

Statistical downscaling and scenario construction of precipitation in Scania, southern Sweden

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Abstract Statistical downscaling models for precipitation in Scania, southern Sweden, have been developed and applied to calculate the changes in the future Scanian precipitation climate due to projected changes in the atmospheric composition. The models are based on multiple linear regression, linking large-scale predictors at monthly time resolution to regional statistics of daily precipitation on a monthly basis. To account for spatial precipitation variability within the area, the precipitation statistics were derived for different regions in Scania. The final downscaling models, developed for different regions and seasons, use atmospheric circulation, large-scale humidity and precipitation as predictors. Among the precipitation statistics examined, only the models for estimating the mean precipitation and the frequency of wet days were skilful. Based on the Canadian Global Circulation Model 1 (CGCM1), a future scenario of these two statistics was created. The downscaled scenario shows a significant increase of the annual mean precipitation by about 10% and a slight decrease in the frequency of wet days, indicating an increase in the precipitation amounts as well as in the precipitation intensity. The main increase of precipitation amounts and intensity occur during winter, while the summer precipitation amounts decrease slightly. The seasonal changes found in precipitation are likely attributed to changes in the westerly flow of the atmospheric circulation.

Keywords Atmospheric circulation; humidity; precipitation; scenario; southern Sweden; statistical downscaling

Introduction

The impact of climate change due to changes in the atmospheric greenhouse gas concentrations have implications for regional water resources and is of fundamental importance in the planning and managing of a sustainable society. To date, Global Climate Models (GCMs) are the best available tools to estimate future global climate changes. However, their spatial resolution is currently in the range of 200–500 km. This resolution is too coarse to study the changing climate and its impact on the environment on regional and local scales, essential for many applications in, for example, agriculture, forestry or civil engineering.

Various downscaling techniques have been developed in order to provide information on finer scales. These methods are generally divided into dynamical and statistical techniques (e.g. Murphy 1999). Statistical downscaling is based on the assumption that regional climate is conditioned by the large-scale climatic state and local or regional physiographic features, such as topography, land–sea distribution and land use (e.g. von Storch 1999). Based on this assumption, observed time series are used to establish an empirical relationship between local variables (predictands) and large-scale variables (predictors). Once these relationships are established from observations, they may be used to obtain local climate information from the large-scale GCMs, which are considered as being skilful in modelling atmospheric features at large scales. The general theory and practice of statistical downscaling are well described in the literature (Rummukainen 1997; Zorita and von Storch 1997; Xu 1999; Giorgi *et al.* 2001; Yarnal *et al.* 2001).

The focus of this study is on statistical downscaling and scenario construction of the monthly statistics of daily precipitation covering both mean and variability measures. It is well established that the greenhouse-gas-induced climate change does not only influence mean precipitation but also may affect precipitation variability and the occurrence of extreme events (Cubasch *et al.* 2001). In the model constructions, the focus is placed on the identification of relevant predictors and the most skilful model rather than on testing different modelling techniques. This was identified as one of the issues of special interest for the development of statistical downscaling in the IPCC third assessment report (Giorgi *et al.* 2001).

The study is performed in Scania, southern Sweden covering an area of about 10,000 km². Scania is one of Sweden's most important agricultural areas and one of the most populated regions, making estimates of regional precipitation changes important from a socio-economic point of view. A large number of precipitation stations located in Scania are included in this study, which enables an estimation of areal precipitation values. By including several monthly statistics of the daily data, covering both mean and variability, as well as by using areal values rather than point values, this work extends earlier studies by Hellström *et al.* (2001). They constructed monthly precipitation scenarios for 40 Swedish precipitation stations, deriving regional changes in precipitation on a seasonal scale.

The large number of precipitation stations in Scania also enables an evaluation of regional differences in the predictions of climate change in the area. Earlier studies by Linderson (2003) showed the existence of different precipitation regimes within Scania, which motivates a detailed study of regional differences in the climate change estimates.

The objectives of this study are: 1) to construct regional precipitation statistics from the daily observations in Scania; 2) to identify relevant large-scale predictors that are important for these statistics; and 3) to establish statistical downscaling models and, if successful, to use them to create a future scenario of the monthly statistics. In hydrological modelling, monthly statistics can be used directly to drive some hydrological models. However, daily values of precipitation may be needed in other cases. Then monthly statistics are useful in the disaggregation of monthly statistics to a daily scale (e.g. Xu 1999).

Data description

The Scanian precipitation network

The observed precipitation data used in the regionalisation of Scanian precipitation consists of monthly values of daily precipitation measurements from 178 gauges between 1974 and 1990. This corresponds to a station density of 1 station/100 km². This dense rain-gauge network was obtained by combining a regional network of daily measurements, the 'Elleson dataset' (Elleson 1993), with precipitation measurements made by SMHI (the Swedish Meteorological and Hydrological Institute). The daily precipitation statistics used to develop the statistical downscaling models were, however, obtained for the period 1961–1990 from measurements from 30 gauges. Also these stations originate from the Elleson dataset and SMHI (Figure 1).

The stations of the Elleson dataset were equipped with the SMHI standard rain gauges. Observations were made at standard time (06:00 UTC) and the quality of the dataset was controlled thoroughly (Niemczynowicz *et al.* 1993). Homogenisation of the data and interpolation of missing data is described by Linderson (2003).

