Statistical Downscaling: Linking Climatic Processes Between Spatial Scales

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Abstract: Interest in the impacts of low-frequency climate variability and climate change on natural resources planning and management has grown in recent decades. Although numerical climate models offer a means of deriving climate scenarios for investigating such impacts, their spatial resolution is too coarse for many applied applications. This situation has led to the development of statistical downscaling methods linking local- and regional-scale weather to large-scale atmospheric circulation. This paper reviews recent progress in statistical downscaling. It presents the current state of knowledge, examines issues regarding the successful application of downscaling techniques, and highlights research opportunities. An example, using a nonhomogeneous hidden Markov model (NHMM) and atmospheric and precipitation data from south-western Australia, shows that a well-constructed downscaling model can be used to diagnose atmospheric circulation changes that drive multidecadal fluctuations in precipitation.

Keywords: Statistical downscaling; Precipitation; Climate models; Climate variability; Climate change

1. INTRODUCTION

Predicting the impacts of low-frequency climate variability and (potential) climate change on water resources is increasingly relevant [Burges, 1998]. The need for predictions based on physical rather than purely statistical models has lead to the development of coupled atmosphere-ocean general circulation models (GCMs) and, nested at finer spatial scales, limited area models (LAMs). Although performing well at simulating large-scale atmospheric fields, GCMs and LAMs over-estimate the frequency and under-estimate the intensity of daily precipitation and thus fail to reproduce the statistics of historical records at local scales [Mearns et al., 1995; Bates et al., 1998]. These limitations have led to the development of statistical downscaling techniques for estimating local scale precipitation from the coarse spatial resolution atmospheric fields of climate models [Xu, 1999]. Disaggregation, also termed 'downscaling' in hydrology and soil science, is not covered here. This paper presents an overview of current statistical downscaling methods linking local scale precipitation to large-scale atmospheric data, includes an example application, and concludes with a discussion of future research directions.

2. TECHNIQUES

Statistical downscaling involves developing semi-empirical relationships between large-scale atmospheric variables (predictors) and local surface variables (predictands). In its most general form:

$$\mathbf{R}_t = F(\mathbf{X}_T) \qquad T \le t \qquad (1)$$

where $\mathbf{R}_t$ represents the local-scale predictand at single or multiple sites at time t; $\mathbf{X}_T$ is the predictor set (a collection of current and past values of large-scale atmospheric variables), and F quantifies the semi-empirical relationship linking the two disparate spatial scales. Most statistical downscaling has focussed on daily station (i.e. point scale) precipitation as the predictand, because daily precipitation is poorly reproduced in numerical climate models and is an important input variable to many natural systems models. Predictor sets can be derived from sea level pressure (SLP), geopotential height, absolute or relative humidity, and temperature variables and combinations thereof. These variables are available at the grid resolution of operational and research numerical climate models. A typical GCM horizontal resolution is of the order 300-500 km. LAMs have typical horizontal resolutions of 50-125 km, with

some as fine as 15 km. Statistical downscaling methods can be classified according to three main techniques: weather classification; regression; or weather generator based.

2.1 Weather Classification

Weather classification methods involve grouping days into a finite number of discrete "weather states" according to their synoptic similarity. Formally:

$$S_t = F_S(X_T) \qquad T \leq t \qquad (2)$$

$$R_t = F_R(S_t) \qquad (3)$$

where S_t is the weather state at time t. Weather state definition, F_S, is achieved using objective methods such as cluster analysis, or subjective circulation classification schemes. F_R is modelled using resampling, regression, or as a probabilistic model [e.g., Hay et al., 1991; Corte-Real et al., 1999]. These methods often poorly reproduce the persistence of wet and dry spells [Wilby, 1994].

