representations of wet-day size distributions compared with the UD model. Given that the GCM does not provide a precise simulation of present-day climate, and that we have compared single grid-box GCM results with quite crude nine-grid-box observed data averages, the GCM performance is remarkably good.

The single-site results obtained from the two airflow models suggest that the mean daily precipitation amounts can be downscaled with a one-sigma error of less than ± 0.2 mm/day, the unconditional wet-day probability to within $\pm 2\%$, and mean wet/dry-spell lengths to an average error of less than ± 0.3 days. In contrast, the standard deviation of monthly precipitation totals was captured only to within 10–30%. All these results, with the exception of the monthly variations, were surpassed by the WGEN and SPEL methods, which necessarily have zero errors for calibrated daily precipitation

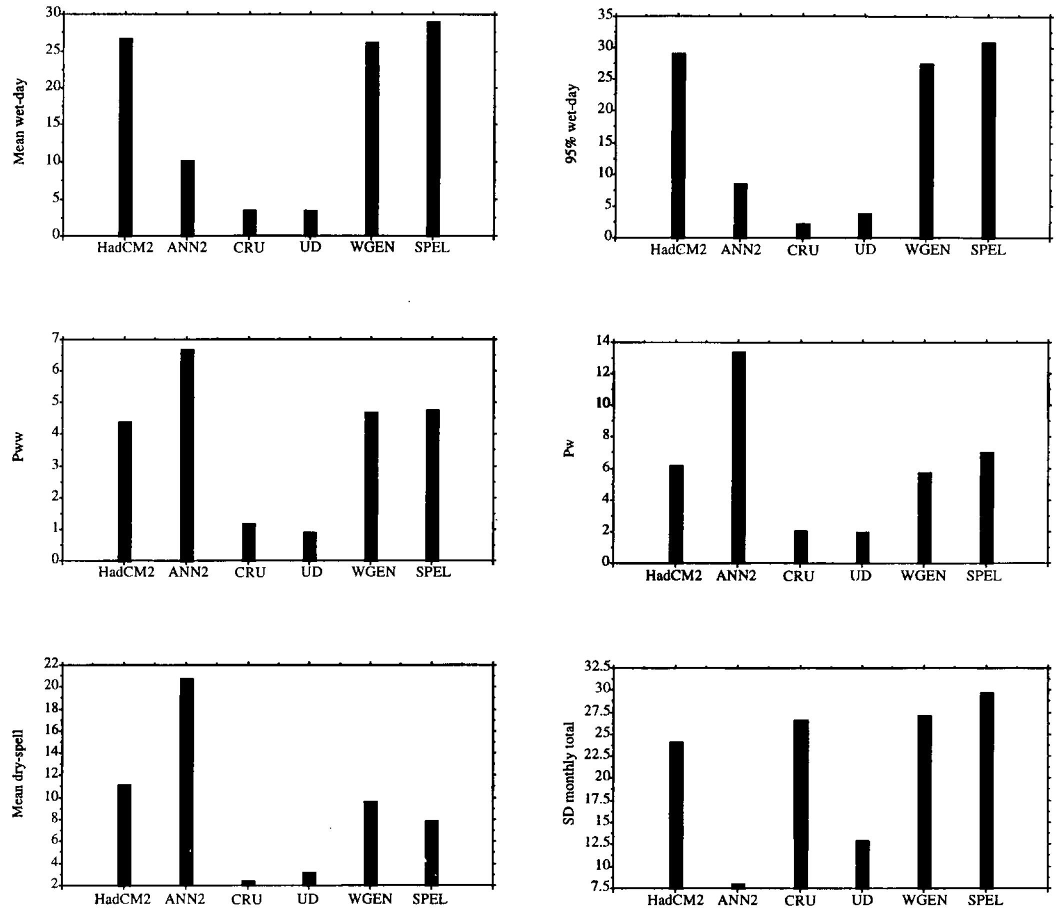

Figure 4 Mean absolute percentage changes in selected precipitation diagnostics between 1980–99 and 2080–99 for downscaling models of grid-box area-average precipitation. Note that the absolute changes in the diagnostics were averaged over all sites and seasons
Source: Wilby *et al.* (1996b)

occurrence and wet-day amounts. However, it is acknowledged that further testing of the WGEN and SPEL methods – using data sets not used in calibration – is required to ascertain the long-term stability of the model's parameters (cf. Wilby, 1997b).