Large-scale climate data

To develop the statistical models, gridded monthly data from the NCEP-NCAR reanalysis project (Kistler *et al.* 2001) for the period 1961–1990 has been used. These include

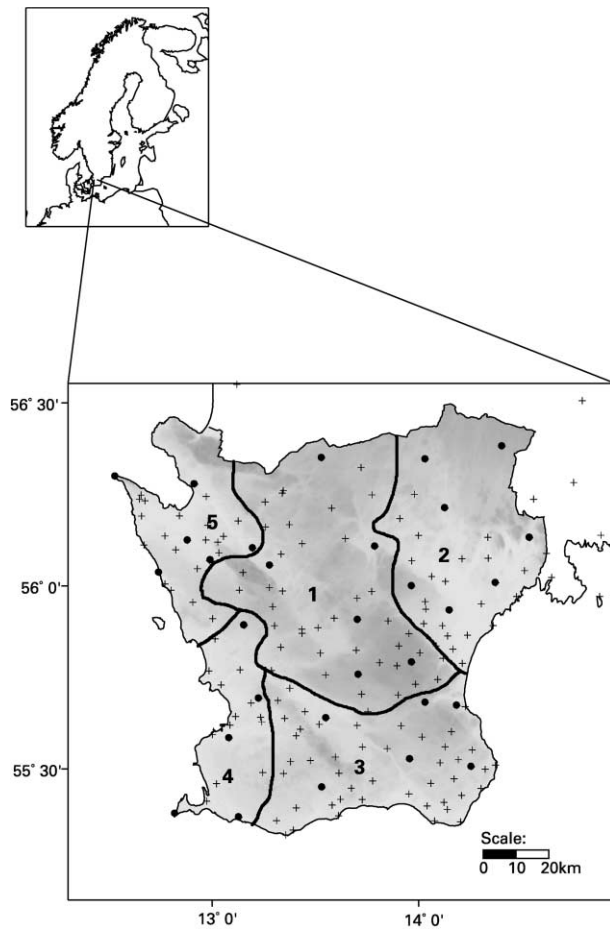


Figure 1 Investigation area. Numbers indicate regions. Dots indicate stations used for the regional series. Crosses (and dots) indicates stations used in the regionalisation. The grey scale shows the topography of the area. Darker shades correspond to higher elevation

mean-sea-level pressure and precipitation, as well as specific humidity and temperature at the 850, 700 and 500 hPa heights. From these fields, a set of possible predictors was formed that were tested and evaluated in the model development.

GCM data

The GCM data used in this study comes from the Global Coupled Model (CGCM1) developed at the Canadian Centre of Climate Modelling and Analysis (CCCma) and described in detail by Flato *et al.* (2000) and Boer *et al.* (2000). The coupled model's atmospheric part has a horizontal resolution of $3.75^\circ \times 3.75^\circ$ using 10 vertical levels, whereas the oceanic part has a resolution of $1.8^\circ \times 1.8^\circ$ and uses 29 levels in the vertical.

The scenario experiment used in this study applies a greenhouse forcing corresponding to the observed one for 1850 until the present day, and thereafter the CO_2 concentration increases at a rate of 1% per year until the year 2100 (IPCC "IS92a" forcing scenario, Houghton *et al.* 1992). Further, this experiment includes the direct effect of sulfate aerosols. Between 1980 and 2050, the prescribed CO_2 concentration is doubled which leads to a mean global temperature increase of 1.6°C and an intensification of the hydrological cycle (Boer *et al.* 2000). From these control and scenario experiments, the predictors necessary for the

statistical downscaling were extracted. The data covers the years 1961–1990 (control) and the years 2041–2070 (scenario).

CGCM1 was chosen in this study since it provided the data necessary to derive the different predictors and since this data was readily available. The model has been evaluated and inter-compared within the Coupled Model Intercomparison Project (CMIP1) as one of 15 GCMs (Lambert and Boer 2001). On a global scale, the model is skilful in reproducing the spatial patterns of interannual variability of mean-sea-level air pressure, but the magnitude is underestimated in the extra-tropical storm track regions. Also for precipitation it was shown that the model reproduces the observed global-scale spatial patterns in the winter and summer seasons. Further, the magnitude and seasonal cycle of precipitation variability is realistically captured in various geographical regions (Flato *et al.* 2000). Evaluating 12 GCMs in Northern Europe, Räisänen (2000) found that the CGCM1-modelled seasonal precipitation exceeded the uncorrected observed precipitation for the period 1961–1990 in that area by about 25–75%, depending on the season. In his study, wet models turned out to also overestimate temperature, which is also the case for CGCM1. To some extent the wet and warm bias in winter might also be attributed to a stronger gradient in mean-sea-level pressure between Central and Northern Europe, resulting in increased advection of warm and maritime air masses from the Atlantic.

Precipitation climate in Scania

General features of the observed precipitation climate

Scania forms the southernmost part of Sweden and corresponds to an area of 10^4 km^2 (Figure 1). The landscape is undulating with low ridges, up to around 200 m above sea level, in a dominant SE–NW extension. The region lies in the zone of prevailing westerlies and has a maritime, warm temperate climate. The area is largely affected by cyclonic activity throughout the year that is strongest during winter when the temperature contrasts between the tropical and polar air masses are the greatest. On average, the region obtains 660 mm of rain per year as estimated from uncorrected observations using 170 gauges (Blennow *et al.* 1999). When taking various losses related to the precipitation measurements into account, the corrected mean precipitation is increased by about 15% (Raab and Vedin 1995), amounting to 750 mm per year. Despite the relatively homogeneous landscape, the spatial precipitation distribution is clearly affected by the topography as well as the land–sea distribution (Linderson 2003). On an annual timescale, precipitation is increased by 150 mm/100 m due to orographic uplift (Blennow *et al.* 1999). The spatial scale at which the precipitation climate varies in Scania has been estimated at 20–100 km, depending on direction (Achberger *et al.* 2003) and is mainly influenced by topography and distance to the coast.

