

## Methods for statistical downscaling of GCM simulations

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**Cover illustration:** An example of the coarseness of GCMs. The daily mean surface temperature for September 9, 1997, is shown in a  $0.5^\circ$  grid (about 50 km resolution) in the left panel and in a  $3^\circ$  grid (about 300 km resolution) in the right panel. The former grid size is easily attainable in regional models. The latter grid size is representative of the resolution in a state-of-the-art GCM.

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## Report Summary / Rapportsammanfattning

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Abstract/Sammandrag  General Circulation Models (GCMs) are used to study the change of climate due to increases in greenhouse gases in the atmosphere. As GCMs operate on large spatial scales, and, furthermore, as the GCM-simulated temporal resolution corresponds to monthly averages at best, the usefulness of GCM data in impact studies and other applications is limited. The present-day free troposphere is modeled relatively well by the coarse GCMs, whereas local or even regional characteristics in surface or near-surface climate variables, their variability and the likelihood of extreme events cannot be obtained directly from GCMs. The same is likely true in the case of climate change experiments with GCMs. The results from GCMs can be superimposed on climatological local-scale time series or interpreted in some other way in order to address the needs of impact studies. This is known as "downscaling" of GCM simulations. In this survey, five different downscaling methods are introduced. These are the conventional, the statistical, the stochastic, the dynamical and the composite methods. Only the statistical and, to a lesser extent, the stochastic approaches are discussed in detail. This survey is a planning document in the SWECLIM program.		
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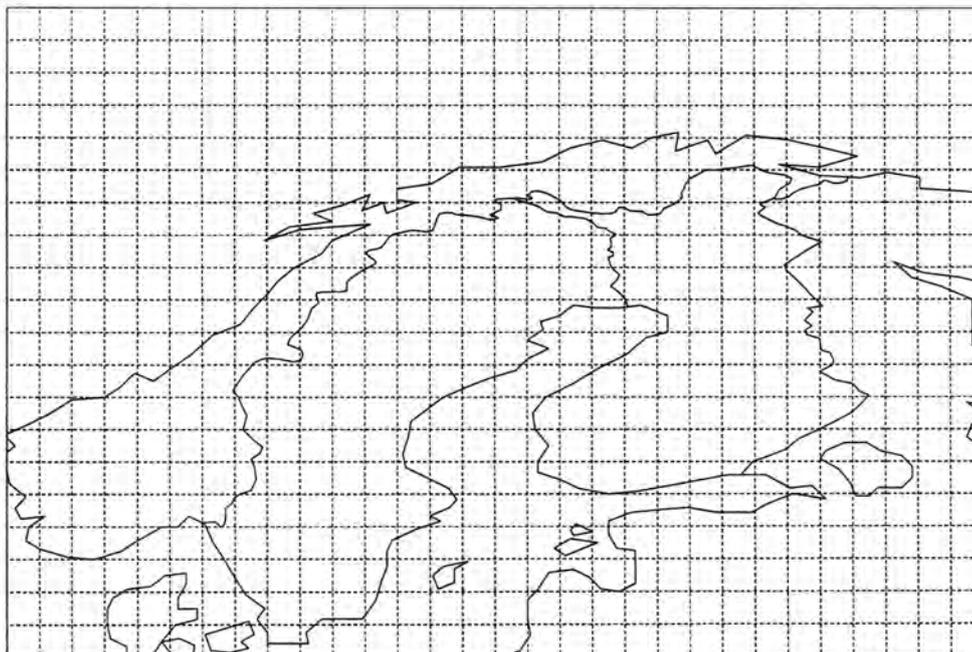
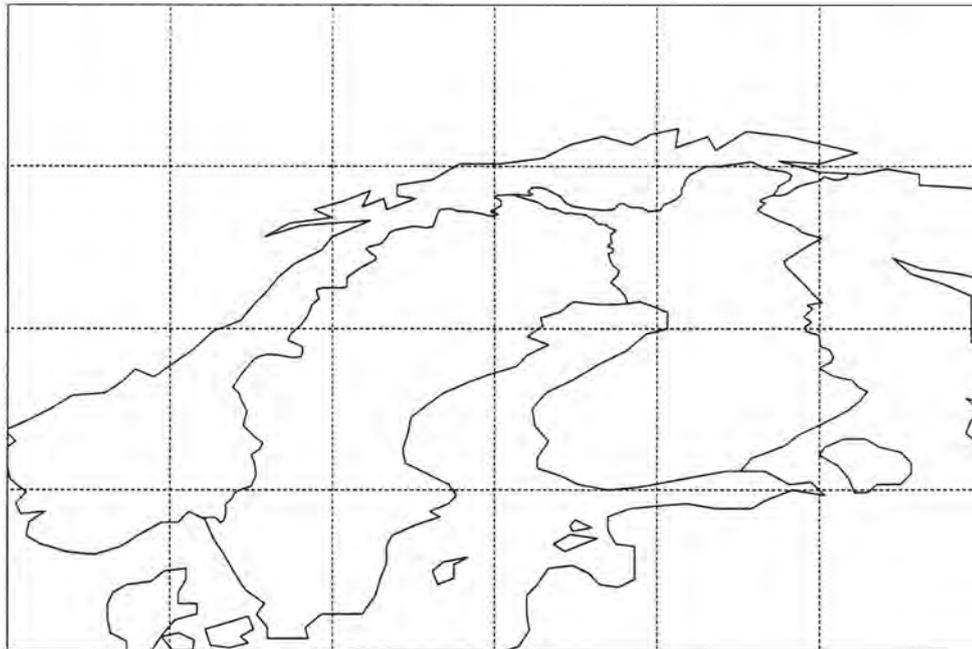
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## 1. Introduction

General Circulation Models (GCM) are the primary tools today to study and estimate the nature of climate change. Based on the physical laws for atmospheric composition and behavior, they attempt to provide a calculable model of the earth's climate system, including internal and external forcing as well as feedback in the climate system. The size of the climate system (atmosphere, oceans, land) and the time range of climate experiments (several decades to thousands of years) places a heavy constraint on the design of the GCMs. This leads to spatial and temporal coarseness. The usefulness of GCM results in impact analyses is limited by the large-scale nature of the computations. Current GCMs operate on horizontal grid resolutions ranging from 200 to 1000 km. Operation on such a large spatial scales prevents the explicit modeling of such climate-modifying local geographic factors as topography and land/water-distribution or vegetation type. Instead, they are included as highly-averaged features. Another source of uncertainty for the local scale is the need to parameterize sub-grid scale physical phenomena, such as cloudiness and precipitation. Consequently, such parameterized variables represent large-scale averages, not local-scale features, in the GCM output. The coarse resolution does not only mean that the results will not be applicable to the local scale but that there can also be an adverse effect on the large-scale results. All this leads to a situation where "skillful scale" of a GCM is taken to be much larger than the formal grid resolution. In the early 1990's, it was estimated that the skillful scale of a GCM would be 4-8 times as large as the formal grid scale. So, a GCM with the grid length of 500 km ( $250,000 \text{ km}^2$ , which corresponds to about 60 % of the area of Sweden) would have a skillful scale of 2000-4000 km ( $4,000,000 - 16,000,000 \text{ km}^2$ , i.e. an area comparable to the whole of Europe), if the grid was made of squares. The coarseness of GCMs is illustrated in Figure 1, where the coverage of a 500 km grid and a 100 km grid is shown over the Scandinavian region. The former grid size is typical of GCMs in the early 1990's whereas the latter, which is still too coarse for many applications, is not attainable by global GCMs at present.

The principal way to "validate" a GCM involves performing a simulation of the present-day climate and comparing the results with observed data. From such experiments, it seems that GCMs can simulate the free tropospheric circulation and temperatures quite well. Other climate elements, such as fronts, precipitation and cloudiness are less well modeled. All GCMs lack in describing regional and local surface variables. The ability to simulate the free troposphere climate, but not the surface climate, is understandable as the free troposphere is more spatially and temporally homogeneous than the earth's surface. Another limitation to the applicability of GCM data is that due to the global domain and long time horizons of the calculations, much more data are generated than what can be stored. This means that only a selection of climate variables are archived in the experiments and even then only at a limited temporal resolution (e.g. daily or maybe monthly resolution).



**Figure 1.** The area of Norway, Sweden and Finland with an overlay of regularly-spaced grid. **Top:**  $5^\circ \times 5^\circ$  grid, which is of the order of a typical GCM. **Bottom:**  $1^\circ \times 1^\circ$  grid, which is more than GCMs can be practically run with, but which is still too coarse to address the need of resolution in many applications. In addition, as discussed in the text, the skillful scale of a GCM can be as coarse as 4-8 times the grid size.

