1. INTRODUCTION

1.1 THE NEED FOR DOWNSCALING

The growing recognition of the enhanced greenhouse effect as a scientific, technological and political problem which needs to be addressed with some urgency has increased the pressures on climatologists to provide appropriate scenarios for use in a wide range of impact studies. Climate scenarios are not predictions of the future, but rather “internally-consistent pictures of a plausible future climate” (Wigley *et al*., 1986). General Circulation Models (GCMs) are considered to provide the greatest potential for scenario construction for enhanced greenhouse effect impact studies, but the current generation typically have a grid resolution of about 300 kilometres at best. This is considerably less than that required for many impact studies, particularly those involving hydrological processes (Hostetler, 1994). This grid resolution is also coarser than that of many important climatic processes, particularly those involving clouds and moisture transport, which must, therefore, be parameterised in GCMs rather than explicitly modelled. The need to interpolate from the relatively coarse model scale to the finer sub-grid scale was originally referred to as the ‘climate inversion’ problem (Gates, 1985). The term ‘downscaling’ is now preferred and can be defined as ‘sensibly projecting the large-scale information on the regional scale’ (von Storch *et al*., 1993).

Impact studies have also created a growing demand for climate scenarios with a high temporal resolution, i.e. for information at the daily, or shorter, timescale. Moving from the global to the regional scale, and from the annual to the monthly and ultimately the daily scale, confidence in the reliability of GCM output tends to diminish (Hewitson and Crane, 1992a,b; von Storch *et al*., 1993; Gates *et al*., 1996; Kattenberg *et al*., 1996; Zorita and von Storch, 1999). While a particular GCM may be able to successfully reproduce observed mean monthly or seasonal temperature, for example, it is likely to be less successful in reproducing daily temperature variability, particularly the higher-order statistics such as standard deviations and extreme values (Palutikof *et al*., 1997). Changes in variability may be particularly important for some impact assessments. Crop yields, for example, are very sensitive to changes in variability (Mearns *et al*., 1996; Riha *et al*., 1996; Mearns *et al*., 1997). Thus, while it might appear reasonable to derive a temperature scenario by interpolating from GCM grid-point values to a station location, the interpolated control-run time series may provide an inadequate representation of present-day climate, confirming the need for downscaling (Palutikof *et al*., 1997).

In the case of precipitation, the arguments for downscaling are reinforced by the nature of what is actually simulated by GCMs. While it has been suggested that simulated grid-box precipitation can be interpreted as point values (Skelly and Henderson-Sellers, 1996), it is more generally accepted that what are being simulated are actually true (i.e. infinitely-sampled) area-averaged means for each grid box (Osborn, 1997; Osborn and Hulme, 1997; 1998). This means that it is not legitimate to compare grid-point values with station point data in validation studies (Osborn and Hulme, 1998). The problems associated with validation of simulated rain-day frequencies and intensities also raise questions concerning the reliability of scenarios derived solely from raw GCM output (Osborn and Hulme, 1998), particularly those suggesting changes in the intensity of daily precipitation (Gregory and Mitchell, 1995; Hennessy *et al*., 1997).

Statistical techniques have been developed to construct 'true' area-average means from observed precipitation data for use in GCM validation studies (Osborn, 1997; Osborn and Hulme, 1997). It is, however, more difficult to work from the other direction, i.e. to derive point estimates (which are required for impact studies) from area-averaged means (Osborn, 1997). Thus there is a particular need for downscaling methods which are applicable to daily precipitation.

The growing demand for climate scenarios with a high spatial and temporal resolution has created a need for downscaling methods which are relatively simple to apply, are parsimonious of computer time, do not require large amounts of observed data, and are transferable between regions. Ideally, these methods should also reflect the underlying physical mechanisms, be easy to validate, and be capable of producing self-consistent scenarios for a range of variables.

1.2 APPROACHES TO DOWNSCALING

1.2.1 Available methods

A number of different downscaling methods have been proposed and can be divided into two general categories; model-based and empirical (Giorgi and Mearns, 1991; Cubasch *et al*., 1996; Hewitson and Crane, 1996; Schubert and Henderson-Sellers, 1997).