The nonhomogeneous hidden Markov model (NHMM), as used herein, was developed to overcome the poor performance of weather classification based methods [Hughes et al., 1999]. A hidden Markov model is a doubly stochastic process, involving an underlying unobserved (hidden) stochastic process that can only be observed through another stochastic process that produces the sequence of observed outcomes. The observed process (such as precipitation occurrence at a set of sites) is assumed to be conditionally, temporally independent given the hidden process. The hidden process (such as the temporal evolution of weather states) is assumed to evolve according to a first order Markov chain [Rabiner and Juang, 1986]. Thus the NHMM weather states are not defined independently of the precipitation data *a priori*, they are multi-site precipitation occurrence patterns identified during model fitting. The NHMM accounts for spatial patterns in precipitation occurrence, reproducing wet and dry spell persistence as well as the inter-site spatial correlations in precipitation occurrence [Hughes et al., 1999]. In its most general form, an NHMM is defined by the probabilistic relationships:

$$P(S_t|S_{t-1}, X_t) \qquad (4)$$

$$P(R_t|S_t) \qquad (5)$$

where X_t is the vector of atmospheric predictors at time t and R_t is the vector of precipitation occurrences at a network of sites at time t. Specific NHMMs are defined by the parameterisations chosen for the precipitation occurrence probability distribution $P(R_t|S_t)$ and the weather state transition matrix $P(S_t|S_{t-1}, X_t)$ (see Hughes et al. [1999] for details). Subsequent to NHMM fitting, the joint distribution of daily precipitation amounts at multiple sites is evaluated through the specification of conditional distributions for each state. An automatic variable selection procedure is used to identify the key neighbouring sites (see Charles et al. [1999a]).

2.2 Regression

Regression based approaches are conceptually simple, determining linear or non-linear relationships between R and X:

$$R_t = F_Y(X_T; \theta) \qquad T \leq t \qquad (6)$$

where θ is the parameter set of the linear or non-linear regression method, F_Y. Methods used include multiple regression [Murphy, 1999], canonical correlation analysis (CCA) [von Storch et al., 1993], and artificial neural networks [Crane and Hewitson, 1998]. The relationships obtained are sensitive to the choice of predictors [Wilby and Wigley, 2000].

2.3 Weather Generators

Weather generators can be conditioned on large-scale atmospheric predictors or weather states [Katz, 1996; Wilks and Wilby, 1999]:

$$R_t = F_W(\theta|X_T) \quad T \leq t \, ; \quad \text{or}$$

$$R_t = F_W(\theta|S_t) \qquad (7)$$

where θ is the parameter set of the weather generator, F_W. Weather generators often simulate precipitation together with secondary variables (e.g., temperatures, solar radiation) in a consistent manner. Wilby et al. [1998] note that parameter modification for future climate scenarios can affect the relationships between the conditional variables. Moreover, weather generators often underestimate the temporal variability and persistence of precipitation [Katz and Parlange, 1998].

2.4 Intercomparison Studies

Several studies have compared statistical downscaling methods or compared methods to LAM based dynamical downscaling. Wilby and Wigley [1997] and Wilby et al. [1998] compared six approaches (two neural nets, two weather generators, and two vorticity based regression methods) using observed and GCM data. The vorticity based regression methods were found to perform better. Validation criteria were root mean squared errors of the following diagnostics: wet-day amount mean, median, standard deviation and 95th percentile; dry-dry and wet-wet day occurrence probabilities; wet-day probabilities; wet- and dry-spell duration mean, standard deviation, and 90th percentile; and standard deviation of monthly precipitation totals. The driving GCM (HadCM2) exhibited very small changes in circulation predictors (within the limits of interannual variability) suggesting the need to incorporate measures in addition to the circulation-based predictors used (e.g., atmospheric moisture based predictors). Using a common set of GCM derived predictors; the various approaches gave significantly different precipitation predictions for changed climate conditions.

Zorita and von Storch [1999] compared their analogue method [Zorita et al., 1995] to (i) a linear regression method based on CCA applied to monthly site precipitation totals and SLP fields; (ii) a classification method based on classification and regression trees (CART) applied to daily precipitation occurrence and SLP fields; and (iii) a neural network, as an example of a non-linear method, applied to daily precipitation amounts and SLP anomalies for the Iberian Peninsular (South West Europe). In general the analogue method performed comparably, or better, than the other more complicated methods while being technically simpler to implement.

Kidson and Thompson [1998] compared the RAMS model (boundary forced by twice-daily 2.5° resolution ECMWF analyses) to a screening regression technique with indices of local and regional flow, using data from 1980 to 1994 for a network of 78 sites across New Zealand. The regression approach better explained the daily variance in precipitation anomalies. The poor relative performance of the RAMS model was due to its inability to resolve orography, a factor of the 50 km grid spacing used. They conclude that the (linear) regression relationships developed could be applicable when the predictors extend a small amount beyond the range of the observed data used in fitting, but that it was preferable to use dynamic models (such as RAMS) for significant climate change when factors such as atmospheric vapour content could influence storm intensity.