Analyses of downscaling results for the present versus future climate (Figure 4) were equally informative. Although downscaled single-site data were the primary concern of the original study, only the results for area-average precipitation are presented here in order that the direct GCM and GCM-forced precipitation models might be compared. Figure 4 shows the mean absolute percentage changes between 1980–99 and 2080–99 for selected diagnostics for each model.

For the area averages, the two ANN methods showed the greatest proportional change in the 14 diagnostics, and the UD vorticity model the least. There was no consensus among models as to which statistic changed by the largest amount. For all but one model, the conditional wet- to wet-day probability (Pww) showed the smallest changes. The majority of models pointed to Yucca Mt as the region with the largest changes: for the regions with the smallest changes, there was no clear consensus, although three models agreed that changes in the Jackson region were less than elsewhere. All but one model selected DJF as the season with the largest changes, SON as the season with the smallest changes.

While the GCM and the downscaling models all showed noticeable (and, sometimes, quite large) changes between the present and future climates, the importance of these changes can only be assessed by calculating their statistical significance. This is a non-trivial task; details are given in Wigley *et al.* (1997). When the changes in each diagnostic statistic were compared with the corresponding interannual variability in the observed data, very few statistics showed changes outside the 90% confidence interval. For the ANN, CRU and UD models, of course, this may be due partly to the fact that models driven by circulation changes are unable to capture the full range of changes in precipitation.

Overall, the CRU and UD vorticity models showed much smaller changes between the present and future climates than the raw GCM precipitation data and the ANN models (see Table 3). This implies either that the links between circulation and precipitation in the GCM are weaker than in the real world, or that changes in circulation patterns account for a relatively small proportion of the changes in GCM precipitation. The converse was true for ANN2, suggesting that the GCM has a stronger precipitation–temperature link than in the real world. In either case, the results indicate that there may be internal intervariable inconsistencies in the GCM (cf. Hulme *et al.*, 1993); which, in turn, may cast doubt on the precipitation changes generated directly by the GCM.

Table 3 Mean absolute percentage changes in precipitation diagnostics between 1980–99 and 2080–99 for downscaling models based on area-average precipitation

Diagnostic ($n = 24$)	HadCM2	WGEN	SPEL	ANN1	ANN2	CRU	UD
Mean wet	26.7	26.2	29.0	10.3	10.2	3.4	3.4
Median wet	36.3	24.8	26.6	13.2	15.3	5.2	2.7
SD wet	26.4	28.1	33.5	8.2	7.2	2.2	4.9
95% wet	29.0	27.5	30.9	9.3	8.6	2.2	3.9
Pdd	8.9	5.5	3.8	14.6	15.4	2.1	3.0
Pww	4.4	4.7	4.8	5.2	6.7	1.2	0.9
Pw	6.2	5.7	7.0	13.9	13.4	2.1	2.0
Mean dry-spell	11.2	9.7	7.9	26.3	20.8	2.4	3.2
Mean wet-spell	14.3	12.1	8.2	27.5	33.8	3.2	2.7
SD dry-spell	22.2	17.4	12.8	36.7	24.8	3.3	4.3
SD wet-spell	22.5	13.7	11.8	31.7	38.1	3.9	3.8
90% dry-spell	16.6	11.9	10.4	30.5	25.8	3.2	5.4
90% wet-spell	15.0	14.5	12.4	36.0	31.9	3.4	2.7
SD monthly	24.2	27.2	29.7	8.2	8.1	26.6	13.0

Note:
The absolute changes in the diagnostics were averaged over all sites and seasons.
Source: Wilby *et al.* (1996b).

