Estimates of heat-related mortality in climate model outputs for present climate conditions

Odhady úmrtnosti v důsledku stresu z horka ve výstupech klimatických modelů pro současné klima

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Abstract

Extreme weather and climate phenomena (including extreme temperatures) severely influence ecosystems and human society. Impacts of climate change are likely to result rather from changes in climate variability and extremes than from an increase in mean temperature which underlines the need for the evaluation of extreme events in present climate simulations. Heat-related mortality is examined here as one of the most direct impacts of weather extremes on society. The study compares estimates of heat-related total mortality in the population of the Czech Republic derived from GCM simulated control climates, statistical downscaling from observation, statistical downscaling from GCM, and a WGEN-like weather generator.

The observed heat-related mortality is reproduced best in stochastic weather generator series; all unadjusted GCM outputs as well as the statistical downscaling models underestimate it. If GCMs are resized so that the mean and variance of the temperature series equal observed values, they perform almost comparably to the weather generator as to mean annual heat-related mortality but still misreproduce its interannual variability. Since GCMs and statistical downscaling fail to reproduce most characteristics of heat-related mortality and extreme temperature events, a scenario of changes in heat-related mortality should be based on weather generator simulations, with parameters of the stochastic model modified according to GCM outputs for a perturbed climate.

Key words: heat stress – heat related mortality – general circulation models – stochastic weather generator

1. Introduction

Extreme weather and climate phenomena are subjects of investigation because of both their current impacts on ecosystems and society and the threat of their possible increases in frequency, duration and severity in the climate perturbed by enhanced concentrations of greenhouse gases in the atmosphere. Impacts of climate change are expected to result rather from changes in climate variability and extreme event occurrence than from an increase in mean temperatures (Parmesan et al., 2000), and even relatively small shifts in the means and variances of climate variables can induce considerable changes in the severity of extreme events (Katz and Brown, 1992; Colombo et al., 1999).

General circulation models (GCMs) are currently the most frequently used tool in climate modelling (IPCC, 2001). They are able to reproduce many features of the observed climate system not only in terms of means but also naturally occurring variability; however, they were not designed for simulating local climates and their reliability decreases with increasing spatial and temporal resolution required.

There are several ways of obtaining site-specific daily time series which are to a different extent based on GCM outputs; one of them is statistical downscaling. It takes advantage of the fact that GCMs simulate large-scale upper-air fields more accurately than the surface local variables (Huth, 1999), and consists in identifying in the observed data the relationships between upper-air variables and local surface ones and applying them to control and/or perturbed GCM runs. The downscaled time series are fitted to a specific site and, if applied to the present climate, can be adjusted to reproduce the original mean and variance.

Another way of obtaining local series of weather elements is the use of stochastic weather generators (Richardson, 1981; Dubrovský, 1997). They produce synthetic time series, replicating the stochastic structure of observed variables, including means, variances, autocorrelations and crosscorrelations. In simulations of a future climate, the modification of their parameters is either based on GCM outputs or defined by incremental scenarios (Wilks, 1992; Dubrovský, 1997).

Here we focus on the comparison of estimates of heat-related mortality (HRM) based on climate model outputs for the present climate. The analysis was performed for the Czech Republic, with the Prague-Ruzyně station temperature series used as a representative one, and the comparison involved the observed, GCM-simulated (2 models), downscaled (3 models) and stochastically generated (5 versions) series of daily maximum air temperature (TMAX) for the period of May to September.

2. Data

a. GCMs

Simulations of present climate of two GCMs were used in this study.

ECHAM3. The ECHAM GCM originates from the European Centre for Medium Range Weather Forecast model, modified in the Max-Planck-Institute for Meteorology in Hamburg. Its version 3 is described in DKRZ (1993). It has a resolution corresponding to a 2.8° gridstep both in longitude and latitude; years 11 to 40 of the control run, in which climatological SSTs and sea ice extent were employed, are examined.

CGCM1. The first version of the Canadian Global Coupled Model is described in Flato et al. (2000). The atmospheric component of the model with the 3.75° x 3.75° grid was coupled to the ocean dynamic model. Daily data are available for one of three transient climate change simulations for the period 1900-2100, which employs an effective greenhouse gas forcing change corresponding to that observed from 1850 to the present, and a forcing change corresponding to an increase in CO_2 at a rate of 1% per year thereafter until 2100. The period 1961-1990 was used as a control one.