The first, model-based, approach includes nesting a finer-scale Limited-Area Model (now usually referred to as a Regional Climate Model or RCM) within a GCM (Giorgi *et al*., 1990; 1992; Jones *et al*., 1995; Lüthi *et al*., 1996; Jones *et al*., 1997; Christensen *et al*., 1997). The current generation of RCMs have a typical spatial resolution of about 50 km. The ability of RCMs to reproduce present-day regional climate over Europe is the subject of ongoing inter-model comparative studies (Machenhauer *et al*., 1996; Christensen *et al*., 1997; Murphy, 1999). These studies indicate that large-scale flow in the RCMs suffers from systematic errors which are similar to those of the underlying GCM. Other problems, such as the underestimation of summer orographic precipitation, are attributed to inadequate land-surface parameterisations and to the need for even higher spatial resolution (Christensen *et al*., 1997). In summary, the nested-model approach is considered to offer the greatest long-term potential (Hewitson and Crane, 1996) but is very computer-intensive and is currently subject to a number of technical problems related, in particular, to model boundary conditions (Schubert and Henderson-Sellers, 1997; Giorgi and Mearns, 1999).

Another, model-based approach is to use a variable resolution GCM (Déqué and Piedelievre, 1995; Déqué *et al*., 1998). The resolution of the ARPEGE model, for example, varies from 60 km over the Mediterranean to 700 km over the southern Pacific (Déqué *et al*., 1998). A third model-based approach is high resolution time-slice experiments in which boundary conditions are taken from the GCM and a higher-resolution version of the same model is run for a few decades or years (Cubasch *et al*., 1995; 1996).

While model-based approaches may offer the greatest long-term potential, they do not currently meet all the criteria identified at the end of Section 1.1. In particular, they are neither simple to apply, nor parsimonious of computer time. Thus model runs are short, typically a few years in length, and only single runs rather than ensemble runs are currently feasible. For many applications, therefore, it may be desirable to use simpler, statistical or empirical approaches, even when an appropriate high-resolution model is available for the region of interest (Kidson and Thompson, 1998; Zorita and von Storch, 1999).

Empirical approaches have the potential to provide a more immediate solution to the downscaling problem (Hewitson and Crane, 1996) and are the focus of much ongoing research effort (Wilby and Wigley, 1997; Wilby *et al*., 1998a; Zorita and von Storch, 1999). Empirical downscaling requires the identification of relationships between the observed large-scale and regional climate, which are then applied to large-scale GCM output. It encompasses methods based on multiple regression (Kim *et al*., 1984; Wigley *et al*., 1990; Palutikof *et al*., 1997; Winkler *et al*., 1997; Easterling, 1999 (and, more recently, neural networks, which can be viewed as a form of non-linear multiple regression; Weichert and Bürger, 1998; Trigo and Palutikof, 1999; Zorita and von Storch, 1999)), canonical correlation (von Storch *et al*., 1993; Heyen *et al*., 1996), non-parametric models (Corte-Real *et al*., 1995a) and studies in which circulation classifications are used to describe the large-scale climate (Cubasch *et al*., 1996; Hewitson and Crane, 1996; Schubert and Henderson-Sellers, 1997). Empirical methods also include the use of stochastic weather generators, which are typically based on Markov Chain processes (Mearns *et al*., 1997; Semenov and Barrow, 1997; Wilby *et al*., 1998a; Wilks and Wilby, 1999). Such weather generators are not explicitly based on the relationships between large-scale and regional climate. Their parameters can, however, be estimated using GCM data as a guide (see Sections 3.4.1 and 6.2).

In this thesis the potential of the circulation-based approach to downscaling, which has many of the desirable features identified at the end of Section 1.1, is explored in depth. Whether using the circulation-based approach or one of the other empirical methods outlined above, there are a number of principles or criteria which need to be considered. Many of these concern the predictor variable(s) used to define the large-scale climate, while others concern the relationships between the predictor(s) and the predictand (i.e. the surface climate):

- Reliable and appropriate observational data sets must be available for the predictor variable(s) and the predictand;
- The predictor variable(s) must be readily available from GCM output;
- The predictor variable(s) must be reliably reproduced by GCMs;
- There must be strong relationships between the predictor(s) and the predictand;
- Ideally, these relationships should be supported by an understanding of the underlying physical processes; and,
- The extent to which the predictor/predictand relationships have changed in the past, and may change in the future, should be addressed (i.e. the question of stationarity).

Some of these criteria also apply to model-based approaches to downscaling. The ultimate reliability or plausibility of both empirical- and model-based scenarios, for example, is limited by the reliability of the underlying GCM. The implications of decisions made during the development of downscaling techniques should also be addressed. While methods can be automated, truly objective techniques do not exist and many of the decisions which must be made are inevitably subjective (Palutikof *et al*., 1997).

