Theor. Appl. Climatol. 82, 245–255 (2005)
DOI 10.1007/s00704-005-0133-4

Theoretical and Applied Climatology
Printed in Austria

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An improvement of analog model strategy for more reliable local climate change scenarios

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With 5 Figures

Received August 4, 2003; revised January 28, 2005; accepted February 8, 2005
Published online April 26, 2005

Summary

Downscaled results derived using a linear regression model are compared with corresponding analysis based on an analog model, and the effect of systematic biases in climate models is examined. Here, a correction of the biases in the climate model is achieved using a common principal component analysis basis and by adjusting the part of the principal components corresponding to the control period. The results suggests that the downscaled results have a distribution more similar to the observations if the systematic biases are corrected for. The analog model can utilise weighted as well as unweighted principal components as input, and the effect of this choice was examined. The results suggest that the weighted principal components yield more realistic results than the unweighted ones.

Analog models are by definition incapable of making extrapolations outside the range of observed values whereas a linear model is well-suited for extrapolation. A combined approach involves superimposing a linear trend from the regression-based model onto the results of the analog model. It is theoretically possible for the combined method to make projections with a realistic level of variance as well as higher values than in the calibration data sample. A comparison between the linear, analog, and the combined strategies suggest that the linear model not always give the strongest trend, but also that the combined method may shift the analog-derived distribution towards higher values.

1. Introduction

Global general circulation models (GCMs) represent an important tool for studying our climate, however, they do not give a realistic description of the local climate in general. It is therefore common to downscale the results from the GCMs either through a nested high-resolution regional climate model (RCM) (Christensen and Christensen, 2002; Christensen et al., 2001, 1998) or through empirical/statistical downscaling (von Storch et al., 1993; Rummukainen, 1997). The GCMs do not give a perfect description of the real climate system as they include 'parameterisations' that involve simple statistical models giving an approximate or ad-hoc representation of sub-grid processes. In order to balance the air-sea exchange of heat and freshwater fluxes, some GCMs also need to employ a so-called 'flux correction' (e.g. because of a mis-match in the horizontal transport in coarse resolution oceanic models and atmospheric models). Several state-of-the-art GCMs do not use flux correction but often produce *local* biases (Benestad et al., 2002) despite giving a realistic representation of the climate system on continental and global scales. furthermore, the downscaling stage may introduce additional

Table 1. A list of typical drawbacks associated with the different models commonly used in climate research

GCMs	May have systematic biases/errors. Unable to give a realistic description of local climate in general. Processes described by parameterisation may be non-stationary.
Nested RCMs	May have systematic biases/errors. Require large computer resources. Processes described by parameterisation may be non-stationary. Often not sufficiently realistic description of local climate (Skaugen et al., 2002b).
empirical downscaling:	
Analog models	Cannot extrapolate values outside the range of the calibration set. Do not account for non-stationary relationships between the large-scale and local climate. Needs a large training sample (often unsuited for monthly means) Do not ensure a consistency in the order of consecutive days.
Linear models	Assume normally distributed data. Tend to reduce the variance (Fig. 1). Do not account for non-stationary relationships between the large-scale and local climate.

errors, but systematic model biases may also severely degrade the downscaling performance. Table 1 gives a brief list of typical shortcomings associated with various models and analyses used in climate research.

It is important to stress that the various downscaling approaches have different strengths and weaknesses and that one method cannot be universally considered as the 'best'. Skaugen et al. (2002b) have evaluated results for Norway from a nested RCM and they found that the RCM did not give sufficiently realistic descriptions of the local climate as required by many impact studies. Empirical downscaling can, however, be used to provide more realistic local scenarios. It is well-known that linear regression (least squares methods) tends to yield lower variance than the original data (Klein et al., 1959; von Storch, 1999). One way to produce realistic variance levels in downscaling is to employ analog models (van den Dool, 1995; Zorita and von Storch, 1997, 1999; Dehn, 1999; Fernandez and Saenz, 2003) instead of linear regression. The analog model basically consists of re-sampling past data according to which coincide with the large-scale circulation regime that corresponds most closely with a given state of the atmosphere (Wilks, 1995, p. 198).

One concern regarding the analog approach is that it is incapable of predicting new record magnitudes since the predicted values are taken from archives of past observations. It is likely that extreme events may become more frequent in the future (Huntingford et al., 2003; Horton et al., 2001; Palmer and Räisänen, 2002; Frich et al., 2002; IPCC, 2002; Skaugen et al., 2002a; DeGaetano and Allen, 2002; Prudhomme and Reed, 1999) and there is a non-zero probability of seeing new record-high values (Benestad, 2004b, 2003b). If the analog model is to be used for studying extreme events for a future climate, it is necessary to modify the models so that they can extrapolate values outside the sample of observed magnitudes.

This paper presents some solutions to reduce the effects caused by the problems listed in Table 1. A method for 'correcting' (adjusting) the GCMs/RCMs is presented and evaluated. Then the question of how the results differ between the linear and analog models is addressed. Finally, a combined-approach, where the trends derived from linear models are combined with the distributions from the analog models, is described and assessed.

