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SIMULATION OF EXTREME TEMPERATURE EVENTS BY A STOCHASTIC WEATHER GENERATOR: EFFECTS OF INTERDIURNAL AND INTERANNUAL VARIABILITY REPRODUCTION

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ABSTRACT

A WGEN-like four-variate (maximum and minimum temperature, precipitation and solar radiation) stochastic daily weather generator Met&Roll is used to provide synthetic weather series for models simulating crop growth and hydrological regime in present and changed climate conditions. Since impacts of climate change will be largely affected by changes in climate variability and extreme events, present climate models should satisfactorily reproduce both interdiurnal and interannual variability of the weather series and the occurrence of extremes. Three improvements of Met&Roll aiming at a better reproduction of interdiurnal and interannual variability have been introduced: (i) lag-0 and lag-1 correlations among solar radiation and daily extreme temperatures are allowed to vary during a year; (ii) a Markov chain of the third order (instead of the first order) is used to model precipitation occurrence; (iii) the synthetic daily weather series is adjusted to fit the series of the monthly means, which is generated using the four-variate first-order autoregressive (AR) model.

Model performance regarding the simulation of extreme temperature events is evaluated against observations at 83 stations covering most of Europe. None of the improvements of the generator lead to a generally better reproduction of extreme high and low temperatures (1 day extremes); the basic version of the generator performs best for annual maxima, whereas the inclusion of the annual cycle of correlations slightly enhances the simulation of annual minima. For multiday extremes, the incorporation of the monthly generator tends to improve heat- and cold-wave characteristics, mainly the chaining of hot and cold days in spells; in western and central Europe, it improves (worsens) the simulation of heat waves (cold waves). Bad reproduction of most extreme event characteristics out of western and central Europe indicates a limited applicability of a generator based on the first-order AR model for temperature outside the mild climate zone and in areas with a high degree of continentality. The validity of assumptions of the generator should be tested using weather series related to a given area before its application in impact studies, and, if necessary, adjustments must be made. Copyright © 2005 Royal Meteorological Society.

KEY WORDS: stochastic weather generator; model evaluation; extreme temperature event; heat wave; cold wave; Europe

1. INTRODUCTION

Stochastic weather generators are often used in climate-change impact studies to provide synthetic weather series for present or changed climate conditions (Riha *et al*., 1996; Mearns *et al*., 1997; Semenov and Barrow, 1997; Dubrovský *et al*., 2000; Tubiello *et al*., 2000; Trnka *et al*., 2004). These weather series are used as inputs to simulation models (e.g. crop growth models, rainfall-runoff models) and the impacts are thereafter assessed by comparing results obtained with the weather series for present and changed climates.

In assessing weather effects of elevated CO_2 on crops, increasing attention is devoted to changes in variability and occurrences of extreme events, such as droughts, frosts and heat waves. Many studies (e.g.

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Riha *et al*., 1996; Mearns *et al*., 1997; Dubrovský *et al*., 2000, 2004; Mavromatis and Hansen, 2001) show that increased variability of daily values, increased interannual variability and increased frequency of extreme weather tend to decrease the mean yields and increase the interannual variability of the yields.

The high-frequency and low-frequency variabilities that are often misreproduced by the daily weather generators have significant effects on modelling weather-dependent processes, as shown in Dubrovský *et al*. (2004). Since the generators often underestimate the interannual variability (Wilks, 1989, 1999; Johnson *et al*. 1996; Katz and Parlange, 1996; Dubrovský *et al*., 2000; Mavromatis and Hansen, 2001), at least two approaches have been suggested to reduce this insufficiency: (i) conditioning the daily generator on circulation indices (Katz and Parlange, 1993; Katz, 1996) or on monthly means of the weather characteristics (Wilks, 1989); (ii) perturbing the monthly parameters using a low-frequency generator (Hansen and Mavromatis, 2001). The approach used in this study resembles the latter technique, as both their method and ours add the low-frequency variability to daily weather series by applying a multivariate first-order autoregressive (AR) model to monthly statistics (see Section 2.2).

One of the main advantages of stochastic generators is that arbitrarily long synthetic weather series that resemble the observed ones in selected statistical characteristics may be simulated. This feature is particularly advantageous if one is concerned with rarely occurring (extreme) events, the probabilities of which may be estimated from these long runs with a smaller uncertainty than from short runs and/or observed weather series.

This paper focuses on a comparison of the simulation of 1 day and multiday hot and cold temperature extremes in the basic version of the stochastic weather generator Met&Roll (Dubrovský, 1997) and its modified versions (Dubrovský *et al*., 2004) that aim at a better reproduction of interdiurnal and interannual temperature variability and dry/wet spell properties. The models' performances are evaluated against observations at 83 stations covering most of Europe. The paper is organized as follows. In Section 2 descriptions of the basic and modified versions of the stochastic weather generator are given; the data and methods of the extreme value analysis are dealt with in Section 3. Section 4 presents a summary of the results of the evaluation of five versions of the generator regarding the simulation of temperature extremes, and the main findings are discussed in Section 5. Conclusions and implications for impact studies follow in Section 6.

2. STOCHASTIC WEATHER GENERATOR MET&ROLL: BASIC VERSION AND ITS MODIFICATIONS

2.1. Basic version (WG-BAS)

Met&Roll (Dubrovský, 1997) is a WGEN-like (Richardson, 1981) four-variate daily weather generator designed to provide synthetic weather series mainly for crop growth modelling (Dubrovský *et al*., 2000, 2004; 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).

In the basic version of the generator, precipitation occurrence is modelled by a first-order Markov chain that is completely determined by two transition probabilities, P_{01} (dry day–wet day) and P_{11} (wet day–wet day); precipitation amount on a wet day is approximated by a gamma distribution, Γ (α, β). 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 AR 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 the 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 generator may be found, for example, in Wilks (1992), Katz (1996) and Mearns *et al*. (1996, 1997), and a detailed description of Met&Roll can be found, for example, in Dubrovský (1997) and Dubrovský *et al*. (2000).

2.2. *Modified versions*

Three modifications were suggested (Dubrovský *et al*., 2004) to improve the reproduction of the high-frequency (interdiurnal; adjustments (i) and (ii)) and low-frequency (intermonthly; adjustment (iii)) variability in the stochastic generator: (i) inclusion of the annual cycle of lag-0 and lag-1 correlations among TMAX, TMIN and SRAD in the generator; (ii) use of a third-order Markov chain to model precipitation occurrence; (iii) application of a monthly generator (based on an AR(1) model) to fit the low-frequency variability. They are described more fully below.

(i) *Annual cycle of matrices of AR(1) model.* The most straightforward adjustment is made by allowing lag-0 and lag-1 correlations among TMAX, TMIN and SRAD to vary during the year. Here, the values of the correlations vary in 14-day steps and their annual cycles are smoothed by robust locally weighted regression (Solow, 1988). The annual cycle of correlations and lag-correlations among the weather variables has also been introduced into the weather generator by Hayhoe (2000).

(ii) *Higher order Markov chain.* A great number of papers exist dealing with modelling daily precipitation occurrence by Markov chains (e.g. Gabriel and Neumann, 1962; Katz, 1977; Gregory *et al*., 1993; Moon *et al*., 1994; Jones and Thornton, 1997; Lana and Burgueno, 1998; Wilks, 1999; Harrison and Waylen, 2000). According to these studies, the optimum order of the Markov chain varies between 0 and 3 and the value depends not only on the site and the season, but also on the choice of the criterion used to compare observed and synthetic weather series. The third-order Markov chain (instead of the first order) is applied in the modified version of Met&Roll, and the transition probabilities of the model are defined separately for the four seasons of the year (e.g. see Jones and Thornton (1997) for the description of a third-order Markov chain model). This modification is justified by the results of the tests, in which a detectable improvement in the simulation of lengths of wet and dry periods has been found when the order of the chain was increased up to three, but further increases resulted in no additional improvement (Dubrovský *et al*., 2004).

(iii) *Monthly weather generator.* The variability of monthly and annual means of the weather variables is usually underestimated by stochastic generators (Madden and Shea, 1978; Wilks, 1989, 1999; Johnson *et al*., 1996; Mavromatis and Hansen, 2001). This may be related to the fact that the common types of generator (including the basic version of Met&Roll) imply zero intermonthly correlations among the monthly means. This feature, however, contradicts observations.