Deriving regional precipitation statistics

To define the regions for which the downscaling models were developed, the Scanian precipitation was regionalised by cluster analysis. The clustering was applied to the first four vectors of an EOF analysis, which was previously performed by Linderson (2003). For this analysis, monthly mean precipitation series of 178 stations for the years 1974–90 were used. Several techniques are available to cluster variables with similar affinities. When the nature and numbers of regions are unknown, a hierarchical agglomerative method is the best alternative (Bonell and Sumner 1992). This method determines the number of clusters after the clustering process is finished and the final number of clusters is based on the similarity level between clusters. Nevertheless, the method assumes an underlying hierarchical structure in the data that may not be present. If no such structure is assumed, a non-hierarchical technique may be preferred, although this method demands a predefined number of classes (Everitt 1986). Depending on the measures chosen for distance and similarity, the results obtained from

the clustering process may differ. In general, it is recommended to test several clustering strategies and to use the one that yields the most logical or easily explained grouping (Everitt 1986).

Both agglomerative hierarchical clustering and non-hierarchical clustering were tested with different number of groups (3–6), and with various distance and similarity measures. Most of the different approaches pointed out one inland cluster surrounded by westerly, easterly and southerly clusters, depending on the number of clusters. The final regionalisation was based on a non-hierarchical clustering with 4 groups. The western group was subjectively divided into one northerly and one southerly group (Figure 1), based on earlier results that showed the difference in precipitation distribution between northern and southern areas of Scania (Linderson 2003).

From each of these clusters, 5–7 stations comprising the daily data for the period 1961–1990 were selected. These daily series formed the basis for deriving monthly statistics describing the character of daily rainfall variability: mean, median, 75% percentile, 95% percentile and standard deviation. The parameters were calculated based on series including all days (i.e. dry and wet days) and series considering only wet days (>0.1 mm/day). Furthermore, the maximum and the frequency of wet days were estimated. All parameters are given in Table 1. For each region and monthly statistic, a mean series was formed from the average value of all stations included in the region. Finally, these series were transformed into a series of anomalies by subtraction of the climatological monthly means for the period 1961–1990.

Development and evaluation of the statistical downscaling model

There are several methods in statistical downscaling, generally divided into transfer functions, stochastic weather generators and weather-typing approaches (e.g. Wilby and Wigley 1997; Giorgi *et al.* 2001). Transfer functions embrace the linear regression between large-scale and local-scale parameters (Hansen-Bauer and Førland 1998; Murphy 2000) as well as canonical correlation analysis (CCA) and singular value decomposition (SVD) (Busuioc *et al.* 1999; Uvo *et al.* 2001). Furthermore, neural networks are used to include complicated non-linear interactions (Hewitson and Crane 1996; Olsson *et al.* 2001). Weather typing employs the use of a classification scheme, either objectively derived for example by PCA (Busuioc *et al.* 2001a; Ekström *et al.* 2002) or subjectively obtained using preset criteria (Jones *et al.* 1993; Schubert 1994; Linderson 2001). Weather generators are statistical models of observed

Table 1 Precipitation statistics used as predictands in the regression model development

Predictands	Abbreviation
<i>Daily precipitation – all days</i>	
Mean	Allmean
Median	Allmedian
75% percentile	Allperc75
95% percentile	Allperc95
Standard deviation	Allstdev
<i>Daily precipitation – wet days (precipitation > 0)</i>	
Mean	Mean
Median	Median
75% percentile	Perc75
95% percentile	Perc95
Standard deviation	Stdev
Frequency of wet days	Freq wet-day
Maximum value	Max

sequences of weather variables, where the weather generator parameters may be conditioned upon a large-scale state, for example atmospheric circulation type (Goodess and Palutikof 1998; Corte-Real *et al.* 1999) or based on relationships between large-scale and local-scale climate parameters (Conway *et al.* 1996; Wilby 1998; Wilks 1999). When using the weather generator and weather-typing approaches, the daily resolution of the large-scale variables is needed.

In this study, a regression-based approach was used. A number of large-scale variables were tested for their usefulness in describing the relation between monthly large-scale data and local monthly precipitation statistics in Scania. Stepwise regression and multiple regression were applied to screen the potential predictors and to establish links between the predictors (large-scale climate variables) and predictands (local precipitation statistics). Stepwise regression was used to search for variables that are useful for explaining various precipitation statistics for different regions and seasons. Thereafter, multiple regression was used to develop separate models for each statistic, season and region. All the models were developed using the same predictors regardless of season, type of statistics and region.

Seasonal models were developed to account for variations in the precipitation-forming processes that might differ from season to season. Compared to monthly models, the seasonal models were developed on a larger amount of data, resulting in higher confidence in the models without increasing the number of years. This is necessary as the data series are relatively short (30 years). The seasons used here are defined as winter (December to February), spring (March to May), summer (June to August) and autumn (September to November).

Choice of predictors

Regional variations in the local climate are highly connected to the large-scale circulation of the atmosphere (e.g. Chen 2000; Linderson 2001). Therefore, the atmospheric circulation is often used as a predictor in statistical downscaling applications. A widely used approach is to summarise the large-scale atmospheric circulation patterns into circulation indices (Yarnal 1993; Yarnal *et al.* 2001). These circulation indices divide the motion of the atmosphere into zonal and meridional flow components as well as a vorticity component and are calculated from gridded mean-sea-level pressure data (Jones *et al.* 1993; Linderson 2001). Circulation indices served as predictors in several studies aiming at the downscaling of precipitation, e.g. for Sweden (Hellström *et al.* 2001), the Netherlands (Buishand and Brandsma 1997), and the British Isles (Conway and Jones 1998; Osborn *et al.* 1999). Further, the spatial precipitation patterns in Scania are largely influenced by these circulation indices (Linderson 2003). However, other factors than the circulation may also be important for precipitation climate in Sweden (Johansson and Chen 2003). As a result, the indices of atmospheric circulation alone are not sufficient to estimate the future precipitation climate (Hewitson and Crane 1996; Wilby *et al.* 1998; Murphy 2000; Busuioc *et al.* 2001b). Some other factors must be included to account for the effect of a temperature increase, as temperature determines the moisture content and thus the amount of precipitable water. Murphy (2000) showed that atmospheric humidity has a low statistical significance in the downscaling models developed for Europe. However, Hellström *et al.* (2001) developed a skilful model for the downscaling of monthly precipitation in Sweden based on circulation indices and large-scale humidity. The type of humidity measure used in downscaling may affect the model results (Charles *et al.* 1999; Beckmann and Buishand 2002).