1.2.2 The circulation-based approach to downscaling

The chosen circulation-based methodology was initially developed and tested in the Guadalentin Basin, southeast Spain, and has also been tested in the Agri Basin, southern Italy (Figure 1.1). A circulation classification was also developed for Lesvos, Greece, but insufficient rainfall data were available for downscaling in this area. These study areas were all target areas in the Mediterranean Desertification and Land Use (MEDALUS) project funded by the European Commission (Brandt and Thornes, 1996; Geeson and Brandt, 2000).

The methodology relates large-scale patterns of a predictor variable, sea level pressure (SLP), to local values of a surface climate variable (daily precipitation at individual stations). This approach is based on the expectation that the predictive capacity of GCMs is greatest at the multiple, rather than the single, gridpoint level (Grotch and MacCracken, 1991; von Storch *et al.*, 1993). The large-scale patterns are defined using circulation types. Provided that consistent and distinct relationships exist between the circulation types and precipitation in the observed data, and making the two major assumptions that these relationships will be unchanged in a future warmer climate regime, and that precipitation changes are driven largely by changes in circulation, perturbed-run GCM output can be used to investigate changes in the frequency and intensity of rain events in response to global warming (von Storch *et al.*, 1993; Hewitson and Crane, 1996; Schubert and Henderson-Sellers, 1997).

Links between large-scale circulation and surface weather have been explored and applied to environmental problems in synoptic climatology for many years (Yarnal, 1993) and provide a sound theoretical basis for this approach (Trenberth, 1995). These links have been used to explore the potential for downscaling from GCM output (see list of studies in Table 1.1) and have been applied to GCM output at the daily and monthly level in order to construct scenarios for precipitation and other variables (see list of studies in Table 1.2).

1.2.3 Previous applications of the circulation-based approach to downscaling

Two major decisions must be made when using the circulation-based approach to downscaling. The first concerns how to model the circulation/surface climate relationship in order that the value of the predictand climate variable can be assigned from knowledge of the circulation type. The choice of model depends, in part, on the temporal resolution required (i.e. daily or monthly, seasonal or annual). Five general approaches have been most widely used:

(i) Markov Chain models – daily resolution (Bardossy and Plate, 1991; Hay *et al*., 1991; Wilson *et al*., 1991; Bardossy and Plate, 1992; Hay *et al*., 1992; Wilson *et al*., 1992; Bogardi *et al*., 1993; Hughes *et al*., 1993; Wilby, 1993; Hughes and Guttorp, 1994; Schubert, 1994; Wilby *et al*., 1994; 1995; Katz and Parlange, 1996; Corte-Real *et al*., 1999a; Hughes and Guttorp, 1999; Katz and Zheng, 1999);

(ii) multiple regression – all temporal resolutions (Corte-Real *et al*., 1995a; Conway *et al*., 1996; Özelkan *et al*., 1996; Brandsma and Buishand, 1997; Enke and Spekat, 1997; Schubert and Henderson-Sellers, 1997; Zhang *et al*., 1997; Kidson and Thompson, 1998; Kilsby *et al*., 1998; Schubert, 1998; Wilby, 1998; Wilby *et al*., 1998b; Busuioc *et al*., 1999);

(iii) Canonical Correlation Analysis – monthly and seasonal resolutions (von Storch *et al*., 1993; Gyalistras *et al*., 1994; Noguer, 1994; Corte-Real *et al*., 1995b; Heyen *et al*., 1996);

(iv) sampling from present-day instrumental analogue data – all temporal resolutions (Kidson and Watterson, 1995; Zorita *et al*., 1995; Conway *et al*., 1996; Cubasch *et al*., 1996; Saunders and Byrne, 1996; Kidson, 1997; Brandsma and Buishand, 1998; Conway and Jones, 1998; Scnur and Lettenmaier, 1998; Zorita and von Storch, 1999; Kidson, 2000); and,

(v) fuzzy-rule based methods and neural nets – all temporal resolutions (Bardossy *et al*., 1994; Hewitson and Crane, 1992c; Hewitson and Crane, 1994; Hewitson and Crane, 1996; Özelkan *et al*., 1996; Crane and Hewitson, 1998; Cavazos, 1999; Zorita and von Storch, 1999).

