# Climate change scenarios for northern Europe from multi-model IPCC AR4 climate simulations

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[1] An empirical-statistical downscaling analysis for monthly mean temperature and precipitation is presented for a multi-model ensemble of the most recent climate scenarios (Special Report Emission Scenario A1b) produced for the upcoming Intergovernmental Panel on Climate Change (IPCC) Assessment Report 4 (AR4). The analysis involves a model evaluation by incorporating common EOF analysis, where the degree of similarity between the spatial structure of large-scale anomalies in re-analysis products and the climate models is examined. The empirical-statistical downscaling incorporates local information for a given set of locations, however, additional geographical information is utilised in the spatial interpolation of the results. A best-estimate of trend is derived through a Bayesian approach. Thus, maps of multi-model mean scenarios for annual mean temperature and precipitation rates for the 21st century are obtained. Positive trends are found in both temperature and precipitation over northern Europe. Citation: Benestad, R. E. (2005), Climate change scenarios for northern Europe from multi-model IPCC AR4 climate simulations, Geophys. Res. Lett., 32, L17704, doi:10.1029/ 2005GL023401.

# 1. Introduction

[2] Empirical-statistical downscaling (E-SDS) analysis offers several advantages over direct global climate model (GCM) output or nested model output based on regional climate models (RCM). In regions with complex physiography, e.g. high mountains, heterogeneous vegetation and landscape structures, deep valleys and fjords, there are often pronounced small-scale structure in climatic variables such as temperature and rainfall. For instance, there are marked differences in the rainfall pattern of the west- and east-facing slopes of the north-south running mountain ranges in southern Norway, where the former receives abundant amounts of rain and the latter tends to be in the 'rain shadow'. Even within the capital of Norway, Oslo, there are significant temperature differences between 'Bygdøy' at the fjord level and 'Tryvann' only a few km away but at 512 m a.s.l.. GCMs with grid-box scales typical of 100 km are therefore not capable of resolving such small-scale structures, and Benestad [2002, hereinafter referred to as B2002] provided a demonstration of how GCMs fail to represent the local climate. Impact studies do require information on a local level, and hence downscaling of GCMs of some form. However, RCMs with a spatial resolution of 10-50 km may not suffice where the physiography is most complex, leaving E-SDS as the most appropriate approach.

[3] E-SDS has some additional advantages as it involves an analysis that gives diagnostics which can be used to assess the GCM skill and the degree of realism [*Benestad*, 2004a]. Since E-SDS is relatively quick and cheap to carry out, it can readily be applied to multi-model ensembles. Furthermore, E-SDS represents a cheap and efficient way of analysing long time series and hence to reconstruct historical climates from 20th century GCM simulations. The advantage of downscaling to reproduce historical climate records is that it is possible to determine how well the GCMs represent the past [*Benestad*, 2003]. One minimum requirement, but not sufficient, for using GCMs for making scenarios for the future, is that the GCMs must be able to describe past climate.

[4] It has been argued that GCMs give a better representation of the upper-air fields than the near-surface data [Busuioc et al., 2001], and therefore E-SDS should use upper-air fields rather than surface fields as predictors. One argument for using surface variables, however, is that GCMs must be able to give a realistic description of the near-surface conditions if they are to be considered reliable. Furthermore, there is the question as to whether the GCMs give a good description of the trends in the upper-air fields because the actual trend is not wellknown in the real world [Seidel et al., 2004]. There is also the question of non-stationarity, i.e. whether the statistical relationship between the predictor and the predictand is not constant. Predictors from more remote regions or representing different elements are more prone to non-stationarities than those that are local and more directly linked to the predictand. One problem may be that the vertical temperature profile may change, and it has been argued that there is a significant temperature trend difference in the free atmosphere and near the surface [Chase et al., 2004]. Changes in the vertical atmospheric structure, if real, may complicate the interpretation of the relationship between upper air quantities and surface variability.

[5] The objective of this paper is to provide a state-ofthe-art assessment of regional climate scenarios for northern Europe. The work presented here is an update of the results presented by B2002, but with some important differences. The present results are derived from the very latest climate simulations carried out for the IPCC AR4 and for a larger set of locations. One important difference between the previous downscaling work and the present is that so-called

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Geographical model of temperature trend

**Figure 1.** Map showing the linear weighted multi-model ensemble annual mean temperature trend derived from the E-SDS results, GRM predictions and residual kriging. Local weighted mean trends values are given for capital cities, selected locations in Greenland, and part of the Arctic for the sake of completeness. Units are °C/decade.

'flux adjustment' is becoming less of a factor in present state-of-the-art GCMs [*Meehl et al.*, 2005].

## 2. Data and Methods

[6] Local monthly mean 2-meter temperature [T(2 m)]and monthly precipitation were taken from the Nordklim data set [*Tuomenvirta et al.*, 2001], the North Atlantic Climatological Dataset [*Frich et al.*, 1996] set (element codes '101' and '601') as well as from Nordic Arctic Research Programme [*Førland*, 2003]. The Norwegian stations were updated with recent observations from the Norwegian Meteorological Institute's Climate archive. The total number of station locations was N = 114 for temperature and N = 124 for precipitation (not counting station overlap in the different data sets). The station locations are marked on the maps in Figures 1 and 2, but the station data are also available from the auxiliary material<sup>1</sup>.