Due to these limitations on the model system and the detail that can be practically archived from model experiments, GCM results provide relatively little information on climate change for impact studies on the regional and the local scale. As this information is needed, a number of techniques have been suggested to infer the likely local (small-scale) characteristics which would accompany the changes which are seen in the large-scale GCM simulations. The "large scale " is defined as anything from the grid-scale of a GCM to its skillful scale (to be defined from comparisons to observed climate) or even to the global scale. One way to bring order to downscaling approaches is to separate between five types: "Conventional methods", "Statistical downscaling", "Stochastic methods", "Dynamical downscaling" and the so-called "Composite methods". These types are presented in Section 2. The goal of downscaling, in the climate change context, is to provide local-scale climate data. The same goal is also addressed by purely empirical methods, which work by locating and employing analogues from the past. These are not considered in this literature survey. The Conventional and the Composite methods superimpose GCM-derived changes on observed local time series. In Statistical downscaling, large-scale surface or free tropospheric variables are used as the predictors. The predictands are then the desired surface or near-surface climate variables. To develop and calibrate Statistical downscaling requires a source of local-scale time series. Whereas Conventional and Composite methods, as well as Statistical downscaling in practice work on spatial downscaling, Stochastic methods include weather generators as well as some other approaches. They aim at high temporal resolution and most often focus on hydrological application. Dynamical downscaling involves running either a high-resolution limited area model with GCM data as boundary conditions, or performing so-called "time-slice" experiments. In the latter, a high-resolution AGCM (atmosphere GCM) run is performed, using the results of a coarser-resolution GCM as the initial and lateral boundary conditions. The AGCM is then integrated for a relative short period. General remarks on the applicability of these techniques are given in Section 3, which is followed by a discussion in Section 4. The works of Giorgi and Mearns (1991), Carter et al. (1993) and IPCC (1996, p. 336-345) are recommended to a reader who is interested in downscaling.

## 2. Methods

### 2.1 Conventional methods

Conventional methods consist of a straight-forward scaling of present-day or climatological local time series with GCM data. The GCM data which are typically used are differences from two GCM runs (e.g. the difference of the monthly-averaged 2 x CO<sub>2</sub> run conditions and the present day run conditions). The use of the differences aims to overcome off-sets between the GCM performance and true observed behavior.

The simplest of the conventional methods is to apply the results from a given GCM grid box uniformly at all of the target locations contained in the GCM grid box. For variables like temperature, the GCM-given changes in climate would be added to observed time series. In the case of a parameter like precipitation, the change would be applied as a percentage change. Due to the coarseness of the GCMs, this can result in unnatural spatial discontinuities as well as failings to take into account the climate-modifying role of local geographical characteristics. Conventional methods can also involve interpolation from more than one GCM grid box which are closest to the target locations. Given the coarseness of GCMs, the information might not be relevant as it would be imported from quite far. In addition, interpolation would smooth the data considerably.

The conventional uses of GCM data, though easy and cheap to apply, work mostly through average changes. They cannot be used to take into account higher-order changes, i.e. changes in variances, extreme events, autocorrelation or non-linear climate change feedback on sub-grid scale cannot be addressed. What is more, the fundamental problem of poor GCM performance even on their own grid-scale, is not ameliorated by the conventional downscaling methods.

### 2.2 Statistical downscaling

#### *On the statistical downscaling approach(es)*

In statistical downscaling, observed, long-term time series are used to construct statistical relationships between local values and large-scale averages of surface variables or free troposphere variables. The relationships are intended to represent the effects of the climate-modifying local factors, such as variable topography etc. This means that the analysis must be performed individually for every desired local site. It appears that the analysis must be done also seasonally or even with a higher temporal resolution. The statistics involved can be simple or extensive, but the final relationships are typically arrived at with some form of regression analysis.

In order to be able to construct the statistical relationships, homogeneous time series of data are required from individual sites. The sites should cover an area comparable to the GCM grid box size. As the relationships will depend on the location, the sites which statistical downscaling is to be applied for have to contribute to the data. Data are probably required from a larger number of local sites than the intended target locations. This is necessary when the relationships are developed or verified by constructing large-scale averages from the local-scale data. Compared to using

independent sets of model and observed data, this assures a correspondence between the local and the large-scale data. The amount of variability within the time series should preferably coincide with or exceed the changes in the GCM simulation which will be the object of downscaling. Otherwise the derived relationships might not be considered valid. In addition, the length of the time series should be such, that verification of the relationships is possible. If there is enough data, only part of the data might be used to deduce the relationships. The rest of the data is used for verification. Care should be taken, though, to avoid dividing the data into periods with clearly different climatic regimes.

When the relationships are developed between large-scale and local-scale data within the same area, the area is typically comparable to a GCM grid size. The relationships can also be developed between data from a larger area, not necessarily coinciding with the source of the local data (which also defines the area of application).

One way to classify statistical downscaling methods is to separate between:

- Downscaling with surface variables is self-explanatory. It involves the establishment of empirical statistical relationships between large-scale averages of surface variables and local-scale surface variables (e.g. Kim et al., 1984; Wilks, 1989; part of Wigley et al., 1990). To develop the relationships, large-scale averages which are constructed from local time series are used. In the application, the same local-scale surface variables will be the predictands. The predictors for each predictand can be the corresponding large-scale average or a combination of large-scale averages.
- Perfect prog(nosis) (PP) is a familiar concept from numerical weather prediction. It involves the development of statistical relationships between large-scale free tropospheric variables and local surface variables. In PP, both the free atmospheric data and the surface data are from observations.
- Model output statistics (MOS) is similar to PP, except that the free atmospheric variables which are used to develop the statistical relationships are taken from model output.

Downscaling with surface variables is probably not the best approach, as GCMs are not capable of simulating surface climate very well. PP and MOS rely on the free atmospheric data and these are better captured by GCMs. PP and MOS are also familiar concepts from numerical weather prediction (see e.g. Klein, 1982) and especially the latter is still in use. In the case of MOS, the applicability of the technique is related to the performance of the model providing the free atmospheric data. MOS-based statistical relationships might have to be redone when the model for large-scale data is changed. PP-based statistical relationships are independent of the model performance, but, of course, depend on the quality and extent of the observed data. Combinations of these two types exist as well. Wigley et al. (1990) used both surface variables and free atmosphere variables for the large-scale fields. Karl et al. (1990) generalized PP and MOS into a method they called "Climatological projection by model statistics" (CPMS). Depending on the choice of means and variances (either from observations or from the model) to be used to standardize the predictors, their CPMS resembles either PP or MOS.

### *Using grid-scale predictors*

A number of predictors (large-scale variables) and predictands have been suggested. The choices adopted in some studies are listed in Table 1, together with the area for which the study was made and a listing of the techniques which were applied.

Kim et al. (1984) used surface fields of temperature and precipitation only. Their work is often mentioned as the first step on employing statistical downscaling in climate change applications. Wigley et al. (1990), however, point out that what Kim et al. actually came up with was the use of the present-day seasonal cycles as an analog and that such a short time might be too short to allow projecting to climate change and they suggest the use of observed interannual variations in calibrating the relationships. Wilks (1989) used daily maximum temperatures, daily minimum temperatures and daily precipitation. Wigley et al. (1990) related local temperature and precipitation to their large-scale averages. They employed also mean sea level pressure (MSLP) and the 700 hPa height, including zonal and meridional gradients, as predictors. Karl et al. (1990) started from 22 free atmosphere predictors, involving both daily means and backward and forward changes for temperature-related variables, relative humidity, atmospheric stability and wind components. Their predictands were the daily maximum temperature, minimum temperature, precipitation and cloud ceiling category. In Jónsson et al. (1994) and Jóhannesson et al. (1995), statistical downscaling results from Kaas (1993b; 1994) are reported for the Nordic region. Their predictors were constructed from the anomalies of from the long-term mean of the 500 hPa height, the average of the 500 and 1000 hPa heights and the 500-1000 hPa thickness. All data were considered as monthly means and they were further combined into three-month seasons. The spatial patterns of these flow and temperature indicators were actually decomposed from GCM fields (control and climate change experiments). To train the downscaling, NMC data (gridded 500 hPa heights and the 1000-500 hPa thicknesses) were projected on these patterns and related to observed station data to obtain the regression relationship between the large-scale and the local-scale variables. The predictands were monthly mean temperature, monthly mean temperature range and monthly mean precipitation. Schubert and Henderson (1997) took relatively high resolution data on MSLP, and coarsened them to a typical GCM resolution. These were then related to daily temperature extremes in Australia.

**Table 1.** Predictors, predictands and techniques in a number of statistical downscaling studies. PCA implies the use of EOFs as well.