To improve the reproduction of the low-frequency variability, the monthly weather generator is used here to produce realistically correlated time series of the monthly means. The daily weather series is thereafter modified to fit the monthly means. Since the monthly means of individual variables are autocorrelated and cross-correlated, the four-variate AR(1) model was chosen to model the time series of the monthly means. The precipitation in the monthly generator (unlike in the daily generator) is modelled by a single continuous variable being one of the four variables simulated by the AR(1) model. As the distribution of the monthly precipitation amounts is highly skewed, the fourth root is applied to the monthly precipitation. Monthly means of solar radiation are less skewed and the logarithmic transformation was found optimal. In result, the four variables used in the monthly generator are $y_1 = \ln\langle\mathrm{SRAD}\rangle$, $y_2 = \langle\mathrm{PREC}\rangle^{0.25}$, $y_3 = \langle\mathrm{TMAX}\rangle$, $y_4 = \langle\mathrm{TMIN}\rangle$, where $\langle X\rangle$ denotes the monthly mean of X. As in the daily generator, the AR model is applied to the standardized variables and parameters of the model are determined separately for the four seasons of the year.

The monthly generator is linked with the daily generator in the following way (Figure 1):

1. The daily weather series is generated by the daily weather generator.
2. The series of the monthly means is generated by the first-order AR model.
3. The daily series generated in step (1) is adjusted to fit the series of the monthly means generated in step (2). Temperatures (precipitation amounts and solar radiation sums) are adjusted additively (multiplicatively).

In the adjustment procedure, the value of the increment applied to the daily series is the same for all days within a month. The increment equals the difference (in the case of the additive modification) or

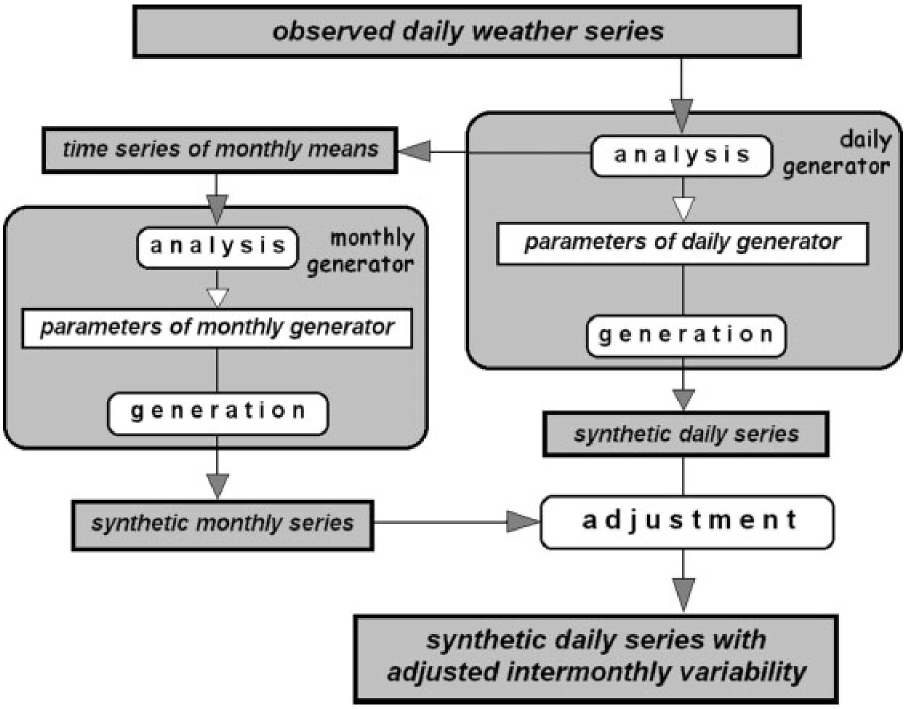

Figure 1. Linkage of the daily weather generator with the monthly weather generator (according to Dubrovský *et al*., 2004)

the ratio (in the case of the multiplicative modification) between the monthly means generated by the monthly generator and monthly means calculated from the daily series generated in the first step. As the intermonthly variability of the magnitude of the adjustment increment is several times lower than the variability of the interdiurnal changes of individual variables, the adjustment procedure only insignificantly affects the overall interdiurnal and diurnal variability.

The implementation of the monthly generator may be compared with the procedure suggested by Hansen and Mavromatis (2001). Both methods add the low-frequency variability to daily weather series by applying a multivariate AR(1) model to monthly statistics. Hansen and Mavromatis (2001) use the AR(1) model to perturb monthly parameters of the generator. In their approach, the aggregate intermonthly variability is a sum of the variability involved in the basic daily generator (with unperturbed parameters) and the added low-frequency correction component. In contrast, the daily series in the present analysis are generated by the daily generator with unperturbed monthly parameters and thereafter postprocessed to fit the monthly series generated by the monthly generator. In this approach, the intermonthly variability in the resultant daily series exactly equals the variability of the series provided by the monthly generator. The final effect of both approaches on the daily weather series should be very similar.

Not all possible combination of the proposed modifications were examined; the versions analysed are listed in Table I. 'A' in an acronym indicates that the annual cycle of correlation was incorporated; '3' denotes the higher (third) order of the Markov chain in the precipitation occurrence model; and 'M' stands for the application of the monthly generator.

2.3. Previous and current evaluation of the generator

Previous validation of the weather generator focused mainly on the basic version (WG-BAS). Dubrovský (1997) tested the applicability of a normal distribution to model daily maximum and minimum temperatures and global solar radiation, the applicability of the gamma distribution and the first-order Markov chain to model

Table I. Specifications of the five versions of the stochastic weather generator used in the experiments

	WG-BAS	WG-A	WG-A3	WG-AM	WG-AM3
Annual cycle of matrices of AR(1) model included	No	Yes	Yes	Yes	Yes
Markov chain order	1	1	3	1	3
Monthly generator implemented	No	No	No	Yes	Yes

precipitation, and examined the variability of monthly means of the four variables in WG-BAS. Huth *et al.* (2001) analysed the reproduction of the time structure of temperature series, the distributions of day-to-day temperature changes and heat and cold waves in WG-BAS and WG-A; and Huth *et al.* (2003) examined distributions of TMAX and TMIN in WG-BAS and WG-A. These latter two papers focused on a comparison of general circulation model-simulated, downscaled and stochastically generated temperature series, and the 'absence of physics' (particularly of effects of cold-front passages and radiation balance) in the stochastic weather generator was found to be the main source of discrepancies between the observed climate and simulated series. Finally, Dubrovský *et al.* (2004) analysed distributions of lengths of dry spells, lag-0 and lag-1 correlations among TMAX, TMIN and SRAD, and variability of monthly, seasonal and annual means of the four variables in all five versions of the generator examined here. The above-described modifications of the weather generator aim at a better simulation of some of the misreproduced characteristics found in the validation studies.

The previous evaluations were confined to the area of the Czech Republic (Dubrovský, 1997; Dubrovský *et al.*, 2004) or a few stations in central Europe (Huth *et al.*, 2001, 2003), and 30-year long synthetic time series were analysed.

The present validation deals with the reproduction of 1 day (mean annual maxima/minima and 20-year return values) and multiday (heat/cold waves) temperature extremes in the basic and the modified versions of the weather generator. 1000-year long synthetic series at more than 80 stations throughout Europe are examined; see Section 3.

3. DATA AND METHODS

3.1. Data

3.1.1. Observed data. Daily maximum and minimum temperatures and precipitation amounts at 78 stations included in the European Climate Assessment (ECA) project (Klein-Tank *et al.*, 2002; Wijngaard *et al.*, 2003) were analysed (Table II). The period employed for the estimation of parameters of the generator, as well as for the analysis of observed extremes, was 1961–90. Some 55% of the stations are classified as 'useful' over the 1946–99 period according to Wijngaard *et al.* (2003); stations with potential inhomogeneities in 1961–90 are located mostly in central Europe. In addition to these data, daily maximum and minimum temperatures and precipitation amounts at five stations in the Czech Republic over the same period were analysed. The stations cover most of Europe.