2. Method and data

The downscaling is based on the common principal component analysis (Flury, 1988; Sengupta and Boyle, 1998) and is described by Benestad (2001). The analysis was implemented with the `R`-environment (Ellner, 2001; Gentleman and Ihaka, 2000), and the actual downscaling was made using the contributed `R`-packages `clim.pact` (Benestad, 2003a, 2004a) and `anm` (Imbert, 2002), where the former package performs the downscaling with the linear model and the latter provides an extra method required for the analog model. The R-software and the contributed packages are freely available from the Internet site `cran.r-project.org/`, and both these packages are open source. The downscaling involved no de-trending, removal of the annual cycle, nor "inflation" (von Storch, 1999) in order to carry out a direct comparison between the linear and analog methods. The linear model used here was a standard linear stepwise multiple regression (R function 'lm') whereas the analog model consisted of a simple search for the nearest point in the principal components (PC) phase space. The linear model was applied first and only the PCs which were retained in the stepwise regression through an Akaike information criterion (AIC) (Wilks, 1995, p. 313) were then used to define the PC phase space used in the corresponding analog search, ensuring that both approaches used exactly the same predictors. The daily precipitation was not Gaussian in this case, and the linear models were therefore not able to yield unbiased predictions of response to variations in the large-scale circulation, yet a least-squares approach would still from a pure mathematical point of view provide a solution for the regression coefficients that yields the lowest root-mean-squared-error, provided the coefficients are smooth functions with respect to the sums of the series (Press et al., 1989, p. 555). The same stepwise regression method would also provide useful information as to which PCs to include in the analog model. Figure 1 shows a comparison between typical variance levels of downscaled

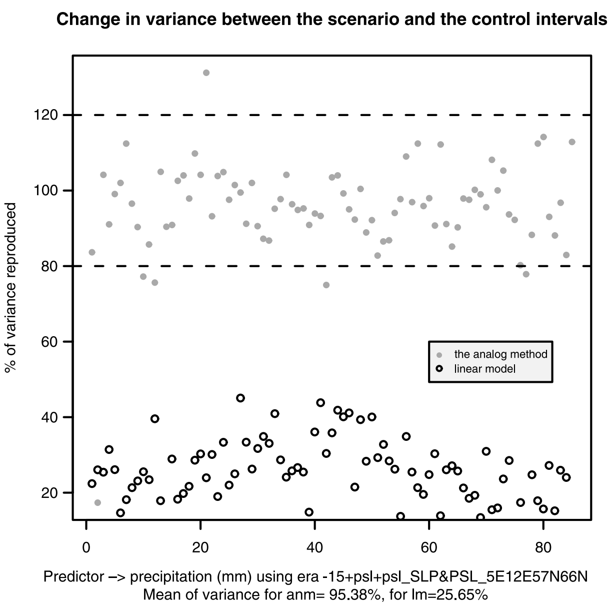

Fig. 1. Comparison between the predicted variance from linear (lm) and analog (anm) models. The results shown are for daily precipitation (Imbert, 2003)

