SIMULATION OF SURFACE AIR TEMPERATURE BY GCMs, STATISTICAL DOWNSCALING AND WEATHER GENERATOR: HIGHER-ORDER STATISTICAL MOMENTS

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ABSTRACT

The third and fourth statistical moments, that is, skewness and kurtosis, are compared for daily maximum temperature in summer and daily minimum temperature in winter between observations, outputs of two global climate models, four versions of statistical downscaling, and weather generator. The comparison is performed at six stations in central Europe. None of the simulation models can be considered as superior to the others. Causes of a good correspondence with and differences from observations are identified e.g. in the treatment of physics in the models, imperfections in physical parameterizations, or a linear transfer of properties from predictors onto predictands in statistical downscaling.

Keywords: daily temperature, higher-order statistical moments, global climate models, statistical downscaling, weather generator.

1. INTRODUCTION

Daily time series of climate variables are required as meteorological input in many studies of climate change impacts. Apart from global climate models (GCMs), which are the tools most frequently used for climate modelling, but of a rather limited ability to simulate processes on short temporal and small spatial scales, there are several approaches to obtaining site-specific daily time series of climate elements. All of them are to a different extent based on GCM outputs, which are thereby translated from large to fine temporal, and particularly spatial, scales. The approaches, generally referred to as downscaling, include regional climate models (RCMs), statistical downscaling, and weather generators.

Before the above simulation methods (including a GCM itself) are used to construct climate change scenarios, they must be validated on present climate conditions. In the majority of validation studies, simulated time series are verified against observations in terms of distance measures such as root-mean-square error and correlation coefficient, and in terms of the first two statistical moments, i.e., the mean and variance. There are, nevertheless, other possible criteria, which may be of importance in specific applications. One of such criteria is higher (third and fourth) statistical moments of simulated distributions, that is, skewness and kurtosis. Although other important aspects of distributions, namely, extreme values and return periods, have been dealt with in several validation studies of GCM and statistical downscaling outputs (*Zwiers and Kharin, 1998; Kharin and Zwiers, 2000; Kyselý, 2002*), skewness and kurtosis have not been validated so far for any of the simulation methods, except for weather generator in the paper by *Dubrovský (1996)*.

A large majority of validation studies concentrates on a single simulation method. It may, however, be beneficial to compare the performance of several simulation methods with each other in order to provide a guide which method should be given preference in a particular climate change impact study, which requires a specific validation criterion to be fulfilled. For daily temperature, such a comparison was performed by *Kidson and Thompson (1998)* between statistical downscaling and a RCM, and by *Hay et al. (2000)* between statistical downscaling and a GCM. Recently, *Huth et al. (2001)* and *Kyselý (2002)* evaluated local daily temperature produced by two GCMs, several statistical downscaling methods and a weather generator; the former study in terms of lag-1 autocorrelations, distributions of day-to-day temperature changes and characteristics of heat and cold waves, while the latter in terms of extreme value distributions and return periods.

The aim of this paper is to expand the studies by *Huth et al. (2001)* and *Kyselý (2002)* to validation of higher-order statistical moments (i.e., skewness and kurtosis) of daily temperature distributions in the time series produced by two GCMs, several statistical downscaling procedures and a weather generator. The analysis is performed for six sites located in central Europe in different climatic settings.

2. DATASETS USED

Daily maximum temperature in the summer period (May to September) and daily minimum temperature in the winter period (November to March) are analyzed at six stations in central Europe: Prague – Ruzyně, Kostelní Myslová and Strážnice in the Czech Republic; Hamburg and Würzburg in Germany; and Neuchâtel in Switzerland. For the location of stations see Fig. 1. The observations span the period 1961−1990, and so do the downscaled time series derived from observed large-scale fields. Stochastically generated series of course cannot be attributed to a specific historic period, but they resemble the observed series in terms of selected statistical characteristics. The parameters of the generator were derived from the above 30-year observed series and the synthetic series produced by the generator are 30 years long as well. The outputs from the ECHAM and CCCM models are 30 and 20 years long, respectively; so are the corresponding GCM-downscaled time series. The GCM gridpoints closest to the stations that were used for comparison are also shown in Fig. 1.

3. SIMULATION METHODS

In order to save space, the description of methods is kept here to a necessary minimum. More information can, in addition to specific references, be found in the paper by *Huth et al. (2001)*.