Several large-scale climate parameters centred over Scania were statistically tested in the development of the model (Table 2). The circulation indices vorticity (Vort), u-wind (u), v-wind (v), resultant wind (F) and divergence (D) are all estimated from gridded MSLP data, following the method of Jones *et al.* (1993); Wilby and Wigley (2000), and previously

Table 2 The large-scale climate variables used as predictors in the regression model development. Bold predictors are used in the final downscaling models

Predictors	Abbreviation
Large-scale precipitation 10 × 10 degrees	P10
Vorticity	Vort
u wind	u
v wind	v
Resultant flow	F
Divergence	D
Specific humidity at 850 hPa 10 × 10 degrees	q850
Relative humidity at 850 hPa 10 × 10 degrees	RH850
Mean temperature at 850 hPa 10 × 10 degrees	T850
Stability index 10 × 10 degrees	KIND

applied to Scania by Linderson (2001). From the precipitation, humidity and temperature fields, large-scale averages serving as predictors were formed by averaging the grid points located in a $10^\circ \times 10^\circ$ large area that has its centre over Scania (15°E , 55°N). These averages were derived both from the reanalysis data and from the GCM. Specific (q850) and relative humidity (RH850), and temperature (T850) at the 850 hPa geopotential height, were used as a measure of the atmospheric humidity. Furthermore, a stability index was used (KIND) based on temperature and dew point temperature at different levels (Murphy 1999). The index is defined as

$$\text{KIND} = (\text{T850} + \text{TD850}) - \text{T500} - (\text{T700} - \text{TD700}) \quad (1)$$

where T850, T700 and T500 are temperatures at the 850, 700 and 500 hPa geopotential heights and TD are dew point temperatures at the 850 and 700 hPa geopotential heights. The index is a measure of the vertical temperature gradient and accounts for the development of convective precipitation. Finally, all predictor time series were transformed to anomaly series by subtracting the monthly mean from each month.

Building and evaluating the downscaling model

Stepwise regression was performed to choose those predictors that are most relevant for the downscaling model (von Storch and Zwiers 1998). This was done for each of the 12 possible predictands, for all 5 regions and 4 seasons. Using stepwise regression, a new variable is added into a multiple regression model, if the regression sum of squares is reduced, in successive stages. For each stage, redundant predictors are excluded. This procedure is repeated until the model is no further improved. Stepwise regression assumes linear relations between the predictors and the predictands, which is not necessarily the case. Thus, prior to the stepwise regression the linearity of the relationships between the predictors and predictands was checked. Only the stability index, KIND, was clearly non-linearly related to the observed precipitation. Thus, prior to the stepwise regression, the index was transformed to achieve a linear relationship. For all predictors used in the final models (GCM control and scenario), the GCM predictors are in the same range as the observed fields (NCEP data) and linear models were thus considered valid for the whole range of all GCM fields.

Focusing on the statistics with the highest explained variance (R^2 values), the predictors frequently occurring in the stepwise regression as significant (at the 0.05 significance level) were selected for further model development. These predictors were the large-scale precipitation, the circulation indices u, v and Vort and the relative humidity at 850 hPa. Since the same set of predictors was used for all multiple linear regression downscaling models,

regardless of season, type of statistics and region, their contribution to the explained variance in the observed precipitation varies with predictand, season or region. In Table 3, t values of the included predictors, that indicate the significance of the predictor, are displayed for selected statistics. Predictors marked as significant have a significant influence on the explained variance of the model and it is thus highly motivated to use them. Due to the nature of the multiple linear regression method, the issue of potential multicollinearity/multicollinearity between predictors had to be addressed. Multiple linear regression assumes statistical independence between predictors. However, this is sometimes difficult to fulfil. If the predictors are closely correlated, these variables contain redundant information, which reduces the confidence of the regression coefficients estimated. As a consequence, it might be difficult to diagnose the most important predictors (von Storch and Zwiers 1998). Multicollinearity is not a problem in stepwise and multiple regression, unless the correlations between the predictors are very high. Various methods exist and provide at least some means of helping detect collinearity (Belsley *et al.* 1980). A frequently used one is the variance inflation factor (VIF). One criteria is that, if the VIF is greater than 10, the multicollinearity is presumed to be serious. An examination of the selected predictors for the observed and modelled datasets showed that all of the VIF were well below 10, which excluded a serious problem with multicollinearity. One exception is vorticity during spring, which is closely correlated with other predictors. Thus, the vorticity is not used for the final model for that season.

Table 3 t values for all final predictors used in the regression model for region 1. Models estimating the predictands mean, standard deviation and 95% percentile of precipitation and the frequency of wet days are shown. Bold: p value < 0.05, bold italic: p value < 0.01

	Winter	Spring	Summer	Autumn
<i>Allmean</i>				
P10	6.1	0.8	2.9	2.9
u	3.6	6.2	1.8	5.2
v	4.1	3.9	1.7	1.7
RH850	-0.2	4.6	1.5	1.0
Vort	2.0	-	1.6	4.2
<i>Freq wet-day</i>				
P10	1.5	-0.2	2.9	-0.2
u	5.4	6.8	6.3	8.3
v	3.2	2.6	2.1	2.8
RH850	3.5	7.8	4.0	3.8
Vort	1.2	-	1.2	3.0
<i>Allstdev</i>				
P10	5.2	0.5	1.3	3.2
u	1.1	3.6	-0.8	1.1
v	2.2	3.0	0.8	0.8
RH850	-0.2	2.1	1.1	-0.7
Vort	0.4	-	1.3	1.9
<i>Allperc95</i>				
P10	4.7	0.6	1.2	2.2
u	2.0	4.5	0.5	2.4
v	2.4	3.8	0.6	0.6
RH850	-0.6	2.8	0.8	1.1
Vort	1.0	-	1.9	1.4