Mearns et al. [1999] compared a circulation classification approach, based on classifying 700 hPa fields, to the NCAR RegCM2 mesoscale model nested within the CSIRO GCM for 5 years of $1{\times}CO_2$ and $2{\times}CO_2$ runs in eastern Nebraska, USA. The RegCM2 model could often reproduce monthly or seasonal precipitation quite well, due to compensating errors in the overestimation of the frequency and underestimation of intensity of precipitation events. Their results exemplify the problem of obtaining different predictions from different approaches, as the predicted changes in mean daily precipitation obtained from the two approaches were different in direction for 40% of months and locations investigated. The statistical downscaling results indicated predominantly mean precipitation increases, whereas RegCM2 produced both increases and decreases for coherent subregions.

Murphy [1999] also compared dynamical to statistical downscaling (linear regression, using a variety of predictors capturing large-scale circulation, surface wind and vorticity, 850 hPa temperature and specific humidity, and a convective stability index) in a study of 976 sites in Europe. Consistent with Mearns et al. [1999], Murphy [1999] found that compensating errors caused by an overactive hydrological cycle lead to a RCM simulated mean monthly precipitation in good agreement with the observed. Comparable skill was shown by the RCM and the statistical downscaling approach at the monthly scale.

3. KEY ISSUES

Three key assumptions, common to all statistical downscaling techniques, apply when downscaling for current and future climates:

- Predictors relevant to the precipitation process are adequately reproduced in the numerical climate model simulations.
- The relationship between the predictors and precipitation remains valid for periods outside the fitting period (time invariance). This needs careful assessment for future climate projection.
- The predictor set sufficiently incorporates the future climate change 'signal'. Some approaches, for example stepwise regression, may exclude predictors based on current climate performance that will be important in future changed climates.

For current climate conditions, the validity of the first two assumptions can be assessed using

observed records of sufficient length. The recent advent of Reanalysis products (NCEP/NCAR and ECMWF) provides multidecadal atmospheric predictor sets useful for testing statistical downscaling methods. Such work is on going within our group [Bates et al., 2001]. Comparing the downscaling results obtained from observed data to those obtained from control run (i.e. current climate) GCM and LAM data provides important validation and diagnosis of numerical climate model performance [e.g., Bates et al., 1998, 2000].

For future climates, Charles et al. [1999b] compared the $2\times CO_2$ projections obtained by downscaling to the LAM grid-scale with those produced by the LAM directly. The NHMM fitted to the daily $1\times CO_2$ LAM data could reproduce the $2\times CO_2$ LAM grid precipitation. Although not validation in the traditional sense, this approach adds confidence to the choice of predictors and that the relationships derived during fitting remain valid for the changed climate. Busuioc et al. [1999] have applied a similar method using monthly data.

4. EXAMPLE APPLICATION

There has been a decline in winter (May-October) rainfall over SWA since about the middle of the 20th century. Since the mid 1970s, this decline has had important consequences for water resources management [IOCI, 1999]. The linkage between the winter rainfall decline and regional changes in atmospheric circulation has been investigated using the NCEP-NCAR Reanalysis dataset for the period 1958–98, observed daily rainfall series for 30 sites across the region, and a six-state NHMM that uses three atmospheric predictors: SLP averaged over five points on a 3.75° longitude by 2.25° latitude data grid, north-south (N-S) SLP gradient, and dew point temperature depression at 850 hPa (DT_d^{850}) [Charles et al., 1999a]. $(DT_d^{850}$ is defined as the difference between the air temperature and the dew point temperatures at 850 hPa, it is therefore a measure of the humidity of the lower troposphere.) The NHMM, fitted using data for the 1978-92 relatively dry period, is able to reproduce the precipitation statistics of the wetter 1958-77 period [IOCI, in press].