Since the downscaled temperatures reproduce the observed means and variances (see below), for a fair comparison between direct GCM outputs and statistical downscaling, distributions of GCM-produced temperatures were resized to have the observed mean and standard deviation (for the examined period of May to September), and both these versions of GCMs (the resized one and non-resized one) were analyzed and compared. The standard de-biasing procedure consisted in subtracting the mean of the simulated series, multiplying the anomalies by the ratio std_{obs} / std_{mod} where std_{obs} is the observed and std_{mod} the simulated standard deviation, and adding the observed mean.

Locations of the GCMs grid-points nearest to Prague are shown in Figure 1.

b. Statistical downscaling

Downscaled temperatures were calculated by the linear regression with stepwise screening from gridded 500 hPa heights and 1000/500 hPa thickness over the region which covers large portion of Europe and the adjacent Atlantic Ocean (for a detailed description of the procedure see Huth, 1999; Huth et al., 2001). The relationships between large-scale fields and local daily maximum temperatures were identified in observation over the period of May to September and then applied both to observation and control GCM outputs. Two possible ways of retaining the variance of the downscaled series, namely the variance inflation (Karl et al., 1990) and the addition of a white noise process (cf. Wilby et al., 1999, Zorita and von Storch, 1999) were applied in downscaling from observation and are compared here (the models are denoted DWI and DWW, respectively). As to downscaling from GCMs, inflation of variance was used as a standard procedure; downscaling was applied for ECHAM3 (denoted DWE).

c. Stochastic weather generator Met&Roll

Basic version (WG-BAS). Met&Roll (Dubrovský, 1997) is a WGEN-like (Richardson, 1981) four-variate daily weather generator which was designed to provide synthetic weather series mainly for crop growth modelling (Dubrovský et al., 2000; Žalud and Dubrovský, 2002). The four variables are daily maximum temperature (TMAX), daily minimum temperature (TMIN), daily sum of global solar radiation (SRAD) and daily precipitation amount (PREC). Precipitation occurrence is modelled by a first-order Markov chain, which is completely determined by two transition probabilities, P_{01} and P_{11}; precipitation amount on a wet day is approximated by a gamma distribution, $\Gamma(\alpha,\beta)$. Parameters of the precipitation model (P_{01}, P_{11}, α, β) are defined for individual months. Standardized deviations of TMAX, TMIN and SRAD from their mean annual cycles are modelled by a tri-variate first-order autoregressive model, AR(1). The means and standard deviations, which are used to standardize the three variables, are determined separately for wet and dry days and depend on a day of the year (their annual cycles are smoothed by robust locally weighted regression; Solow, 1988). Matrices of the AR(1) model, which are derived from the lag-0 and lag-1 correlations among the three standardized variables, are constant throughout the year. A description of this type of the generator may be found, e.g., in Wilks (1992) and Katz (1996), and a detailed description of Met&Roll, e.g., in Dubrovský (1997) and Dubrovský et al. (2000).

Modified versions. Three modifications were suggested to improve the reproduction of the high-frequency (interdiurnal; adjustments i and ii) and low-frequency (intermonthly; adjustment iii) variability in the stochastic weather generator: (i) incorporation of the annual cycle of lag-0 and lag-1 correlations among TMAX, TMIN and SRAD in the generator; (ii) use of the 3rd order Markov chain to model precipitation occurrence; and (iii) application of the monthly generator (based on an AR(1) model) to fit the low-frequency variability. They are more closely described in Kyselý and Dubrovský (2004).

Not all possible combination of the proposed modifications were examined; the analyzed versions are listed in Table 1. 'A' in acronym indicates that the *a*nnual cycle of correlations was incorporated; '3' denotes the higher (*3*rd) order of the Markov chain in the precipitation occurrence model; and 'M' stands for the application of the *m*onthly generator. 1000-yr long series simulated, using parameters derived for the 1961-1990 period, with five versions of the weather generator are examined here.

d. Observations

Temperature data. The models have been evaluated against observed daily maximum air temperature (TMAX) at the Prague-Ruzyně station. Since the GCM and downscaled series span 30 years corresponding to 1961-1990, the same period was used in the observed data.