The large-scale precipitation (P10) represents the synoptic scale processes in the atmosphere, including changes in air humidity and movements of the air. P10 was shown to be an important predictor in all models, but not sufficient to be used alone as a predictor of the local precipitation statistics in Scania (Tables 4 and 5). Thus, even if the amount of precipitation that falls within a smaller region is highly dependent on P10, it is modified by other factors. There is a clear difference in the shape of the seasonal cycle (mean and standard deviation) of P10 compared to the observed precipitation in Scania: the seasonal cycle of P10 seems to be more influenced by continentality with a clear summer peak, while the observed precipitation has a more maritime character.

The indices u and v substantially increase the explained variance in several models. The maritimity of the region is generally influenced by the zonal airflow (u). Furthermore, local wind directions vary with the values of the u and v indices. Airflow from the sea causes orographic enhancement of the precipitation when the humid air is forced to rise over land. Earlier results show that westerly winds give higher precipitation amounts in the northwest of Scania and at elevated inland areas while easterly winds give precipitation on the eastern part of Scania (Linderson 2003).

RH850 also substantially increases the explained variance for several statistics and this is in agreement with the results by Murphy (2000); Beckmann and Buishand (2002).

Table 4 Explained variance (R^2 adj.) of selected predictands by the predictor P10

	Winter	Spring	Summer	Autumn
Allmean	68.7	36.8	48.7	56.0
Freq wet-day	47.0	39.1	48.2	37.1
Allstdev	53.8	18.1	22.1	36.9
Allperc95	53.5	24.8	25.9	35.9

Table 5 Explained variance of the final downscaling models for the predictands with the highest explained variance

	Region	Winter	Spring	Summer	Autumn
Allmean	1	75.1	61.5	53.1	69.0
	2	70.0	51.8	49.4	70.0
	3	67.2	49.7	35.5	58.8
	4	66.3	53.0	51.4	67.2
	5	66.4	53.6	51.1	70.3
Allperc95	1	55.5	42.9	27.2	39.4
	2	47.3	30.5	27.4	31.8
	3	46.9	29.7	16.1	31.6
	4	43.3	31.9	22.1	37.1
	5	42.6	29.3	26.4	37.6
Allstdev	1	54.4	30.8	21.9	38.4
	2	49.3	23.2	21.7	38.5
	3	47.0	21.3	13.5	32.0
	4	49.2	27.0	23.6	34.3
	5	46.0	26.2	18.2	34.9
Freq wet-day	1	67.3	72.1	72.9	68.1
	2	76.6	68.5	67.1	76.0
	3	73.3	70.8	72.5	65.1
	4	71.5	74.3	65.0	60.9
	5	69.1	73.3	74.5	71.8

The general importance of RH850 as a predictor for the frequency of wet days can be due to the fact that the scale of relative humidity corresponds rather to the occurrence of rain than to the precipitation amounts. When the relative humidity of the air reaches its maximum value, the air is saturated with water vapour and precipitation occurs but the amount of precipitation may vary. In springtime, RH850 is an important predictor that clearly raises the explained variance of the models. This can be a consequence of the chilling effect of the cold water of the sea surrounding Scania on the air temperature, resulting in a locally higher stability as well as lower specific humidity. This is supported by the results of Linderson (2001), showing that the cyclonic weather type is most frequent in springtime even though there is a minimum in the precipitation amount falling over the area.

The importance of vorticity as a predictor is most evident in autumn. This may reflect the fact that the cyclonic activity in general has a large influence on the observed precipitation in Scania during this time. Precipitation that is formed in connection with low-pressure systems may also be enhanced due to the relatively high temperatures of the sea during autumn, leading to unstable conditions and a higher amount of moisture in the relatively warm air.

Some of the originally proposed predictors did not contribute to increasing the explained variance of the regression models. In contrast to the results of Murphy (2000), the stability index did not improve the regression. Neither the divergence nor the resultant flow increased the explained variance. This is most likely due to the fact that these variables are highly correlated with the chosen predictors. Therefore, these predictors were excluded. Finally, P10, RH850, Vort, u and v were used as predictors for the final downscaling models.

The R^2 values of the established models show that the explained variance varies depending on statistics. As an example, R^2 values are given for four selected predictands in Table 5. In general, model performance is better for statistics developed from the complete time series than for statistics based on only wet days. This might be explained by the high percentage of dry days, which makes these measures sensitive to single events not captured by the monthly resolution of the predictors. The performance of the models estimating the statistics for the extremes and variability of precipitation is generally not satisfactory. The 95% percentile and the standard deviation were the statistics representing extreme values and variability with the highest R^2 values (Table 5). Judging from the level of the R^2 values, mean precipitation and the frequency of wet days are the only statistics that could be considered to be reasonably well estimated for all seasons. Hence, the final model was established only for these two variables. Table 5 further shows a clear seasonal dependence in the R^2 values with lower explained variance during spring and summer. This is in accordance with earlier results (Linderson 2003) and is due to the increased influence of local factors on the precipitation process during these seasons.

Cross-validation was used to validate the models, as it enables an independent verification of relatively short time series (von Storch and Zwiers 1998). All available data except for a small sample is used for model development. The procedure is repeated for different samples of the data. In this way, a sequence of verifications can be used to create verification statistics. This method is especially relevant here as the data period is only 30 years. Due to the relative shortness of the data period, models were developed seasonally. It is also assumed that the statistical relations established by using the 30-year data are valid for future climates, as for all other statistical downscaling methods. The cross-validation for the selected statistics showed that the models are skilful for all seasons.