Study	Target study area	Large-scale predictors	Local predictands	Techniques
Kim et al., 1984	Oregon, USA	Mean large scale temperature and precipitation	Monthly surface temperature and precipitation	PCA, linear regression
Wilks, 1989	Three regions in the US, essentially parts of Kansas, Iowa and the Dakotas.	Daily maximum and minimum temperature, daily precipitation, square root of the daily precipitation	Maximum and minimum temperature and daily precipitation.	Data standardization, varimax rotated PCA, least squares regression for each month (and stochastic weather generation)
Karl et al., 1990	Five locations in the US: Fairbanks, AL, Spokane, WA, Bismarck, ND, Topeka, KA, Charleston, SC	24-h mean 850-500 hPa thickness, MSLP, 500 hPa height, 850 and 500 hPa RH, K-index and the 24-h backward and forward changes of the above, 24-h mean wind components at 850 and 500 hPa	Maximum temperature, minimum temperature, precipitation, cloud ceiling category	CPMS: PCA, CCA and inflated regression analysis
Wigley et al., 1990	Oregon, US	Surface temperature and precipitation, MSLP, 700 hPa height, zonal and merid. gradients of MSLP and 700 hPa height	Monthly surface temperature and precipitation	Multiple regression for each month, with and without screening with simple regression
Zorita et al., 1992	Iberian peninsula	Observed North Atlantic gridded SLP and SST	Winter season (DJF) precipitation	PCA, CCA
von Storch et al., 1993	Iberian peninsula	Observed and GCM North Atlantic gridded MSLP	Winter season (DJF) precipitation	CCA, simple regression
Noguer, 1994	Iberian peninsula	GCM North Atlantic gridded MSLP	Monthly mean winter precipitation (Also other seasons, but without validation.)	PCA, CCA, simple regression
Matyasovszky et al., 1994	Nebraska, USA	Daily atmospheric circulation pattern (CP) types from 500 hPa geopotential	Daily surface temperature	Relating observed surface temperatures to the CPs with an autoregressive process
Kaas, 1993b; Jónsson et al., 1994; Jóhannesson et al., 1995	Ten Nordic sites	500 hPa height, the average of the 500 and 1000 hPa heights and 500-1000 hPa thickness	Monthly means of surface temperature, its daily range and precipitation	PCA, multiple linear regression and inflated regression
Hewitson, 1994	Continental US	gridded surface pressure + 3-day backhistory	Daily surface temperature	PCA, polynomial regression (incl. squares and cross products), stepwise multiple regression
Zorita et al., 1995	The Columbia river basin and the mid-Atlantic region in the US	gridded SLP	Daily precipitation	PCA and: 1) weather type analysis with CART, 2) analog-based rainfall generator
Cubash et al., 1996	Iberian peninsula	North Atlantic MSLP and 700 hPa temperatures	Daily precipitation	PCA, analog-based rainfall generator
Schubert and Henderson-Sellers, 1997	Australia	Gridded MSLP at GCM resolution	Daily T extremes	PCA, varimax rotation, regression

### *PCA, EOFs and CCA – techniques to manipulate the set of predictors*

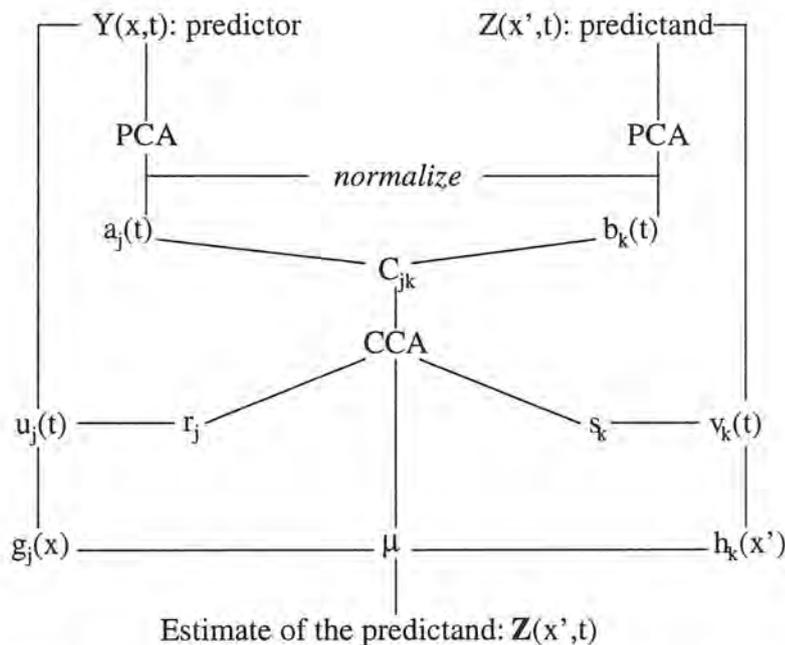
In general, if only few predictors (1-3) are chosen, the problem of relating them to the predictands can be handled with conventional regression analysis (e.g. Wigley et al., 1990). However, as it cannot be *a priori* known which combination and how many predictors are required for an acceptable relationship, extensive tests will have to be made to optimize the method. If, on the other hand, one starts with several predictors, there are ways to simplify the system in an ordered manner. Stepwise regression can be applied to remove redundant predictors or predictors which prove not to contain significant information on the surface variables (also applied by Wigley et al., 1990). Alternatively, principal component analysis (PCA) is often used in the literature to reorganize the system and to concentrate the observed variance of the desired predictor into only a few empirical orthogonal functions or EOFs, for short. Accordingly, depending on the authors, PCA can also be called EOF analysis or something similar. PCA works through matrix manipulation of the covariance or the correlation matrix of the input data, and, formally, amounts to calculating the eigenvectors and eigenvalues of the input matrix. Covariance matrices are suited when there are no large differences between the spatial variance of the variables. If there are large differences, then correlation matrices are recommended. PCA organizes the data into a form with "better" statistical properties. To be more exact, PCA performs a decomposition of the input correlation/covariance matrix into a sum of products of the time-dependent, but temporally uncorrelated scores, and location (but not time) -dependent loadings which are the Empirical Orthogonal Functions (EOFs). Equation (A.1) from Noguer (1994) is shown here to illustrate the components of PCA:

$$Y(x, t) = \sum_{j=1}^J a_j(t) e_j(x),$$

where  $Y$  is the input matrix,  $a_j$  are the scores,  $e_j$  are the loadings (EOFs),  $x$  is the location,  $t$  is time and  $j$  is the mode. The EOFs incorporate the spatial variance of the input data. Their eigenvalues give the part of the variance which is explained by each EOF. When this is found out, only those modes, which describe most of the variance can be retained, whereas the rest are assigned to noise. To help in making the separation, some works refer to a technique known as the "N rule" (e.g. Overlander and Priesendorfer, 1982) of which Karl et al. (1984) describe even a modified version. Hewitson (1994) mentions, in addition, an "effective multiplet" test (North et al., 1982). The last step in writing out the downscaling relationships is always a form of regression analysis, which links the scores (time-dependency) of the leading EOFs to linear combinations of the large-scale predictor fields, the EOFs defining the spatial patterns. Sometimes rotation techniques are applied after PCA and before the regression. Rotation is said to prevent the numerical creation of characteristic patterns, which would be masking the real information.

In order to work the system even further, canonical correlation analysis (CCA) can be used to relate the set of the retained predictors to the set of desired predictands (Karl et al., 1990; Zorita et al., 1992; Noguer, 1994). CCA is a technique to find the optimally time-correlated combination of the spatially-distributed predictors and

predictands. This optimal correlation is established between linear combinations of both groups, rather than single variables. Mathematically, CCA is a coupled eigenvalues problem of the cross-covariance and autocovariance matrices of the predictor and predictand sets. One reason to do this is to assure consistency between the predictands. Canonical correlation must then be followed by some form of regression analysis. For example, Karl et al. performed inflated multiple regression to relate the predictors (now in the form of canonical variable scores) to the predictands. Wigley et al. (1990), who kept their downscaling method simple all the way, examined the significance of the predictands by performing the analysis with two regression methods: 1) including all of the predictors and 2) prescreening the predictors, based on their individual correlation coefficients with the predictands. The flow chart of Noguer (1994) is shown in Figure 2 to illustrate the steps in applying PCA and CCA in constructing a statistical downscaling method.



**Figure 2.** An illustration on how to construct a statistical downscaling technique using PCA and CCA, after Noguer (1994). The  $a_j$  and  $b_k$  are the principal components of the predictor field  $Y$  and the predictand field  $Z$ .  $C_{jk}$  is the cross-covariance matrix. The  $r_j$  and  $s_k$  are the eigenvectors of  $C_{jk}$ . The canonical component vectors are in  $g_j$  and  $h_k$  and the estimate of the predictand is in the canonical pattern  $Z$ .

### *Mean sea level pressure and weather types as predictors*

When the predictors are grid-box averages or the spatial and/or temporal gradients of the large-scale variables from one GCM grid box only, there is little information on the type of air mass advection which affects the target region. The large-scale gridded distribution of a variable, telling about the atmospheric circulation state, has also been used as a predictor. For example, Zorita et al. (1992), von Storch et al. (1993), Noguer

(1994) and Cubash et al. (1996) have linked the gridded North Atlantic area MSLP (the significance of SST was found out to be indirect only by Zorita et al., 1992) to the seasonal precipitation on the Iberian Peninsula. The MSLP field tells about the tropospheric circulation, so the idea boils down to using a form of weather types. A similar idea is used by Hewitson (1994) and Zorita et al. (1995). A form of weather typing is also used by Matyasovszky et al. (1994), though under the name of atmospheric circulation types (CP). Zorita et al. (1995) started with a PCA on the gridded MSLP fields. They went on to try out two different methods to derive daily local precipitation statistics: 1) Classification and Regression Trees analysis (CART) and 2) an analog-based precipitation generator, both operating on the leading EOFs of the MSLP fields. CART was used for an objective classification of atmospheric circulation into weather types affecting the target region. These weather types were then identified from observed MSLP data and the corresponding daily precipitation data were binned to the weather type. The results were applied to GCM data, from which the weather type was first identified to allow for sampling the local precipitation from the earlier constructed bins. The authors note, by the way, that the method is applicable also for sites which did not contribute to the development of the relationships. In the second, analog-based method, the daily local precipitation was specified as the best match between a five-day sequence of the five leading large-scale MSLP EOFs and the observed five-day sequences of the same parameter. After finding the best match, the corresponding observed precipitation data was assigned to the predictand. Cubash et al. (1996) mention shortly a variant of the second method of Zorita et al. (1995): characterization of the large-scale state from the five leading EOFs of MSLP and 700 hPa temperature field on three consecutive days. Their large-scale atmospheric predictor is therefore a 30-dimensional vector, which must be matched to the corresponding best observed quantity to find out the daily precipitation data from the observations which can be assigned to the predictand.