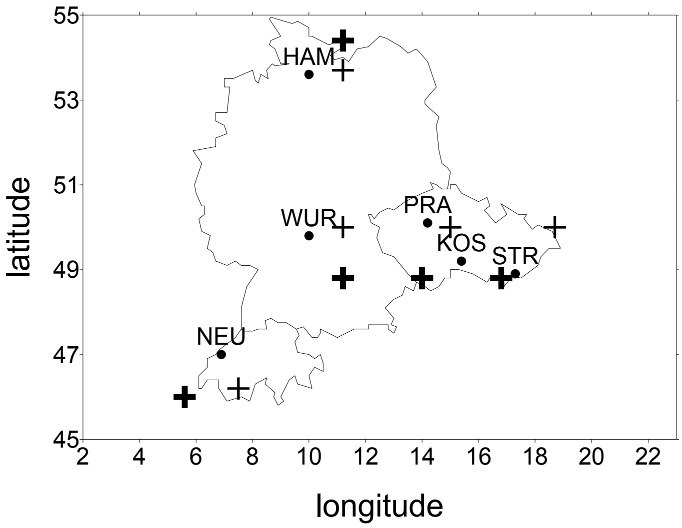

Fig. 1. Location of stations (dots) and the closest GCM gridpoints (bold crosses for ECHAM, light crosses for CCCM). Notation of stations: NEU = Neuchâtel; WUR = Würzburg; HAM = = Hamburg; KOS = Kostelní Myslová; STR = Strážnice; PRA = Praha-Ruzyně.

3.1. GCMs

The simulations of present climate (control runs) of two GCMs are analyzed: ECHAM3 and CCCM2. The ECHAM3 GCM (developed in the Max-Planck Institute for Meteorology in Hamburg from the ECMWF prediction model) has a T42 resolution, corresponding approximately to a 2.8° gridstep both in longitude and latitude. A detailed description of its version 3, used here, is given in *DKRZ (1993)*. Here we examine years 11 to 40 of the control run, in which climatological SSTs and sea ice extent were employed. The validation of daily extreme temperatures produced by ECHAM3 for selected areas of the Czech Republic was performed by *Nemešová and Kalvová (1997)* and *Nemešová et al. (1998)*.

The Canadian Climate Centre Model (CCCM) of the second generation is described in *McFarlane et al. (1992)* where also its basic validation is presented. The CCCM model has a T32 resolution, roughly corresponding to a 3.75° × 3.75° grid. Its interactive lower boundary consists of a mixed layer ocean model and a thermodynamic ice model. 20 years of its control integration have been available. The validation of its surface temperature characteristics over central Europe was performed by *Kalvová et al. (2000)* and *Huth and Pokorná (2001)*.

3.2. Statistical downscaling

The downscaled temperatures are calculated by a multiple linear regression with stepwise screening from gridded 500 hPa heights and 1000/500 hPa thickness. This method turns out to perform best among other linear methods (*Huth, 1999*). The domain

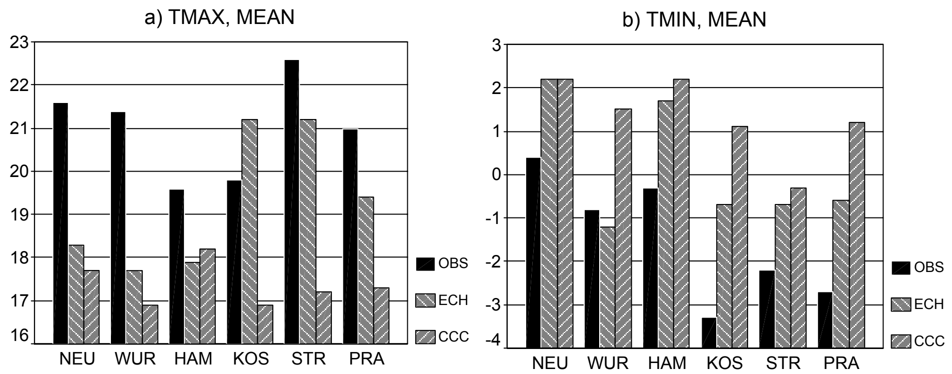

Fig. 2. Mean temperature (in °C) at six stations in observations (OBS) and the ECHAM (ECH) and CCCM (CCC) GCMs: (a) maximum temperature in summer, (b) minimum temperature in winter.

on which the predictors are defined covers most of Europe and extends over the adjacent Atlantic Ocean; it is bounded by the 16.9°W, 28.1°E meridians, and the 32.1°N and 65.6°N parallels.

