Statistical Downscaling of Precipitation from Large-scale Atmospheric Circulation

Comparison of Methods and Climate Regions

FREDRIK WETTERHALL
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Abstract

A global climate change may have large impacts on water resources on regional and global scales. General circulation models (GCMs) are the most used tools to evaluate climate-change scenarios on a global scale. They are, however, insufficiently describing the effects at the local scale. This thesis evaluates different approaches of statistical downscaling of precipitation from large-scale circulation variables, both concerning the method performance and the optimum choice of predictor variables.

The analogue downscaling method (AM) was found to work well as “benchmark” method in comparison to more complicated methods. AM was implemented using principal component analysis (PCA) and Teweles-Wobus Scores (TWS). Statistical properties of daily and monthly precipitation on a catchment in south-central Sweden, as well as daily precipitation in three catchments in China were acceptably downscaled.

A regression method conditioning a weather generator (SDSM) as well as a fuzzy-rule based circulation-pattern classification method conditioning a stochastical precipitation model (MOFRBC) gave good results when applied on Swedish and Chinese catchments. Statistical downscaling with MOFRBC from GMC (HADAM3P) output improved the statistical properties as well as the intra-annual variation of precipitation.

The studies show that temporal and areal settings of the predictor are important factors concerning the success of precipitation modelling. The MOFRCB and SDSM are generally performing better than the AM, and the best choice of method is depending on the purpose of the study. MOFRBC applied on output from a GCM future scenario indicates that the large-scale circulation will not be significantly affected. Adding humidity flux as predictor indicated an increased intensity both in extreme events and daily amounts in central and northern Sweden.

Keywords: Statistical, Downscaling, Precipitation, Large-scale circulation, PCA, TWS, Weather pattern, Regression, Weather generator

Fredrik Wetterhall, Department of Earth Sciences, Villav. 16, Uppsala University, SE-75236 Uppsala, Sweden

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The author of this thesis was responsible for the data preparation, simulations, analysis and writing in all papers.
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# Abbreviations

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<th>Description</th>
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<tr>
<td>90amount</td>
<td>Precipitation on days exceeding 90&lt;sup&gt;th&lt;/sup&gt; percentile</td>
</tr>
<tr>
<td>90days</td>
<td>Number of days exceeding 90&lt;sup&gt;th&lt;/sup&gt; percentile</td>
</tr>
<tr>
<td>90perc</td>
<td>90&lt;sup&gt;th&lt;/sup&gt;-percentile of rain day amounts in mm/day</td>
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<tr>
<td>AM</td>
<td>Analogue method</td>
</tr>
<tr>
<td>ANN</td>
<td>Artificial neural networks</td>
</tr>
<tr>
<td>CCA</td>
<td>Canonical correlation analysis</td>
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<td>CP</td>
<td>Circulation pattern</td>
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<tr>
<td>EOF</td>
<td>Empirical orthogonal function</td>
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<tr>
<td>GCM</td>
<td>General circulation model</td>
</tr>
<tr>
<td>GPH850</td>
<td>Geopotential height at 850 hPa</td>
</tr>
<tr>
<td>GWT</td>
<td>European Grosswetterlagen</td>
</tr>
<tr>
<td>HADctl</td>
<td>HADAM3P control simulation</td>
</tr>
<tr>
<td>IPCC</td>
<td>Intergovernmental Panel on Climate Change</td>
</tr>
<tr>
<td>max5</td>
<td>Maximum 5-day precipitation in mm</td>
</tr>
<tr>
<td>maxdry</td>
<td>Maximum dry spell in days</td>
</tr>
<tr>
<td>MOFRBC</td>
<td>Multi-objective fuzzy rule based classification</td>
</tr>
<tr>
<td>LWT</td>
<td>Lamb’s weather types</td>
</tr>
<tr>
<td>MF</td>
<td>Moisture flux</td>
</tr>
<tr>
<td>MSLP</td>
<td>Mean sea-level pressure</td>
</tr>
<tr>
<td>NCAR</td>
<td>NCEP/NCAR reanalysis</td>
</tr>
<tr>
<td>NAOI</td>
<td>North Atlantic oscillation index</td>
</tr>
<tr>
<td>NHMM</td>
<td>Non-homogenous hidden Markov model</td>
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<tr>
<td>PCA</td>
<td>Principal component analysis</td>
</tr>
<tr>
<td>RCM</td>
<td>Regional climate model</td>
</tr>
<tr>
<td>RH850</td>
<td>Relative humidity at 850 hPa</td>
</tr>
<tr>
<td>(C)RPS</td>
<td>(Continuous) Ranked probability score</td>
</tr>
<tr>
<td>SDSM</td>
<td>Statistical downscaling model</td>
</tr>
<tr>
<td>SH850</td>
<td>Specific humidity at 850 hPa</td>
</tr>
<tr>
<td>SOI</td>
<td>Southern Oscillation index</td>
</tr>
<tr>
<td>SS</td>
<td>Skill score</td>
</tr>
<tr>
<td>SWP</td>
<td>Swedish weather patterns</td>
</tr>
<tr>
<td>TWS</td>
<td>Teweles-Wobus scores</td>
</tr>
<tr>
<td>U850</td>
<td>Zonal wind at the 850-hPa-level</td>
</tr>
<tr>
<td>V850</td>
<td>Meridional wind at the 850-hPa-level</td>
</tr>
<tr>
<td>wetday</td>
<td>Average wet day amount in mm</td>
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Introduction

Climate change and scenarios

An area without access to clean fresh water is impossible to inhabit permanently as sufficient water resources are essential for the survival and well-being of mankind. Basic industries, such as agriculture, fishing and hydropower, are also sensitive to water shortage, and many intra- and international conflicts are caused by disagreements on the distribution of water resources. The problem can also be the opposite, where an abundance of water in the form of heavy precipitation and floods can cause extensive damages to people and society at large. Civilization has coped with these problems by engineering constructions such as deep wells, dams, irrigation systems etc, but also these are vulnerable to extreme events. A future climate change where extreme events in the form of flooding and droughts become more frequent and more severe is a real and major threat to our society.

There has for a long time been a growing consensus within the scientific community that we are facing a change in the global climate (Vörösmarty et al., 1993). The concentration of CO₂ in the atmosphere has increased with 30 percent since the start of the industrial revolution and if the emissions of CO₂ in the future remain at the same level as today, the concentration will double in 100 years (Houghton et al., 2001). The best instruments to study the effect this has on the climate are General Circulation Models (GCM). Simulations indicate that the increase in radiatively active gases will have significant consequences, such as temperature increase, rise in sea level, melting glaciers etc (Wilby and Wigley, 1997). The spatial resolution of GCMs is increasing but still they simulate our climate at a very coarse spatial scale; in the order of 250 by 250 km. The effects of a climate change will differ locally, so there is a need to transfer the information from GCMs to the local scale. The UK Department of Environments (DOE, 1996) stated nine years ago: “Even if global climate models in the future are run at high resolution there will remain the need to ‘downscale’ the results from such models to individual sites or localities for impact studies. Downscaling methodologies are still under development and more work needs to be done.
Most scientists agree that increasing greenhouse gases will lead to changes in the climate, but how precipitation is affected is not easy to predict. Precipitation is governed by complicated physical processes, and has an inherent stochastical, nonlinear and intermittent nature (Bárdossy and Plate, 1991; Deidda, 1999). This makes a purely deterministic physical model of daily precipitation useless. The GCMs have trouble simulating precipitation occurrence and amounts correctly (Mearns et al., 1995; Bates et al., 1998; Xu, 1999b) and one interesting method to overcome this is to use a stochastic model in space and time. By conditioning this model to characteristics of observed or modelled large-scale circulation, a statistical downscaling system is created that can be used to asses local effects of global changes in mean and variability.

The study of climate is mainly the study of the long-term statistics of the weather (Zwiers and von Storch, 2004). The most apparent problem in climate is the lack of sufficiently long data series. It is therefore very important to state which assumptions are made in a climate study in order to understand to which extent the results are valid. Despite the lack of data, climate impact studies are needed to evaluate possible effects of a climate change on water resources.

Most climate change studies are carried out under the assumption that an increase of radiatively active gases leads to an increase in the greenhouse effect. The warming effect of these gases, mainly H₂O and CO₂, has been known to the scientific community for more than 100 years (Arrhenius, 1896). The climate of the earth is also governed by other factors, such as solar irradiance, surface albedo, surface energy fluxes, cloud properties, surface temperature (Loaiciga et al., 1996), that are not or only partly influenced by anthropogenic activity. Thus the climate has an internal natural variability on large temporal and spatial scales (von Storch et al., 2000).