In addition to backhistory of the weather types, Hewitson (1994) included also their interactions. He employed seven leading EOFs (determined with PCA) of the gridded MSLP over the continental US to specify the type of the daily circulation. A "polynomial" regression was then developed to regress the target surface temperature to a sequence of MSLP EOFs of the day in question and of the two previous days. Such a three-day sequence was found to work better than a two-day one or a four-day one. The term of "polynomial" arises from the fact that in addition to each of the retained seven EOFs, also their squares and cross products were included. A regression equation for each location therefore had 252 variables to begin with. Stepwise multiple regression was thereafter applied for each site, which reduced the number of factors in the regression equations to 7-26. These relationships could then be applied to observed and GCM data.

#### *Data transformations and limitations for statistical downscaling*

The predictors and the predictands in statistical downscaling are often used in the form of transient anomalies. This is in agreement with the fact that more confidence is put on the ability of GCMs to describe climate change than the ability of GCMs to model the

state of the climate at any particular time. I.e., even though a GCM might not reproduce the details or the absolute values of the present-day climate, the same GCM might address well the response of the climate to forcing from a changed CO<sub>2</sub> concentration. In a downscaling application, the GCM-calculated large-scale changes will then replace the large-scale anomalies which were used to develop the downscaling relationship(s). The GCM data are therefore superimposed on observed time-mean local climate behavior.

Data weighting/standardization/transformation is employed by some authors. When large-scale averages are constructed from local data, to develop and/or to test the downscaling, it is common to use station weights to account for the uneven spatial distribution of the sites. Data standardization and possibly deseasonalization and detrending aims to reduce possible internal bias(es) and trends in the data sets and to remove modes of variance which are caused by seasonal cycles. For example, Kim et al. (1984) scaled their transient local deviations with the resp. standard deviations. Wilks (1989) subtracted a time-dependent mean (calculated differently for temperature and for precipitation) and divided the result with the monthly standard deviations. Karl et al. (1990) mention that their CPMS can be used alternatively with observed and with model-produced means and variances to standardize the data. Hewitson (1994) used multi-day filters for the MSLP and temperature fields in training his downscaling.

The downscaling for the daily precipitation is quite more demanding than downscaling for temperature. The reason for this is, of course, the discontinuity which is characteristic of precipitation. To address it from GCM data, downscaling with analogs to observed records, as discussed earlier, or stochastic weather generators (see 2.3) can be used.

Statistical downscaling might not be applicable to all of the desired sites. If there is no or not enough observed local data, downscaling cannot be done. In such a case, use of a nested LAM (see 2.4) might have to be used, though the problem of verification of the results would still remain. If there are sites or seasons at a particular site when the local climate is not related to the conditions in the free troposphere, statistical downscaling will not be applicable either. Such problem cases will be identified when the derived regression method is tested with independent data.

#### *Kaas (1993b) – example of application*

The work by Kaas (1993b) has already been mentioned. Some of his results are presented here as an example of applying statistical downscaling of GCM data for the Nordic region. Two of the considered sites were Swedish ones; Stockholm and Östersund.

Kaas took 27 years of SYNOP data (means of temperature, daily temperature range and precipitation) from ten Nordic sites, 27 years of NMC analyses over the North Atlantic and northern Europe (500 hPa heights and 500-1000 hPa thicknesses) and results for two 30-year periods from MPI ECHAM-1 GCM control and transient experiments (500 hPa heights and 500-1000 hPa thicknesses). All data were retrieved as monthly means. Kaas applied PCA, multiple linear regression and inflated regression on these data. The annual cycle was not removed in this work (this was done in Kaas, 1994). Kaas extracted EOFs from the two sets of GCM data to make sure that they

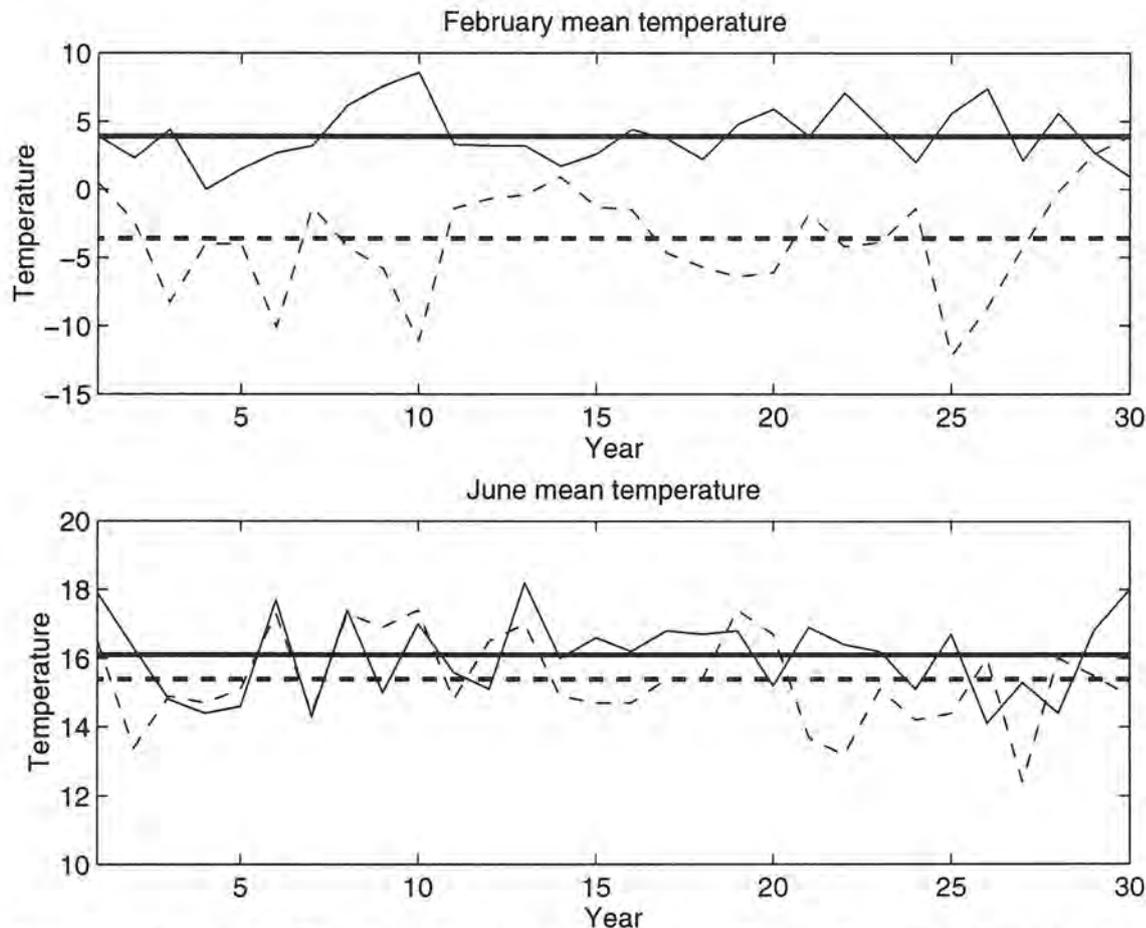
would reflect the variability as seen by the GCM. In order to train the regression, NMC 500 hPa height and 500-1000 hPa thickness data were then projected on these EOFs. This provided the time-dependency of the large-scale fields which could then be regressed with the local-scale SYNOP time series. EOFs were also extracted from the observed fields and it was shown that the number (but not the order of importance) of the leading EOFs, needed to explain the large-scale variability, was the same, regardless of the source of the data. Some additional manipulations were needed to keep the system orthogonal and to make sure that the correct variance was still represented in the regression.

Kaas checked the performance of this downscaling by examining how well it could reproduce observed conditions. In the case of the seasonal mean temperature, the correlation between the actual observations and the construction from NMC analyses using the developed regression was over 0.9 in winter and between 0.81 and 0.94 in summer. Quantile-quantile plots (observed data vs. downscaled data) were employed to check if there were features which could not be captured by the inherently linear method. An additional check on the performance of the method was done by dividing the observed period into two parts, defining the parameters of the downscaling method with the first part only and by running the downscaling with these parameters against the second part of the data. This was shown for the winter season only. The correlations between the downscaled and the observed data were somewhat reduced (to 0.76-0.93), assumedly due to having less input to the training of the regression and/or due to natural variability being present in a different manner during the two periods. In the case of mean precipitation, the correlations were less than in the case of the mean temperature. For the winter season, correlation coefficients in the range of 0.71-0.89 were retrieved, whereas for the summer season, the range was 0.53-0.82. In the case of the mean daily temperature range, the results were much more diffuse. Depending on the location, the correlation reached to 0.86 (Stockholm in the winter) or plunged to 0.14 (Thorshavn in the summer).