For all seasons, there are considerable differences among the regions in one or more regression coefficients. Mainly, the influence of the u wind varies among the regions. Figure 2 shows the regression coefficients standardised by the standard deviation for the winter season. The coefficients of the u wind are higher for regions 1 and 5 and lower for regions 2, 3 and 4. This is in accordance with results found by Linderson (2003) where the

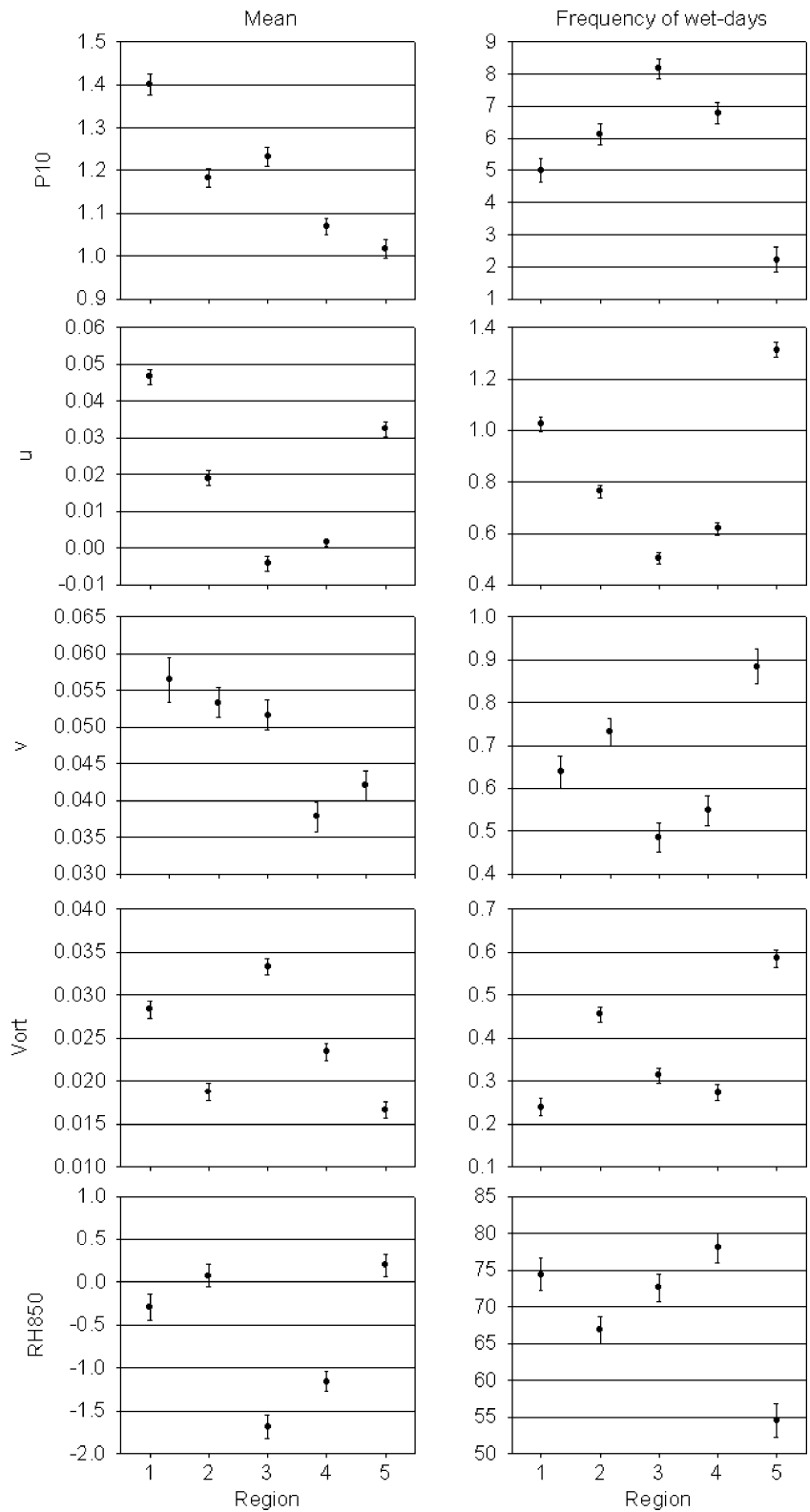


Figure 2 Standardised regression coefficients of the winter downscaling models with 95% confidence intervals

wind direction was shown to influence both the daily and the monthly precipitation distribution in a similar way. The v-wind coefficients for the mean are lower for the westerly regions 4 and 5. The magnitude of the coefficients for the u and v wind reflects the exposure to wind from the sea, giving higher precipitation amounts due to orographic enhancement. Considering mean precipitation, the regional differences in the coefficients for P10 mainly reflect differences in the observed amounts. For Vort and RH850, the patterns are not clear. The southerly regions tend to follow each other, with lower coefficients for RH850 and higher Vort coefficients for mean precipitation and a combination of higher coefficients for RH850 and lower coefficients for Vort for the frequency of wet days. The northerly regions 2 and 5 show the opposite pattern. As the regional differences in terms of the regression coefficients are considerable and most likely physically reasonable, the regions were kept for the scenario constructions.

Scenario construction

To obtain the downscaled scenarios, the final regression models were fed with the predictors u, v, Vort, P10 and RH850 obtained from the CGCM1 control and scenario runs. To compensate for the bias in the GCM seasonal cycle (e.g. Winkler *et al.* 1997; Huth and Kyselú 2000), the anomalies of all GCM predictors were calculated with reference to the control climate. Then the anomalies were fed into the statistical model to obtain the anomalies in local precipitation. Finally, the seasonal cycle of the observed local precipitation was added to the modelled anomalies. Expressing the changes in the precipitation statistics in percent of the observed climate, the annual increase in mean precipitation is 10.8% (+72 mm/yr) estimated as an average for all five regions. The change is statistically significant at the 95% level. A general feature in simulations of climate changes for the last decades of the 21st century is an increase of winter precipitation over northern latitudes as well as an increase in precipitation over Europe (Giorgi *et al.* 2001). Recent estimates of the future precipitation climate in Sweden indicate a change in mean precipitation between -5 and +10% in southern Sweden using both statistical and dynamical downscaling (Hellström *et al.* 2001). Bergström *et al.* (2001) estimated the change in mean precipitation to range from +3 to +6% in southern Sweden based on dynamical downscaling.