GCMs deal best with the large-scale dynamics and parameterise regional and local processes (Wilby and Wigley, 1997). This is partly because the hydrodynamics of the atmosphere is nonlinear and the energy that is fed into the system at the cyclonic scale is cascaded, through nonlinear interactions, to the smallest scales. This cascade is parameterised because of numerical modelling limitations. The coarse resolution in GCMs is another reason why many sub-grid scale processes, such as cloud formation, convective rainfall, infiltration, evaporation, runoff etc are parameterised (Zorita and von Storch, 1999). In the last ten years the hydrologic schemes in GCMs have developed towards higher complexity and integration. Even so, the non-linearity of the climate system makes it difficult to directly use deterministic estimation of
precipitation from GCMs for hydrological modelling purposes (Bárdossy et al., 2001). Methods for transforming output from GCM to local weather variables are needed.

Numerical models of natural systems are describing non-closed systems, and are philosophically speaking therefore impossible to validate. There is however a large need to improve the quality of these models and to estimate their benefits in operational use (Refsgaard and Henriksen, 2004). In the rest of this paper the term verification refers to verification of the programming code, calibration refers to testing the model setup against observed data, and validation refers to testing the model against independent data, not used in the calibration.

**Downscaling**

Downscaling is in this thesis defined as the creation of a relationship between the large-scale circulation (predictors) and local weather variables (predictands). The term downscaling is a bit misleading since the methodology is actually increasing the resolution, therefore scaling up the picture. But downscaling is more referring to the process of moving from the large-scale predictor to the local predictand, *i.e.*, moving from the large scale to the small scale (Fig. 1).

![Figure 1](Image)

*Figure 1.* Schematic drawing of the basic principles of dynamical and statistical downscaling from GCM output.
The two main methods are dynamical (physically-based) and statistical (empirical) downscaling. In dynamical downscaling, a regional climate model (RCM) is applied to large-scale circulation using GCM output as boundary conditions (Xu, 1999a). The fundamental assumption in statistical downscaling is that there exist empirical relationships between atmospheric processes at different spatial and temporal scales (Wilby et al., 1998b). These relationships can be related to predictor variables through a transfer function. There is always the subjective choice of which predictor variables to incorporate into the model.

The following criteria have to be fulfilled for a downscaling method to be successful (Hewitson and Crane, 1996):

- Large-scale predictors are adequately reproduced by GCMs
- The relationship between the predictors and the predictands are valid for periods outside the calibration period
- Climate-change signals are sufficiently incorporated in the predictors

Fulfilling the second criterion is the most difficult and questionable. No predictor fulfills all three criteria, so the choice is to use a restricted number of predictors that meet one or two criteria, or use a wide range of predictors to cover all. The argument for using many predictors is obvious, all criteria will be met. The disadvantage is that the degree of freedom in the predictor set is increased, and the results become more difficult to interpret.

A recipe for downscaling is outlined by Hewitson and Crane (1996) and presented here, with modifications by the author.

1. Reduction or processing of the predictor
2. Comparison of GCM circulation with observed circulation
3. Spatial analysis and selection of predictor and predictand domain
4. Temporal analysis of the predictor and the predictand
5. Temporal manipulation of the predictor, e.g. time-lagging
6. Calibration of transfer function between predictor and predictand
7. Evaluating the relationship
8. Application to GCM data

Items 3 to 7 are carried out in a recursive fashion until an optimum result is reached for the target objective. This may involve choice of predictor variables and weighting functions, all depending on the methods used. All steps may not always be taken, but they should always be considered.
Objectives and aims

The overall objective of this thesis was to identify and establish statistical relationships between daily precipitation and large-scale circulation of the atmosphere. Results from this analysis could then be used to evaluate the profits and shortcomings of different statistical-downscaling methods. Given that the methods were considered reliable in transferring climate signals in the predictors to the predictands they could then be applied to improve the simulation of water resources in climate-change scenarios.

The overall objective was divided into specific aims:

- To implement the analogue method as a downscaling tool for a well studied area in order to evaluate its ability to serve as a benchmark to more complicated methods (paper I)
- To evaluate the statistical relationship between large-scale circulation and precipitation using different statistical downscaling methods (paper II)
- To evaluate the geographical generality of the established statistical downscaling methods in areas with large differences in climate and precipitation (paper III)
- To develop the methods concerning their ability to capture extreme events in the studied areas (paper II and III)
- To evaluate a statistical downscaling method on GCM output to study the effect of a predicted climate change on water resources for two areas in Sweden (paper IV)

The selected study region for papers I, II and IV was an intensively studied area in south-central Sweden. To test the global applicability of the methods, three areas in coastal and inland China were selected for paper III. The GCM in paper IV, HadAM3P, was used to evaluate the effect of a climate change on precipitation.

In order to compare the methods as accurately as possible the predictor set was restricted to MSLP in papers I-II. In papers III-IV other large-scale variables were added to the predictor set in order to evaluate the downscaling methods ability to capture the climate change signal.
Material and methods

Statistical downscaling

The statistical downscaling methods discussed here are divided into three main groups; analogue methods, regression methods and conditional probability approaches (Bárdossy, 2000). The grouping is based on the downscaling approach. The last group has two main subgroups, weather patterns and weather states, which are closely related. This classification is not perfect, since many methods are hybrids (Xu, 1999a), but it serves as a starting point for discussion. The analogue method is not so often found in the literature as the others, but offer a simple technique that can be used as a benchmark (Zorita and von Storch, 1999). Other approaches to divide downscaling techniques into subgroups have been proposed (Rummukainen, 1997). See Appendix 1 for an overview of case studies of statistical-downscaling methods using precipitation as predictand. For an overview of statistical downscaling studies in the Nordic countries see Hanssen-Bauer et al. (2005).

There are advantages and shortcomings of statistical downscaling in comparison with dynamical downscaling. The main features of statistical downscaling are (Heyen et al., 1996):

- Personal computers can be used for the calculations
- There is no need for detailed knowledge about the physical processes
- Long and homogenous time series are needed for fitting and confirming the statistical relationship

The second feature is modified by the fact that many statistical downscaling methods rely on known physical understanding and processes that are important for the predictand. It is often true, however, that the exact formulation of the processes is not important for statistical downscaling.
The transfer function in statistical downscaling is in principal created by translating anomalies of the large-scale flow into anomalies of some local climate variable (Zorita and von Storch, 1999). Advantages of statistical downscaling approaches are that they are easy to implement, computationally cheap and that calibration to the local level is an integrated part of the procedure (Solman and Nunez, 1999). Furthermore, they require very few parameters, which make these methods attractive for many hydrological applications (Wilby et al., 2000). In order for a downscaling method to give results that can be applied in hydrologic and/or ecological models and be calibrated against local data, it has to fulfil certain criteria (Hewitson and Crane, 1996, Wilby et al., 1998a):

- Large-scale circulation drives the dominant rainfall-generation mechanism for local- and region-scale precipitation
- The downscaling relationship derived from observational data is time invariant
- As far as possible the scheme should be globally applicable

Precipitation is a strongly intermittent and nonlinear process, and precipitation fields are characterised by anomalous scaling laws (Deidda, 1999; Bárdossy et al., 2001). It is also shown that the spatial behaviour of precipitation is dependent of the time scale; precipitation is more intermittent for shorter time periods (Katz, 1999). Using stochastic models for the downscaling of precipitation can be of help when trying to understand the probabilistic structure of precipitation (Hughes et al., 1999). These models have long been used to model hydrologic events, such as run-off. If they are derived from the atmospheric processes that drive precipitation, they can predict what governs precipitation patterns (Hughes et al., 1999).

Seasonal dependencies

When discussing statistical downscaling it is also important to consider seasonality. For the temperate zone with clearly defined seasons, the driving forces for the precipitation differ over the year, thus causing intra-annual anomalies in the downscaling results. Precipitation during summer months is driven by convection to a greater extent than during winter months. This result is shown in many studies (e.g., Huth and Kysely, 2000; Wilby, 1994), and is an important factor to consider when creating classification schemes. A solution to the problem can be to divide the year into four seasons. The growth season of plants is an example where the timing and amount of precipitation is crucial as there is a non-linear relationship between the amount
of rain and the water-use efficiency of plants (Barrow and Semenov, 1995). A large part of the precipitation that occurs during extreme events runs directly off the soil and is not available for plants.

Validity in a perturbed climate

Downscaling methods must be valid in a perturbed climate in order to be useful tools in studies of a future climate change. The methods are supposed to estimate the difference between climate situations and must, therefore, function under a situation different from under which it was developed (Huth and Kysely, 2000). The climate must be stationary, i.e., no major shift in the physical processes governing the climate must occur, for a downscaling scheme to be considered operationally valid outside the calibrated and validated range.

One approach to evaluate the ability of a model to cope with different climate situations is to calibrate the model on data from the driest seasons and then validate it on the wettest seasons in the calibration period and vice versa. This is a simple test of the methods sensitivity to different climate situations. The model can also be tested against extreme years in order to test the stability (Wilby, 1994). If the time series used in the downscaling are long enough it is reasonable to believe that they contain many different situations, including those situations that will be more frequent in a perturbed future climate. The problem will be minimised if the method can model those situations and if the range of variability of the large-scale variable in a future climate is of the same order as today.