After assessing the performance of the downscaling, Kaas went on to apply it to the transient GCM results (see Cubash et al., 1992). Compared to direct model output (changes diagnosed from GCM grid boxes are assigned as such to the target locations within the GCM grid box in question) from the GCM (Kaas, 1993a), the large-scale pattern of change was found to be quite the same in the case of the temperature. On smaller spatial scales, some differences were seen. In the case of precipitation, differences between the direct model output and the downscaled results were more obvious. Quantitative results are not given.

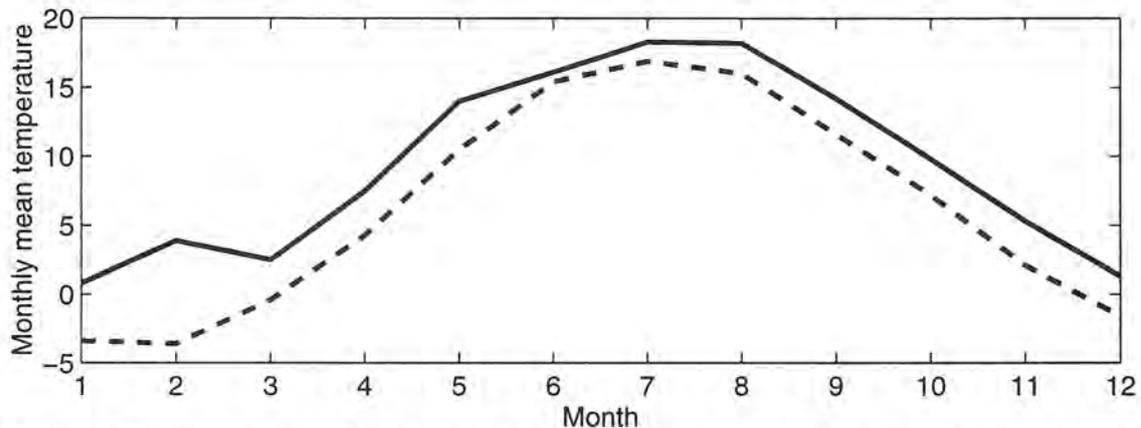
The time series of the downscaled 30 years of GCM temperatures (Kaas, 1993, p. 41) are shown in Figure 3 for Stockholm for February and June. The observed February and June monthly means for 1961-90 are also shown. In the case of Stockholm, these two months showed the maximum and the minimum temperature response between the transient ECHAM-1 experiment and the corresponding control experiment. The regression relationship for the monthly mean temperatures included 13 EOFs for the winter season and 8 EOFs for the summer season in the case of Stockholm. Note that in Kaas (1993), the downscaled transient data are probably compared to data which are termed "observed average for 1961-90" (see also Kaas, 1993; p. 23). These data do not, at least in the case of Stockholm and Östersund, match the reported reference normals

(Alexandersson et al., 1991). So, the data used by Kaas (1993) are probably from the ECHAM-1 control experiment. Alternatively, unchecked statistics, collected daily during 1961-90 might have been used.



**Figure 3.** Upper panel: The downscaling results of Kaas (1993) on 30 years of January mean temperatures from the ECHAM-1 transient experiment for Stockholm (solid line) and the observed 1961-90 data for Stockholm-Bromma (dashed line). The averages over these data are shown as the heavy lines. Lower panel: As above, but for the June mean temperatures.

For most of the considered sites the interpretation of the ECHAM-1 seasonal mean temperature changes with this statistical downscaling method has been indicated to agree with the direct model output (Jónsson et al., 1994. p. 17-18), in terms of the long-term monthly means! How much this had to do with the selection of the sites, the performance of the GCM in the control simulation and the magnitude of the predicted climate change signal is not certain. However, it seems that as long as the signal of climate change remains small, a statistical downscaling method does not add a lot to conventional downscaling of GCM data. The fundamental value of downscaling GCM data as in Kaas (1993) is that instead of trying to use the grid box values of surface temperature and precipitation, the gridded (area distribution) of free troposphere flow diagnostics are used as the starting point. As mentioned in the introduction, the latter type of data is simulated better by GCMs than the former type.



**Figure 4.** The average annual cycle of monthly mean temperature at Stockholm for the two 30-year periods. The downscaled ECHAM-1 data (Kaas, 1993, p. 41) are drawn with the solid line. The 1961-90 observed reference normals are drawn with the dashed line.

Looking at heavily time-averaged statistics can also mask the potential usefulness of applying downscaling. As an example, the annual cycle of monthly mean temperature for Stockholm, calculated from 30 years of ECHAM-1 results and 30 years of observations, is shown in Figure 4. Comparing Figures 3-4, it is obvious that the same type of means, over a number of years, can be obtained, even though interannual variability (and variability on shorter time scales as well) is markedly different. To draw on the potential of downscaling, the aims should probably include higher-order statistics of climate than the time-averaged features.

### 2.3 Stochastic methods

Stochastic weather generators, in addition to providing local-scale data, aim to overcome the coarse temporal resolution of GCM data. Weather generators are a means to achieve long series of synthetic daily weather data, which is identical to the observations in a statistical sense. As in statistical downscaling, which often focuses on the spatial scale, the necessary parameters for the method are specified from data. When observed time series have been used to determine the parameters, the output of the weather generator has the realistic statistical characteristics. In climate change applications, the parameters can be adjusted according to the GCM data.

#### *The Richardson weather generator – basic example*

Richardson (1981) gives an example of a weather generator. He used a first-order Markov chain, in which the state of a day as either "wet" or "dry", is determined from the wet/dry-state of the previous day. Other daily weather parameters (maximum and minimum temperature and solar radiation) were then set, according to the wet/dry-state of the day. Basically, he used observed local data to determine the probability that a wet day would follow a dry day ( $P_i(W/D)$ ) and the probability that a wet day would follow a

wet day ( $P_i(W/W)$ ). These two probabilities fixed also the other two alternatives in the Markov chain:

$$P_i(D/W) = 1 - P_i(W/W) \quad (\text{Richardson, 1981; Eq. 1})$$

$$P_i(D/D) = 1 - P_i(W/D) \quad (\text{Richardson, 1981; Eq. 2})$$

To estimate the amount of precipitation on a wet day, Richardson (1981) used an exponential distribution, and fixed the distribution parameter from observations. Other distributions could have been used for the precipitation amount, the structure of the weather generator does not depend on this choice.

The other generated weather variables, in this case the daily maximum and minimum temperature and solar radiation, were conditioned on the wet/dry status of the day. The observed local data were reduced into time series of residuals (i.e. by removing the local mean and dividing by the local standard deviation, both of which are time-dependent and have their annual cycles removed), separately for the wet days and for the dry days. The residuals were then analyzed for time dependence and for interdependence. The generation model for the daily series is then defined as:

$$\chi_t = A\chi_{t-1} + B\varepsilon_t \quad (\text{after Richardson, 1981; Eq. 5})$$

Where  $\chi$  is a matrix for the residuals for the day,  $t$  means present day,  $t-1$  the previous day, the  $A$  and  $B$  are matrices which are tuned so that the observed time dependence and interdependence of the residuals are maintained.  $\varepsilon$  is a matrix of independent random forcing elements. To calculate  $A$  and  $B$ , nine cross-correlation (lag 0 and lag 1) and three serial correlation (lag 1) coefficients are needed for each time and location. Including the dry/wet transition probabilities and the precipitation amount distribution parameter, the total number of local parameters for each day is 15 in this weather generator. In Richardson (1981), an examination of the local series justified keeping some of them as constants. The final step in generating the weather data, after the wet/dry -state is decided on, is to apply the appropriate means and standard deviations to return the generated residuals into the daily temperature and solar radiation data. Note that the residuals should be approximately normally distributed.