Time series of the steady-state probabilities for two of the six states (States 3 and 5) are shown in Figure 1. The corresponding precipitation probability patterns and SLP fields are shown in Figure 2. Although interannual variability is evident across the 1958-98 period, it is apparent that the frequency of State 3 declined from 1958 to the mid–70s and remained stationary since. In

contrast, the frequency of State 5 increased markedly around the mid–70s and remained stationary since.
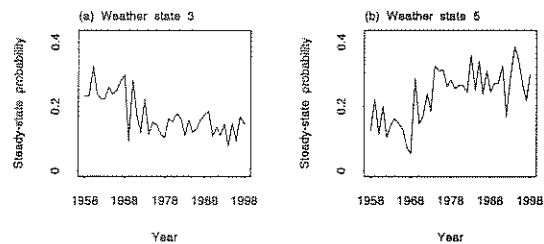

Figure 1. Interannual variability of steady-state probabilities for (a) State 3 and (b) State 5.
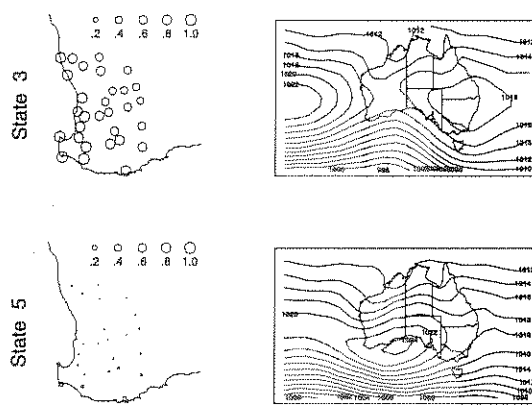

Figure 2. Precipitation probabilities (diameters of circles indicate site precipitation occurrence probabilities) and SLP fields for States 3 and 5.

A reduction in the frequency of State 3 indicates a reduction in the occurrence of moist westerly or southwest winds bringing rainfall to the western half of the region. An increase in the frequency of State 5 indicates an increase in the number of dry days across SWA. This is due to an increase in the frequency of dry easterly or northeast winds around high pressure systems centred to the east of the region.

Thus application of the NHMM allows attribution of multidecadal regional precipitation fluctuations to changes in synoptic climatology. Identifying the large-scale mechanisms responsible for these changes is the subject of on-going research [IOCI, in press].

5. FUTURE DIRECTIONS

Statistical downscaling models are useful research tools for investigating the relationship between large-scale climatic processes and local climate

variables, such as precipitation. A well implemented and tested statistical downscaling investigation:

- provides simulated precipitation sequences reproducing observed statistics and accounting for natural climate variability, for multiple sites at the point spatial scale required for impacts modelling (e.g., hydrological, agricultural, ecosystem modelling) - thus overcoming the "scale problem" of the coarse horizontal resolution of numerical climate models;
- allows efficient generation of multiple simulations for assessing confidence limits and predictand variability;
- can diagnose changes in atmospheric circulation patterns responsible for multidecadal precipitation variability; and,
- can produce climate change projections at the spatial scale required for impacts modelling, with a degree of confidence conferred from associated LAM comparisons.

There are on-going challenges for the future development, assessment, and application of statistical downscaling . Priorities include:

- Increasing the number of studies in semiarid and tropical regions, as the majority of applications have been in temperate, midlatitude regions in the Northern Hemisphere. Our group has begun work in tropical Queensland [Charles et al., 2001].
- Assessing the ability to capture variability across the continuum of temporal scales, from daily to interannual to interdecadal.
- Assessing the time invariance of downscaling relationships and the related issues of validating climate change methodologies.

The majority of statistical downscaling applications have had a climate change focus. The Intergovernmental Panel on Climate Change Third Assessment Report (IPCC TAR) lists 80 studies published since 1995, using 23 different statistical downscaling methods! The IPCC TAR [Giorgi and Hewitson, 2001] and Wilby and Wigley [1997] recommend that statistical downscaling methods be rigorously assessed by comparing results with high-resolution dynamical model simulations.

Additionally, exciting opportunities will arise when statistical downscaling is coupled with long-lead numerical climate model forecasting. The aim is to produce a seasonal forecast tool useful for hydrological and agricultural prediction (e.g., probabilistic water supply or crop yield projections up to a year ahead). Research in these areas is on-going [IOCI, in press].

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