Approach (iv) includes the simplest method in which mean precipitation (or a precipitation efficiency factor) is calculated for each circulation pattern and weighted by its frequency of occurrence to estimate total precipitation (Saunders and Byrne, 1996). This method is thus only appropriate for downscaling at the monthly or coarser temporal resolution, but other analogue methods allow downscaling at the daily scale (Brandsma and Buishand, 1998; Conway and Jones, 1998; Schnur and Lettenmaier, 1998).

Here, the first approach (i) is adopted and a statistical weather generator is used in which rainfall occurrence is conditional upon the circulation type of each day. In the initial set of simulations, the transition from one circulation type to another is also modelled as a Markov Chain process. In the second set of simulations, rainfall occurrence is conditional on the circulation type defined from SLP in the GCM and on whether the previous day was wet or dry.

The second decision which must be made is to choose an appropriate automated circulation classification scheme (Huth, 1996). The major distinction is between schemes based on existing circulation-type catalogues, such as Lamb Weather Types (LWTs) (Lamb, 1972, used by Wilby *et al*. 1994; 1995; Conway *et al.*, 1996; Conway and Jones, 1998) and Grosswetterlagen (Hess and Brezowsky, 1969, used by Bardossy and Plate, 1991; 1992; Schubert, 1994), and schemes based on statistical methods (Huth, 1996). The statistical methods most frequently used in downscaling studies include:

- Principal Components Analysis (PCA) (Wilson *et al*., 1992; Bogardi *et al*., 1993; Hughes and Guttorp, 1994; Noguer, 1994; Corte-Real *et al.*, 1995a; Cubasch *et al*., 1996; Hewitson and Crane, 1996; Heyen *et al*., 1996; Schubert and Henderson-Sellers, 1997; Zhang *et al*., 1997; Kidson and Thompson, 1998; Schubert, 1998; Biau *et al*., 1999);
- Canonical Correlation Analysis (CCA) (Zorita *et al*., 1992; von Storch *et al*., 1993; Corte-Real *et al*., 1995b; Busuioc *et al*., 1999);
- cluster analysis, usually in conjunction with PCA (Wilson *et al*., 1991; Bogardi *et al*., 1993; Kidson and Watterson, 1995; Enke and Spekat, 1997; Kidson, 1997; Zhang *et al*., 1997; Corte-Real *et al*., 1999a; Kidson, 2000); and,
- Artificial Neural Nets (ANN) and fuzzy-rule based methods (Hewitson and Crane, 1992c; Bardossy, 1994; Bardossy *et al*., 1994; Hewitson and Crane, 1994; Bardossy *et al*., 1995; Özelkan *et al*., 1996; Verdecchia *et al*., 1996; Crane and Hewitson, 1998; Weichert and Bürger, 1998; Cavazos, 1999; Trigo and Palutikof, 1999).

The correlation-based typing method developed by Kirchofer (1974) has also been used for downscaling (Saunders and Byrne, 1996; 1999). (It is noted that this typing method has been shown to give unacceptable results when attempting to summarise a region's synoptic regime with a relatively small number of synoptic types (Blair, 1998).) A method for identifying "hidden" circulation states using a novel statistical method (the expectation-maximisation algorithm in a Markov Chain model) has recently been tested (Hughes and Guttorp, 1999; Katz and Zheng, 1999; see also Charles *et al*., 1999; Bellone *et al*., 2000). The latter method is an example of a 'bottom-up' approach to circulation classification, i.e. the circulation states are identified from the pattern of precipitation occurrence rather than from circulation itself.

A distinction can be made between those studies listed in Tables 1.1 and 1.2 which provide very discrete circulation classifications, i.e. conventional synoptic circulation types (such as Bardossy and Plate, 1991; Hay *et al*., 1991; Hay *et al*., 1992; Wilby *et al*., 1994; Schubert, 1994; Frey-Buness *et al*., 1995; Kidson and Watterson, 1995; Saunders and Byrne, 1996; Wilby *et al*., 1995, and all studies which use PCA, EOF and cluster analysis) and those which provide a more continuous description of the circulation regime (such as von Storch *et al*., 1993; Corte-Real *et al*., 1995b; Conway *et al*., 1996; Brandsma and Buishand, 1997; Crane and Hewitson, 1998; Kilsby *et al*., 1998; Wilby *et al*., 1998b).