3.1.2. Simulated data. The 1000-year long synthetic series of daily maximum and minimum temperatures and precipitation amounts were generated at the 83 stations for each version of the weather generator. Since there were no input data for solar radiation at a large majority of stations, this variable was omitted from the simulation; the effect on the other variables is negligible. Precipitation amounts are not examined here; however, the simulation of precipitation (namely, the differences between the first-order and third-order Markov chain models for precipitation occurrence) might have an influence on the temperature series, as their means and standard deviations are conditioned on the precipitation occurrence.

3.2. Methods

3.2.1. Extreme value analysis (analysis of 1 day temperature extremes). Mean annual maxima of TMAX and minima of TMIN were calculated in each series, and 20-year return values of TMAX and TMIN were

Table II. List of stations

Country	Location	Latitude N (°:′)	Longitude W/E (°:′)	Altitude (m a.s.l.)
Belgium	Uccle	+50:48	+04:21	100
Croatia	Zagreb-Gric	+45:49	+15:59	157
Czech Republic	Klatovy	+49:24	+13:18	430
Czech Republic	Praha-Ruzyne	+50:06	+14:15	364
Czech Republic	Hradec Kralove	+50:11	+15:50	278
Czech Republic	Brno-Turany	+49:10	+16:42	241
Czech Republic	Ostrava-Mosnov	+49:42	+18:07	251
Denmark	Vestervig	+56:46	+08:19	18
Denmark	Nordby	+55:27	+08:24	4
Denmark	Koebenhavn-Landbohoejskol	+55:41	+12:32	9
Finland	Helsinki	+60:10	+24:57	4
Finland	Jyvaskyla	+62:24	+25:41	137
Finland	Sodankyla	+67:22	+26:39	179
France	Bourges	+47:04	+02:22	161
France	Toulouse-Blagnac	+43:37	+01:23	152
France	Bordeaux-Merignac	+44:50	−00:42	49
France	Chateauroux	+46:52	+01:43	160
France	Perpignan	+42:44	+02:52	43
France	Lyon-Bron	+45:44	+04:56	172
France	Paris-Montsouris	+48:49	+02:20	75
Germany	Muenster	+51:58	+07:36	63
Germany	Hamburg-Fuhlsbuettel	+53:33	+09:58	26
Germany	Bremen	+53:03	+08:47	4
Germany	Trier	+49:45	+06:39	144
Germany	Kaiserslautern	+49:27	+07:47	248
Germany	Karlsruhe	+49:01	+08:23	114
Germany	Stuttgart	+48:43	+09:13	401
Germany	Schwerin	+53:39	+11:23	59
Germany	Dresden-Wahnsdorf	+51:07	+13:41	246
Germany	Berlin	+52:27	+13:18	55
Germany	Potsdam	+52:23	+13:04	81
Germany	Bamberg	+49:53	+10:53	282
Germany	Zugspitze	+47:25	+10:59	2960
Germany	Hohenpeissenberg	+47:48	+11:01	977
Germany	Muenchen	+48:10	+11:30	515
Germany	Jena-Sternwarte	+50:56	+11:35	155
Greece	Corfu	+39:37	+19:55	4
Iceland	Reykjavik	+64:08	−21:54	52
Iceland	Stykkisholmur	+65:05	−22:44	8
Iceland	Dalatangi	+65:16	−13:35	9
Iceland	Vestmannaeyjar	+63:24	−20:17	118
Ireland	Valentia-Observatory	+51:56	−10:15	9
Ireland	Birr	+53:05	−07:53	70
Ireland	Malin-Head	+55:22	−07:20	20
Luxembourg	Luxembourg-Airport	+49:37	+06:13	376
Netherlands	De-Kooy-Den-Helder	+52:55	+04:47	0
Netherlands	De-Bilt	+52:06	+05:11	2
Netherlands	Eelde-Groningen	+53:08	+06:35	4
Netherlands	Vlissingen	+51:27	+03:36	8
Norway	Bjoernoeya	+74:31	+19:01	16
Portugal	Lisboa-Geofisica	+38:43	−09:09	77

Table II. (*Continued*)

Country	Location	Latitude N (°:′)	Longitude W/E (°:′)	Altitude (m a.s.l.)
Portugal	Porto	+41:08	−08:36	93
Portugal	Braganca	+41:48	−06:44	690
Russia	Kojnas	+64:45	+47:39	64
Russia	Petrozawodsk	+61:49	+34:16	110
Russia	Ust-Tzilma	+65:26	+52:16	68
Russia	Petsjora	+65:07	+57:06	59
Russia	Troitzko	+62:42	+56:12	139
Russia	Pskow	+57:49	+28:25	45
Russia	Smolensk	+54:45	+32:04	239
Russia	Wologda	+59:19	+39:55	130
Russia	Kostroma	+57:44	+40:47	126
Russia	Elatma	+54:57	+41:46	136
Russia	Tambov	+52:48	+41:20	128
Russia	Izevsk	+56:50	+53:27	159
Russia	Koersk	+51:46	+36:10	247
Russia	Orenburg	+51:41	+55:06	117
Russia	Armavir	+44:59	+41:07	159
Spain	San-Sebastian	+43:18	−02:02	259
Spain	Navacerrada	+40:47	−04:01	1890
Spain	Salamanca	+40:57	−05:30	790
Spain	Valencia	+39:29	−00:23	11
Sweden	Vaexjoe	+56:52	+14:48	166
Sweden	Linkoping-Malmslatt	+58:24	+15:32	93
Sweden	Oestersund	+63:11	+14:29	376
Sweden	Stensele	+65:04	+17:09	325
Switzerland	Basel-Binningen	+47:33	+07:35	316
Switzerland	Saentis	+47:15	+09:21	2490
Switzerland	Zuerich-Sma	+47:23	+08:34	556
Switzerland	Lugano	+46:00	+08:58	273
Ukraine	Lugansk	+48:34	+39:15	59
Yugoslavia	Beograd	+44:48	+20:28	132
Yugoslavia	Nis	+43:20	+21:54	202

estimated by fitting the generalized extreme value (GEV) distribution to the sample of annual extremes. The method of L-moments (Hosking, 1990) was used here to estimate parameters of the GEV distribution, since it is computationally less expensive and for small to moderate sample sizes (which corresponds to the size of the observed datasets in the present analysis) superior to or comparable to the maximum likelihood method.

3.2.2. Heat and cold waves. Heat (cold) waves are defined in terms of anomalies of TMAX (TMIN) from the mean annual course as periods of at least three successive days with $\mathrm{TMAX} - M_{\mathrm{TMAX},d} \geq \mathrm{P95}_{\mathrm{TMAX},d}$ ($\mathrm{TMIN} - M_{\mathrm{TMIN},d} \leq \mathrm{P05}_{\mathrm{TMIN},d}$). Here, $M_{\mathrm{TMAX},d}$ ($M_{\mathrm{TMIN},d}$) denotes the 'normal' value of TMAX (TMIN) on day d ($d = 1$–365), and $\mathrm{P95}_{\mathrm{TMAX},d}$ ($\mathrm{P05}_{\mathrm{TMIN},d}$) stands for the 95th (5th) percentile of the empirical distribution function of $\mathrm{TMAX} - M_{\mathrm{TMAX},d}$ ($\mathrm{TMIN} - M_{\mathrm{TMIN},d}$) on day d. To obtain $M_{\mathrm{TMAX},d}$ and $M_{\mathrm{TMIN},d}$, the mean annual cycles of TMAX and TMIN were calculated and smoothed using 11-day running means to filter out short-term fluctuations; values of the 95th (5th) percentile were set for each day d from the empirical distribution function of $\mathrm{TMAX} - M_{\mathrm{TMAX},d}$ ($\mathrm{TMIN} - M_{\mathrm{TMIN},d}$) in a 61-day interval $\langle d - 30, d + 30 \rangle$. (The percentiles were thus determined from samples containing 61(days) × 30(years) = 1830 observations. The choice of the length of the interval in which empirical distribution functions are considered to estimate the percentiles (61 days here) has a small effect on the percentile values, and negligible effects on results of the models' evaluations.) The same threshold values of P95 and P05 were employed in both the observed and generated data.