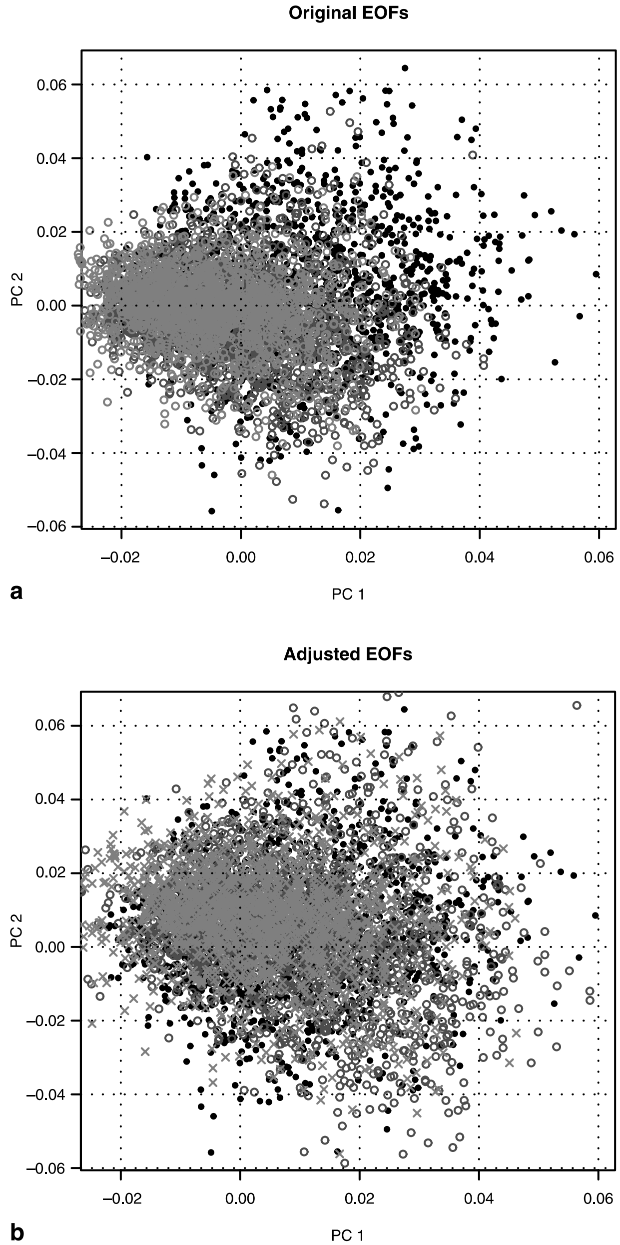

Fig. 2. An illustration of how the RCM results are adjusted in order to ensure that the PCs describing the RCM control-period (CTL) have the same location and spread as the observations. The adjustment consisted of centering and scaling the CTL part of the PCs to match the ERA-15 data, i.e. subtracting the mean value for the CTL part, multiplying with the fractional standard deviation ($s_{\text{ERA-15}}/s_{\text{CTL}}$), and adding the mean for the part of the PCs representing ERA-15. Panel **a**) shows a scatter-plot between PCs 1 and 2 for the observations and the unadjusted results for the CTL, whereas **b**) shows the adjusted PCs. The example shown here is for the December–February daily T(2 m) field covering the region 7° E20° E–60° N70° N

results for daily precipitation using the analog and the linear models, respectively.

The use of common principal components has to the authors' knowledge only recently been introduced in empirical downscaling (Benestad, 2001), and this new type of reference frame allows for a simple 'correction' of systematic biases in the climate model results. This correction entails an adjustment of the model results and involves forcing the mean value and standard deviation of the PCs describing the GCM/RCM for the "present-day" climate (control period, or 'CTL') to be the same as in the observations (ERA-15), and then use the same offset and scaling for the future. The adjustment process is illustrated in Fig. 2. The climate scenarios (henceforth referred to as 'SCE') was represented by the RCM results driven by ECHAM4/OPYC3 for the period '2030'–'2049'. Table 2 gives an overview of the acronyms and symbols used here.

The term 'linear trend' is in this context used to mean the long-term temporal evolution of a given quantity, and is estimated through the linear regression in time (t): $\hat{y}(t) = c_0 + c_1 t$. The combination of the analog and linear methods (hereafter referred to as the 'combined approach') consisted of adding the linear trend derived from the linear-based downscaling to the de-trended results from the analog-approach. The linear trends in the results from the analog model were subtracted (de-trended) in order to avoid double counting.

The empirical downscaling used two predictors: large-scale sea level pressure (SLP) fields for downscaling of precipitation and large-scale

Table 2. Definition and explanation of symbols, abbreviations and variables

CTL	Results from the control integration ('1980'–'1999') from the RCM.
ECHAM4/GSDIO	A particular GCM.
edf	Empirical distribution function.
EOF	Empirical Orthogonal Functions (similar to PCA).
ERA-15	The 15-year ECMWF reanalysis (www.ecmwf.int).
GCM	Global Climate Model.
GSDIO	A transient model run with ozone, direct and indirect effects of aerosols as well as greenhouse gases.
HIRHAM	A particular RCM.
PC	Principal Component (see PCA): 'unweighted' = ordinary PC (standardised), 'weighted' = ordinary PC (scaled by corresponding principal values).
PCA	Principal Component Analysis (Wilks, 1995).
RCM	Regional Climate Model.
SCE	Results from the scenario integration ('2030'–'2049') from the RCM.
SLP	Sea level pressure (units used = hPa).
STARDEX	**Sta**tistical and **R**egional dynamical **D**ownscaling of **Ex**tremes for European regions URL: "http://www.cru.uea.ac.uk/cru/projects/stardex/".
T(2 m)	2 meter air temperature (°C).

Table 3. A summary of the regression results for the four sites in Norway associated with the downscaling using a linear regression model. The lower values for R^2 in Nesbyen in winter can be explained by a higher frequency of inversions for this location

Location	Parameter	R^2	F-statistic	Degrees	Pr(>|t|)
Bergen	precip	0.36	78.45	7 and 984	<2.2e – 16
Nesbyen	precip	0.23	63.06	6 and 1257	<2.2e – 16
Oslo	precip	0.22	44.43	8 and 1255	<2.2e – 16
Tromsø	precip	0.22	49.99	7 and 1256	<2.2e – 16
Bergen	T(2 m)	0.75	534.2	7 and 1256	<2.2e – 16
Nesbyen	T(2 m)	0.64	324.5	7 and 1256	<2.2e – 16
Oslo	T(2 m)	0.79	579.4	8 and 1255	<2.2e – 16
Tromsø	T(2 m)	0.82	703.8	8 and 1255	<2.2e – 16