1.3 THE DEVELOPMENT OF THE CIRCULATION-TYPE APPROACH TO DOWNSCALING

Here, an automated method based on LWTs (Jenkinson and Collison, 1977; Jones *et al*., 1993) is used to classify the circulation on a daily basis. This method has a number of advantages for downscaling. It is computationally simple and is based on a single, widely-available, free atmosphere variable: daily gridded SLP. Free atmosphere variables are reasonably well simulated by GCMs, at least over some regions (Crane and Barry, 1988; Hansen and Sutera, 1990; Hewitson and Crane, 1992a) and are therefore considered to have advantages over surface variables as predictor variables (Karl *et al*., 1990; Palutikof *et al*., 1997). Observed gridded SLP data sets have a resolution comparable to that of GCMs. The automated LWT scheme is easy to interpret and has a sound physical basis in synoptic climatology.

The LWT-catalogue was initially developed for the British Isles using subjective methods (Lamb, 1972) and has been used to predict present-day daily rainfall in the British Isles (Wilby *et al*., 1994; 1995). The automated version categorises surface flow by direction (with a resolution of 45°) and type (cyclonic/anticyclonic, light/hybrid flow) (Jenkinson and Collison, 1977; Jones *et al*., 1993). It has been applied to control-run GCM output for the British Isles (Hulme *et al*., 1993). In theory, it can be applied anywhere in Northern Hemisphere mid-latitudes. The underlying air flow indices derived from this method have been used to reconstruct present-day daily precipitation in the UK (Conway *et al*., 1996; Conway and Jones, 1998; Kilsby *et al*., 1998) and to downscale daily precipitation in the USA (Wilby and Wigley, 1997; Wilby *et al*., 1998a) and Japan (Wilby *et al*., 1998b). Here, the surface flow categories (i.e. discrete circulation types), rather than the underlying air flow indices, are used and the potential of the approach is developed and tested in a Mediterranean climate regime.

Thus, the first two major objectives of the thesis work are to:

- take an existing automated circulation typing scheme and investigate whether it can be successfully applied in a very different, Mediterranean, climate regime; and,

- to investigate whether this scheme can be used to condition and provide parameters for a weather generator in order to simulate daily rainfall in a highly seasonal precipitation regime.

The downscaling approach adopted here is empirical, but a particular objective of the work is to explore the underlying physical processes. In respect of the first objective above, this means demonstrating that each circulation type has a characteristic pressure pattern which produces the expected type and direction of flow over the study regions. In respect of the second objective, this requires the identification of consistent and distinct relationships between the circulation types and daily precipitation in the study regions which can be explained in terms of the underlying synoptic situation. These aspects are not usually considered in detail in empirical downscaling studies, but are seen as a vital and distinctive part of the thesis work.

Another issue which is considered important in the context of the thesis is the presentation of the scenario results. Particular emphasis is given to the identification of appropriate methods for testing the performance of the downscaling method and for evaluating the magnitude of the projected changes in precipitation. More innovatively, in the later stages of the thesis work, the conditional weather generator has been used in a genuine Monte Carlo fashion which allows a fully probabilistic approach to impact assessment, and is also applicable to sensitivity studies. A method of using the conditional weather generator results to identify scenarios which minimise the impact of errors in the underlying GCM simulations has also been developed.

While the major aims and objectives of the thesis outlined above concern the development of empirical downscaling methods, it is considered that the work also has implications for GCM development and synoptic climatology. The validation studies, of SLP and the circulation types, for example, help to improve understanding of synoptic variability in GCMs. The evaluation of the typing scheme and of circulation/surface climate relationships provides information about the synoptic climatology of the study regions and provides an appropriate basis for more detailed studies of past variability. The author of this thesis has, for example, used the new circulation-typing scheme developed here to explore circulation/rainfall links and past rainfall changes over Spain as part of the Atmospheric Circulation Classification and Regional Downscaling (ACCORD) project funded by the European Commission (see http://www.cru.uea.ac.uk/cru/projects/accord/).

1.4 THE THESIS STRUCTURE

The basic circulation-type scheme and the underlying SLP data sets are described in Chapter 2. Because the existing automated scheme is being transferred to new regions (the Guadalentin Basin in the first instance), it must be demonstrated that it remains physically valid. This is done using SLP composite maps. Initially, daily output from the UK Meteorological Office high resolution GCM run in transient mode, referred to as UKTR (Murphy, 1995a,b; Murphy and Mitchell, 1995), was used for the thesis work. The ability of this GCM to reproduce the observed circulation types is discussed in Chapter 2, and simulated perturbed minus control run changes in circulation-type frequency investigated.