According to this definition, heat and cold waves may occur in any period of a year. The terms hot days and cold days refer to days with TMAX $- M_{\mathrm{TMAX},d} \geq \mathrm{P95}_{\mathrm{TMAX},d}$ and TMIN $- M_{\mathrm{TMIN},d} \leq \mathrm{P05}_{\mathrm{TMIN},d}$ respectively hereafter.

The evaluation of the reproduction of heat and cold waves focuses on their mean annual durations and the percentage of hot and cold days occurring in spells.

4. RESULTS

The reproductions of the characteristics of extreme temperature events examined in the five versions of the stochastic weather generator are shown in Figures 2–9 in terms of spatial patterns of the deviations between simulated and observed climates, and summarized using the mean errors and absolute mean errors of the evaluated characteristics in Table III (hot temperature extremes, whole of Europe), Table IV (cold temperature extremes, whole of Europe) and Table V (hot and cold temperature extremes, five European regions: central Europe (defined as the region 45–52.5 °N, 7.5–22.5 °E), western Europe (42.5–55 °N, 0–12.5 °E), the Iberian Peninsula (36–44 °N, 10 °W–2.5 °E), northern Europe (55–70 °N, 10–30 °E) and eastern Europe (45–65 °N, 30–50 °E)).

Table III. Mean error (ME) and absolute ME (AME) of mean annual maxima of TMAX, 20-year return values of TMAX, mean annual duration of heat waves, and inclusion of hot days into heat waves in five versions of the weather generator. The best model results in each of the characteristics is in bold

	Mean annual maximum of TMAX (°C)		20-year return value of TMAX (°C)		Mean annual duration of heat waves (days)		Inclusion of hot days in heat waves (%)	
	ME	AME	ME	AME	ME	AME	ME	AME
WG-BAS	**0.37**	**0.85**	**0.56**	**1.50**	−0.90	1.83	−8.0	8.8
WG-A	0.52	0.96	0.66	1.57	−0.74	1.73	−6.7	8.1
WG-A3	0.51	0.95	0.63	1.54	−0.79	1.71	−6.7	8.0
WG-AM	0.71	1.08	1.09	1.84	**0.37**	**1.68**	**−4.4**	**6.4**
WG-AM3	0.72	1.09	1.13	1.88	**0.37**	1.70	−4.5	6.5

Table IV. ME and AME of mean annual minima of TMIN, 20-year return values of TMIN, mean annual duration of cold waves, and inclusion of cold days into cold waves in five versions of the weather generator. The best model results in each of the characteristics is in bold

	Mean annual minimum of TMIN (°C)		20-year return value of TMIN (°C)		Mean annual duration of cold waves (days)		Inclusion of cold days in cold waves (%)	
	ME	AME	ME	AME	ME	AME	ME	AME
WG-BAS	−0.82	**1.18**	0.15	**2.52**	−1.91	1.95	−8.3	8.3
WG-A	**−0.53**	**1.18**	0.24	2.58	−2.00	2.03	−8.8	8.8
WG-A3	**−0.53**	1.19	0.21	2.58	−1.94	1.97	−8.5	8.5
WG-AM	−0.61	1.29	**−0.14**	2.68	−1.77	1.91	−7.6	7.8
WG-AM3	−0.62	1.30	−0.17	2.68	**−1.74**	**1.87**	**−7.4**	**7.6**

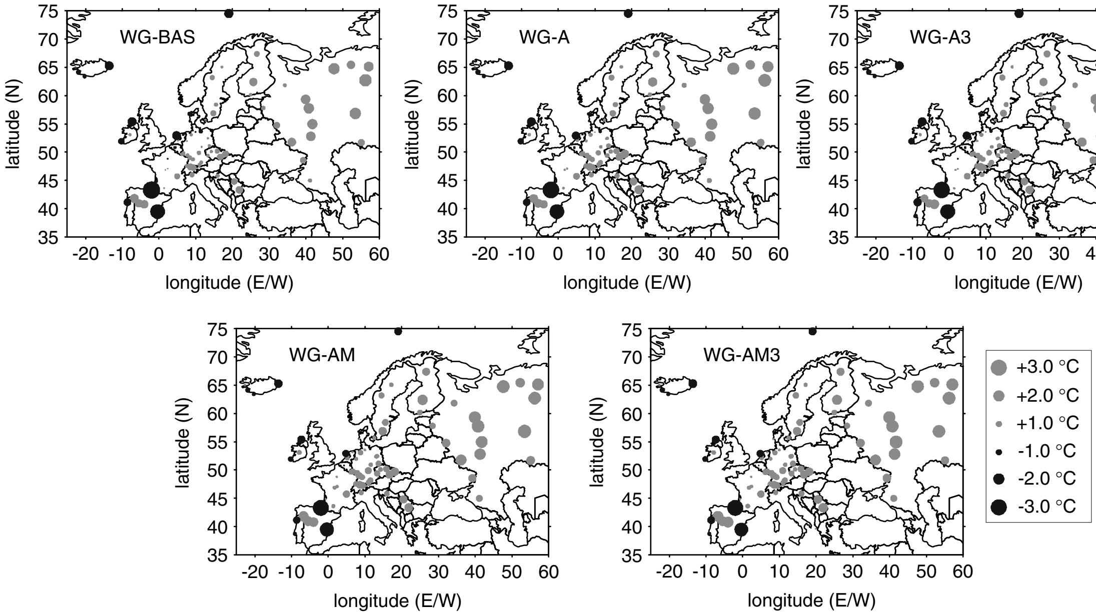

Figure 2. Reproduction of mean annual maxima of TMAX in five versions of the weather generator. Differences between stochastically generated and observed series are shown

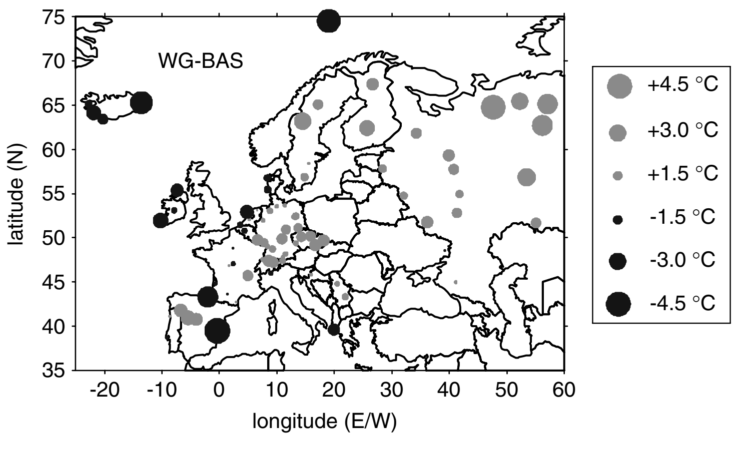

Figure 3. Reproduction of 20-year return values of TMAX in WG-BAS. Differences between stochastically generated and observed series are shown

4.1. Mean annual maxima of TMAX

Patterns of differences between simulated and observed mean annual temperature maxima are depicted in Figure 2. Most spatial features are very similar in all five versions of the weather generator; the mean annual maxima are generally too high in large parts of Europe, but too low mainly at some western European and Iberian stations (see also Table V). The differences between the mean annual maxima in the synthetic and observed series are statistically significant at the 5% significance level at 38 out of 83 stations in WG-BAS, according to both the two-sided Wilcoxon–Mann–Whitney rank-sum test and the two-sided t-test, and at 48 to 57 stations in the other versions of the weather generator. Bad performances in Russia and the Iberian Peninsula (differences as large as 3 °C compared with observations) likely result from the fact that temperatures do not follow the normal distribution in these areas, and even moderate departures from the