The mean annual frequency of wet days decreases by 1.4% (-2 days/yr) but this decrease is not statistically significant. A decrease of the number of wet days at mid-latitudes has also been observed by Beckmann and Buishand (2002).

For all regions in Scania, the mean precipitation increases while the frequency of wet days decreases (Figure 3). The change in frequency of wet days is larger in the northwestern regions (1 and 5). For mean precipitation, the largest change occurs in region 1 and the smallest in region 5. Nevertheless, the differences are rather small. The magnitude of the changes (expressed as percentages) for the individual months is shown in Figure 4(a) and (b). The change is rather similar between regions but varies clearly with season. Since the regional differences are rather small, a mean of all regions was used for further analysis of the change in precipitation statistics.

The mean precipitation increases mainly during winter, but also in late autumn, whereas it will decrease during spring and summer. Furthermore, the frequency of wet days increases in winter (December to February) and decreases in the period April to November (Figure 5(a)). The change in mean precipitation is significant on the 95% level in June, December, January and February and for the frequency of wet days in June, January and February. Figure 5(b) and (c) show how the predicted changes influence the seasonal cycle of mean precipitation and the frequency of wet days. Both mean precipitation and the frequency of wet days increase in winter and decrease in June compared to today's conditions. Due to the pronounced increase predicted in February, the precipitation minimum in late winter is

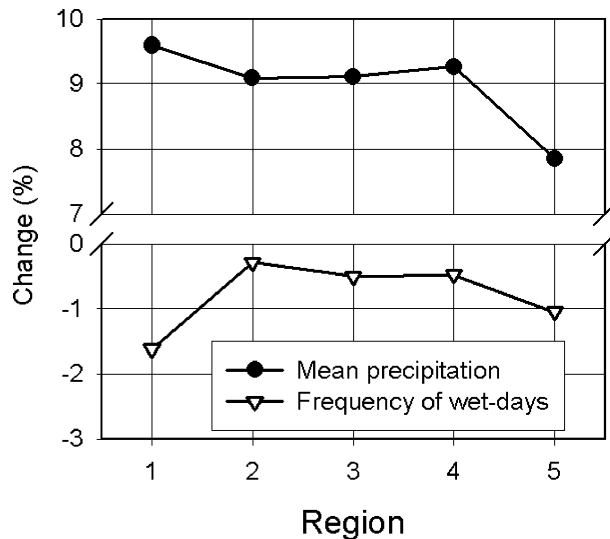


Figure 3 Regional difference in the changes of annual mean and frequency of wet days. The differences are expressed as a percentage of the observed climate

delayed while the predicted decrease in June results in a delay of the summer increase. The results are in accordance with Palmer and Räisänen (2002), who found that winter precipitation will increase in Northern Europe. Studies in Northern Germany and the Netherlands also show an increase in precipitation during the winter half-year and a decrease during the summer half-year (Beckmann and Buishand 2002).

The difference between the change in frequency of wet days and the change in mean precipitation indicates an increase in the precipitation intensity almost all year round. In winter, the increase in mean precipitation is 2–3 times as high as the increase in frequency of wet days. A number of dynamical downscaling efforts also show an increase in the intensity over Scandinavia, mainly during autumn (Christensen *et al.* 2001). The difference in changes between mean precipitation and the frequency of wet days is influenced by the predictors used. The frequency of wet days is more dependent on RH850 than on P10. Even the type of humidity predictor used in statistical downscaling can influence the results (Charles *et al.* 1999; Beckmann and Buishand 2002).

Comparisons of the change in downscaled precipitation with the change in predictors reveal some interesting features of the influence of the predictors, as shown in Table 6. There is a winter increase and summer decrease in u , Vort and P10 which all contribute to the increased winter precipitation and decreased summer precipitation. These changes in winter and spring indicate an enhanced westerly flow with an increased cyclonic activity over the area. In summer, the flow decreases, resulting in less maritime air masses. The large summer decrease in v , leading to colder and more stable air masses, enhances the decrease in precipitation during summer and diminishes a possible increase in precipitation due to increased westerly flow during autumn. The change in relative humidity is small over the year with a slight decrease on an annual basis.

Summary and concluding remarks

The purpose of this study was to develop statistical downscaling models for a number of monthly statistics of daily precipitation in Scania and to construct future precipitation scenarios of selected statistics based on a GCM (CGCM1) projection. Furthermore, a number of frequently used large-scale predictors were evaluated for their suitability in