The downscaling procedure is designed so that it retains the mean of the original time series. It is important to retain also variance; in this study two ways of doing that are applied and compared. The commonly used way, variance inflation, consists in enhancing each day's anomaly by the same factor, defined by the share of variance explained by downscaling (*Karl et al. 1990*). The alternative was proposed by *von Storch (1999)*: the variability of a downscaled series is enhanced by adding noise. Here we adopt the enhancement of the variance by a white noise process, similarly to *Wilby et al. (1999)* and *Zorita and von Storch (1999)*.

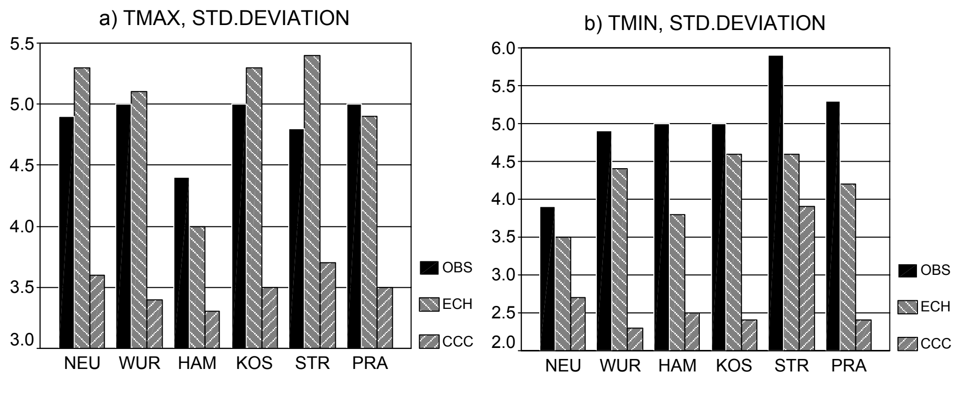

Fig. 3. As in Fig.2 except for standard deviation.

First, the relationships between large-scale fields and local temperature are identified in observations. The large-scale fields used as predictors are taken from the NCEP reanalyses (*Kalnay et al., 1996*), interpolated using bicubic splines from the original $5° \times 5°$ grid onto ECHAM's grid with double spacing, that is, $5.6° \times 5.6°$. The geopotential data from CCCM are interpolated onto the same grid. In observations, the regression is performed between standardized anomalies of large-scale fields and standardized anomalies of local temperatures, for both seasons separately. In the application of downscaling to GCM outputs, the simulated large-scale fields are first normalized by their own mean and standard deviation. Then they enter the regression equations developed on observed data. This procedure eliminates a GCM's bias and allows the observed mean and standard deviation to be reproduced in the GCM-downscaled time series. The variance of the downscaled output is enhanced by inflation only.

3.3. Weather generator

The stochastic weather generator Met&Roll used in this study is designed to produce synthetic series of four daily variables: precipitation amount, maximum temperature, minimum temperature, and sum of global solar radiation. The precipitation occurrence is modelled by the first order Markov chain, the precipitation amount on a wet day is sampled from the Gamma distribution. Standardized anomalies of maximum and minimum temperature and solar radiation are modelled by the three-variate first order autoregressive model; their means and standard deviations are conditioned by a precipitation occurrence and the day of the year. The parameters of the precipitation model are determined separately for each month. The annual cycle of the lag-0 and lag-1 correlations among both temperatures and solar radiation is taken into accout in agreement with observations. The statistical structure of synthetic series produced by the generator was validated in detail by *Dubrovský (1997)*; its description can also be found in *Dubrovský et al. (2000)*.

3.4. Summary

Altogether eight time series of daily maximum temperature in the summer period and of daily minimum temperature in the winter period are examined in this study. They originate from:

(i) observations (OBS),
(ii) GCM outputs from ECHAM3 (ECH) and CCCM2 (CCC),
(iii) statistical downscaling from observed large-scale fields (predictors) with variance reproduced by inflation (DWI) and white noise addition (DWW),
(iv) statistical downscaling from predictors simulated by the ECHAM3 GCM (DWE) and CCCM2 GCM (DWC),
(v) weather generator (WGA).