In downscaling, there are problems with stability and non-stationarity (Wilby, 1994) and one should be careful when applying a model to the output of GCM simulations. If the climate is non-stationary, the underlying assumptions of the statistical link has to be considered unaffected by the climate change in order for the model to considered valid. The physical laws governing the climate are not likely to change, but the parameterisation of the physical processes refers to a specific climate, which may make the model results questionable for a changed climate. It can be noted that in order to overcome the problem with non-stationarity, a multivariate approach is recommended (Wilby, 1997). This is not possible in all methods, in which case sufficient data should be included in order to ensure statistical integrity of the results. Non-stationarity can also be taken into account with a stochastic model conditioned on the observed inter-annual variability (Wilby, 1997).
Stochastic precipitation models

The definition of a stochastic model is that the predicted variable is simulated probabilistically (Gregory et al., 1993). Because of the chaotic and non-linear behaviour of precipitation it is not meaningful to use deterministic models to generate long term precipitation series (Bárdossy et al., 2001; Stehlik and Bárdossy, 2002). If a downscaling technique is stochastic, the output of such a model can be used as an input to runoff models directly (Wilby et al., 1994). Stochastic models in weather generators are also useful in evaluating essential features of the precipitation process, such as intermittency, duration of wet and dry spells and the positively skewed distribution of intensity (Katz, 1999). A disadvantage with weather generators is that they fail to capture the seasonal and inter-annual climate variability, due to the simplicity of the models (Wilks and Wilby, 1999).

The analogue method

The analogue method (AM) is a very simple method, with some definite advantages. The basic idea is to assume an analogy between a large-scale variable, either observed or simulated by a GCM, and historical records of the same variable and to compare the records. The simultaneously observed weather is then associated with the simulated large-scale pattern (Zorita and von Storch, 1999; Bárdossy, 2000). In practice, the target predictand $S(t)$ at time $t$ is simulated by selecting the predictand at the time $u$, at which the characteristics of the predictor $F(u)$ most closely resemble those of the target predictor $F(t)$. The predictor $F(u)$ is called the analogue to $F(t)$.

$$\hat{S}(t) \in S(u) \quad u \in U, \quad t \notin U, \quad U \subset T, \quad (u,t) \in T$$

The analogue is then selected as the time that minimizes:

$$\min \| F(U) - F(t) \| \quad (1)$$

This approach demands long data series to incorporate a sufficient number of extreme events. Some decades of data are sufficient for local climate variables. The obvious disadvantage is that maximum amount of a modelled day cannot exceed the maximum amount in the observed values, but modelled wet spells can exceed observed amounts.
PCA

The principal-component analysis (PCA) is an often used method in meteorology. Basically it identifies correlated patterns of variability within the predictor field anomalies (Huth and Kysely, 2000; von Storch and Zwiers, 1999). The first step of PCA is to find the principal correlation between a number of variables by standardising the data set and analysing the eigenvalues and eigenvectors of the variance-covariance matrix (Johnson and Wichern, 1998). The anomaly of a field is defined as the deviation at each grid point from the average pressure for a standardisation period. The standard period was 1961-1990 in this thesis if nothing else is stated.

A successful PCA identifies a number of patterns which explains a major part of the variability. The explained variance of each PC is expressed in the eigenvalues and by keeping only those PCs that contribute significantly to the variability the degrees of freedom is reduced and the “noise” is filtered out. A scree-diagram, where the standardised eigenvalues are plotted from the largest to the smallest, can guide how many PCs to keep. A rule of thumb is to discard the PCs whose eigenvalues are below the “elbow” of the diagram. For a more extensive description of PCA, see Appendix 2.

TWS

The Teweles-Wobus Score (TWS) compares similarities of the SLP field, $P(k,t)$, by comparing N-S and E-W gradients instead of its anomalies at each grid point. TWS was originally developed to evaluate the quality of geopotential-height forecasts (Teweles and Wobus, 1954), but has recently been employed in analogue downscaling studies (Obled et al., 2002). The analysis summarises differences in the predictor in a score (TWS) and the target predictor is the day with the smallest TWS. For a more extensive description, see Appendix 3.

Weather-pattern method

Conditional-probability methods differ from the previous methods in the sense that the linkage between the predictor and predictand is more complex and has elements of stochasticity. The validation of such a method should be based on parameters involving a time structure, such as number of extreme events and persistence of dry and wet spells, rather than the direct observed values (Zorita and von Storch, 1999). Two main approaches exist; weather patterns and weather states.
Weather-pattern methods involve linking observational station data to given weather classification schemes (Wilby and Wigley, 1997). These classification schemes can be either subjectively or objectively derived but they are pre-supposed to be internally consistent and synoptic (Wilby et al., 1994). Objectively derived classification includes principal components, CCA, fuzzy rules, compositing, neural networks, correlation-based pattern recognition techniques, k-means clustering and analogue procedures (Stehlik and Bárdossy, 2002). A subjective weather pattern scheme has been proposed by Lamb (1950, 1972) for the British Isles, and the European Grosswetterlagen (Baur et al, 1944) for European mainland.

When the classification scheme is selected, the next step is to condition the local surface variables to the weather pattern (Wilby and Wigley, 1997). This is done by deriving probability distributions for observed data, for example the probability of a wet day following a wet day, seasonal and areal distributions and amount of rain on a wet day (Stehlik and Bárdossy, 2002).

The steps in weather-pattern methods (Xu, 1999a; Wilby and Wigley, 1997; Wilby, 1994) are:

1. Classify atmospheric circulation into a limited number of classes
2. Condition the local variables to the corresponding weather pattern
3. Simulate the predictand (local variable) using Monte Carlo techniques or GCM output as forcing data.
4. Simulate the amount of precipitation in case of a wet day

An advantage of the method is its simplicity and that it is easy to apply it to different areas simultaneously as the circulation pattern remains the same for a large region (Bárdossy and Plate, 1991). Wilby (1995) combined weather patterns with frontal analysis and saw an improvement of the result in terms of the statistical distributions and rain amount. The method performed less well in a very complex weather situation (Özelkan et al., 1998). It is important to make sure that the created weather patterns have real physical meaning, especially if they are objectively created (Chen, 2000). This can be checked by comparing weather patterns to real weather situations.

**MOFRBC**

The Multi-objective fuzzy-rule-based classification method (MOFRBC) is a semi-objective method to classify a state variable with logical and probabilistic statements (Bárdossy et al., 1995; Stehlik and Bárdossy, 2002, Bárdossy et al., 2002). The term fuzzy rule means that a set of logical state-
ments concerning the state variable has to be fulfilled to a certain degree of fulfillment (DOF) for the rule to be true, unlike binary logic where no deviation from the rule is accepted. In the case of MOFRBC the rules are defined to represent circulation patterns in the predictor. MOFRBC define 5 possible values for each grid point in the predictor set with the physical meaning as follows; 1 for very low, 2 for intermediate low, 3 for intermediate and 4 for very high anomalies in the predictor. The value 0 is for indifferent values in the grid point. Note that most grid points are assigned to 0 and that the non-zero grid points may (and usually do) vary between the circulation patterns. A short mathematical description is given in Appendix 4.

Regression

A definition of regression methods is given by Wilby and Wigley (1997): “Generally involve establishing linear or nonlinear relationships between sub grid-scale (e.g. single-site) parameters and coarser-resolution (grid-scale) predictor variables”. Often used regression methods in this field of science include Artificial Neural Networks (ANN, Olsson et al., 2001; 2004; Hewitson and Crane, 1996) and Canonical Correlation Analysis (CCA, von Storch et al., 1993; Biau et al., 1999; Busuioc et al., 2001a). The models and techniques range from simpler multiple regression schemes to more sophisticated models, such as a method to link the covariances of atmospheric circulation and of local weather variables in a bilinear way (Burger, 1996).

Studies using regression methods can also be classified according to which parameters are used for the study. One approach is to use the same variable for the large-scale predictors as for the local-scale predictands, for example temperature, but most studies use different parameters.

The steps in regression methods (Heyen et al., 1996) are:

1. Identify a large-scale parameter G (predictor) that controls the local parameter L (predictand). If the intent is to calculate L for climate experiments, G should be simulated well by climate models.
2. Find a statistical relationship between L and G.
3. Validate the relationship with independent data
4. If the relationship is confirmed, G can be derived from GCM-experiments to estimate L.

The idea proposed in step 1, that the predictor should be well simulated by GCMs, is a key issue in this method. As mentioned before, the whole idea
of using statistical downscaling of climate variables is to evaluate the effects of a climate change. The GCM is still the best tool to predict the future climate. A weak point in this context is the assumption that the statistical relationships derived will prevail in a perturbed climate.