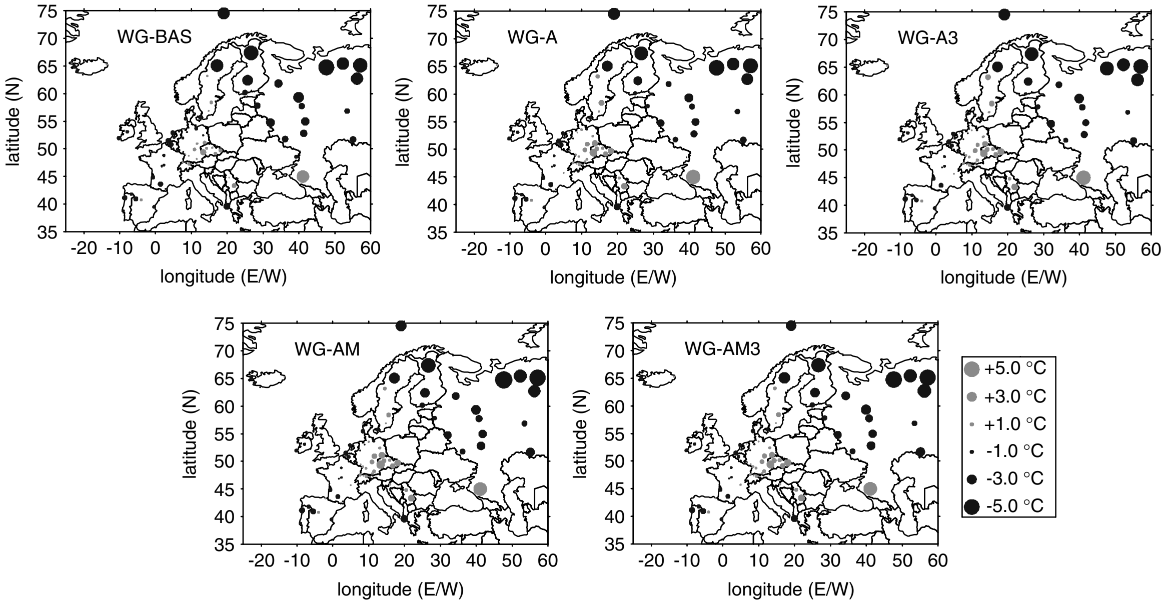

Figure 4. Reproduction of mean annual minima of TMIN in five versions of the weather generator. Differences between stochastically generated and observed series are shown

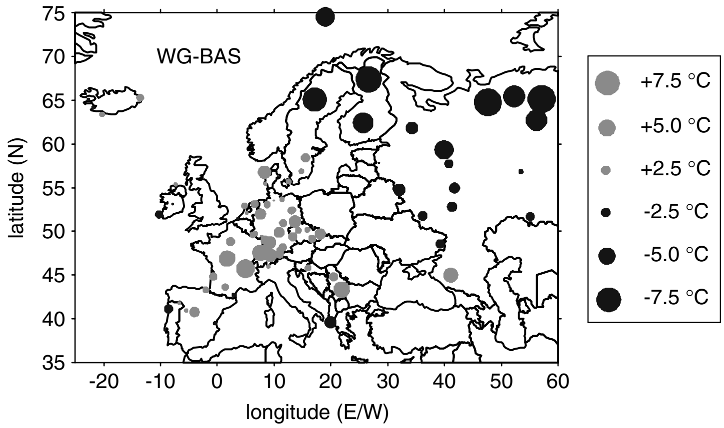

Figure 5. Reproduction of 20-year return values of TMIN in WG-BAS. Differences between stochastically generated and observed series are shown

normal distribution may strongly affect the reproduction of extremes (see also Section 5.3 and Figure 10). Relatively small differences among various versions of the weather generator and a superiority of WG-BAS are obvious from Table III as well; WG-BAS fits the observed maxima almost perfectly if the mean error over a large area of Europe is evaluated. Models perform best in western and central Europe around 50 °N (Table V), where the bias exceeds 1.0 °C rather exceptionally.

4.2. The 20-year return values of TMAX

The performance is worse than for mean annual maxima of TMAX in all parts of Europe, but it remains relatively good mainly at western and central European stations around 50 °N (Figure 3; only results for WG-BAS are shown, since the patterns are similar for all other versions of the generator). The simulated 20-year

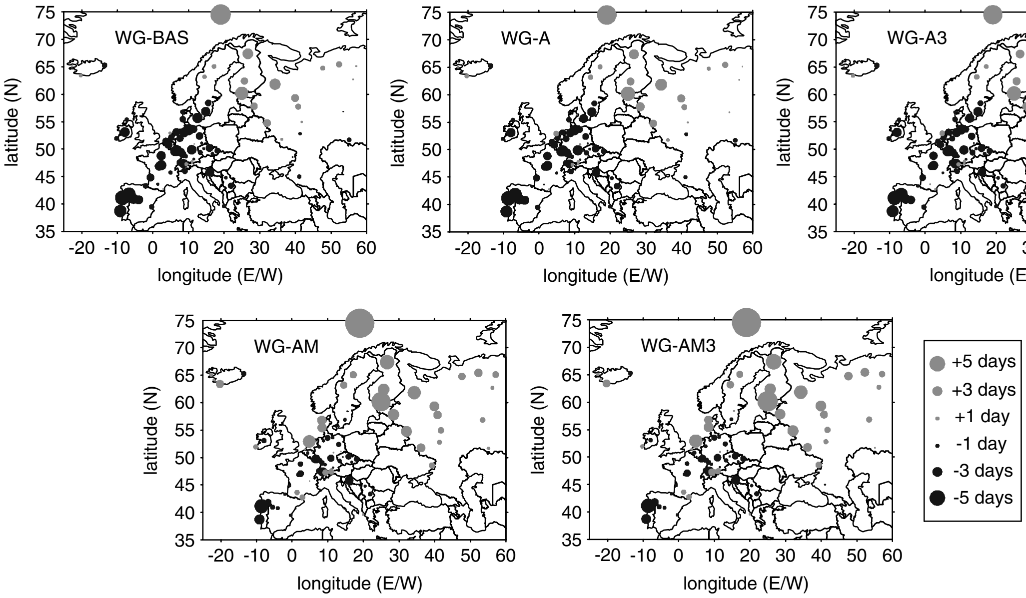

Figure 6. Mean annual duration of heat waves in five versions of the weather generator. Differences between stochastically generated and observed series are shown

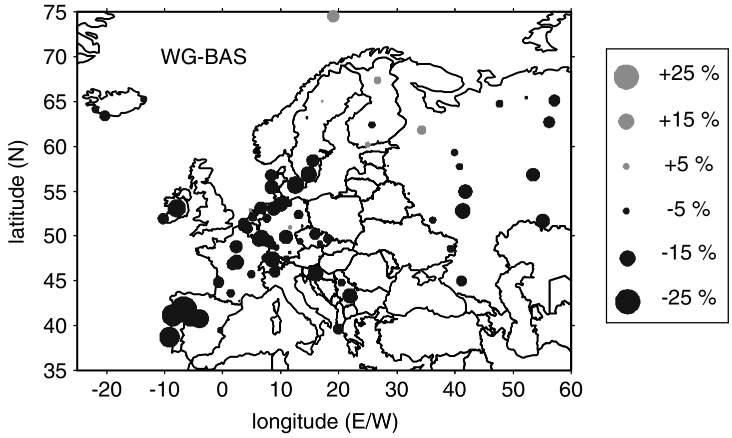

Figure 7. Percentage of hot days occurring within heat waves in WG-BAS. Differences between stochastically generated and observed series are shown

return values of TMAX tend to be too high over most of Europe, and WG-BAS performs best (Table III). The bias exceeds 4.0 °C at four stations, but usually it is smaller than 2.0 °C.