4. RESULTS

4.1. Mean and standard deviation

First of all, let us have a quick look at the first two moments, i.e., the mean and standard deviation. The downscaling with variance inflation (datasets DWI, DWE and DWC) reproduces both the mean and standard deviation exactly by definition. The time series produced by downscaling with white noise addition and by the weather generator (datasets DWW and WGA) have their population mean and standard deviation equal to the observed sample mean and standard deviation, from which their sample statistics may slightly differ. The difference of both the mean and standard deviation from observations is, nevertheless, negligible, not exceeding 0.2°C for any case. The only biased temperature series come from direct GCM outputs. Both GCMs overestimate minimum temperatures in winter and underestimate maximum temperatures in summer (Fig. 2): CCCM at all the six stations, ECHAM at five of them. This is a well-known feature of these models in central Europe (*Nemešová and Kalvová, 1997*; *Kalvová et al., 2000*). CCCM strongly underestimates the temperature variance in both seasons (Fig. 3); ECHAM underestimates it less markedly in winter and exhibits no coherent error in variance in summer. The

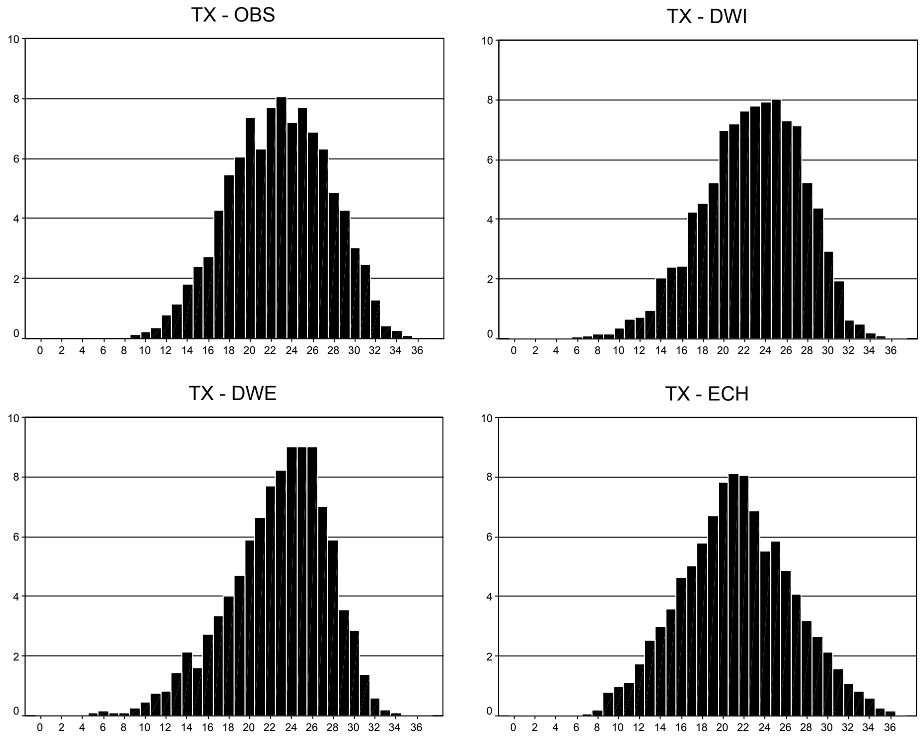

Fig. 4. Histograms of daily maximum temperature at Strážnice in summer as observed and simulated by the seven simulation methods.

misreproduction of variance is due largely to deficiencies in the treatment of physical processes in the GCMs; this is discussed in *Huth et al. (2001)*.

4.2. Histograms

The features of temperature distributions are first illustrated in histograms of daily maximum and minimum temperatures at the Strážnice station, binned into 1°C intervals (Figs. 4 and 5). For maximum temperatures in summer (Fig. 4), the cold bias and the underestimation of variance by CCCM are obvious. As a result, there are almost no days in the CCCM climate with maximum temperatures exceeding 30°C, which in all other time series occur commonly. Well observable is also a negative skewness of the DWE and DWC distributions.

Winter minimum temperature distributions (Fig. 5) are clearly less peaked for the downscaled and stochastically generated time series than for the observed ones. The ECHAM distribution is correctly shaped in its central part, indicating a good reproduction of the skewness and kurtosis, but lacks the very tails: there are too few extremely warm and cold winter days in the ECHAM climate. In CCCM, the minimum temperature distribution is unrealistic: temperatures close to zero dominate (the interval between –0.5