SDSM

The models that are used in climatic studies to simulate the weather parameters with the same variability as observed values are called weather generators and the most used is WGEN proposed by Richardson (1981). The Statistical Downscaling Model SDSM (Wilby et al., 1999; 2002a) is a hybrid between a multi-linear regression method and a stochastic weather generator. Large-scale point predictors are used to condition local-scale weather-generator parameters, both concerning precipitation occurrence and amount. The parameter values are conditioned on a monthly basis. The model has been applied in many catchments in North America (Wilby and Dettinger, 2000) and Europe (Wilby et al., 2002b; paper II). For a more extensive description, see Appendix 5.

Validation methods

The classifications were evaluated using measures of their ability to classify patterns with large differences in precipitation structure. These measures were designed for precipitation occurrence \( I_1 \) and amount \( I_2 \).

\[
I_1 = \frac{1}{T} \sum \sqrt{(p(CP(t)) - \overline{p})^2}
\]  

\[
I_2 = \frac{1}{T} \sum \ln \left( \frac{z(CP(t))}{\overline{z}} \right)
\]

where \( T \) is the number of classified days, \( p(CP(t)) \) is the probability of precipitation on day \( t \) and \( z \) is the mean precipitation amount on day \( t \) with classification \( CP \), and \( \overline{p} \) is the probability of precipitation for all days. Along with these also frequencies were evaluated. The probability scores (RPS) are commonly used to evaluate forecasts (Epstein, 1969, Murphy, 1971, Jolliffe and Stevenson, 2003) and are calculated by classifying a random variable \( X \) with \( K \ (> 2) \) thresholds,
that define the events \( A_k = \{ X \leq x_k \} \) for \( k = 1, 2, \ldots, K \) with the forecast probabilities \( \hat{p}_1, \hat{p}_2, \ldots, \hat{p}_K \). The binary indicator variable for the \( k \)th event is denoted \( o_k \) and defined as \( o_k = 1 \) if \( A_k \) occurs and 0 otherwise.

\[
RPS = \frac{1}{N} \frac{1}{K} \sum_{n=1}^{N} \sum_{k=1}^{K} (\hat{p}_k - \hat{d}_k)^2
\]

\[
CRPS = \frac{1}{N} \sum_{n=1}^{N} \int_{-\infty}^{\infty} \left[ F(x) - H(x-x_0) \right]^2 dx
\]

\( N \) is the number of forecasts. CRPS is the continuous extension of RPS where \( F(x) \) is the c.d.f. \( F(x) = p(X \leq x) \) and \( H(x-x_0) \) is the Heaveside function that has the value 0 when \( x - x_0 < 0 \) and 1 otherwise. In order to quantify the skill of the probability score, the skill score (SS) is calculated as:

\[
SS_{(C)RPS} = 1 - \frac{(C)RPS_{FP}}{(C)RPS_{RP}}
\]

where \((C)RPS_{FP}\) denotes the forecast score and \((C)RPS_{RP}\) is the score of a reference forecast of the same predictand. The \( SS_{(C)RPS} \) is a validation tool that compares how the distribution of an ensemble of forecasts predicts the observed value that is sensitive to bias as well as variability in the forecasted values. A skill score close to 1 means a successful simulation; if the skill score is negative the method is performing worse than the reference forecast. Skill scores are sensitive to extreme events (von Storch and Zwiers, 1999), which is suitable for the purpose of this study, but are insensitive to systematic errors such as a constant bias or a constant difference in amplitude.

**STARDEX indices**

An important issue in climate studies is to evaluate the risks of an increase in extreme events, such as droughts, flooding storm events etc (Houghton et al., 2001). STARDEX (2001) is a European project to coordinate downscaling methods, evaluate predictors and suggest evaluation criteria. The project focuses on extreme indices, such as \( \text{max}5 \), \( \text{maxdry} \) and \( 90\text{perc} \). These indices were used to evaluate the downscaling methods in papers II and III.
Data and study areas

Selecting the appropriate predictors for the predictand is a crucial part of the downscaling exercise. The suitability of predictor variables depends on the predictand and the aim of the study. A thorough investigation of the predictor–predictand relationship is important to understand the response a climate change may give to the predictands. The predictor variables were kept to a minimum in papers I and II in this thesis, but were expanded to include more variables in papers III and IV.

Predictors

A literature study shows that atmospheric circulation variables are the most commonly used predictors when downscaling precipitation, especially MSLP (Appendix 1), but also humidity, temperature and geostrophic winds are employed as predictors. According to Wilby et al. (1998b) and Giorgi et al. (2001) an ideal predictor should:

1. be physically and conceptually sensible
2. ideally be continuous, in order to model extreme events
3. be accurately modelled and readily provided by GCM output
4. be strongly correlated to and account for a large part of the variability of the predictand
5. exhibit a temporally stationary link with the predictand
6. preserve observable correlations between downscaled parameters
7. be responsive to greenhouse-gas forcing

Predictors may fulfil these criteria more or less and the selection of suitable predictors is always to some degree subjective. The choice of predictors is ultimately governed by the availability and the method chosen. Reanalysis projects carried out in USA by NCEP/NCAR (Kalnay et al., 1996) and in Europe by ECMWF (Källberg, 2002) have produced gridded, global multivariable data available to the scientific community. Reanalysis data from the NCEP/NCAR data were used as observed predictors in this thesis. The GCM data in paper IV were from the Hadley Centres HADAM3P model (Pope et al., 2000; Johns et al., 2003).

The goal with most downscaling studies is to evaluate effects of a climate change on the local scale, and items 3 and 6 in the above list are essential in this sense. Variables that are not sensitive to climate change are not suited for downscaling, but in combination with other more sensitive variables they may still be used. An example is MSLP, the most often used predictor,
which is not as sensitive to climate change as for example humidity and temperature, but still is useful in studies due to the importance of correctly modelling the atmospheric circulation.

GCMs are constantly developing, incorporating more and more processes governing the climate and increasing the spatial resolution of output data. It is nonetheless a time-consuming task to pre-process GCM data to be able to use it in a downscaling study.

The spatial variability is important when the outcome of a downscaling model is precipitation. For hydrological modelling purposes it is important to have good spatial resolution (Bárdossy et al., 2001). Variability in space differs between seasons due to different atmospheric patterns (Stehlik and Bárdossy, 2002). The variability in summer can be large because of local convective precipitation, while the weather in other seasons can be governed by larger circulation patterns and thus have larger spatial covariance. Another important aspect is that there might be spatial offsets in the correlation patterns between predictors and predictands (Wilby and Wigley, 2000). These disturbances may be caused by small-scale variations at remote grid points within circulation types and be a function of the time scale used in the study (Brinkmann, 2002). These variations often have a large importance for the occurrence of precipitation, which is troublesome since classification schemes do not pick up these small perturbances. Regression methods that utilize grid points directly may be more effective to capture these centres of importance, which can be shifted by a small change in the circulation (Brinkmann, 2002).

Predictor settings

In papers I and II the predictor was restricted to gridded MSLP in order to reduce the degrees of freedom and to be able to compare the methods in an objective manner. The gridded MSLP in paper I was the Trenberth and Paolino (1980)-corrected MSLP series continuing from 1899 to present with a spatial resolution of 5° by 5° degrees long-lat. The NCEP/NCAR reanalysis data with a spatial resolution of 2.5° x 2.5° long-lat were used in paper II. In paper III a range of atmospheric variables were added to the predictor set, such as geopotential height, specific humidity and meridional and zonal winds at 1000-, 850-, 700- and 500-hPa-levels.

Output from the Hadley Centre GCM HADAM3p model was used in paper IV. This model is a successor version of HadAM3H (Pope et al., 2000; Johns et al., 2003). The used simulations were driven by observed sea-surface temperatures and sea-ice distributions for the period 1961-1990 and simulations under the IPCC SRES scenario emissions A2 and B2 for the
time period 2070–2100 (Houghton et al., 2001). This model underestimates the wetday and extreme indices such as maxdry and max5 and greatly overestimates the number of wet days. The seasonal cycle of precipitation is not correctly modelled, so there is a definite need to correct the precipitation if the results are to be used in a climate-impact study.

The choice of the best predictor for precipitation downscaling in Sweden should include both atmospheric-circulation indices and a climate-change indicator, such as specific humidity according to Hanssen-Bauer et al. (2005). Specific humidity and geostrophical winds were included as predictors in paper IV.

Predictands

It is important to know if there are any inhomogeneities in the observed predictand data because of change in instrumentation, change in the surroundings of the measuring site etc. A homogeneity test (Alexandersson, 1986) was applied on the precipitation series in all studies. Data sets with gaps or significant inhomogeneities were discarded. It is also important to know what corrections have been made to the data-set. As pointed out earlier, time series over decades with large variability are preferred in order to capture as many climate situations as possible.