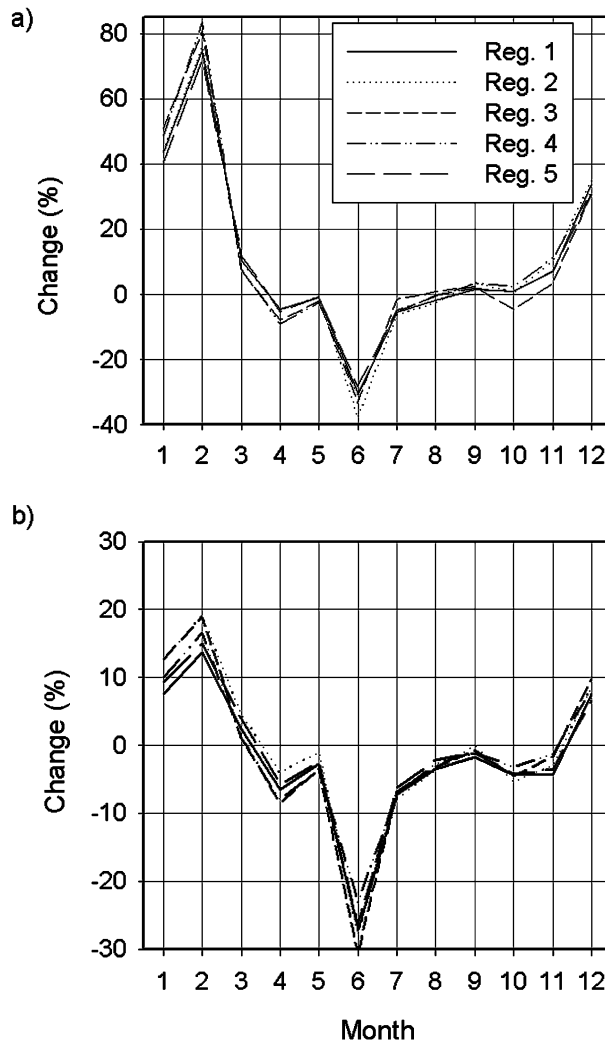


Figure 4 Regional differences in the changes of the seasonal cycles for two statistics. (a) Mean precipitation. (b) Frequency of wet days

statistical downscaling. To account for differences in the observed spatial precipitation regime, Scania was divided into 5 regions and corresponding statistics and downscaling models were developed for each of these regions.

Based on results of the stepwise regression with all possible predictors and a number of monthly precipitation statistics, the final downscaling models were established using large-scale precipitation and relative humidity as well as the circulation indices corresponding to u wind, v wind and vorticity as predictors. Skilful models are only found for the mean precipitation and the frequency of wet days. The R^2 values are generally low for measures of extreme statistics and statistics of only wet days.

Despite the relatively high similarities in the Scanian precipitation variability, there are differences among regions in the relationship between observed precipitation and the large-scale variables. These differences could be physically explained. However, regional

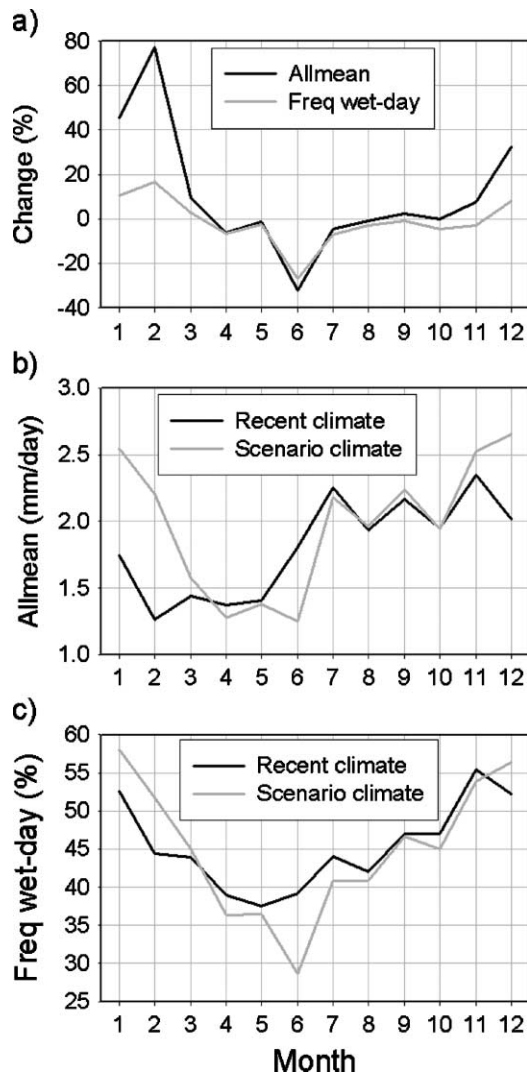


Figure 5 Change of the seasonal cycle for mean precipitation and frequency of wet days. (a) Change in percent of observed climate, (b) observed monthly means and monthly means with percentage changes added to today's climate, (c) as (b) but for the frequency of wet days

scenarios for mean precipitation and the frequency of wet days showed roughly the same results, implying a consistent long term change over the whole region.

The downscaled precipitation shows an annual increase in the mean precipitation of 10.8% (+72 mm/yr) that is statistically significant at the 95% level. The annual frequency of wet days is decreased by 1.4% (-2 days/yr). The difference between the change of mean precipitation and the change in the frequency of wet days indicates an increase in the precipitation intensity almost all year round, especially during winter. The mean precipitation increases from November to March and decreases from April to August. A corresponding increase in the frequency of wet days occurs between December and March while the decrease occurs in April to November. The major changes correspond to a large increase in precipitation in winter, a delay of the observed summer increase and a prolonged winter maximum. This indicates a more maritime precipitation climate in the scenario climate compared to the control climate. These possible changes have important implications for society, both with respect to the

Table 6 Seasonal percent change between GCM control and scenario downscaled precipitation for the predictors

	Winter	Spring	Summer	Autumn	Year
P10	21	8	-5	7	8
RH850	0	-1	-2	-3	-2
u	13	19	-30	13	3
v	0	-8	-26	-54	-9
Vort	48	38	-89	-8	-3

enhanced occurrence of flooding in connection with the increased winter precipitation, and for water management, e.g. in agriculture, if irrigation is needed during spring and summer. A wetter spring climate may also affect the drying up of the soil, causing a delay in the start of the agricultural growing season.

According to the change in the large-scale climate predictors used in the downscaling model, an increase in westerly flow in the winter and spring is associated with an increase in precipitation during these seasons. The summer decrease of precipitation is linked to a decrease in westerly flow and an increase of northerly flow.

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