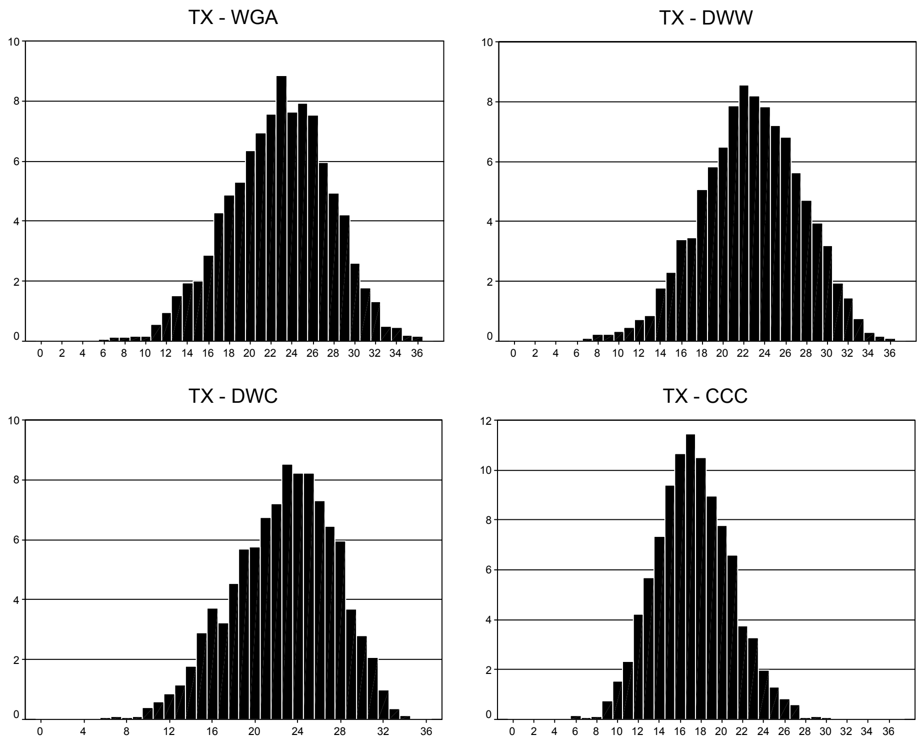

Fig. 4. continued

and +0.5 °C contains almost 44% of all days, compared with 9.6% in the observed), the freezing days are rare (only 17% of days with temperatures below −0.5 °C, but 58% in the observed), and the occurrence of temperatures above +1.5 °C is also underestimated. These features, common to all stations except Neuchâtel, are responsible for extremely high kurtosis.

4.3. Skewness

The third statistical moment, skewness, is defined as

$$(n-1)^{1/2} \frac{\sum \left(x_i - \bar{x}\right)^3}{\left[\sum \left(x_i - \bar{x}\right)^2\right]^{3/2}}$$

where $\bar{x}$ is the sample mean, and n is the sample size. The skewness of the temperature distributions is displayed in Fig. 6. The dashed horizontal lines represent the critical values for skewness to be different from zero at the 5% significance level. The critical

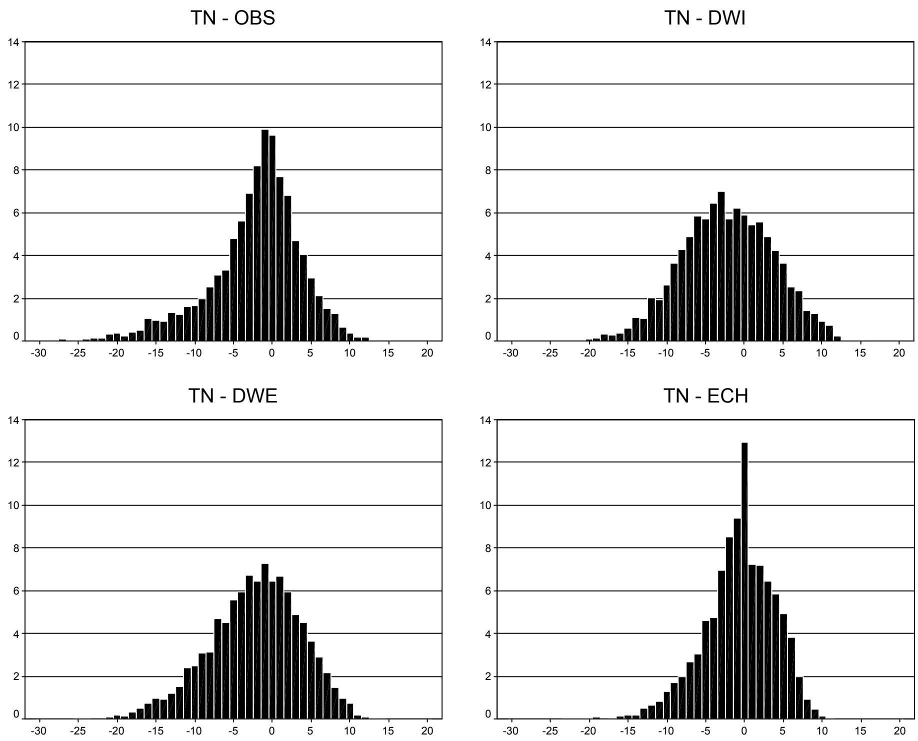

Fig. 5. As in Fig. 4 for minimum temperature in winter.