Study areas

The study area in papers I and II was located in south-central Sweden (Fig. 2). It consists of seven precipitation station series obtained from SMHI, four around Uppsala and three around Sala. The stations were selected to represent precipitation in the southern NOPEX catchment (Halldin et al., 1999) as a support for climate research within the area. The precipitation series were corrected according to Eriksson (1983). In paper IV, precipitation stations from the whole of Sweden were available through the SWECLIM project. From this data set, eight stations in the Swedish part of the Torne älv catchment in northernmost Sweden were added. This particular area is a study basin within PILPS 2 project (Nijssen et al., 2003). To optimize circulation patterns for the whole of Sweden, 40 precipitation data sets with no data missing in the period 1961–1990 were extracted and used in the classification.
Figure 2. Location of the precipitation stations used in the Swedish study. The circles denote the stations used in papers I, II and IV, boxes are the Torne älv catchment in paper IV and the stars are the stations used for classification of the Swedish circulation patterns in paper IV (from paper IV).
The methods were evaluated on three catchments in mainland China (Fig. 3) in paper III. These catchments were selected to evaluate the methodology in a different climate zone and in a part of the world where very few statistical downscaling studies had been undertaken (Fan et al., 2005). The data were provided by the National Climate Centre of China. No correction was made to the Chinese data since the correction factors were not known.

Figure 3. Map of mainland China with locations of the three study areas in paper III
Results

Predictor settings

The optimum predictor settings for PCA in paper I were a small area covering Sweden for daily precipitation and only the grid points directly over the study area for monthly precipitation (paper I, Fig.3). The TWS method had a much larger predictor area, especially for daily precipitation. The monthly simulations with TWS had two areas, one over Sweden and a second south of Iceland (paper I, Fig. 3). The main finding was that downscaling of monthly precipitation needed a smaller predictor area than daily precipitation.

In paper II where the focus was on seasonal precipitation the predictor areas were generally smaller for winter and spring and largest for summer for PCA and for autumn for TWS (Fig.4). The time windows showed similar patterns with the largest temporal window in winter and spring and larger...
during summer and autumn. The areal pattern for MOFRBC was similar, with the largest spatial coverage in summer.

The difference between seasons was not seen in the two coastal catchments in the Chinese study (paper III), neither in the area of the predictor nor in the time window (Fig. 5). The most interesting feature was that the inland Laoyukou catchment had much larger optimum time and space windows for PCA than for TWS. The optimum area window for MOFRBC was somewhat larger for Laoyukou than for the coastal stations.

The predictor settings for SDSM differed with season, both in Sweden and China. The ranked correlation between MSLP and precipitation was weaker in Sweden and located west of the stations during the winter season (paper II, Fig 6). In the summer season the correlation was stronger and centred over the station. The correlation between MSLP and precipitation was much stronger during the winter than summer season in the Chinese study (paper III, Fig. 3). The centre of the correlation patterns for all stations was in the sea just off the Chinese coast. In the second version of the model (SDSMh) S850 and S700 were the most selected predictors, and MSLP was more often selected in winter than in summer.
Classifications with MOFRBC were made for three regions in paper (IV), one in the north (Torne catchment), one in the south central (NOPEX) and one with stations covering the whole Sweden (Fig. 2). The patterns were optimised on ranked precipitation, and the predictor with highest $I_1$ and $I_2$ was MSLP for the NOPEX (Fig 6) and Torne catchments. The optimum classification of weather patterns for the 40 stations in Sweden (SWP) were obtained with GPH850 as large-scale predictor variable. This classification was used to downscale precipitation from the HADAM3P model for the two sub catchments NOPEX and Torne.

![Figure 6. Mean normalised H850 anomalies with the SWP classification for the period 1961-1990 (from paper IV).](image)

**Downscaling skill**

The analogue methods downscaled persistence and transition properties of daily precipitation better than the randomised simulation in the NOPEX area (Table 3, paper I). The seasonal properties were better captured in the monthly simulations than the reference simulation. The two methods behaved a bit different, but in general worked equally well. Efficiency improvements in monthly simulations were significant for each step of the PCA technique, whereas results from TWS were not conclusive. The opposite situation was present for the RPS of the monthly downscaling, with the most noticeable improvement using the TWS technique.
In paper II MOFRBC method performed best concerning the distribution properties $RPS_{prec}$ and $RPS_{dry}$ for all seasons, except $RPS_{dry}$ for autumn, and SDSM performed second best. In contrast, SDSM performed overall best for $RPS_{wet}$. The analogue methods did not perform poorly, but it was only during winter that they could do better than the more sophisticated methods for the statistical properties. The analogue methods also outperformed the more complicated methods during winter in terms of the STARDEX variables (Table 5, paper II). It was noticeable that MOFRBC managed to downscale maximum length of dry spells best for all seasons except summer, otherwise the method performed poorly during winter and spring for the STARDEX indices. All methods, except MOFRBC, underestimated precipitation amount for a rainy summer day. MOFRBC was also the method that down-scaled the STARDEX variables best for the wettest summers, except for maximum length of dry spell. The TWS method performed best overall during dry summers, but no method captured the magnitude of difference between wet and dry climate conditions very well.

The SDSM performed best concerning $RPS$ for all stations and seasons in China (Table 5, paper III), and MOFRBC was the second best. Adding humidity as predictor did not affect the probability scores significantly. To make the evaluation of the STARDEX properties easier, skill scores were calculated, with the time step of each season respectively (Fig. 7). The results were generally better for the coastal stations than for the inland Laoyukou station whereas maxdry and max5 for the latter were reasonably well downscaled. Summer precipitation indices were generally better downscaled than winters for the coastal stations (Baixi and Jouzhou).

The importance of using humidity as predictor was evident when MOFRBC was applied to output data from HADAM3P in paper IV. When MOFRBC was run without MF there was a small increase in max5 during winter, but otherwise the results indicated no change. The MOFRBC conditioned with moisture flux (MOFRBCh) increased the wet precipitation indices for all seasons for Torne, and all seasons except max5 during summer for NOPEX.
Time variations

The intra-annual variations were well captured for all downscaling methods and areas (Fig. 8, Fig 7 paper III). The imposed time window on the Swedish stations (paper I-II) was essential in order to capture the seasonal variation. A common feature of the downscaling methods in the NOPEX studies (papers I and II) was that August amounts were underestimated and amounts for winter months were well captured. The high resolution predictor data used in paper II improved the seasonal amounts for AM compared to paper I.
Figure 8. Observed and downscaled precipitation of monthly precipitation amounts averaged over NOPEX region for the validation period 1979–1994 (from paper II).

The seasonal variations were even larger in China, but this was also well captured with all methods. The variation of monthly precipitation amounts increased with MOFRBCh, but it also had the setback that the annual cycle became somewhat skewed (Fig. 7 paper III). For the MOFRBCh the precipitation during late summer and early autumn was greatly underestimated for Laoyukou and Baixi, but the early months of the year improved. SDSMh overestimated the summer precipitation compared to SDSM.

Adding moisture flux also affected the intra-annual variation in the case study. Monthly precipitation amounts were overestimated in winter–spring and underestimated in late summer and fall. Adding humidity also increased the difference between HADctl run and scenario simulations.
Discussion

Predictor settings

The small area window for PCA (paper I) had the consequence that the first principal component explained 94 percent of the variance, whereas the differential window sizes (paper II) accounted for more of the variance in the principal components of lower rank. The area window decides the degrees of freedom in the predictor since only the principal components that account for a large portion of the variance should be kept in a study, typically those that together account for 85-90 percent of the variation (Fig. 9). This may not be a disadvantage if the precipitation is governed by local processes, but that is not the case for all seasons in Sweden. Precipitation amounts are closely correlated with elevation and convective precipitation during the warm months are dependent on local variables (Johansson and Chen, 2003) although the general westerly circulation is also important.

![Figure 9. Cumulative explained variances of the ten first principal components of the MSLP field over Sweden for different area windows.](image)

The primary circulation pattern may not be the most important for precipitation. The lower ranked principal components may be more important
for precipitation occurrence and amounts and the relative importance may also differ between seasons (Brinkmann, 2002). Figure 4 expresses this in the area windows, where precipitation in winter has a much smaller window than in summer, indicating that precipitation in summer is governed by a more complex structure with a larger areal resolution and smaller spatial patterns.

The situation was different in China where the optimum area windows did not depend as much on season, but rather on the location of the predictands. The areal windows for the coastal stations were a bit smaller for winter than for summer. A larger difference would have been expected since the mechanisms for precipitation are very different for different seasons. During summer the precipitation is governed by the moist summer monsoon, which is a very large circulation system. The circulation during winter is dominated by the dry winter monsoon, and precipitation is highly correlated with low pressure in the Chinese Sea just outside the station area. This implies a more local influence on the winter precipitation for the coastal stations, but the difference from summer is not that large, which was seen in the predictor setting for SDSM without moisture flux (Fig. 3, paper III).