The characteristic Mediterranean precipitation regime of the Guadalentin Basin study region is described in Chapter 3. Relationships between the circulation types and daily rainfall in the Basin are then investigated. Consistent and distinct relationships are identified which can be modelled using a weather generator, in which precipitation occurrence is conditional on the circulation type of each day and the transition from one circulation type to another is also modelled as a Markov Chain process. It is shown that this conditional weather generator can be used to translate the GCM changes in circulation-type frequency into rain-day changes.

The rain-day scenarios presented at the end of Chapter 3 are intended as illustrative results and demonstrate the potential of the circulation-based approach to downscaling. A number of issues arising from the initial development and testing of the methodology are discussed in Chapter 4 and addressed in later Chapters of the thesis. These issues include:

- The need for a better understanding of the physical processes underlying the circulation-surface climate relationships;
- The failure of the GCM to reproduce the observed circulation-type frequencies;
- The poor reproduction of the persistence and variability of precipitation in the weather generator;
- The implications of the very small circulation-type frequency changes in the GCM; and,
- The assumption of stationarity in the circulation-surface climate relationships.

After completion of the initial analyses described in Chapters 2-4, and summarised by Goodess and Palutikof (1998; 2000), daily output from the HADCM2 set of GCM simulations (Johns *et al*., 1997) became available and was used for all the analyses described in Chapters 5-7. The development of a new circulation typing scheme using the HADCM2 grid for three study regions is described in Chapter 5. These regions are the Guadalentin Basin in southeast Spain, the Agri in central Italy and Lesvos, one of the eastern-most Greek islands. They provide a transect across the Mediterranean Basin centred on 40° N (Figure 1.1). The new scheme corrects, in part, for errors in the GCM simulation of SLP. Because a different SLP grid is now used, it is shown that the circulation types remain valid for the Guadalentin Basin and that there are distinct and consistent relationships between the circulation types and daily rainfall. The typing scheme is also shown to be valid for the Agri and circulation-type/precipitation relationships in this region are investigated. Insufficient instrumental data were available for this stage of the analysis to be undertaken for Lesvos. Finally in Chapter 5, the ability of the HADCM2 model to reproduce the circulation types in all three regions is considered, and circulation-type frequency changes for 2030-2039 and 2090-2099 are described.

The development of a new conditional weather generator for the simulation of daily rainfall occurrence and amount is described in Chapter 6. In order to allow the construction of daily scenarios which are consistent throughout a group of stations, or for other variables, the circulation types are not modelled as a Markov Chain process as before, but are taken directly from the observations or GCM output. Precipitation occurrence is conditional on the circulation type and on whether the previous day was wet or dry. Rainfall amount is conditional on the circulation type. The new conditional weather generator was run 1000 times for each simulation set. Two groups of simulations were performed. For the first group, a cross-validation approach was used to evaluate model performance. For the second group, HadCM2 output was used to construct daily rainfall scenarios for 1970-1979; 2030-2039 and 2090-2099 for stations in the Guadalentin and Agri study regions. The results are presented in the form of frequency histograms which are considered to have a number of advantages for scenario development. Finally in Chapter 6, the scenarios are evaluated, focusing on issues such as changes in the persistence of wet and dry day spells and the occurrence of extreme events.

Chapter 7 focuses on the issues raised in Chapters 5 and 6 and on ways in which the methodology presented in the thesis could be further refined and developed. In particular it aims to answer the following questions:

- How do the Guadalentin and Agri study regions differ?
- Why does the downscaling method appear to work, but not always, and is it reasonable to assume that the observed circulation/surface climate relationships are

stationary and will remain so in a high greenhouse gas world?

- Can the downscaling method be used to produce self-consistent scenarios for multiple sites and/or parameters?

Table 1.1: Studies in which circulation/surface climate relationships are modelled as a precursor to downscaling GCM output. ANN: Artificial Neural Net; CCA: Canonical Correlation Analysis; EOF: Empirical Orthogonal Function; GPH = Geopotential Height; LWTs: Lamb Weather Types; MARS: Multivariate Adaptive Regression Splines; PCA: Principal Component Analysis; SLP: Sea Level Pressure.