values were determined by a Monte Carlo method assuming that the data were drawn from the first-order autoregressive process, which is an acceptable approximation for both the maximum and minimum daily temperatures in mid-latitudes. 1000 samples of the same size as the observed and modelled series were generated for both the maximum and minimum temperatures, with the autoregressive parameter set for each simulation method as the average of the lag-1 autocorrelations among the six stations (e.g., 0.76 in summer and 0.82 in winter for observed data; 0.84 in summer and 0.83 in winter for downscaling with variance inflation; etc.). Finally, the average of absolute values of the 2.5% and 97.5% percentiles of the distribution of skewness (which is symmetric around zero) was taken as the critical value for skewness to be different from zero at the 5% significance level. The same procedure was applied for kurtosis in Section 4.4.

In summer, the observed skewness is significantly positive at Hamburg, negative (slightly above the significance level) at Neuchâtel and Kostelní Myslová, and close to zero elsewhere (Fig. 6a). This pattern is partially reproduced by the weather generator. All the downscaled series are negatively skewed, which is statistically significant for all the series at all stations. Note that the white noise addition (DWW series) leads to a less negative skewness than the inflation (DWI series). The skewness in both GCMs is mostly slightly positive, but not significantly different from zero.

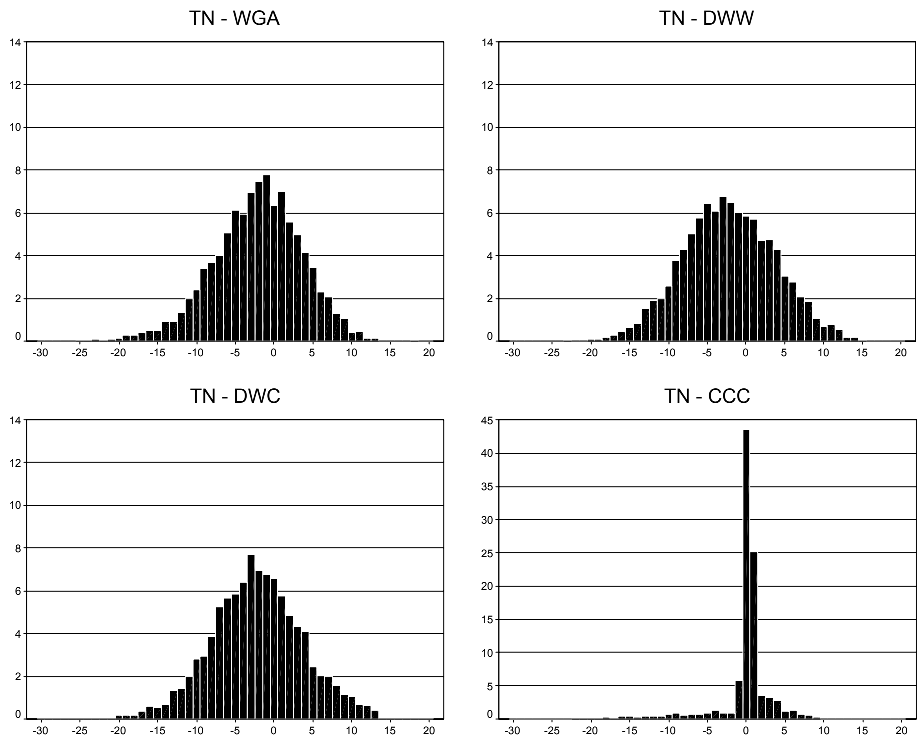

Fig. 5. continued

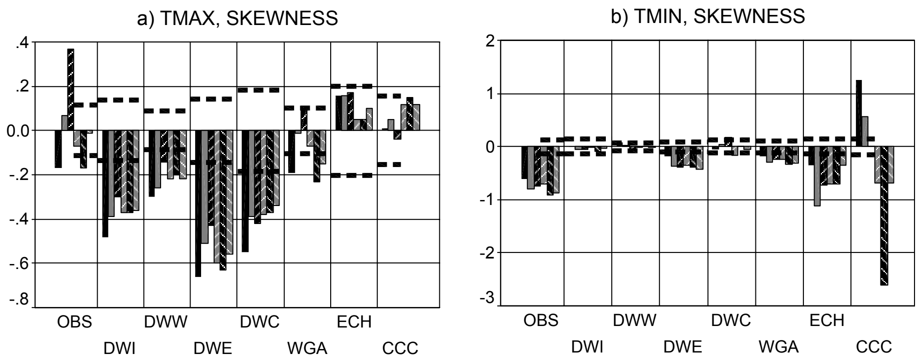

Fig. 6. Skewness of a) maximum temperature in summer and b) minimum temperature in winter for observations, and the seven simulation methods (for their notation see the text) at six stations. The stations are shown in each cluster of bars in the following order (from left): Neuchâtel, Würzburg, Hamburg, Kostelní Myslová, Strážnice, Praha-Ruzyně. The horizontal dashed lines indicate the critical values for skewness to be different from zero at the 5% significance level, averaged over the stations for each method separately.

The observed minimum temperatures in winter are negatively skewed (Fig. 6b), that is, they have a heavy left tail, with skewness highly exceeding the significance level at all stations. The ECHAM GCM appears to reproduce this feature most successfully. The sign of skewness, but not its magnitude, is reproduced in the temperatures from the weather generator and in those downscaled from ECHAM; the other downscaling methods produce near-zero values. The CCCM model fails to reproduce the skewness of winter minimum temperature.