The classification patterns for China with MOFRBC were created entirely automatically with no subjective input. A subjective classification for Baixi catchment was created using Lamb (1972) circulation fields, but the indices $I_1$ and $I_2$ were higher for the objective classification. This indicated that the method can be applied on regions where no prior classification is available.

MOFRBC's ability to classify the CP frequency sufficiently for the MSLP classification indicated that HADAM3P reproduces the circulation well for the control period. The correlation between HADctl- and NCAR-derived CPs was weaker for the upper-atmosphere predictors. The CP classification for GPH850, however, ranked highest for $I_1$ and $I_2$ when all stations were used, so this classification was selected as the best for Sweden. The reason why GPH850 was better than MSLP for the whole of Sweden might be that local orographic effects are more evident in MSLP, and large-scale synoptic circulation is stronger in GPH850, thereby making it a better predictor variable for large areas.

Using classification patterns that are optimised for the whole of Sweden instead of patterns optimised for only a few stations have advantages and drawbacks. The negative effect is that the patterns are not optimised for the selected region, and thus may give lower values of $I_1$ and $I_2$ than for a local classification. The advantage is that the same classification can be used for any region in Sweden, thus making it easier to evaluate climate change effects on larger areas and saving computation time.
Downscaling skill

Papers I-III show that AM is suitable as a benchmark in comparison with more sophisticated methods. In order for it to be employed as a benchmark method it has to work better than a random weather generator. The benefit of using AM as a comparison tool is that it provides a sharper instrument than just a reference simulation. The correlation structure between stations is preserved and since the reshuffling of predictands is conditioned on the predictor the persistence and transition properties of the simulated series are better captured than with a totally stochastic weather generator.

The MOFRBC was the best overall method concerning dry spells (papers II and III) and this can be explained by the use of classification patterns. The persistence of a certain weather situation is enhanced by the discretisation of the circulation into patterns, which makes the method less sensitive to small changes in the predictor field. MOFRBC gave good results in such different climates as Sweden and China, which supports the idea of the global applicability of the method. Maxdry were not much affected by the climate change scenario, but the results indicate a minor decrease for NOPEX in winter and spring. This has no real impact on the water resources for the study areas.

MOFRBC had a tendency to over-estimate wetday, but this is partly because the method was built with emphasis on extreme events (Stehlik and Bardossy, 2002). Adding moisture flux improved the precipitation model in the Chinese study (paper III), but had a negative effect on the results for the intra-annual variation.

The SDSM uses the information in the predictors in a quite different manner than MOFRBC, which is also evident for some indices. Both methods could capture the max5 for Sweden equally well, but wetday and RPSprec were better captured with SDSM. This may indicate that the method is more sensitive to small variations in the predictor field. The global applicability for SDSM is supported since the method gave good results for different climate regions.

Humidity is an important parameter in precipitation downscaling, both in terms of timing and occurrence. Here, the focus was to study the performance of different methods using a predictor set that was restrained to only atmospheric circulation (papers I-II) in order to use AM as a benchmark. The results from the simulations with SDSMh and MOFRBC in the Chinese catchments stress the importance of humidity in climate change studies. The precipitation indices were better captured, but also the inter-annual correlation of precipitation totals (Table 5 paper III).
The climate signal in the HADAM3P was better captured with MOFRBC, and the results indicated an increase in wetday and max5, for both areas. The advantage of using a two-step method as the MOFRBC is that the effects of changes in circulation and humidity flux can be studied simultaneously. This study may however have left out important climate-signal predictors, and inclusion of other predictors, such as fronts suggested by Wilby (1995), or vorticity (Chen et al., 2005), could improve the precipitation model.

Time variations

The methods good ability to capture intra-annual variations can be attributed to the implicit and explicit treatment of seasonality. The imposed time window on AM eliminated the possibility that the analogue was selected from a season other than the target predictand. The distribution parameters in MOFRBC and SDSM were monthly conditioned, which decreased the probability of modelling heavy precipitation during dry seasons. The problem with the skewed annual precipitation cycle with the MOFRBC needs to be further investigated. The HADAM3P has a bias in specific humidity with a tendency of too wet conditions over UK and Scandinavia (STARDEX, 2005). This may explain why the HADctl simulations were wetter than the NCAR simulations over the control period for the NOPEX catchment.
Conclusions

- The analogue method was implemented as a downscaling tool and worked well as a benchmark method for more sophisticated methods. PCA and TWS show different skills in downscaling but none of them are superior to the other.

- Temporal and spatial analysis of the predictand-predictor relationship was found to be crucial in statistical downscaling studies in order to obtain useful results.

- The downscaling methods successfully captured extreme events in areas with large differences in both climate and precipitation (Sweden and China). It was concluded that there is no overall “best method” to use in downscaling studies. The method to be preferred depends on area and objective of the study.

- Adding humidity as predictor improved the downscaling in China concerning the extreme indices and seasonal and annual amounts, but skewed the annual precipitation cycle modelled by MOFRBCh.

- The climate-change signal is stronger in predictor variables such as humidity than in large-scale circulation of air pressure, so a combination of predictors is recommended.

- The climate change scenarios simulated by the HADAM3P model indicated an increase in wetday and max5 for all seasons in the studied areas, especially for the Torne catchment.
Future research – *a post scriptum*

The work pursued in this thesis is progressing along two major avenues at the time of writing. I intend to explore both in future planned publications.

Firstly, the precipitation model in the MOFRBC will be developed further, with a better implementation of moisture flux and a better description of the precipitation distribution. The work so far has included exponential and gamma distributions in the precipitation model instead of a truncated normal distribution. Development to simulate gridded precipitation of high resolution is also initiated, which will be most welcome in runoff modelling. The method should also be able to model larger areas, such as the Baltic Sea drainage basin. The limitation would then be to what extent optimised circulation patterns could be classified.

The second avenue is to use the downscaled precipitation series in runoff modelling, thus evaluating the effects of a future climate change on local surface hydrology. I intend to do this both for Sweden and China, which demands that other hydro-meteorological variables, such as temperature, evaporation and soil moisture, are either downscaled along with precipitation or calculated from GCM scenario output in some other way.
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your love and support.
Tillgången på vatten och vattenresurser har alltid varit en viktig fråga för människans överlevnad och samhällets utveckling. De första civilisationerna grundades i floddalar, där vatten kunde utnyttjas till jordbruksdricksvatten och som transportmedel. Extremhändelser som torka och översvämning har alltid medfört stora konsekvenser, och även om vi med modern teknik kan skydda oss mot och förebygga konsekvenser av naturkatastrofer medför de fortfarande stora mänskliga och materiella förluster. En ökad frekvens och omfång av extrema vädersituationer till följd av en klimatförändring är ett reellt hot mot morgondagens samhälle.

Det bästa verktyget för att simulera klimatförändring orsakade av ökade utsläpp av så kallade växthusgaser är generella cirkulationsmodeller (GCM). I början användes de i prognossyfte för att simulera stora vädersystem, men idag har de utvecklats till stora system för att simulera alla delar av jordens klimat. Dagens modeller inkluderar atmosfärs- och oceancirkulationer, energi- och massutbyte mellan land, hav och atmosfär, hydrologiska kretslopp och ämnesomvandlingar i atmosfären. Fördelen med GCMer är att de modellerar hela klimatsystemet globalt och kan således inkludera processer som verkar över stora områden. Nackdelarna är dels att de är kostsamma att köra, både i form av resurser och tid, och att de på grund av storskaligheten har svårighet att simulera småskaliga processer på ett tillfredsställande sätt.

Nederbörd är en mycket komplicerad icke-linjär process som kan ha stora lokala variationer. Om och hur mycket det regnar styrs dels av storskaliga vädersystem, dels av lokala faktorer såsom orografi, markanvändning och konvektiv turbulens. Det är ett välkänt problem att GCMer har svårighet att korrekt simulera nederbörd, både vad gäller säsongssberoende, lokala variationer och extremhändelser. Det finns således ett stort behov av att omvandla utdata från dessa modeller till vädersituationer i det lokala planet. En lösning på problemet är nedskalning, där information från storskaliga parametrar (prediktorer) kopplas till lokala väderparametrar (prediktander).

Det finns två huvudmetoder för nedskalning: dynamisk (fysikalisk) och statistisk (empirisk). I dynamisk nedskalning låter man en regional modell styras av utdata från en global modell, och får därmed som namnet antyder en dynamisk koppling mellan modellerna. I den dynamiska modellen simu-
leras utdata med hjälp av fysikaliska samband. I statistisk nedskalning gör man kopplingen med hjälp av statistiska metoder som översätter klimatsignaler i prediktorerna till effekter på det lokala väderet. Den metoden innebär att man inte försöker beskriva vädersystemen fysikaliskt, utan snarare att man fångar underliggande mönster i cirkulationen som är viktiga för prediktanden.