two-meter temperature fields (T(2 m)) for the local temperature. The predictors describing the observed large-scale SLP and T(2 m) anomalies were obtained by dynamically downscaled ERA-15 (Gibson et al., 1997) data using the HIRHAM (Haugen et al., 1999) RCM. Similarly, downscaled results from Max-Planck Institute for Meteorology's ECHAM4/OPYC3 GSDIO experiment (Roeckner et al., 1999, 1998, 1992; Oberhuber, 1993) were used to represent the climate scenario as well as providing a control integration. The GSDIO integration followed the IS92a emission scenario and included direct and indirect effects of aerosols as well as tropospheric ozone. One new aspect of this study is the two-stage approach, where the results from ERA-15 and ECHAM4/OPYC3 first are downscaled using the HIRHAM RCM, and subsequently empirical downscaling techniques are applied to the RCM results in order to refine the description of the local climate further. The advantage of the two-stage approach is that a smaller predictor domain can be utilised, as the RCM produces more realistic regional climate over Scandinavia than do the GCMs. A smaller predictor domain implies a lower degree of non-stationarity between the large (synoptic) and the local scales.

Here, the results are presented only for winter (December–February) days, and the interval 1980–1993 was used for calibration of the linear and analog models (1354 daily data points). Two different set-ups were used for the analog model: i) a 'weighted' approach where the PCs have been scaled according to their principal values (eigenvalues), and ii) 'unweighted' where standardised PCs ($|PC_i| = 1$ where i is the empirical orthogonal function number) are used. Thus, the weighting has the same effect as 'stretching' the PC phase space. The linear empirical downscaling is described in further detail in Benestad and Hanssen-Bauer (2003), and the analog models have been evaluated by Imbert (2002) for a large number of locations in Norway who reported correlations for precipitation in the ranges 0.34–0.67 for the linear, 0.10–0.56 for unweighted, and 0.07–0.60 for weighted analog models within the calibration period 1980–1993. The corresponding results for the daily 2-meter temperature are 0.07–0.89 (linear), 0.06–0.78 (unweighted analog), and 0.72–0.91 (weighted

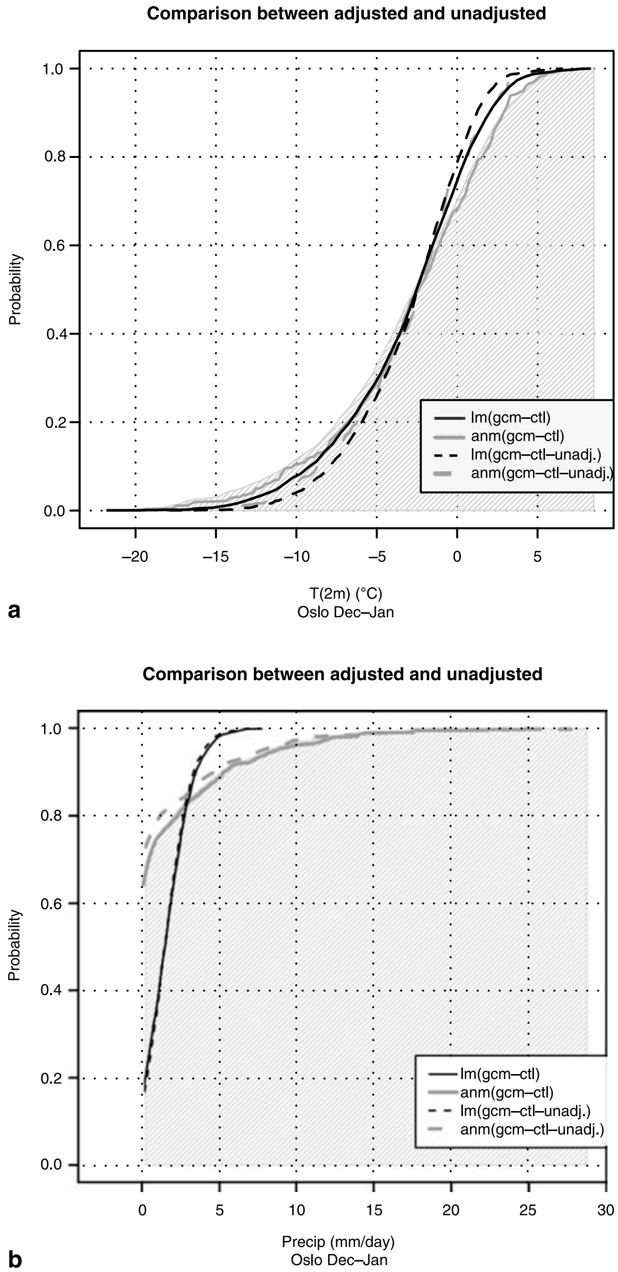

Fig. 3. A comparison between edfs for the daily winter temperature and precipitation in Oslo derived from the RCM control-period with unadjusted and adjusted principal components (see Fig. 2). The border between the white and the shaded area marks the edf for the observations. Panel **a**) shows the results for the temperature derived using the T(2 m)-field, whereas **b**) shows the results for the precipitation based on SLP. The legend notation 'lm(gcm-ctl)' refers to the linear downscaling of the CTL from the RCM using adjusted PCs, 'anm(gcm-ctl)' to analog downscaling of the CTL with adjusted PCs, 'lm(gcm-ctl-unadj.)' to linear downscaling of the CTL using original PCs, and 'anm(gcm-ctl-unadj.)' to analog downscaling of the CTL using original PCs. Negative precipitation values obtained with the linear models have been removed