Mortality data. Daily data on all-cause (total) mortality in the Czech Republic (population of about 10 million inhabitants) over the 19-year period 1982-2000 were available. Excess daily mortality was established by calculating deviations of the observed number of deaths from the expected number of deaths for each day of the examined period. The expected number of deaths was computed so that it takes into account effects of the long-term trend in mortality (decline during the period under study, mainly due to socio-economic and life-style changes which have followed the 1989 'Velvet Revolution'), the annual cycle (lower mortality in late than early summer, cf. Lerchl, 1998) and the weekly cycle (slightly lower mortality on weekends than weekdays); see Kyselý and Kříž (2003) for more details on the standardization procedure. A similar method was applied e.g. by Guest et al. (1999), Smoyer et al. (2000) and Whitman et al. (1997). Hereafter, the term mortality refers to all-cause mortality (expressed as the number of deaths) in the Czech Republic.

3. Methods

Heat-related mortality (HRM). HRM in the Czech Republic has been examined in several recent papers (Kyselý and Kříž, 2003; Kyselý and Huth, 2004). Here, mean observed excess total mortality was set for 1 °C wide intervals employing the 5-month May to September period (Figure 2); it takes positive values for TMAX ≥ 25 °C, and is lowest at TMAX = 18 °C (cf. Keatinge et al., 2000). HRM in each year is then defined in two ways, as (i) the sum of excess total mortality on all days with TMAX ≥ 25 °C (HRM25), and (ii) the sum of differences between excess total mortality and mean excess total mortality at TMAX = 18 °C on all days with TMAX ≥ 19 °C (HRM19). In the latter case, 'excess' mortality relates to the optimum temperature rather than to the baseline, and 'excess' is taken to be zero for the optimum temperature of 18 °C (to reduce the influence of sampling variability, the zero level of mortality was set for a 3 °C wide interval around 18 °C). HRM19, which comprises all days on which temperature is above the optimum value, is then higher than HRM25, which measures mortality on hot days with (mostly) positive deviations of mortality from the baseline.

4. Results: estimates of HRM in climate model outputs

Since the relationship between mean excess mortality and TMAX was set over the period of 1982-2000 (because of the mortality data available), when mean TMAX was about 1.2 °C higher than in 1961-1990 (the period to which climate model outputs relate), simulated mean annual HRM should be lower than observed one over 1982-2000. [If observed TMAX in 1961-1990 are additively adjusted by +1.2 °C, 'reconstructed' mean annual HRM and its standard deviation estimated from observed and adjusted TMAX in Prague in 1961-1990 are in a good agreement with observed mean annual HRM and its standard deviation for the 1982-2000 period.] Because of the different periods, HRM estimated from climate model simulations is evaluated against HRM 'reconstructed' from observed TMAX in 1961-1990, and not against observed HRM in 1982-2000. Although the 'reconstructed' estimate of HRM over 1961-1990 neglects any long-term acclimatization to heat stress which might take place, it is not an unreasonable approach here since only differences against and among models, not absolute values of HRM themselves are focused on. An alternative approach, which consists in an additive adjustment by +1.2 °C of all model TMAX outputs, and a comparison against observed instead of 'reconstructed' HRM, was applied with similar results, too.

In all model outputs, mean annual HRM, its standard deviation, and maximum and minimum annual values over 30 years were estimated from simulated TMAX. In case of the ECHAM3 GCM and statistical downscaling from ECHAM3, the estimated values were multiplied by a correction factor for the number of days in the May-September period (150 days in ECHAM3 vs. 153 days in observation and all other datasets). If TMAX higher then the maximum observed TMAX (i.e. 36 °C) was simulated in a model, the estimate of mean excess mortality on this day was based on an extrapolation from mean excess mortalities at three highest TMAX (34 °C, 35 °C and 36 °C) for which estimates from the observed data could be made.

Statistical characteristics of annual HRM estimated from individual models are shown in Table 2 for two versions of the HRM estimates, computed as (i) the sum of excess total mortality on all days with TMAX ≥ 25 °C (HRM25), and (ii) the sum of differences between excess total mortality and mean excess total mortality at TMAX = 18 °C (optimum temperature) on all days with TMAX ≥ 19 °C (HRM19).

Both GCMs grossly underestimate HRM25 and HRM19; if their outputs are resized to preserve the observed mean and variance of temperature, the performance is much better. However, the interannual variability of HRM25 and HRM19 is strongly overestimated even in the resized outputs of ECHAM3, which leads to the occurrence of years with extremely high or low HRM.