#### *Tuning of a weather generator with GCM data*

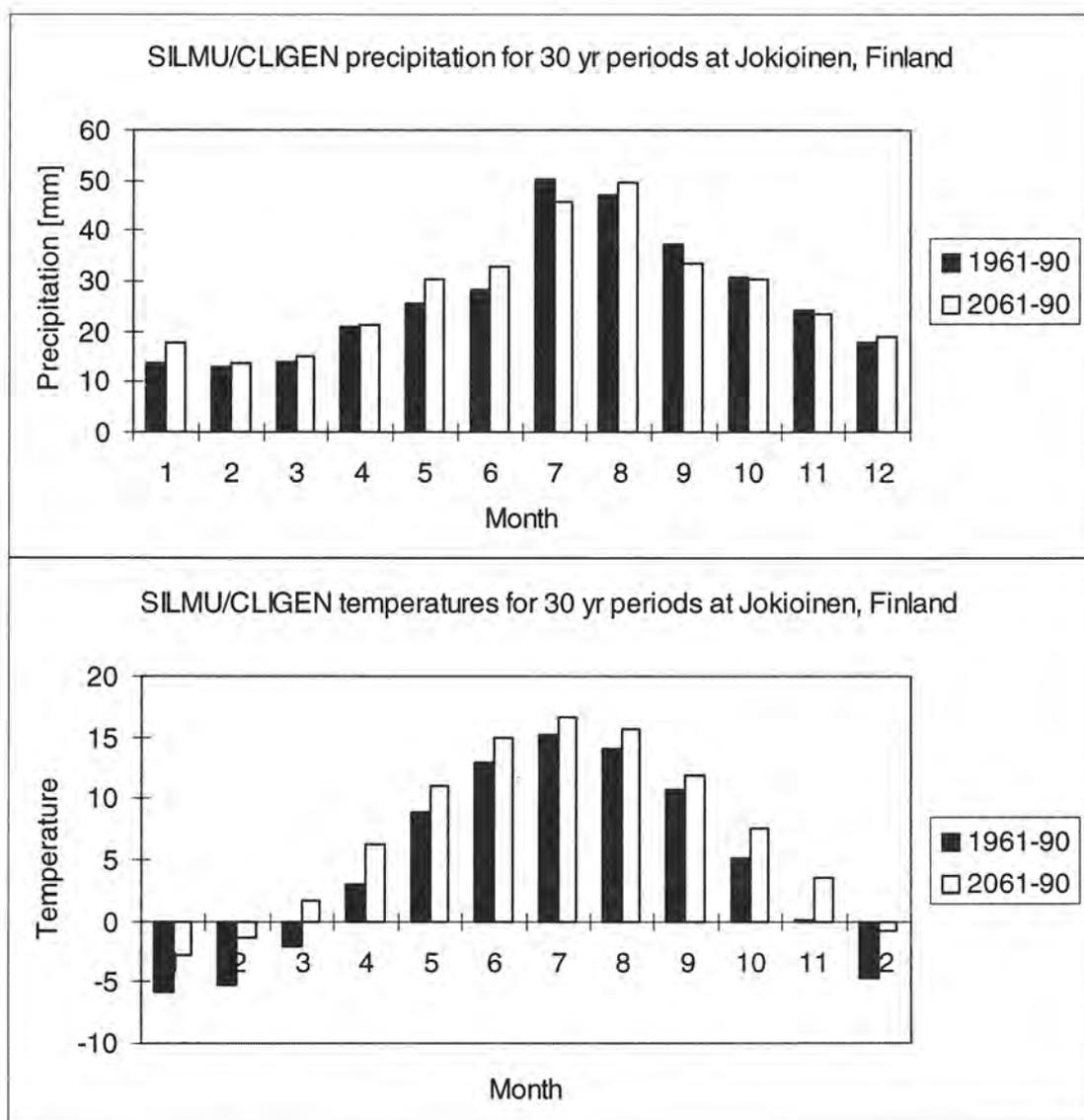
Wilks (1992) used a slightly-modified Richardson's weather generator and introduced a way to apply it also with GCM data on large-scale climate change. In short, he used the changes in the monthly statistics (means and variances) to modify the parameters in the weather generator. Changes were made in both the precipitation part and in the temperature/solar radiation part of the weather generator. As a gamma distribution was used to model the daily precipitation amount (thus requiring two distribution parameters), he had four parameters for the precipitation part. Two of these had to be constrained, as only one could be constructed from the monthly statistics changes. Wilks chose to assume that the wet-dry transition probabilities would remain unchanged.

Another example of applying a weather generator to GCM data is discussed by Semenov and Barrow (1997). They used decadal time-slice data from climate change integrations with the UKMO GCM to perturb the parameters of their weather generator (LARS-WG). Initially, the parameters were defined from 30-year periods of observed station data. The perturbations were defined from undownscaled GCM data on precipitation intensity, duration of wet and dry day series and means and standard deviations of temperature on wet/dry days. The LARS-WG is available via [www/ftp](http://www/ftp).

#### *Practical application of a weather generator*

In the Finnish SILMU-program, a weather generator (CLIGEN) similar to the Richardson's and Wilks' was developed (Posch, 1992; Posch, 1994; Carter et al., 1995; Carter et al., 1996). The occurrence of precipitation was modeled as in Richardson (1981) and the precipitation amount was modeled with a gamma distribution as in Wilks (1992). The precipitation-related parameters were calculated from observations at 564 sites in Finland during the years of 1961-90, but the weather generator was built with an interpolation routine so that time series could be created for other locations as well. Parameters for the creation of other daily weather parameters, namely the daily mean temperature and cloudiness, are based on data from a smaller number of locations. The generation of the daily mean temperature and cloudiness is similar to the generation of temperatures and solar radiation by Richardson (1981). In Carter et al. (1995; 1996) the updating of the CLIGEN weather generator, to be used in climate change research, is reported. This involves adjusting CLIGEN parameters with information on large-scale seasonal temperature and precipitation changes.

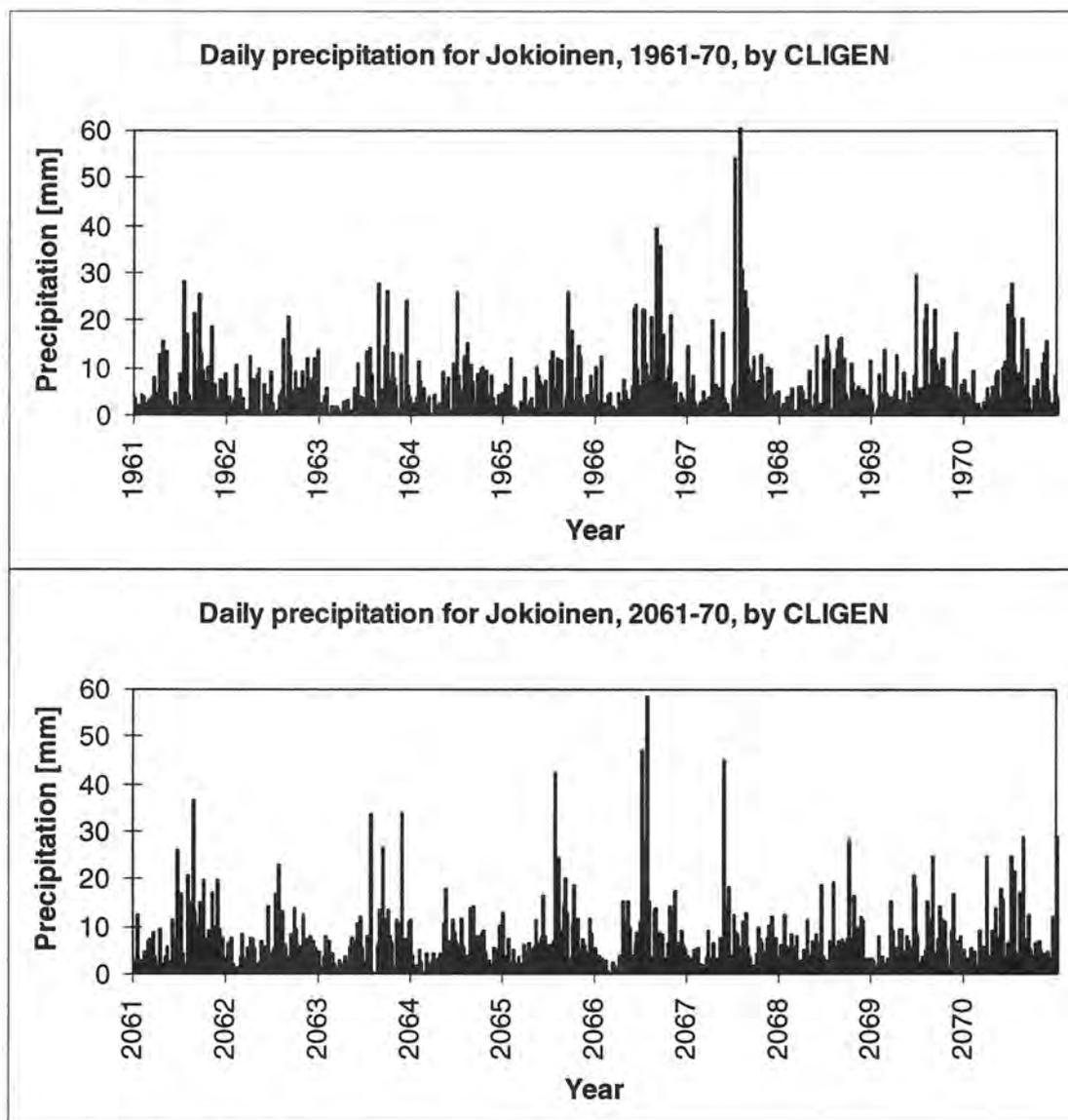
As an example, two 30-yr periods were simulated with CLIGEN for the Jokioinen Observatory in southern Finland. The first period was 1961-90 and the second period was 2061-90. For the latter period, it was assumed that climate was in a new equilibrium state, with seasonal precipitation and temperature changes with respect to the present-day conditions. The monthly mean precipitation and temperature for these two periods are shown in Figure 5. The input to CLIGEN was given as large-scale seasonal precipitation and temperature changes. For this example, these changes were set as Spring:  $\Delta P$ : + 10%,  $\Delta T$ : +3°; Summer:  $\Delta P$ : + 5%,  $\Delta T$ : +1°; Autumn:  $\Delta P$ : -5 %,  $\Delta T$ : +2°; Winter:  $\Delta P$ : +20%,  $\Delta T$ : +4°. The local (as generated by CLIGEN) seasonal mean temperature and precipitation changes differed from the prescribed regional-scale changes. For precipitation, CLIGEN came up with the seasonal changes of +8 %, +2 %, -7 % and +13 % from spring, summer, autumn and winter, respectively. For temperature, the generated local changes were +2.9°, +2°, +2.7° and +3.6° for the same four seasons. The simulated precipitation time series is shown in Figure 6 for the first 10 years in the 30-yr periods, to illustrate how CLIGEN treats daily variability.