Nackdelarna med statistisk nedskalning är osäkerheten i huruvida de statistiska sambanden gäller i ett framtida klimat, att det krävs långa tidsserier av de ingående variablerna samt osäkerheten i klimatmodellerna. Den stora fördelen med metoderna är att de kräver väldigt lite datorkraft, det kan göras på en vanlig persondator. Metoden kan ge resultat med en hög geografisk upplösning eftersom varje mätstation på marken kopplas till den globala modellen.

Det övergripande syftet med denna avhandling var att utvärdera och utveckla metoder för statistisk nedskalning av nederbörd. Huvudfokuset ligger på viktiga statistiska egenskaper hos nederbörd såsom längd av torrperioder, extremhändelser och dagliga nederbördsmängder snarare än årsvariationen. Mer i detalj var målen:

- att utvärdera hur den analoga metoden (AM) fungerar som måttstock vid statistisk nedskalning i förhållande till mer komplicerade metoder
- att undersöka statistiska samband mellan prediktorer och prediktander med hjälp av olika nedskalningsmetoder för att hitta de prediktorer som är bäst lämpade för att förklara skillnader i prediktandens statistiska egenskaper
- att utvärdera generaliteten hos olika metoder för statistisk nedskalning genom att tillämpa dem på områden med stora skillnader vad gäller klimat och nederbörd
- att med hjälp av statistisk nedskalning undersöka effekten av olika klimatscenarion simulerade av en GCM på nederbörd för olika områden i Sverige

Studien utfördes inledningsvis på ett antal stationer i Mälardalen där de lokala förhållandena är väl kända, dels på tre områden i Kina med ett annat nederbördsmönster än Sverige. I klimatscenariostudien studerades förutom området i Mälardalen även ett område i norra Sverige (Torneälvs avrinningsområde). Nederbördens i Sverige varierar över året med störst nederbörd i augusti–september och minst på vintern. Nederbördens i Kina domineras av monsun-cirkulationen vilket ger
stora mängder under sommaren (april–augusti) då varmt fuktig luft strömmar in från syd-sydöst, och torrare klimat under vintermonsunen med kallare och torrare luft från inlandet. Tidpunkten och intensiteten på sommarmonsunen varierar dock kraftigt från år till år. De sydliga stationerna vid kusten får dessutom in stora mängder regn under sensommaren från cykloner i Kinesiska sjön.


De tekniker som användes för att analysera prediktorfältet i AM var dels principalkomponentsanalys (PCA), dels Teweles-Wobus Scores (TWS). PCA, även kallad empiriskt orthogonala funktioner (EOF) inom meteorologin, analyserar den korrelerade variationen hos ett antal tidsvariabler. I detta fall är variablerna noderna i ett rutnät av medeltrycket vid havsytan (MSLP) eller geopotentialhöjden till olika tryckytor (GPH). Om prediktorerna är korrelerade i rummet eller tiden delar PCA upp variationen i principalkomponenter (PC), och genom att endast använda sig av de PC som förklarar störst del av variationen filtreras prediktorn och ett fåtal variabler erhålls som kan användas i kopplingen till nederbörd. TWS jämför gradienter i prediktorfältet i longitudinal och latitudinell riktning och räknar fram ett mått på överensstämmelsen mellan olika fält. Analogen blir helt enkelt sedan det fältet med lägst TWS.

Två mer sofistikerade metoder användes också i nedskalningen, en regressionsmetod (SDSM) med villkorig koppling till en vädergenerator och en väderklassificeringsmetod (MOFRBC) med en stokastisk nederbördsmodell. SDSM kalibreras genom att ett antal prediktorer med hög korrelation till prediktanden styr sannolikheten och fördelningsfunktionen för nederbörd. Prediktorerna standardiseras genom att subtrahera medelvärdet och dividera med standardavvikelsen för en kontrollperiod. Nederbördens genereras sedan genom en slumpgenerator på de stations- och månadsvis kalibrera-de parametrarna.

MOFRBC använder sig av klassificerade, typiska circulationsmönster (CP) hos prediktorn. Klassificering av vädermönster har länge använts inom meteorologin och har traditionellt beståt av subjektiva bedömningar av circulationsstypen utifrån vissa förbestämda kriterier. MOFRBC klassificerar
CP i två steg. Först optimeras CP utifrån prediktanden så att typiska mönster med stora skillnader i nederbörd erhålls. Målet är att separera våta och torra CP. Klassificeringen görs sedan med hjälp av oskarp logik ("fuzzy rules logic"), där prediktorfältet sorteras in i en viss typ om de i tillräckligt stor grad uppfyller kriterierna för varje CP. Nederbördens modelleras sedan med en autokorrelerad och rumsligt korrelerad modell utifrån CP och månad.


I de första två studierna över Mälardalen användes endast MSLP som prediktor för att kunna jämföra metoderna så objektivt som möjligt. Resultaten visade att AM fungerar bra jämfört med en referenssimulering som utgjordes av en helt stokastisk AM. Det optimala prediktorfältet visade sig vara större för daglig än månatlig nederbörd. MOFRBC och SDSM gav generellt sett bättre resultat än AM för olika statiska mått på daglig nederbörd. MOFRBC överskattade nederbörd på en våt dag, speciellt på vintern, men metoden var bäst på att modellera längre torrperioder. SDSM modellerade statistisk fördelning av nederbörd bäst för vinter och vår. Det blev tydligt att klimatsignalen inte var helt tillfredsställande fångad när resultaten för de fem torraste och fem våtaste somrarna jämfördes. Ingen modell kunde uppvisa samma variation mellan olika klimat som den observerade nederbördens.

I nedskalningsstudien över Kina fungerade de två mer komplicerade metoderna också bättre än AM, men det var stor skillnad på resultat berorande på område. För de två områden som låg nära kusten fungerade alla metoder bra, speciellt för vintermånaderna (oktober–april). För det område som låg längre norrut och långt från kusten fungerade metoderna sämre. Detta indikerade att nederbördens i det området styrs av andra prediktorer än de som användes i studien, eller av andra lokala processer som inte metoderna tog hänsyn till. När metoderna inkluderade luftfuktighet och geostrofiska vindar förbättrades resultaten framför allt vad gäller korrelationen av nederbörds-mängd inom och mellan år.

Resultaten från nedskalningen från en GCM med MOFRBC gav avsevärt mer realistiska nederbördserier än den som erhålls direkt från GCMen, både vad gäller säsongsvariationen och extremhändelser. GCMen lyckades inte simulera statistiska egenskaper eller säsongsvariationen på ett trovärdigt sätt.
Studien visade också på vikten av att välja rätt prediktorer i en klimatstudie. Frekvensen av cirkulationsmönster ändrades inte avsevärt under olika framtidscenario, vilket innebar att om endast CP användes för att modellera nederbördens visade resultaten endast en liten ökning, men inte så mycket som väntat och inte för alla stationer. Längden på torrpoker minskade något. När luftfuktighet användes i nederbördsmodellen visade resultaten på en avsevärd ökning av nederbörd under dagar med nederbörd, och extremnederbörd men övriga statistiska mätt såsom sannolikhet för att en våt dag följs av en våt dag påverkas inte mycket. Ökningen av nederbörd var så mycket som 15–20 % för bägge områden för de flesta årstider.

Avhandlingen kan sammanfattas i följande slutsatser:

- AM fungerar bra som måttstock vad gäller statistisk nedskalning i jämförelse med mer sofistikerade metod. PCA och TWS har olika fördelar och nackdelar men är i stort sett likvärdiga metoder
- En nogrann analys i tid och rum i förhållandet prediktand-prediktor är oerhört viktigt i nedskalningsstudier för att uppnå bra resultat
- Nedskalningsmetoderna fungerade bra på områden med olika klimat. Ingen metod kan sägas vara den bästa. Den metod som bör väljas beror på syftet med studien
- När luftfuktighet inkluderades förbättrades nedskalningen av nederbörd för Kina, särskilt vad gäller mängd nederbörd på årstids- och helårsbasis
- Klimatsignalen är starkare i prediktorer såsom luftfuktighet än i storskalig variation av av lufttryck. En kombination av prediktorer rekommenderas vid fällstudier av en klimatförändring
- Nedskalade klimatscenari från HADAM3P-modellen indikerar en ökning av nederbörd över Sverige för perioden 2071–2100 vad gäller mängden regn på en våt dag och 5-dagars nederbörd. Ökningen verkade i huvudsak orsakas av en ökning i luftfuktighet snarare än en förändring av den storskaliga circulationen
Appendix 1. Case studies

Table 1. Selected statistical downscaling studies.