analog). A very small subset of the stations achieved correlation scores less than 0.60 as a result of problems with missing data, and both the linear and analog models produce higher scores for these locations when the missing data were removed prior to the analysis. The correlations for the precipitation are generally lower than for temperature, and it is only the analog model that can reproduce realistic variance levels (Fig. 1).

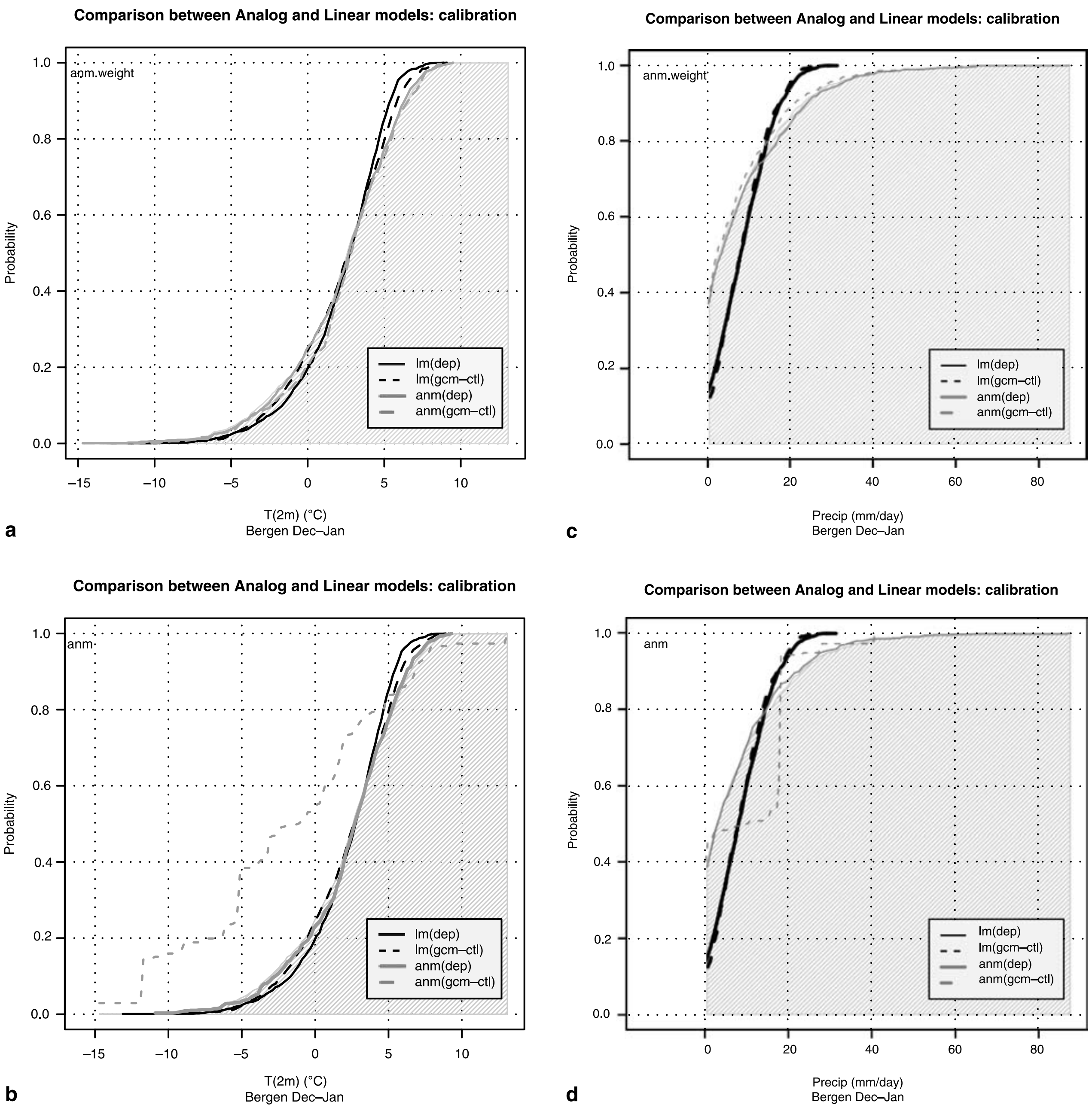

Fig. 4. Same as Fig. 3, but for the comparison between edfs for Bergen temperature and precipitation derived using unweighted and weighted principal components. **a**) Unweighted temperature, **b**) weighted temperature, **c**) unweighted precipitation, **d**) weighted precipitation. These results were derived using the adjusted PCs. The unweighted PCs are standardised whereas the weighted PCs have been scaled by the principal values. The legend notation 'lm(dep)' refers to the linear downscaling of ERA-15, 'lm(gcm-ctl)' to linear downscaling of CTL, 'anm(dep)' to analog downscaling of ERA-15, and 'anm(gcm-ctl)' to analog downscaling of CTL. Negative precipitation values obtained with the linear models have been removed