**Figure 5.** CLIGEN monthly mean precipitation (top) and temperature (bottom) at Jokioinen, Finland, for two 30-yr periods: 1961-90 and 2061-90.

*Limitations of weather generators and a word on other stochastic methods*

Weather generators which are based on Markov chains seem to lack in describing some extreme events (e.g. heavy precipitation) or long duration extremes (e.g. droughts). Racsko et al. (1991) refer to earlier work where the latter deficiency is identified as a characteristic of the Markov chains. They present another type of a weather generator, which is based on series of sequences of dry and wet periods (having a length of some days). For precipitation amount during a wet period, different distributions were used for "small", "medium" and "large" precipitation. The other generated variables, the temperature and the number of sunshine hours, were modeled as conditioned on the wet/dry periods.



**Figure 6.** CLIGEN-generated daily precipitation time series for Jokioinen, Finland, for 1961-70 (top) and 2061-70 (bottom).

Weather generators are suited to address the needs of hydrological applications, as well as some other impact study areas. There are also other stochastic and non-parametric methods which take as their input large-scale atmospheric parameters (e.g. weather types or atmospheric circulation patterns, temperature and precipitation, MSLP) and produce the probabilities of local occurrence of precipitation and the precipitation amount (e.g. Moo, 1992; Bárdossy and Plate, 1992; Hughes and Guttorp, 1994; Corte-Real et al., 1995). Neural networks are also known to have been applied in downscaling work. As in the case of the weather generators, these other approaches can be extended to other variables than precipitation as well. Observed time series are still needed to fix the necessary parameters in the models.

## **2.4 Dynamical downscaling**

Dynamical downscaling methods have the same goal as the statistical and stochastic methods, i.e. they aim to extract the local-scale from the large-scale GCM data. So, they all produce local-scale information, based on the GCM results. The main difference between the statistical/stochastic and the dynamical downscaling is that whereas the performance of the former is restricted by the link to the observed data, the latter includes a physical representation of the climate system. Dynamical downscaling has been attempted with three approaches, each of which is a sort of a "time-slice" of a long, coarse-resolution GCM experiment:

- running a regional scale limited area model (LAM) with the coarse GCM data as geographical or spectral boundary conditions (also known as "one-way nesting").
- performing global-scale experiments with high-resolution AGCMs, with the coarse GCM data as initial (and partially also boundary) conditions.
- use of a variable-resolution global model (with the highest resolution over the area of interest).

The practical application of dynamical downscaling is limited by the computational demand that the increase in resolution demands. The first two dynamical downscaling approaches mentioned above also share the same caveat as other downscaling methods, namely the sensitivity to the performance of the GCM providing the large-scale data. This is especially true in the case of a one-way nested LAM, which, to quote Jones et al. (1995) "acts purely as a physically based nonlinear interpolator of the existing GCM output". Nevertheless, dynamical downscaling is an attractive alternative as this method 1) is based directly on physical principles and 2) can explicitly provide for the important local control on the climate. As in the case of statistical downscaling, data from different GCMs can be put through dynamical downscaling. Dynamical downscaling operates on some (high resolution) grid-point scale and thus the results will be in the form of spatial averages. These might still require some other form of downscaling (statistical or a repeated nesting) when truly local data are desired.

## **2.5 Composite methods**

Composite methods can offer an easy way to construct a number of scenarios and/or combine the results of several GCMs. The advantage is that uncertainties in the climate response (which is different from a GCM to a GCM) and/or emission scenarios can be accommodated. In Academy of Finland (1993), two examples of composite methods are reported. In the first method, a set of simple models is used to calculate global mean annual temperature and sea level rise from a specified emission and climate sensitivity scenario. The model set includes feedback processes. To arrive at regional scale, grid-scale GCM-given changes in climatic variables (absolute or relative changes, depending on the type of the variable) between a 2 x CO<sub>2</sub> GCM equilibrium data and the corresponding GCM control run data are employed. The differences are scaled with the ratio of the time-dependent global mean change (from the set of simple models) and the equilibrium GCM climate sensitivity. To arrive at the local scale, conventional (see 2.1)

downscaling methods can be employed to provide the climate change perturbation of the present-day or climatological time series.

Information can also be averaged from more than one GCM in the composite methods. The GCM-specific equilibrium climate sensitivities are then used to weigh the contribution of the included models. Provided that the GCM grid box resolutions can be matched, the result is a regional-scale change in the desired climate variables. To arrive at local scale, conventional downscaling methods might be applied as the final step in the approach.

### 3. General remarks on downscaling results

The studies which have been considered in this overview have mostly been performed for different regions. When the same region has been under study (e.g. Oregon by Kim et al., 1984 and Wigley et al., 1990), the training data might not have been the same. The series of papers on North Atlantic MSLP and precipitation on the Iberian Peninsula present a nice chain of development of addressing a specific downscaling problem, which, however, is not directly applicable to the Nordic region. In general, different regions are not similarly suited for downscaling of large-scale information to the local scale, and, so far, only few regions have been studied. Therefore a minute comparison of the various studies is not felt to be informative. General conclusions can be given though.

The most general conclusion is that there is local-scale information attainable from GCM data. The use of statistical downscaling has resulted in a different picture of surface climate than what is obtained from looking at GCM grid scale data only. However, the explanatory power of statistical downscaling varies within the studied region and from season to season. A few generally-applicable results can be mentioned:

- For a particular predictand, an obvious (but not necessarily sufficient) predictor is its large-scale average. There is no standard definition for a set of sufficient predictors for any given predictand.
- MSLP-distribution, free troposphere variables and weather types can be used to include atmospheric circulation handles on the predictands.
- Predictors can be taken from nearby regions (GCM grid boxes) as well, not only from the grid box which covers the target locations.
- The downscaling of precipitation or other data on daily resolution requires special consideration. Weather generators, other stochastic approaches and a modified analog approach have been employed.
- The value of performing statistical downscaling of GCM results (in terms of adding realistic detail in the local climate description) is not evaluated very well in the different approaches.

There are not many studies, in which different approaches are combined in looking at the same data and region. This has been done by Cubash et al. (1996) who used the information from five transient GCMs, forced with CO<sub>2</sub>-increase, to estimate temperature and precipitation changes in southern Europe. At the time of reaching the 2 x CO<sub>2</sub> level, dynamical downscaling was performed with a T106-resolution GCM (so-called "time slice" experiment). They employed also statistical downscaling (the method used by them is briefly discussed in 2.2), but only for a part of their study region, namely the Iberian Peninsula. These dynamical and the statistical downscaling results were compared. The former method gave a rather spatially homogeneous pattern of precipitation changes, whereas the latter method gave spatial structure.

Cubash et al. (1996) are also a part in the set of downscaling analyses which have been performed on the wintertime seasonal precipitation of the Iberian Peninsula

(Zorita et al., 1992; von Storch et al., 1993; Noguer, 1994; Cubash et al., 1996). Zorita et al. (1992) used only observations to relate MSLP to precipitation. Von Storch et al. (1993) applied the approach on particular GCM data, but they could not get the observations-based downscaling relationship established from the GCM data. Noguer (1994) used data from a different, higher-resolution GCM. Interestingly enough, he did reproduce the observed downscaling relationship between North Atlantic MSLP and wintertime monthly precipitation in the Iberian Peninsula. He tried it out also for the other seasons, without being able to compare the results to observations. The relationship held for the spring and the fall, but not for the summer. In the latter case, he concluded that local precipitation was controlled by local factors and not by the flow over North Atlantic.

There are some climate change evaluations which have been conducted for the Nordic region using downscaling methods (Kaas, 1993a, 1993b; Jónsson et al., 1994; Jóhannesson et al., 1995; Carter et al., 1996; Carter, 1996). With respect to SWECLIM, these could be used for comparisons/contrasting results. Of course, it is possible and probably necessary to dig directly into various GCM experiments and extract the results for the Nordic region. Both conventional and statistical techniques can and should be used. The former would represent a sort of benchmark against which the performance of the latter can be evaluated. Results from conventional and statistical downscaling provide a benchmark for dynamical downscaling work.

## **4. Discussion**

### **4.1 Use of Statistical downscaling in SWECLIM**

In SWECLIM, the use of statistical downscaling methods has two proposed applications:

- to downscale directly from a large-scale GCM
- to downscale from the SWECLIM climate LAM

Both applications address directly the end-users' need of local-scale information on climate change. With the first application, the output of more than one GCM can be processed to provide for "error bars" in the SWECLIM regional climate scenario(s). Alternatively, the combined result of the statistical downscaling from a number of GCMs can be thought of as the consensus local-scale estimate of climate change from large-scale models. The first application provides also a comparison to the SWECLIM dynamical downscaling results. Statistical downscaling from large-scale GCMs is, however, only a secondary approach in SWECLIM. This is due to the dependency of the statistical/stochastic methods on the observational record and the exclusion of climate feedback on the local scale. The primary approach is the dynamical downscaling with a regional climate model, relying on physical principles of the local-scale climate system.