IV Challenges for downscaling

As implied by the foregoing discussions, downscaling techniques are not without limitations. These should be taken into consideration when embarking upon future downscaling studies. In many cases, the caveats offer scope for future refinements, or further research into and development of the techniques.

The whole ideology of downscaling presupposes that, as a result of anthropogenic forcing, there will be significant (and predictable) changes in, depending on the method used, the stochastic simulation parameters or downscaling predictor variables (such as weather patterns). The reality and significance of such changes in the historical past have already been demonstrated (see, e.g., Weare and Hoeschele, 1983; Wilks, 1989; 1992; Schubert, 1994; Wilby, 1994). For the future, the predictability of the changes is still an open question. In the model comparison study reported above, it was found that the circulation changes in the HadCM2 model were relatively small, generally within the limits of interannual variability. On the other hand, it was shown that circulation changes alone may not be enough to derive realistic precipitation changes, and that the inclusion of temperature as an additional predictor variable adds little. Clearly, some account must be taken of the effect on precipitation of changes in atmospheric moisture content unrelated to changes in the circulation – a challenge for the future.

To date, most downscaling studies have been conducted for daily or monthly precipitation in temperate, midlatitude regions of the Northern Hemisphere; relatively few have examined semi-arid or tropical locations. There has also been an elevational bias towards low-altitude sites partly reflecting concerns over data homogeneity (Groisman and Easterling, 1994; Groisman *et al.*, 1996) and network design (Briggs and Cogley, 1996). Because of this topographic bias there has also been greater attention to downscaling liquid as opposed to frozen precipitation, or the two have simply been lumped together. Further work is required to fill these gaps.

Wilby (1994) identified three further challenges to downscaling which pertain to issues of classification, scale and stability. First, most weather classification schemes are inherently parochial because of the important controlling influences of regional and local-scale factors such as topography or ocean/land distributions. There is a need for more general classification systems.

Secondly, downscaling approaches seldom capture climate variability at all temporal or spatial scales. For example, Conway *et al.* (1996) compared two generically similar downscaling approaches and found that mean daily precipitation probabilities, wet-day amounts and persistence were well represented, but interannual variations in annual rainfall totals were less well modelled. This is a well-known problem (see, e.g., Gregory *et al.*, 1993, and earlier references therein).

Thirdly, a potential obstacle to the confident application of some downscaling approaches to future climate scenario generation is the apparent lack of stability of key relationships. For example, Wilby (1997b) has shown that, even within a single circulation regime, precipitation diagnostics may vary considerably from year to year. For UK precipitation, Wilby *et al.* (1995) attributed this intraweather-class variability partly to subtle changes in the dominant precipitation mechanism (whether stratiform or convective in origin). Alternatively, Sweeney and O'Hare (1992) have speculated that changes in the intensity of circulation development, and/or shifts in depression trajectories, may be important. This type of nonstationarity can, of course, be accounted for by developing more complex statistical models (within the constraints of model reliability imposed by data availability). This, in turn, however, puts greater pressure on the driving GCMs to provide reliable predictions for a greater range of variables.

These factors should be borne in mind when examining long-term changes in the relationships between atmospheric circulation variables and precipitation characteristics. They have contributed to the development of downscaling approaches that employ continuous, independent circulation variables (such as vorticity, and flow strength and direction) rather than discrete weather types (e.g., Conway *et al.*, 1996; Wilby *et al.*, 1996a). Similarly, Hewitson and Crane's (1992a; 1992b; 1996) use of ANNs offers a means of overcoming the problems of temporal and spatial nonstationarity through the development of multivariate downscaling schemes that incorporate a wider range of continuous atmospheric variables such as geopotential heights, temperature and humidity.

It is evident, therefore, that there remain considerable opportunities for the development and comparison of existing downscaling methods. In particular, it is recommended that rigorous testing and comparison of statistical downscaling approaches with limited area models be undertaken. Much can be learnt from applying a number of different approaches in combination and from evaluations of the relative merits of regression, weather pattern, stochastic and dynamic models. However, such research presupposes the continued development of high-quality climate data sets for model calibration and validation.

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