The local temperature and precipitation used as predictands in this analysis were daily mean values taken from the Norwegain Climate Station Database (“Klimadatavarehuset”). The winter precipitation observations included the water equivalent for snow, but has not been corrected for loss of snow due to catch deficiency of the gauges (Førland and Hanssen-Bauer, 2000). The precipitation series contain errors due to undercatch of the gauges as well as being non-Gaussian. In places with mild winters along the west coast of Norway (e.g. in Bergen) most of the precipitation falls as rain, and the undercatch is less severe than for inland stations.

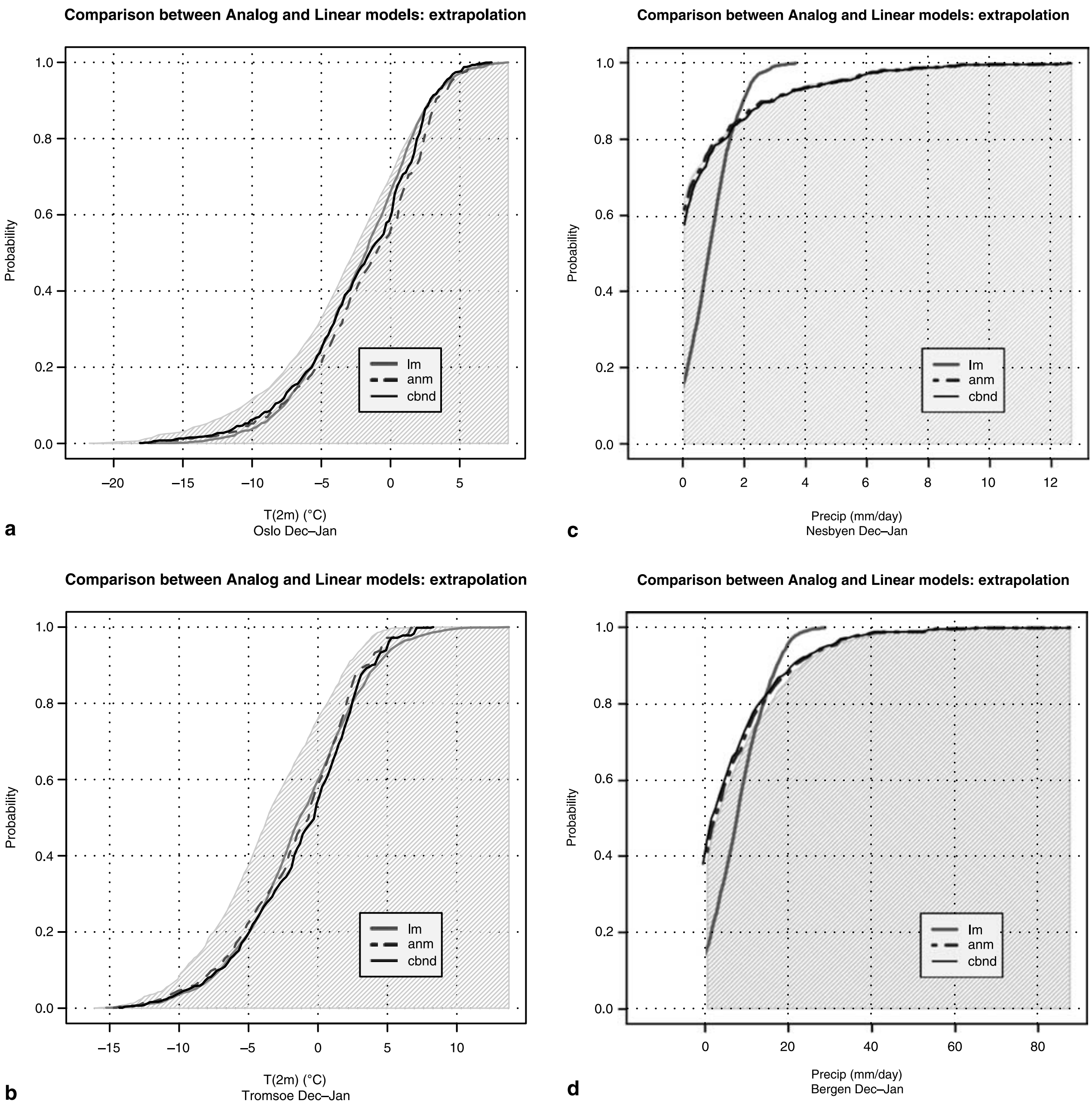

Fig. 5. Similar as Fig. 3, but comparing the results from the linear, analog and combined methods for the projected (assuming a global warming) 2030–2049 temperature in **a**) Oslo, **b**) Tromsø, as well as precipitation in **c**) Nesbyen, and **d**) Bergen. The analog model used weighted PCs and adjusted PCs for this example. The weighted PCs have been scaled by the principal values and the adjusted PCs have same mean and standard deviation for CTL part as ERA-15. The legend notation ‘lm’ refers to the linear downscaling of SCE, ‘anm’ to analog downscaling of SCE, and ‘cbn’ to combined linear-analog downscaling of SCE. Negative precipitation values obtained with the linear models have been removed

The downscaling was carried out for four sites in Norway with different climate characteristics (Table 3). Bergen has a coastal climate with mild and wet winters, and Nesbyen has a continental climate and is located in the bottom of a valley with frequent inversions. The local climate in Oslo can be described as a mix between continental and coastal climate, and Tromsø offers an example of an Arctic coastal climate type.

3. Results

Figure 3 shows the empirical distribution functions (edf) for downscaled winter temperature (a) and precipitation (b) in Oslo using unadjusted and adjusted PCs. For the temperature (predictor = T(2 m)), the adjusted PCs give a better description of the distribution, whereas the adjustment has little effect on the precipitation (predictor = SLP). The SLP from the RCM have similar mean values and standard deviations within CTL as the observations, and therefore an adjustment does not have a significant effect for the SLP (not shown). The edf from the analog model is closer to the observations than for the linear model, especially as the linear model does not give a realistic distribution for the daily precipitation (b).

The effect of using weighted PCs (i.e. scaled by the principal values) is examined in Fig. 4, where panels (a) and (b) show the results for unweighted and weighted downscaling of the daily winter temperature in Bergen and panels (c) and (d) the corresponding analysis for daily winter precipitation. Weights primarily affect the analog results, as the step-wise regression analysis compensates for the amplitudes of the individual PC. The results in Figs. 3 and 4 show that the analog model gives a good description of the distribution functions if the PCs are unadjusted and weighted.