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<td>Charles et al., 2004</td>
</tr>
</tbody>
</table>
Appendix 2. PCA

The procedure compares the p eigenvectors, $C$, with the largest eigenvalues, $\lambda$, of the covariance matrix $R$ of $A$. The dimensionality of the problem is then greatly reduced:

$$RC = C\lambda$$

where $C = c_1, c_2, \ldots, c_p$ are the p eigenvectors (or principal components, PC) of $R$, and $\lambda$ denotes the eigenvalues of $R$. The anomaly field can be written as:

$$A(k,t) = \sum b_j(t)c_j(k) + \varepsilon(k,t)$$

where $b_j(t)$ is the projection of the anomaly field onto the $p^{th}$ principal component, $c_p$, and $\varepsilon(t)$ is the variability not described by the $p$ leading principal components.

A selection method is then devised. Consider an atmospheric anomaly pattern which has expansion coefficients $Z = z_1, z_2, \ldots, z_p$ in the same PC field as $B(t)$. The analogue of $Z$ is the $B(t)$ that minimises:

$$\sum_{i=1}^{p} (z_i - b_i(t))^2$$

Zorita and von Storch (1999) extended the PCA technique by introducing weights ($d_i$):

$$\sum_{i=1}^{p} |d_i(z_i - b_i(t))^2|$$

The weights are used to find the proportion of the PC patterns that has the largest influence on the target precipitation.
Appendix 3. TWS

The Teweles-Wobus Score (TWS) compares the shape of the SLP field, $P(k,t)$, by considering its gradients instead of its anomalies at each grid point. TWS was originally developed to evaluate the quality of geopotential-height forecasts (Teweles and Wobus, 1954). The method uses pressure gradients in N-S and E-W directions and the analogue is the field (from time $u$) that minimises:

$$TWS(t) = \frac{\sum_{k=i}^{j} g(k,t) + \sum_{k=j}^{i} g(k,t)}{\sum_{k=i}^{j} G(k,t) + \sum_{k=j}^{i} G(k,t)}$$

(11)

$$g(k,t) = \left| (P(k-1,u) - P(k+1,u)) - (P(k-1,t) - P(k+1,t)) \right|$$

(12)

$$G(k,t) = \max \left[ \left| P(k-1,u) - P(k+1,u) \right| , \left| P(k-1,t) - P(k+1,t) \right| \right]$$

(13)

where $g(k,t)$ is the difference in pressure gradient at grid point $k$ between the analogue (at time $u$) and the observed SLP field (at time $t$). Summation of gradients in N-S direction is denoted by $i$ and in E-W direction by $j$. $G(k, t)$ is the larger gradient of the two.
An object \((a_1,\ldots,a_k)\) is given the classification \(B_i\), \(i = 1, 2, \ldots, n\), depending on its DOF to a set of arguments \(A_{i,k}\) and its membership functions \(\mu_{A_{i,k}}\) for each rule \(V(k) = v(1)^k, v(2)^k, \ldots, v(n)^k\). The fuzzy rules are the indices of the membership functions are defined as triangular fuzzy numbers for the standardized (minimum value 0, maximum value 1) grid points that are included in each rule \(v\). The arguments AND \((F_a)\) and OR \((F_o)\), and the DOF \(D_i\) for each \(v\) is calculated as

\[
D_{iv} = \gamma_v F_a \left( \mu_v \left( a^v_k \right) \right) + \left( 1 - \gamma_v \right) F_o \left( \mu_v \left( a^v_k \right) \right)
\]  

(14)

where \(k = 1, 2, \ldots, K\) denotes the grid point location. The fuzzy arguments \(F_a\) and \(F_o\) are defined as:

\[
F_a(x_1, x_2, \ldots, x_R) = \prod_{r=1}^{R} x_r,
\]

(15)

\[
F_o(x_1, x_2) = x_1 + x_2 - x_1 x_2, \quad 0 \leq x \leq 1
\]

(16)

When the membership functions are more than two the convenient computation of \(F_o\) is implemented recursively as:

\[
F_o(x_1, x_2, \ldots, x_N) = F_o(F_o(x_1, x_2, \ldots, x_{N-1}), x_N)
\]

(17)

The weight \(\gamma_o\) is applied to loosen up the AND and OR statements to a mix of the two. Setting \(\gamma_o=0.7\) loosens the AND to A LEAST A FEW and OR to MOST OF. The value of 0.7 was selected by trial and error (Bárdossy et al., 1995).

If a classification is impossible it is given the label unclassified. Fuzzy rules have proven to give as good results as subjectively derived weather patterns, with the advantage that it can be performed on places where subjec-
tive weather patterns do not exist. An example of a fuzzy rule classification is the development of objectively derived weather patterns, i.e. pressure contours, from a large scale variable (Stehlik and Bárdossy, 2002).

The precipitation model is dependent on the circulation pattern and day of year \( t \) (Bárdossy and Plate, 1992; Stehlik and Bárdossy 2003). Let \( A = \{ \alpha_1, ..., \alpha_n \} \) be the set of atmospheric patterns from where the observed atmospheric pattern \( A_i \) is taking its value. The modelled precipitation amount \( Z \) at time \( t \) and point \( u \) is a random function

\[
Z(t,u) = \begin{cases} 
0 & \text{if } W(t,u) \leq 0 \\
W^\beta(t,u) & \text{if } W(t,u) > 0 
\end{cases}
\]  

(18)

where \( W(t,u) \) is a normally distributed random function for any location \( u \). The parameter \( \beta \) is a positive exponent that skewes \( W^\beta(t,u) \) to fit the precipitation distribution (Bárdossy and Plate, 1992). The relationship between \( W(t,u) \) and \( A \) is obtained by approximating \( \mu_0 \) and \( \sigma_0 \) of the Gaussian distribution through amount and distributions in time and space (Stehlik and Bárdossy, 2002). This approach links the discrete-continuous distribution \( Z(t,u) \) to a normally distributed function, which makes it easier to model multivariate processes. The distribution of precipitation at a certain location is CP dependent and is expressed as:

\[
P[Z(t,u) < z | \tilde{A} = \alpha_i, Z(t,u) > 0] = F_i(z | u) 
\]  

(19)

Moisture flux is implemented by first assuming a quasi-linear relationship between precipitation and moisture flux (Yang et al., 2005). Moisture flux is defined as geostrophic wind multiplied the specific humidity. The parameters of the Cp-dependant Gaussian distribution \( W(t,u) \) are replaced by the parameters \( \mu_i \) and \( \sigma_i \), estimated by means of the maximum likelihood function:

\[
\mu_i(t,u) = \mu_0 + a^* MF(t,u) 
\]  

(20)

\[
\sigma_i(t,u) = \sigma_0 
\]  

(21)
Where \( \phi \) denote the density distribution and \( \Phi \) the cumulative distribution of the Gaussian distribution, \( MF \) is the daily moisture flux, and \( a \) is a coefficient from the linear relationship between \( MF \) and precipitation.

The expected value is therefore dependent on both CP, humidity flux and time of year. The random process \( W(t,u) \) is defined as

\[
W(t,u) = r(t^*) \left[ W(t-1,u) - W(t^*-1,u) \right] + C_i(t^*,u) \Psi(t,u) \tag{23}
\]

where \( r(t^*) \) is the autocorrelation for one day time lag, \( i \) the CP on day \( t-1 \), \( C_i(t^*,u) \) is a matrix of spatial and space-time covariations and \( \Psi(t,u) \) is a random vector of independent normalized random variables. The autocorrelation function is independent on the circulation pattern, but dependent on the annual cycle, which in turn is approximated by a Fourier series, usually with three parameters.
Appendix 5. SDSM

The method is generally described as (Wilby et al., 2002a):

\[ \omega_i = \alpha_0 + \sum_{j=1}^{n} \alpha_j \hat{u}_i^{(j)} \]  

(24)

where \( \omega_i \) is the conditional probability of precipitation occurrence on day \( i \), \( \hat{u}_i \) are the normalized predictors and \( \alpha_j \) are the estimated regression coefficients. Precipitation occurs if \( w_i \leq r_i \), where \( r_i \) is a stochastic output from a linear random-number generator. The precipitation amount is modelled through:

\[ Z_i = \beta_0 + \sum_{j=1}^{n} \beta_j \hat{u}_i^{(j)} + \varepsilon \]  

(25)

\[ Z_i = \phi^{-1}[F(y_i)] \]  

(26)

where \( Z_i \) is the z-score calculated from the estimated regression coefficients \( \beta_j \) and the normally distributed stochastic error term \( \varepsilon \). Precipitation amount is then calculated from the cumulative distribution function \( \phi \) of the empirical distribution function \( F(y_i) \) of the daily precipitation amounts \( y_i \). It can be noted that the same predictors are used to model precipitation occurrence and amounts and that the predictors are standardized by subtracting the climatological mean and dividing with the standard deviations over the calibration period.
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