4.4. Kurtosis

The fourth statistical moment, kurtosis, which is a measure of the 'peakedness' of a distribution, is displayed in Fig. 7, again with the 5% significance limits denoted by dashed lines. Kurtosis is defined as

$$(n-1)\frac{\sum\left(x_i-\bar{x}\right)^4}{\left[\sum\left(x_i-\bar{x}\right)^2\right]^2}-3 \ .$$

A distribution with positive kurtosis has heavier tails and a more peaked central part than the normal distribution. The kurtosis of maximum temperature in summer is negative except for Hamburg where it is slightly positive (Fig. 7a). This pattern is approximated by ECHAM only; other simulation methods result in kurtosis values near zero or slightly positive.

In winter, positive kurtosis is observed at all stations. The series produced by downscaling and weather generator possess kurtosis not reaching values significantly different from zero in most cases. On the other hand, both GCMs produce minimum

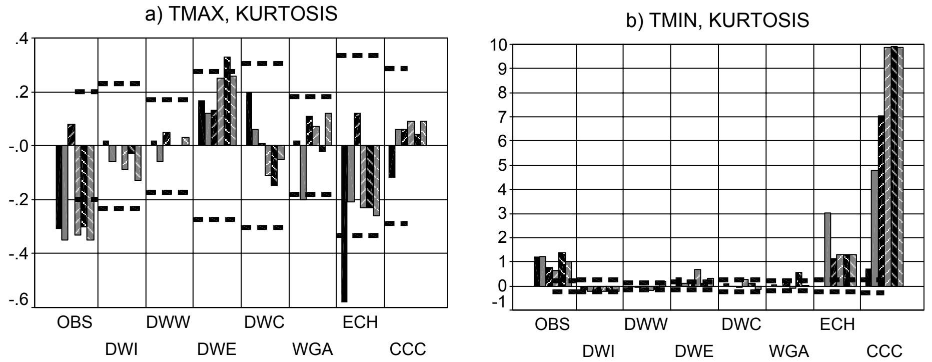

Fig. 7. The same as in Fig. 6 for kurtosis.

temperature distributions with positive kurtosis, which attains fairly realistic magnitudes in ECHAM, but is highly overestimated in CCCM (Fig. 7b).

5. DISCUSSION

A common feature of observed minimum temperature distributions in winter is their heavy left tail (that is a relative abundance of very low temperatures), which leads to a negative skewness at all stations. This is mainly a result of radiative cooling of surface. Very low temperatures also contribute to positive kurtosis of observed distributions. Both these features are fairly successfully reproduced by the ECHAM GCM, which hints that it simulates physical processes relevant to surface radiation balance in winter correctly. On the other hand, CCCM fails in reproducing the higher-order moments in winter; most notable are the extremely peaked distributions, manifested by very high kurtosis values at most stations. The cause of this failure consists in the land-surface scheme, which requires all soil water to freeze or thaw before ground temperature is allowed to cross the freezing point (*Palutikof et al., 1997*; *Laprise et al., 1998*). This is also the main reason for a strong understimation of variance. Recent analyses, however, indicate that the problems reported here persist in the new coupled version of the model, CGCM1 (*Kharin and Zwiers, 2000*).