Figure 5 shows the edfs for downscaled temperature in Oslo and Tromsø as well as precipitation in Nesbyen and Bergen. In Oslo (a), the trend predicted by the linear regression was weaker than for the analog model, whereas the linear model predicted stronger long-term warming in Tromsø (b). The general similarity between projected temperature distribution obtained with the analog and the linear models is noteworthy. The greatest differences between these two approaches are seen in the upper tail of the projected temperature distribution for Tromsø (b). Similar results for precipitation in Nesbyen and Bergen are shown in panels (c) and (d). Although the shapes of the distribution from the linear and analog models differ, their location are similar, and adding the trend from the linear model has little effect on the distribution. In general, the downscaled results suggest insignificant changes in the precipitation due to changes in the circulation patterns, in good agreement with the conclusions of Benestad (2002).

4. Discussion and conclusions

For some fields, such as T(2 m), an adjustment correcting for systematic model biases is required in order to obtain realistic distributions in the downscaled results. As described in the method section above, the adjustment consisted of setting the mean and standard deviation of the part of the PCs describing the CTL to the same values as those of the observations (downscaled ERA-15). The adjustment forces the CTL from RCMs to have similar features as those observed in terms of the location and spread of the PCs. The PCs describe the weighting of the empirical orthogonal functions (EOFs) (Lorenz, 1956; North et al., 1982; Preisendorfer, 1988) for the combined data, and hence the common spatial climatic patterns for both ERA-15 and the RCM. A large offset or a scaling factor substantially different from unity is an indication of substantial systematic bias in the RCM results. The offset and scaling factor can be used for comparing the RCM skill.

The results indicated that generally the PCs ought to be scaled by the principal values from the EOF analysis in order for the analog model to give good results. Such a weighting puts more emphasis on meaningful (leading) EOFs and reduces the effect of noise (high-order EOFs).

The analog model is in principle able to predict changes in the shape of the distribution as long as the range of values remains constant. The fact that the analog and linear methods produce a similar shift in the location of the distribution function for temperature, suggests that the synoptic situations projected by the RCMs corresponding to warm days in present-day climate are to become more common in the future. The results from the combined method in Fig. 5 add little extra in this case because of the analog and linear methods produce similar distributions (this may not always be the case), and the tails of the distributions still present a problem as the linear model suggests a more dramatic increase in the frequency of extreme warm temperatures than do the analog and combined methods. Another shortcoming associated with analog models is that they do not ensure a consistency in the order of consecutive days if weather regimes are not well-defined, however, this may to some degree depend on the evolution in the PC phase space and clustering of past states as defined by the predictors.