All statistical downscaling models underestimate both mean annual HRM and its variance; nevertheless, downscaling from ECHAM3 improves the estimates of HRM compared to the raw GCM output, and yields a much more realistic sampling variability of annual HRM even when compared to the resized GCM. The reason is a better reproduction of the shape of the distribution of TMAX provided by statistical downscaling from ECHAM3.

The stochastic weather generator, whatever version is considered, is the best model in reproducing HRM under present climate conditions; both mean annual HRM and its variance are almost unbiased. It is noteworthy particularly for HRM19 where the model's bias does not exceed 1% in any of the five versions examined. Improvements towards more sophisticated models of the weather generator, which incorporate the annual cycle of lag-0 and lag-1 correlations, a higher Markov chain order for the precipitation occurrence, and the monthly generator, have only negligible (and ambiguous) effects on its performance compared to the basic version WG-BAS.

5. Conclusions

Of the models examined, the five versions of the weather generator are the best five models in reproducing statistical characteristics of heat related mortality (HRM). Hence the scenario of possible future changes in HRM should be based on the weather generator simulations, with parameters of the stochastic model modified according to GCM outputs for a perturbed climate. Since this scenario will not take into account effects of a long-term acclimatization, which will moderate or suppress impacts of climate change on HRM, and other potential future trends and influences (cf. Davis et al., 2003; Donaldson et al., 2003), it is likely to represent, despite the ageing population, an upper estimate of changes in HRM in a future climate.

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Table 1. List of climate models and their brief specifications.

class of models	acronym	specification	period examined
global climate models (GCMs)	ECHAM3	control climate	years 11-40 of the control simulation
	CGCM1	transient climate change simulation	1961-1990
	ECHAM3-r	control climate temperature outputs resized to preserve the observed mean and variance	years 11-40 of the control simulation
	CGCM1-r	transient climate change simulation temperature outputs resized to preserve the observed mean and variance	1961-1990
statistical downscaling	DWI	downscaling from observation variance retained by inflation	1961-1990
	DWW	downscaling from observation variance retained by adding white noise	1961-1990
	DWE	downscaling from the ECHAM3 control climate variance retained by inflation	years 11-40 of the control simulation
stochastic weather generator	WG-BAS	no annual cycle of matrices of AR(1) model Markov chain order = 1 monthly generator not used	1000 yr long simulation
	WG-A	annual cycle of matrices of AR(1) model incorporated Markov chain order = 1 monthly generator not used	1000 yr long simulation
	WG-A3	annual cycle of matrices of AR(1) model incorporated Markov chain order = 3 monthly generator not used	1000 yr long simulation
	WG-AM	annual cycle of matrices of AR(1) model incorporated Markov chain order = 1 monthly generator used	1000 yr long simulation
	WG-AM3	annual cycle of matrices of AR(1) model incorporated Markov chain order = 3 monthly generator used	1000 yr long simulation

Table 2. Mean, standard deviation, and maximum and minimum of annual heat-related mortality in the Czech Republic estimated from climate model outputs for the present climate (1961-1990). OBS 1982-2000 denotes observed HRM over the 1982-2000 period, OBS 1961-1990 stands for HRM estimated from observed temperature data in Prague for the 1961-1990 period. Maximum and minimum for the stochastic weather generator were set from a randomly chosen 30-yr sample.

	HRM for TMAX>=25 °C				HRM for TMAX>=19 °C			
model	mean	std	maximum	minimum	mean	std	maximum	minimum
OBS 1982-2000	560.0	202.2	884.2	66.7	1283.3	302.9	1840.1	457.7
OBS 1961-1990	391.3	164.4	692.8	114.8	996.0	261.4	1462.2	524.9
ECHAM3	247.6	233.3	892.3	0.0	684.2	394.6	1744.8	138.3
CGCM1	8.7	9.1	42.3	0.0	183.7	49.9	304.5	101.0
ECHAM3-r	420.6	353.7	1454.0	9.4	1008.0	507.0	2452.9	295.4
CGCM1-r	376.4	151.6	778.3	154.0	980.2	211.8	1460.2	615.2
DWI	316.0	115.4	500.3	90.3	949.3	219.1	1349.0	473.0
DWW	343.6	105.7	531.6	170.8	957.5	191.9	1255.1	584.7
DWE	277.3	135.1	634.3	35.9	926.7	226.2	1412.6	445.0
WG-BAS	385.5	176.0	746.5	148.9	1000.4	249.2	1469.1	598.6
WG-A	383.8	149.9	658.2	178.2	996.7	211.1	1353.6	660.6
WG-A3	379.6	155.7	676.9	130.0	991.5	220.5	1433.3	640.3
WG-AM	388.3	170.7	887.0	117.8	1005.0	249.2	1715.9	657.7
WG-AM3	388.9	177.2	986.6	100.7	1005.9	255.1	1757.4	599.2