4.3. Mean annual minima of TMIN

If the models are evaluated in terms of the absolute difference of the given characteristics between the synthetic and observed series, then all versions of the weather generator perform worse for mean annual minima of TMIN (Figure 4, Table IV) than mean annual maxima of TMAX. They yield annual minima too high in central Europe, too low in northern Europe and most parts of Russia, and slightly lower compared with observations in western and southwestern Europe. However, the simulation remains reasonably good in large parts of western Europe (see also Table V), where the bias is usually lower than 1.0 °C, and the

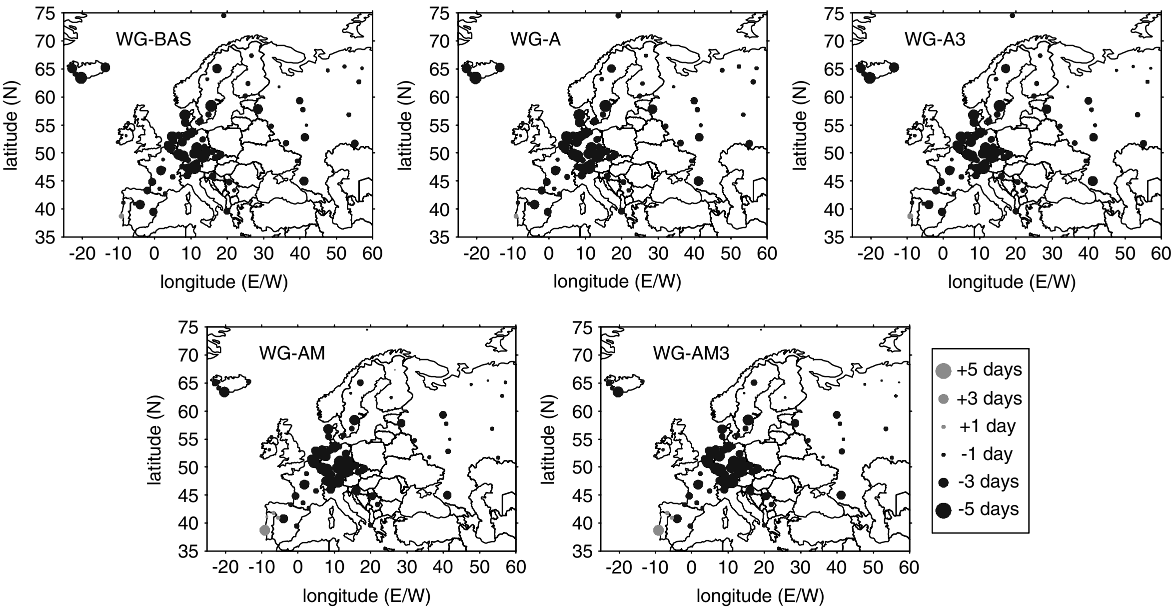

Figure 8. Mean annual duration of cold waves in five versions of the weather generator. Differences between stochastically generated and observed series are shown

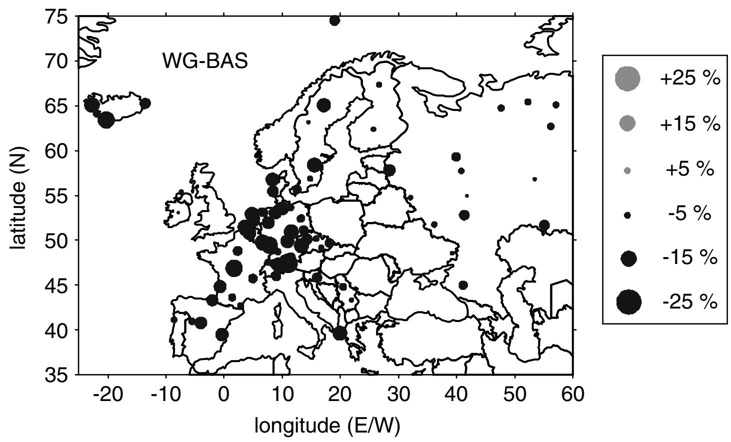

Figure 9. Percentage of cold days occurring within cold waves in WG-BAS. Differences between stochastically generated and observed series are shown

overall number of stations where the difference compared with observations is statistically significant at the 5% level (between 31 and 35 stations in all five versions of the weather generator, according to both the Wilcoxon–Mann–Whitney test and the t-test) is smaller than for mean annual maxima. This effect (larger absolute differences between observed and synthetic data, but a lower number of stations where they are significant) stems from the enhanced variance of annual minima compared with annual maxima. Differences among various versions of the generator are again relatively small; the introduction of the monthly generator leads to slight deterioration of the results, and the models that include the annual cycle of correlations (WG-A, WG-A3) are the best if the mean error and the absolute mean error over large parts of Europe are evaluated (Table IV).

Table V. ME and AME of characteristics of temperature extremes in five European regions (see Section 4 for region definitions) in two versions of the weather generator (WG-BAS/WG-AM3)

		Central Europe	Western Europe	Iberian Peninsula	Northern Europe	Eastern Europe
Number of stations		22	29	8	9	9
Mean annual maximum of TMAX (°C)	ME	0.55/0.91	0.22/0.58	−0.41/−0.13	0.67/1.08	1.47/1.91
	AME	0.55/0.91	0.47/0.68	1.54/1.69	0.67/1.08	1.47/1.91
20-year return value of TMAX (°C)	ME	1.13/1.65	0.52/1.15	−0.23/0.34	1.38/1.86	1.78/2.51
	AME	1.19/1.68	0.91/1.36	2.02/2.32	1.38/1.86	1.80/2.51
Mean annual minimum of TMIN (°C)	ME	0.26/0.74	−0.29/−0.03	−0.68/−0.76	−1.68/−1.35	−2.52/−2.53
	AME	0.45/0.80	0.48/0.51	0.83/0.97	1.95/1.87	2.52/2.53
20-year return value of TMIN (°C)	ME	2.37/2.47	2.01/1.90	0.53/0.05	−1.89/−2.73	−3.79/−4.44
	AME	2.37/2.47	2.11/2.02	1.34/1.53	2.99/3.09	3.79/4.44
Mean annual duration of heat waves (days)	ME	−1.33/−0.81	−1.68/−0.45	−2.77/−1.51	0.68/2.40	1.22/2.60
	AME	1.50/1.20	1.88/1.26	2.77/1.85	2.43/2.66	1.41/2.60
Inclusion of hot days in heat waves (%)	ME	−6.5/−5.1	−8.1/−4.2	−14.9/−10.9	−4.5/0.3	−5.7/−3.3
	AME	6.8/5.5	8.5/5.6	14.9/11.5	7.0/6.2	7.4/6.0
Mean annual duration of cold waves (days)	ME	−2.38/−2.85	−2.25/−2.52	−1.11/−0.12	−1.97/−1.32	−1.37/−0.97
	AME	2.38/2.85	2.25/2.52	1.49/1.50	1.97/1.33	1.37/0.97
Inclusion of cold days in cold waves (%)	ME	−9.8/−11.3	−10.6/−11.0	−6.8/−4.0	−7.1/−4.1	−4.6/−2.9
	AME	9.8/11.3	10.6/11.0	6.8/5.1	7.1/4.8	4.6/3.5

4.4. The 20-year return values of TMIN

The performance is much worse than for both the 20-year return values of TMAX and the mean annual temperature minima (Figure 5). The bias exceeds 4.0 °C at 14 stations (in WG-BAS; cf. with four stations in the case of 20-year return values of TMAX). The 20-year return values of TMIN are too high in western, central and southeastern Europe, and they are too low in northern Europe and Russia.

4.5. Duration of heat waves

The mean annual duration of heat waves is overestimated in northern and northeastern Europe, and underestimated at most sites in central and western Europe and the Iberian Peninsula (Figure 6); the reproduction is best in central Europe around 50 °N (in WG-BAS). Differences among various versions of the weather generator are more pronounced than in the case of 1 day extremes. The incorporation of the monthly generator increases the frequency of heat waves all over Europe, and considerably improves the simulation of their mean annual duration in western and central Europe (Table V) and if evaluated over the whole of Europe (Table III). The number of sites where the differences in the mean annual duration of heat waves between the synthetic and observed series are significant at the 5% level is lower compared with the test results for mean annual maxima (Section 4.1); the differences are significant at 18 to 21 stations according to the two-sided Wilcoxon–Mann–Whitney test in WG-BAS, WG-A and WG-A3, and only at 13 and 15 stations in WG-AM and WG-AM3. The improvement in the reproduction of the mean annual duration of heat waves due to the application of the monthly generator is significant at 35 stations in both WG-AM and WG-AM3.