The second application, if proven successful, would facilitate the execution of the regional model experiments in SWECLIM. Instead of running the experiments on a very high resolution, e.g. corresponding to a 10 x 10 km or 20 x 20 km grid, the regional climate model could be run on a 50 x 50 km grid, thus reducing the computational load and allowing for longer or more numerous model experiments. In addition, to address the needs of hydrological modeling, statistical downscaling (in space or in time) might have to be applied in any case.

### **4.2. Choosing a Statistical downscaling method**

To devise a statistical downscaling method requires the determination of the following components: the statistical technique(s), the set of predictors, the set of predictands, and a way of the testing the results. It is impossible to derive from literature strict guidelines for these, as each and every study has been developed and tested using data from a particular region. Empirical relationships, in general, should not be used outside their domain of applicability, which in this case translates to the downscaling region. In addition, the end-users' needs and the availability of the observed and model data might not be the same as in the published works. So, the SWECLIM statistical downscaling method needs to be tailored.

The SWECLIM statistical downscaling method can be built from a more or less standard set of tools (PCA, CCA, regression). Provided that there is a basic understanding of what these tools can do and cannot do, they can be applied using statistical software.

When downscaling is to be applied to GCM data, free atmosphere variables (and MSLP) would seem to make proper predictors, rather than surface variables only. This

means that either PP or MOS would be employed. This takes into account the fact that GCMs capture better the free atmosphere variables than surface variables. Observed surface data is required by both techniques. Unless it is desired to attach the downscaling technique to a particular GCM (in which case MOS would be used with data from the present-day simulation of the GCM which will be used as the source of the climate change data), either PP with data from meteorological soundings or with the ECMWF reanalysis data should be used.

The final regression equations which express the statistical relationships will be different for all of the target locations. The equations are probably also time-dependent, the nature of which should be determined (e.g. the need to model the relationships as seasonal, monthly etc. ones).

### *The predictands*

The choice of the predictands is ultimately governed by the need of the end-users, but limited by the availability of local time series. Probably the most likely predictands include such primary climate variables as daily surface temperature (daily mean, daily maximum and daily minimum temperatures or the daily temperature range), storminess (i.e. windspeed), daily total precipitation, snow depth, water content and duration of the snow cover, sea ice, and such derived variables as evapotranspiration, runoff and soil moisture. Predictands such as humidity, cloudiness, radiation parameters, the formation of secondary air pollutants and sea-level rise might also be desired, either as direct results to end-users or as proxies for some desired predictands which cannot be obtained directly.

### *The predictors*

Typically-employed predictors can be divided into temperature-related ones, precipitation-related ones and circulation-related ones. The choice of the predictors is limited by the availability of the large-scale variables. This limitation pops up in two stages: when the method is built up (what kind of observed data are available?) and then when the method is to be applied to some GCM (which large-scale fields are available and on which spatial and temporal resolution?). Of course, the large-scale variables which are picked out for the predictors have to carry information on the local-scale variables. In any case, the fact that GCMs produce a better simulation of the free troposphere behavior than the surface behavior suggests choosing free troposphere variables as the predictors. The fact that GCMs perform best on large scales and on time-averaged basis (e.g. monthly or seasonal means) suggest the use of other than direct output of a GCM for the grid box covering the target location(s). Predictors involving spatial gradients, spatial distributions, temporal tendencies or predictors including time-lagged components carry information from the large-scale state into the local scale which cannot be resolved by basic area/time-averaged predictors from a single GCM grid box. For example, pressure tendency tells more about the weather than an instantaneous reading of pressure. A spatial distribution of MSLP, on the other hand, tells about the recent origin (moisture content, temperature) of an air mass which is arriving to the target region.

The inclusion of weather types or similar data into the set of predictors might make it possible to use statistical downscaling even in the case of some non-linear features of climate change, such as a shift in the storm tracks if comparable variability has occurred in the past. Pure geopotential heights, however, might make tricky predictors, as in a changed climate they will probably reflect both temperature changes and circulation changes.

To reduce the risk of omitting predictors with a large information content, a large number of variables should initially be considered as predictors. The number of the predictors can then be reduced by looking (mathematically or by visual examination) at the individual correlations of the potential predictors and the desired predictands. Alternatively, CCA can be employed without the need of minute examination of the significance of each predictor.

The first step in constructing a statistical downscaling approach for the Nordic region is to draw on the climatological expertise in the region in order to define the availability and quality of observed data. For Sweden, the obvious surface data would consist of the 1961-90 observations of temperature, precipitation, MSLP, which should be of good quality and also readily available from a large number of locations. Depending on the needs of the end-users, other surface variables might have to be looked at. For the free tropospheric variables, the data availability is probably less. For SWECLIM, meteorological soundings could be obtained from Norway, Sweden (Visby, Bromma, Landvetter, Luleå, Östersund and Sundsvall) and Finland (Sodankylä, Jokioinen and Luonetjärvi). These data could then be averaged to represent the large-scale fields, analogous to the GCM data for which the downscaling is meant to address. The question of data availability and quality should be clarified through the respective meteorological institutes. The ECMWF/ERA data is another source of free tropospheric data. However, these are available only from 1980 to the 1990's, which is a short period in this context. The NCEP reanalysis data are another possibility. NCEP aims to go back in time to the 1950's with their reanalysis, so, eventually, they would be well suited as input to constructing a statistical downscaling method.

Such large-scale predictors as MSLP, geopotential heights and layer thicknesses, wind direction and speed, as well as layer/level humidities would be available from meteorological soundings and both ECMWF and NCEP reanalysis. Suitable derived variables to describe the free troposphere, such as vorticity, would be available from NWP analyses only. The practical benefit of using either ECMWF or NCEP analyses would be that the data would already be in a regular grid (thus straight-forward to manipulate). In addition, as the analyses are based on the observations, they would correspond to the observed surface data (and they would actually also include the meteorological soundings). Use of gridded free tropospheric fields should equal to the same potential as the use of weather types.

### *Testing of the downscaling*

Regardless of how a method is chosen and constructed, its testing is important (to talk about verification or validation might be stretching terminology too far...). In order to make it possible, the utilized data series should be long to permit a division into two parts. One part is then used to construct the method, whereas the other is retained for

testing. As climate varies naturally from year to year and decade to decade, the derived statistical method will not explain the test period to the same degree.

Even within the data used to devise the method, the explanatory power of the method will not be 100 %. Actually, an explanatory power of 100 % might be interpreted that the method is too constrained to the development data and thus performs less well in an application. Usually the examination of EOFs defines the amount of variance which is explained already when the technique is constructed. The uncertainty in the derived regression coefficients should also be defined.

Even if a specific downscaling method seems to pass a specific set of tests, it may fail in rigorous application as the relationships which are developed with some particular data do not necessarily work with another set of data (e.g. relationships developed on present-day data vs. GCM data on climate change or relationships developed on observed data vs. model data or relationships developed on data from one GCM vs. data from another GCM).

#### *Inherent assumptions and limitations*

Statistical downscaling of GCM-data on climate change is built on the implicit assumption that the statistical relationships between the large-scale predictors and the local predictands would not be affected by climate change. On relatively short time scales (up to a few decades), this problem should not be too grave, as the anticipated (and GCM-simulated) scale of change is still of the order of the natural interannual and interdecadal variability. Downscaling which is developed using observed data spanning decades would thus address the likely ranges of change. If there is a strong local control of climate arising from geographical features, this is even more true. Strong non-linearity in climate change, on the other hand, could crash any downscaling approach.

#### *Final remarks*

Precipitation and parameters which need to be derived for hydrological applications require very careful consideration in downscaling. Due to the discontinuous nature of precipitation, a downscaling method which works fine on temperature might be inaccurate in the case of precipitation. The use of weather types (possibly with analogs) or other indicators for circulation/advections has been used with some success. However, to apply weather types as a predictor for daily precipitation requires that 1) representative weather types are defined for the region and that 2) daily data has been stored from the GCM which is downscaled. Stochastic methods offer a shortcut from the large-scale to the daily local events. They should probably be employed if GCM data will not be available on a daily basis. The applicability of for example weather generators is limited by the same two factors as the applicability of statistical downscaling methods, i.e. the relationships are built from observed data and the quality of the local-scale results will reflect the quality of the GCM data which is fed into the downscaling. With some weather generators, there seems to be a limitation of the failure to describe extreme/persistent events. Use of weather generators might, however, prove worthwhile in the case that long, daily-scale precipitation time series would be needed by an end-user, for example to perform risk analysis.

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## **Appendix I** Abbreviations

AGCM Atmosphere General Circulation Model  
CART Classification and Regression Trees (analysis)  
CCA Canonical Correlation Analysis  
CPMS Climatological Projection by Model Statistics  
ECMWF European Centre for Medium-range Weather Forecasts  
EOF Empirical Orthogonal Functions  
ERA ECMWF Re-Analysis  
GCM General Circulation Model  
LAM Limited Area Model  
MOS Model Output Statistics  
MSLP Mean Sea Level Pressure  
NCEP National Centers for Environmental Prediction  
PC Principal Components  
PCA Principal Components Analysis  
PP Perfect Prog(nosis)

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