Climate and weather extremes have been the subject of study in the EU project STARDEX (http://www.cru.uea.ac.uk/cru/projects/stardex/) under the Fifth Framework Programme (2002–2005) as one of its overall objectives is to "provide scenarios of expected changes in the frequency and intensity of extreme events". The scientific objectives encompasses the identification of robust methods for inferring extreme events through downscaling and providing a standard set of indices describing extremes in Europe. Methodologies for statistical downscaling or modelling extremes are often invalid under changing conditions, but one approach involving computation of a set of indices or upper/lower percentiles may be one solution. Alternatively, the recurrence of records and trends in extreme-event counts or threshold analysis (Benestad and Chen, 2004) can provide useful diagnostics.

The daily precipitation is not Gaussian and hence ordinary regression models will not give an unbiased estimate of the values. One solution can be to normalise the data prior to the regression analysis (e.g. a power transform) or the use of logistic regression (Frei and Schär, 2001). A transform would usually involve separating 'rainy' days with 'non-rainy' days and is beyond the scope of the present paper. The linear model is used here merely as a reference, and the focus of this study is to investigate different ways to improve the analog model approach. In either case, errors due to undercatch of snow caused by local wind conditions could require correction factors up to ~ 4 in the most severe cases (Førland and Hanssen-Bauer, 2000). Table 3 suggests that the R^2 values for Bergen with mostly liquid precipitation is higher than for locations with more snowfall. Measurement errors deteriorate statistical correlations and affect the variance of the linear model predictions. It is possible that part of the difference in R^2 in Table 3 is related to undercatch errors, however, there is not enough information in these results to draw a firm conclusion from only four R^2-estimates and four geographical locations. Nevertheless, there is a sound physical reason behind the wintertime SLP pattern and precipitation for most locations in Norway, as it is well-known that a combination of advection of moist maritime air and orographic lifting creates favourable conditions (Hanssen-Bauer and Førland, 2000).

The evaluation of the combined method suggests that in some cases (Tromsø) it yields distribution shifts towards higher values, and hence is capable of making extrapolations, i.e. producing values outside the range of values in the calibration sample. Although this solution can in theory predict changes in extreme values as a result of a trend, it cannot account for changes in extremes due to an altered variability in e.g. the large-scale circulation patterns. Moreover, a study by Katz and Brown (1992) has suggested that the frequency of climatic extremes depends more strongly on changes in the variability rather than changes in the mean climatic state, and the results in Fig. 5b suggest that the linear model projects an increase in the frequency of very warm temperatures that is disproportional to the changes in the mean value. Hence, the addition of a mean trend to the analog method results may not suffice for studies of future extreme values. A different solution to improving the downscaling with analog models has been suggested by Hanssen-Bauer (private communications) who proposed to include warmer seasons in the calibration of the model. For instance, the present analog model for the winter season could extend the search for nearest point in PC phase space representing the winter months to also include spring, summer, and autumn months to account for a warmer future climate. The limitation of this approach is, of course, that this approach would not be applicable for models for the summer season. This approach will be evaluated in future studies.

It is important to note that different RCMs/GCMs tend to give different results on a local and regional scale (Benestad, 2002; Räisänen, 2001a; Räisänen and Palmer, 2001; Räisänen 2001b), and it is therefore important not to focus on results from just one RCM/GCM GCM for making scenarios for the future. The primarily purpose of this paper has been to document differences and similarities between various downscaling approaches, and the general similarity between the downscaled daily temperatures from the analog and linear methods suggest that a high level of confidence can be attributed to the downscaling models. Since the focus here has been on options within the analog modelling (weighting, adjusting, and combining linear and analog approach) we have not evaluated possible benefits of the two-step-method consisting in statistically downscaling RCM results as opposed to from GCM results directly. No conclusions should therefore be drawn about the usefulness of the 2-step-method from this paper.

Acknowledgement

This work was done under the Norwegian Regional Climate Development under Global Warming (RegClim) programme, and was supported by the Norwegian Research Council (Contract NRC-No. 120656/720) and the Norwegian Meteorological Institute. The analysis was carried out using the R (Ellner, 2001; Gentleman and Ihaka, 2000) data processing and analysis language, which is freely available over the Internet (URL http://www.R-project.org/). The dynamical downscaling and pre-processing of the RCM reults was performed by Jan Erik Haugen at the Norwegian Meteorological Institute, and Inger Hanssen-Bauer and Eirik Førland have contributed with valuable ideas through discussions.

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Verleger: Springer-Verlag GmbH, Sachsenplatz 4–6, 1201 Wien, Austria. – Herausgeber: Prof. Dr. H. Graßl, Max-Planck-Institut für Meteorologie, Bundesstrasse 55, 20146 Hamburg, Germany. – Redaktion: Josef-Baumann-Gasse 1, 1210 Wien, Austria. – Satz und Umbruch: Thomson Press (India) Ltd., Chennai. – Druck und Bindung: Grasl Druck & Neue Medien, 2540 Bad Vöslau. – Verlagsort: Wien. – Herstellungsort: Bad Vöslau – Printed in Austria.