In the downscaling, there is no explicit physical factor supporting the occurrence of very low minimum temperatures in winter; hence the distributions tend to become unrealistically symmetric and Gaussian, as witnessed by near-zero skewness and kurtosis. The exception is the downscaling from ECHAM, whose correct sign (but not magnitude) of both skewness and kurtosis may be a result of a transfer of statistical properties from predictors. This effect is strongly pronounced in skewness of maximum temperature in summer, which is negative for all downscaling methods. This reflects the negative skewness of 500 hPa heights, which is observed over almost the whole area from which the downscaling predictors are selected (White, 1980); this is correctly reproduced by both GCMs. The negative skewness of predictors is then transferred directly to the downscaled temperatures through the linear regression.

Another notable feature is a relatively good reproduction of skewness in both seasons (apart from magnitudes at some stations) by the weather generator. This occurs although there is no mechanism involved in the generator to drive it directly. There is, however, a mechanism capable of affecting the skewness indirectly. As both maximum and minimum temperatures are modelled by the normal distribution with means and standard deviations conditioned on the precipitation occurrence, their distributions are a weighted superposition of two normal distributions. For example, if the probability of a wet day occurrence is below 50%, the temperature mean for a wet day is lower than that for a dry day, and the standard deviations for both wet and dry days are the same, then a negative skewness is produced. The deviations from zero skewness due to this mechanism are rather small but can contribute to the fact that the skewness of maximum temperature at Hamburg is opposite to other stations because of a higher probability of wet days. This mechanism can be considered the major contributor to the skewness of the observed temperatures in summer, since the radiative effects seem to be of secondary importance. In winter, another mechanism helps the weather generator to simulate the sign of minimum temperature skewness correctly. Due to the randomness of the generator, a wrong combination of extreme daily temperatures (minimum higher than maximum) is occasionally generated. The values must be adjusted artificially to fit the trivial condition of maximum not being lower than minimum, which tends to make the skewness of minimum temperature more negative. Since the probability of generating the wrong combination of extreme temperatures decreases with increasing daily temperature range, this mechanism has much larger effect in winter than in summer. Experiments with large stochastically generated samples indicate that in winter when the daily temperature range is comparable with standard deviations of both temperatures, this mechanism explains most of the negative skewness.

The last comment concerns the comparison of two ways of reproducing the variance in downscaling. There is no remarkable difference between the inflation and white noise addition, except the fact most notable for maximum temperature skewness, that white noise addition results in higher statistical moments slightly closer to zero. This is an expected result since the white noise addition consists in a superposition of the original downscaled distribution possessing a non-zero skewness and kurtosis, with a Gaussian one that has both skewness and kurtosis zero.

6. CONCLUSIONS

We have demonstrated the degree to which the simulation methods (GCMs, statistical downscaling and weather generator) are able to reproduce the third and fourth statistical moments of daily maximum and minimum temperature distributions, and discussed possible causes of the agreements and discrepancies. The main conclusions can be summarized in the following:

- The GCMs (ECHAM and CCCM) differ in their ability to capture the relevant physical processes in winter. Whereas ECHAM succeeds in reproducing the heavy left tail of minimum temperatures, which is the main cause of negative skewness and positive kurtosis, CCCM fails in it because of deficiencies in its land-surface scheme.

- Downscaling transfers directly the statistical properties of predictors to predictands, which sometimes results in unrealistic features such as negatively skewed maximum temperature in summer.
- Weather generator reproduces the observed skewness (at least in its sign) in both seasons, but for different reasons: whereas in summer, it captures the process (a superposition of two conditional distributions, one for wet and the other for dry days) that likely causes also the observed distributions to be skewed, in winter, the negative skewness coincides with observations by chance only since it is a result of artificial corrections of the generated extreme daily temperatures.

This study complements two recent studies by *Huth et al. (2001)* and *Kyselý (2002)* who examined the ability of the simulation methods discussed here to reproduce different properties of minimum and maximum daily temperature series: persistence, distributions of day-to-day temperature change, characteristics of heat and cold waves, and return periods of extreme values. If the results are taken together, it becomes obvious that different methods have specific advantages and drawbacks relative to other methods, and that no method can be considered superior in all aspects.

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