4.6. *Percentage of hot days occurring in heat waves*

Inclusion of hot days into heat waves (ratio of the number of hot days occurring in heat waves to the total number of hot days, which measures the persistence of temperature extremes, i.e. chaining of hot days in spells) is underestimated at a large majority of stations (Figure 7), with a few exceptions mainly in northern Europe (for an explanation see Section 5.1). Typical values of the percentage of hot days occurring in heat waves are around 40% in observations and 32–36% in the five versions of the weather generator. The strongest negative bias, reaching −25%, is found in southwestern Europe, where it is connected with a frequency of heat waves that is too low. In Portugal, for example, about 45% of hot days occur in heat waves in the observed data, whereas this is only 20–25% in WG-BAS, and the mean annual duration of heat waves is halved compared with observations. The underestimation of the inclusion of hot days in heat waves is reduced compared with WG-BAS in the other versions of the weather generator, most noticeably when the monthly generator is introduced (Table III). The percentage of sites having a negative bias decreases from 90.4% in WG-BAS to 79.5% in WG-AM3.

4.7. *Duration of cold waves*

The mean annual duration of cold waves is underestimated all over Europe (Figure 8); the only exceptions are a few stations in the Iberian Peninsula. The underestimation is relatively large in central Europe where it is likely related to the too high temperature minima, particularly in winter. The differences between the generated and observed mean annual durations of cold waves are significant at the 5% level at 24 (in WG-BAS) to 33 stations (WG-AM) according to the Wilcoxon–Mann–Whitney test. The introduction of the monthly generator improves the performance in northern and eastern Europe and (to a lesser degree compared with heat waves) if evaluated over the whole of Europe, but the results deteriorate in central and western Europe (Tables IV and V). The improvement due to the incorporation of the monthly generator is significant at 14 (15) stations in WG-AM (WG-AM3); however, at 27 (24) stations, located mainly in central and western Europe, the monthly generator worsens the reproduction of the mean annual duration of cold waves significantly.

4.8. *Percentage of cold days occurring in cold waves*

The percentage of cold days occurring in spells is underestimated at all stations (Figure 9); it is the only characteristic evaluated for which the bias has the same sign throughout Europe (in WG-BAS and WG-A; there are some exceptions in the other versions of the generator). The negative bias is again, as for hot days and heat waves, reduced when the monthly generator is applied (Table IV) — see discussion in Section 5.2. Compared with hot days and heat waves, cold days have a lower tendency to chain into spells (the mean percentage of cold days occurring in cold waves is 36% in observations and 27–29% in the five versions of the weather generator).

The regional differences in the models' performances are evaluated in Table V in terms of the ME and the AME of the characteristics of temperature extremes examined in five selected European regions. For most characteristics, western and central Europe are areas with the lowest ME and AME; the exceptions are 20-year return values of TMIN, the percentage of cold days occurring in spells, and particularly the duration of cold waves, which is strongly underestimated in these regions.

Among the five versions of the weather generator, WG-BAS yields the most realistic characteristics of 1 day temperature extremes, and the incorporation of the monthly generator (WG-AM, WG-AM3) improves the simulation of heat and (to a lesser degree) cold waves.

5. DISCUSSION

Three modifications were utilized to improve the reproduction of low-frequency and high-frequency variabilities in the four-variate stochastic weather generator Met&Roll. Dubrovský *et al*. (2004) found out that: (i) the inclusion of the annual cycle of the correlations has an ambiguous effect on the lag-1 correlations among weather characteristics standardized unconditionally on the precipitation occurrence, and an insignificant effect on the output from agricultural crop growth and hydrological rainfall-runoff simulation models; (ii) the increased order of the Markov chain improves modelling of long dry spells, and correspondingly enhances reliability of the output from each simulation model; (iii) conditioning the daily generator on the monthly generator has the most positive effect, since it significantly improves the reproduction of the variability of monthly, seasonal and annual means of the weather characteristics, which is particularly pronounced in more realistic outputs from the rainfall-runoff model.

Some of the general features of the reproduction of temperature extremes by the weather generator, and their relationships to other statistical characteristics of the synthetic series, are discussed below.

5.1. Generator underestimates the percentage of hot/cold days occurring in spells

This is a general feature of all the versions of the weather generator; it is more pronounced for cold days than hot days. A likely explanation takes into account the fact that the weather generator underestimates the lag-1 correlations of temperature (Huth *et al*., 2001). This seems to be in contradiction with the fact that autocorrelations are among the generator's parameters and should, therefore, be replicated accurately. Nevertheless, the lag-0 and lag-1 correlations of TMAX and TMIN were derived from series that were standardized using means and standard deviations determined separately for wet and dry days. During the generation process, the generator produces standardized anomalies first, which are then turned into temperatures by multiplying by the standard deviations and adding to the means, both conditioned on the precipitation occurrence. The day-to-day changes of the temperatures generated are thus a result of a superposition of the AR(1) model of the standardized temperature and the first/third-order Markov chain model of the precipitation occurrence, which implies a suppression of the lag-1 correlations relative to the original AR model. This leads to the lower accumulation of temperature extremes in the stochastically generated data. Furthermore, temperature extremes in observed series tend to be more persistent compared with the AR(1) process, which supports the underestimation of their temporal accumulation in the synthetic series generated.

5.2. Introduction of the monthly generator improves heat/cold-wave characteristics and worsens the simulation of 1 day extremes

The better reproduction of the ratio of the intermonthly to intramonthly variability after the incorporation of the monthly generator (Dubrovský *et al*., 2004) was expected to improve the characteristics of heat and cold waves. This improvement is reflected in a better simulation of both the mean annual duration of heat and cold waves and the accumulation of hot and cold days in spells, although the latter is still far from being realistic, particularly for cold days. Another effect that supports chaining of temperature extremes if the monthly generator is applied is the slight increase in the lag-0 and lag-1 correlations among TMAX and TMIN (Dubrovský *et al*., 2004).

On the other hand, the simulation of 1 day temperature extremes deteriorates if the monthly generator is involved in the model. This is due to the fact that, without the monthly generator, both hot and cold 1 day extremes tend to be too pronounced; an increase in the intermonthly variability supports a more frequent occurrence of extremes, and 'more extreme' values (i.e. values more distant from central parts of TMAX and TMIN distributions) are obtained in the synthetic series.

5.3. Large discrepancies between simulated and real climates exist, mainly in eastern and northern Europe; the generator is most successful in western and central Europe around 50°N

The largest discrepancies between the simulated and observed data, e.g. reaching as much as 5 °C for mean annual minima, are observed mainly in eastern and northern Europe, i.e. in areas that are far from regions for which WGEN-like weather generators are commonly applied. The reason for these large deviations from observations is that the model assumptions are not valid in some areas; the most conspicuous 'invalid assumption' is that distributions of TMAX and TMIN (or, rather, distributions of their residuals from the mean annual course conditioned on the precipitation occurrence) are normal. In fact, they depart from the normal distributions supposed by the AR(1) model used in the generator (Figures 10 and 11); even moderate departures may have a great effect on the tails of the distributions and, thus, lead to a completely unrealistic simulation of extremes. It is particularly obvious, for example, for the left tail of TMIN at Sodankyla (Finland); the fifth percentile of TMIN is 2.0–2.2 °C higher in the stochastically generated data than in observed data, and the first percentile is by 0.6–1.2 °C lower. Such distortions of the empirical distributions (compared with the normal distribution) are not captured by the model employed in the weather generator. The assumptions of the generator should be tested before its use in impact studies and, if necessary, adjustments consisting, for example, in an application of a more sophisticated time-series model or a more realistic treatment of residuals (which are supposed to follow the normal distribution in the present versions of the generator), should be made.

The reproduction of the temperature extremes is usually best in western and central Europe at around 50 °N, but this is not true for cold waves in central Europe. The reason for the latter is again a departure of TMIN in central Europe from the normal distribution, as discussed for the winter season in Huth *et al*. (2001). The heavy left tail of TMIN cannot be reproduced by the 'classical' WGEN-like generator in this area.

5.4. Order of the Markov chain in the precipitation occurrence model has a negligible effect on temperature extremes

Dubrovský *et al*. (2004) found that the third-order Markov chain improves the reproduction of dry spells, but the improvement was not marked enough to have an effect on those weather/climate characteristics affected by the precipitation occurrence. Since the application of the higher order Markov chain has no effect on the probability of the precipitation occurrence on any given day $d (d = 1–365)$, the distributions of TMAX and TMIN (as well as distributions of their annual maxima and minima) are not affected.