Study	*Method of circulation classification*	*Surface variables reconstructed*	*Circulation/surface climate relationship*
Bardossy and Plate, 1991; 1992	Grosswetterlagen circulation types.	Daily precipitation.	Semi-Markov Chain model (with conditional probabilities).
Biau *et al*., 1999	PCA of SLP.	Monthly and daily winter precipitation.	Kriging in the EOF space.
Bogardi *et al*., 1993	PCA and k-means cluster analysis of 500 hPa GPH.	Daily precipitation.	Modified version of Bardossy and Plate (1992).
Brandsma and Buishand, 1997	Air flow indices (three directions of flow) and temperature.	Daily precipitation.	Prec./temp. relationships, generalised linear models: 1. Parametric, 2. Non-parametric.
Brandsma and Buishand, 1998	Air flow indices.	Daily precipitation and temperature.	Non-parametric nearest-neighbour resampling.
Cavazos, 1999	Neural network (self-organizing maps, 700-500 hPa GPH thickness and SLP tendency).	Daily precipitation.	Feed-forward ANN.
Conway *et al*., 1996	Automated LWTs/air-flow indices.	Daily precipitation.	1) Regression, 2) Conditional sampling.
Conway and Jones, 1998	LWTs and air flow indices based on SLP.	Daily precipitation.	Random resampling – days sorted by circulation and wet/dry status.
Corte-Real *et al*., 1995b	CCA of SLP and 500 hPa GPH.	Monthly precipitation and temperature.	CCA.
Hay *et al*., 1991	6 pre-defined weather types.	Daily precipitation.	Markov Chain model (for weather types and precipitation), with error term for precip. amount.
Hewitson and Crane, 1992c; 1994	PCA and ANN: SLP and 500 hPa GPH.	Daily precipitation.	ANN.
Hughes and Guttorp, 1994	PCA of SLP data.	Daily precipitation.	Non-homogeneous hidden Markov model.
Hughes and Guttorp, 1999	“Hidden” 6-state index (SLP and 850 hPa GPH) identified using the expectation-maximisation algorithm.	Daily precipitation.	Non-homogeneous hidden Markov model.
Katz and Parlange, 1996	Simple monthly SLP index.	Daily precipitation.	Markov Chain model.

Table 1.1: …..continued.

Study	*Method of circulation classification*	*Surface variables reconstructed*	*Circulation/surface climate relationship*
Katz and Zheng, 1999	“Hidden” 2-state SLP index identified using the expectation-maximisation algorithm.	Daily precipitation.	Non-homogeneous hidden Markov model, parameters dependent on hidden 2-state circulation index.
Kidson, 1997	Cluster analysis of EOFs of 1000 and 500 hPa GPH.	Daily and monthly precipitation, temperature, sunshine and wind.	Mean quintile values for three predictors: 1) Mean cluster frequency 2) Mean EOF value 3) Daily anomalies.
Kidson and Thompson, 1998	EOFs of 1000 and 500 hPa GPH.	Daily and monthly temperature/precip.	Screening linear regression.
Kidson, 2000	PCA and cluster analysis of 1000 hPa GPH.	Monthly temperature and precipitation.	Identification of best analogues.
Kilsby *et al.*, 1998	Air-flow indices based on SLP.	Mean daily precipitation.	Linear regression with 2 sets of predictors: 1) air-flow indices, 2) geographical variables.
Özelkan *et al.*, 1996	Lag-correlation and fuzzy indexing of monthly 500 hPa GPH.	Monthly precipitation.	1) fuzzy-rule based model 2) mulivariate linear regression.
Schubert, 1994	Grosswetterlagen circulation types.	Daily temperature and precipitation.	Markov Chain model.
Schubert and Henderson-Sellers, 1997	PCA of SLP data.	Daily temperature.	Multiple regression.
Wilby, 1993; Wilby *et al.*, 1994	LWTs.	Daily precipitation.	Markov Chain model.
Wilby *et al.*, 1995	LWTs.	Daily precipitation.	Markov Chain model (with weather fronts).
Wilby, 1998	Air flow indices based on SLP (and NAO index, North Atlantic SST).	Daily precipitation.	2nd order polynomial regression model.
Wilson *et al.*, 1991	k-means cluster analysis of SLP and 850 hPa GPH.	Daily precipitation.	Semi-Markov model.
Wilson *et al.*, 1992	4 methods tested, of which PCA is best.	Daily precipitation.	1) Markov Chain model (for circulation types), 2) Hierarchical model (for precipitation).
Zhang *et al.*, 1997	PCA and k-means cluster analysis of SLP.	Winter monthly precipitation.	MARS models.