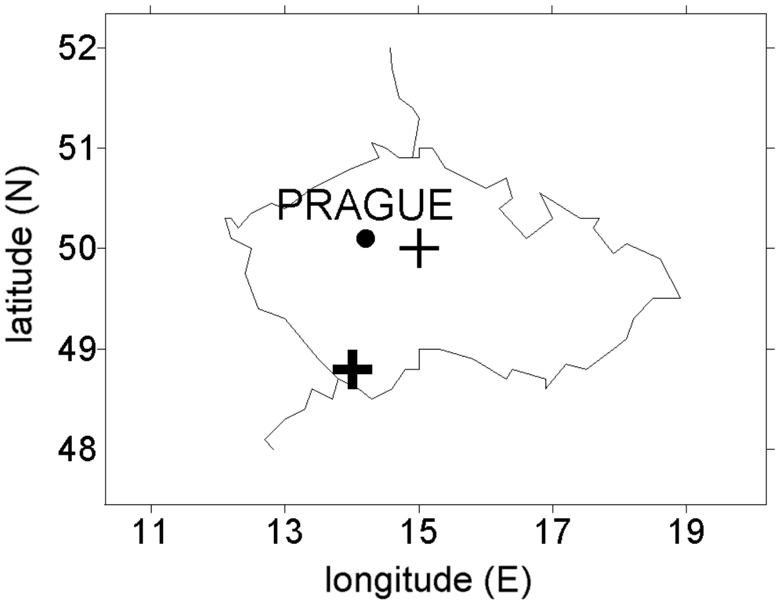

Fig. 1. Location of the nearest GCM gridpoints (bold cross for ECHAM3, thin one for CGCM1).

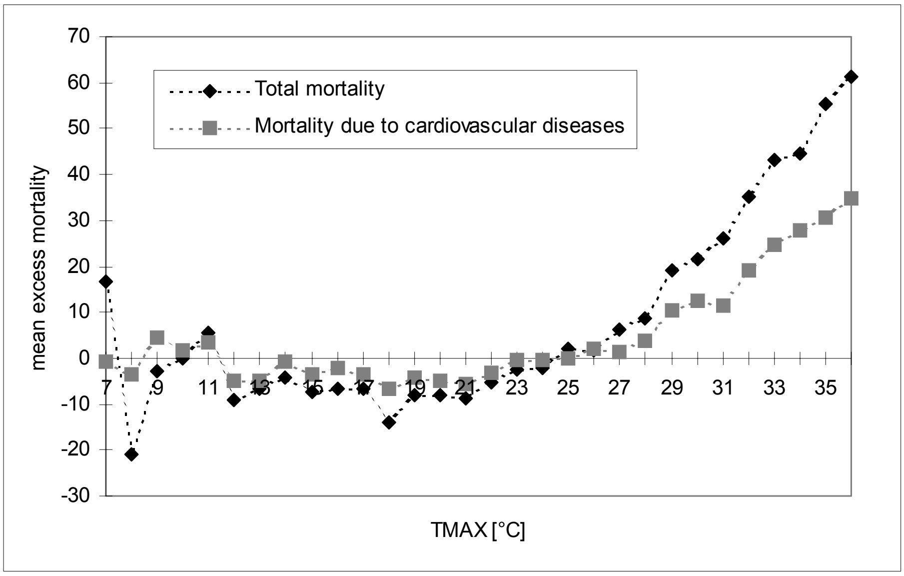

Fig. 2. Dependence of mean excess total mortality in the Czech Republic (set for 1 °C wide intervals, expressed as the number of deaths) on daily maximum temperature. A similar figure for mean excess mortality due to cardiovascular diseases is shown for comparison.