[7] The predictor for the local temperature was the monthly mean large-scale T(2 m) anomalies from the ERA40 re-analyses [*Simmons et al.*, 2004] and the corresponding predictor for local precipitation was the ERA40 total precipitation (R. E. Benestad et al., On statistical models for local precipitation, submitted to *International Journal of Climatology*, 2005). The gridded reanalysis data were combined with IPCC SRES A1b-based climate scenarios from a GCM. (The following GCMs are included: CNRM-CM3, GFDL-CM2.0, GFDL-CM2.1, GISS-AOM, GISS-EH, GISS-ER, INM-CM3.0, IPSL-CM4, ECHAM5/MPI-OM, MRI-CGCM2.3.2, CCSM3, PCM, and UKMO-HadCM3. References and further details are provided in the auxiliary material.) The

E-SDS consisted of a stepwise multiple regression between the 8 leading common EOFs for the combined data and one time series representing monthly temperature of precipitation in one location (B2002). The domain was determined automatically from the region of positive anomaly correlation between the predictand and the predictors' grid-box values for each month and each site respectively.

[8] One new aspect of present analysis was that it incorporated a post-process quality control in order to attach less weigh to the least realistic results, hence adopting a Bayesian-type [*Wilks*, 1995] approach. The post-processing step graded the quality of the results according to the realism of the spatial regression weights, how the trends of adjacent months relate to each other (i.e. expecting February trends not to be very different from January and March and so on), realistic seasonal values and variability, strong E-SDS regression results, and unrealistic size of the predictor domain. Because the spatial correlation tends to be non-zero and the spatial extent of regions of significant positive correlation tend to be limited, unrealistically large or small predictor domains may be indications of a failure to detect the optimal domain.

[9] Maps were constructed based on predictions with a geographically based stepwise multiple regression model (GRM) following *Benestad* [2004b], but using the quality weighted mean multi-model ensemble trend as the dependent and (i) distance from the coast, (ii) zonal and (iii) latitudinal position, (iv) altitude, (v) north-east slope, and (vi) east-west slope as the independent variables. From these, the stepwise screening identified which parameter has real influence on the climate elements: distance from the coast, altitude, latitude and longitude for T(2 m) and latitude, longitude, and north-south and east-west slopes for precipitation. The GRM accounted for 66% of the spatial variance of the T(2 m) trends (p-value:  $5 \times 10^{-15}$ ) and 33% of the precipitation trends (p-value:  $4 \times 10^{-7}$ ), suggesting significant skill. Furthermore, a split-sample evaluation using part of the data for calibrating the model and the remaining independent data for verification,





**Figure 2.** Same as Figure 1, but for precipitation. Units are mm/month per decade.

<sup>&</sup>lt;sup>1</sup>Auxiliary material is available at ftp://ftp.agu.org/apend/gl/ 2005GL023401.

demonstrates that the skill is real (auxiliary material). The residuals of the GRM results were added through a standard spatial interpolation kriging routine [*Matheron*, 1963]. Only the shaded area in Figures 1 and 2 and locations marked with grey circles were used in the GRM analysis (71 stations used in the GRM analysis for T(2 m) trends and 91 for precipitation).

[10] Further details on strategy, quality control, and spatial interpolation are given in the auxiliary material.

### 3. Results

[11] Figure 1 shows the geographical distribution of the mean annual temperature trends for the interval '2000'-'2099' and Figure 2 corresponding precipitation rates. The GRM could describe 66% of the spatial variance in the temperature trends, and the most important parameters were the zonal location (p-value = 0), meridional location (p-value = 0.01), altitude (p-value = 0.03) and distance from the coast (p-value = 0.10), indicating stronger annual mean warming in the northeast, at higher altitudes, and in the interior. This pattern is also seen in Figure 1, although the residuals are added in the form of kriging. The strongest warming is estimated for the high mountains in southern Norway, and the interior of Finland, Sweden and Norway. Least warming, according to these results, are expected for the British Isles, east coast of Greenland and Iceland.

[12] The E-SDS analysis for the annual mean precipitation indicated positive future trends in general (mean value for the locations was 0.5 mm/month per decade), as a result of the SRES A1b emission scenario. The GRM for precipitation indicated that the important parameters were the north–south and east–west location as well as the north–south and east–west location as well as the north–south and east–west slopes (33% of the geographical variance). The sum of the GRM and kriging analysis shown in Figure 2 indicates weaker trends over the British Isles and the Benelux countries and strongest trends in localised parts of Norway. The local enhancement of the precipitation can at least partly be explained in terms of sloping topography and orographic lifting. The precipitation results exhibit a marked precipitation gradient along a southwest–northeast running axis.

#### 4. Discussion and Conclusions

[13] The present analysis was applied to the annual as opposed to seasonal trends, and historical observations suggest that there may be different trends in different seasons [*Hanssen-Bauer and Førland*, 2000], but the seasonal dependency of the trends is outside the scope of this paper. Due to the Bayesian approach adopted, an assessment of uncertainty ranges will not be straight-forward and is therefore considered here. Downscaling analysis by *Benestad* [2002] and others point to stronger winter-time warming, and the present finding with more pronounced warming at higher levels may suggest shorter snow season and change in the seasonality of the river flow. A trend towards higher precipitation also has implications for river run-off. [14] The present analysis suggests qualitative similar results as obtained by B2002 for temperature, implying that the trends are robust despite different GCM scenarios, strategies and E-SDS models. The analysis for precipitation, on the other hand, point to more annual precipitation in the future, in contrast to the lack of trends in B2002.

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