Table 1.2: Studies in which circulation/surface climate relationships are used to downscale GCM output. ANN: Artificial Neural Net; CART: Classification and Regression Trees; CCA: Canonical Correlation Analysis; EOF: Empirical Orthogonal Function; GPH = Geopotential Height; MARS: Multivariate Adaptive Regression Splines; PCA: Principal Component Analysis; SLP: Sea Level Pressure.

Study	*Method of circulation classification*	*Surface variables reconstructed*	*Circulation/surface climate relationship*	*GCM*
Busuioc *et al*., 1999	CCA of SLP	Seasonal precipitation.	CCA/regression.	ECHAM3
Corte-Real *et al*., 1995a	PCA	Winter monthly precipitation.	MARS model.	UKTR
Corte-Real *et al*., 1999a	PCA and k-means clustering.	Daily precipitation.	Markov chain model.	HadCM2
Crane and Hewitson, 1998	ANN: 1000, 700 and 500 hPa GPH & specific humidity.	Daily precipitation.	ANN.	GENESIS
Cubasch *et al*., 1996	EOFs of 700 hPa GPH.	Daily winter precipitation.	Analog method (as Zorita *et al*., 1995).	ECHAM
Enke and Spekat, 1997	Cluster analysis of 1000, 700 and 500 hPa GPH.	Seven daily variables, including precipitation.	Conditional step-wise screening regression (including 700 hPa humidity).	ECHAM (control-run only)
Frey-Buness *et al*., 1995	Pre-defined circulation types (based on direction of flow).	Daily winter precipitation.	Fine-mesh regional simulations, results weighted by frequency.	ECHAM (control-run only)
Gyalistras *et al*., 1994	EOFs of monthly SLP and temperature at 2m.	Winter/summer, five daily variables including precipitation.	Based on von Storch *et al*., 1993 (CCA) and 'Perfect Prog'.	ECHAM
Hay *et al*., 1992	6 pre-defined conceptual types (based on wind and cloud).	Daily precipitation.	Markov Chain-based model.	GFDL
Hewitson and Crane, 1996	PCA of SLP and 500 hPa GPH.	Daily precipitation.	Lag correlations and ANN.	GENESIS
Heyen *et al*., 1996	EOFs of monthly SLP.	Monthly winter Baltic sea level.	CCA (as von Storch *et al*., 1993).	ECHAM
Hughes *et al*., 1993	CART, SLP data.	Daily precipitation and temperature.	1) Markov Chain model (precip.), 2) Autoregressive model (temp.).	GFDL
Kidson and Watterson, 1995	13 synoptic types (from cluster analysis of SLP EOFs).	Daily precipitation, temperature, sunshine and wind.	Composite quintile means, weighted by frequency of type.	CSIRO
Noguer, 1994	EOFs of monthly SLP.	Monthly precipitation.	CCA/regression (von Storch *et al*., 1993).	UKMO
Saunders and Byrne, 1996	Kirchofer (1974) classification of SLP and 500 hPa GPH.	Monthly precipitation.	Precipitation efficiency ratio (weighted by frequency of type).	CCC

Table 1.2: …..continued.

Study	*Method of circulation classification*	*Surface variables reconstructed*	*Circulation/surface climate relationship*	*GCM*
Schnur and Lettenmaier, 1998	CART, SLP data.	Daily precipitation.	Recursive sampling from observed data.	MPI
Schubert, 1998	PCA of SLP.	Daily precipitation.	Multiple regression (as Schubert & Henderson-Sellers, 1997).	CSIRO
von Storch *et al*., 1993	CCA of monthly SLP.	Winter precipitation anomalies.	CCA.	ECHAM
Wilby and Wigley, 1997; Wilby *et al*., 1998a	1) ANN. 2) Air flow indices.	Daily precipitation.	1) ANN. 2) Resampling/non-linear multiple regression.	HadCM2
Wilby *et al*., 1998b	Air-flow indices.	Daily precipitation, temperature and relative humidity.	Markov Chain model and multiple regression.	HadCM2
Zorita *et al*., 1995	CART, SLP data.	Daily precipitation.	1) Based on CART, sampling from binned data, 2) Analog method.	GFDL and MPI