As means and variances of TMAX and TMIN are conditioned on the precipitation occurrence, an influence of the order of the Markov chain on heat and cold waves (which are often associated with dry periods) may have been expected. However, no effect of the Markov model order on the characteristics of multiday temperature extremes was found, including also the mean length of individual heat/cold waves (not examined

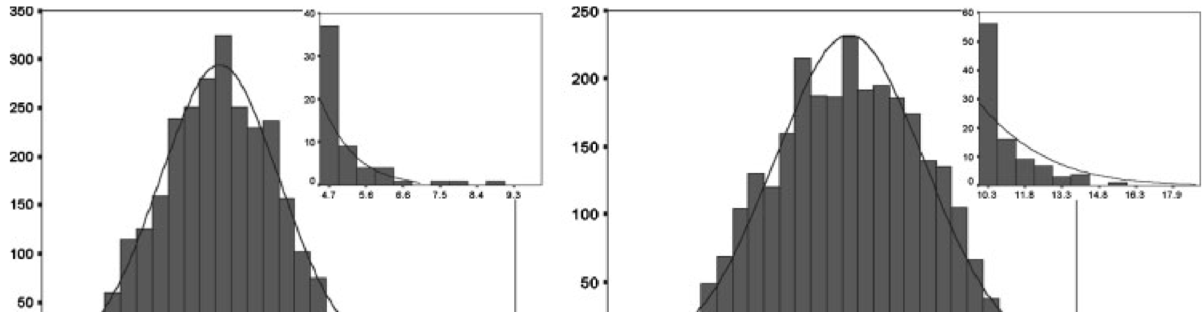

Figure 10. Distribution of residuals from the mean seasonal course of TMAX at stations San Sebastian (Spain, left) and Troitzko (Russia, right) in summer (June–August). Normal curve is fitted to the data; the right tail of the distribution is shown in detail

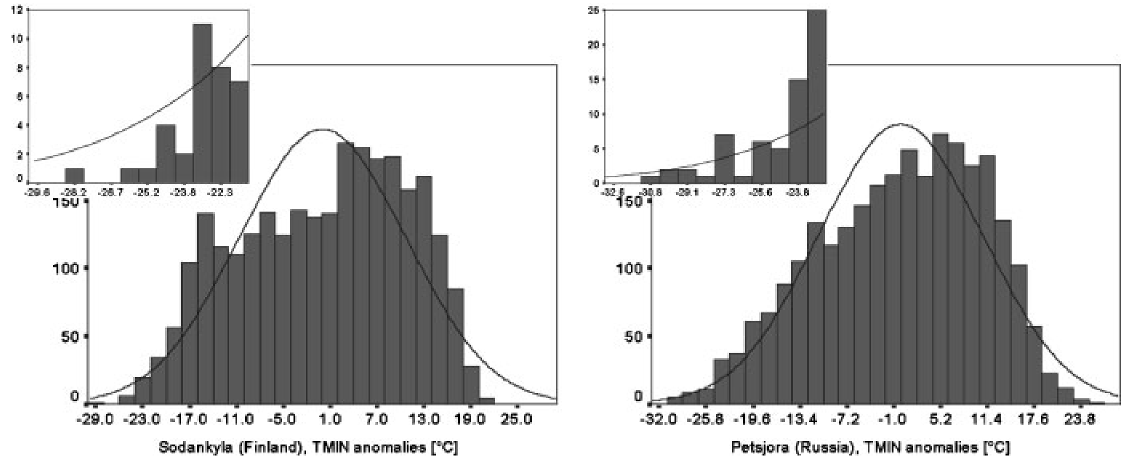

Figure 11. Distribution of residuals from the mean seasonal course of TMIN at stations Sodankyla (Finland, left) and Petsjora (Russia, right) in winter (December–February). Normal curve is fitted to the data; the left tail of the distribution is shown in detail

in Section 4); the influence of the other two modifications of the weather generator is much more pronounced. The explanation is that the differences between dry and wet means of TMAX and TMIN, and the improvement in the reproduction of dry spells when the third-order Markov chain is introduced are not large enough to feed through into the mean characteristics of heat and cold waves.

5.5. Inclusion of the annual cycle of lag-0 and lag-1 correlations among TMAX and TMIN worsens (improves) the reproduction of annual maxima (minima)

The observed cycles of the lag-1 correlations attain their maxima in winter and minima in summer (see Huth *et al*. (2001) and Dubrovský *et al*. (2004)) over large parts of Europe. This makes the day-to-day temperature variability lower and the persistence higher in winter in the WG-A series (with the annual cycle of lag-1 correlations implemented) compared with the WG-BAS (without such a cycle); the opposite holds in summer. Lower (higher) day-to-day variability compared with WG-BAS in winter (summer) leads to less (more) pronounced extremes. Thus, the underestimation of the mean annual minima (which occur in winter) in WG-BAS is at least slightly suppressed in WG-A, whereas the overestimation of summer maxima is enhanced if the annual cycle of correlations is incorporated in the generator. The same effect has been discussed by Huth *et al*. (2001) for periods of extreme temperatures at six central European stations in winter and summer: the inclusion of the annual cycle of correlations led to deteriorating characteristics of extreme temperature periods in summer and improvements in winter in WG-A compared with WG-BAS.

The effect becomes negligible if all-year data are involved. This is the case of heat and cold waves, the definitions of which are based on anomalies from the annual cycles of TMAX and TMIN (see Section 3.2).

5.6. The 1 day temperature extremes are too pronounced in the generator

This effect stems from the fact that the lag-1 correlations of TMAX and TMIN in the stochastically generated series are too low in both seasons compared with observations (also see Section 5.1). This makes the day-to-day temperature variability in the synthetic series larger than in the observed series, and the enhanced day-to-day changes lead to extremes that are more distant from the relevant means.

6. CONCLUSIONS AND IMPLICATIONS FOR THE USE OF STOCHASTIC WEATHER GENERATORS IN IMPACT STUDIES

This paper addresses the effects of improving interdiurnal and intermonthly variability reproduction in the stochastic daily weather generator Met&Roll (the basic version of which follows the Richardson WGEN generator) on the simulation of temperature extremes. The modifications of the basic version of the generator examined consist of: (i) the inclusion of the annual cycle of lag-0 and lag-1 correlations among TMAX and TMIN; (ii) the use of a third-order (instead of the first-order) Markov chain to model precipitation occurrence; (iii) the application of a monthly generator (based on a first-order AR model) to fit the low-frequency variability. Dubrovský *et al.* (2004) found that the introduction of the monthly generator is the most important of these modifications, since it considerably improves the reproduction of the intermonthly to interannual variability of weather characteristics, and, in the indirect validation, leads to more realistic outputs from a hydrological rainfall-runoff model.

For 1 day temperature extremes, none of the improvements of the weather generator leads to their considerably better reproduction. On the other hand, the basic version of the generator performs satisfactorily in western and central Europe around 50 °N, and (to a lesser degree) if the errors are averaged over most of Europe. The basic version is the best one for annual maxima, whereas the inclusion of the annual cycle of lag-0 and lag-1 correlations between TMAX and TMIN slightly improves the reproduction of annual minima. The performance of the weather generator is worse for 20-year return values than for mean annual temperature extremes.

The largest discrepancies between the simulated and real climate are found at eastern and northern European stations, where empirical distributions of both TMAX and TMIN depart considerably from a normal distribution assumed by the model. This indicates a limited applicability of a generator based on the AR(1) model; a more sophisticated time series model, or at least a more realistic treatment of TMAX and TMIN residuals is necessary in these areas. The reproduction of temperature extremes is usually best in western and central Europe at around 50 °N, where the assumptions of the stochastic model are met reasonably well. However, cold waves are simulated poorly in central Europe due to the heavy left tail of the empirical distributions of TMIN, which is not captured by the generator.

The weather generator strongly underestimates the inclusion of hot and cold days into spells. This effect is partly reduced by the introduction of the monthly generator, which improves the reproduction of the ratio of the intermonthly to intramonthly temperature variability. However, the inability of the model to capture real-world accumulation of extremes still remains its largest drawback with regard to the simulation of extreme temperature events. In western and central Europe, the implementation of the monthly generator improves the reproduction of heat waves but worsens that of cold waves.

Apparently, the heat and cold waves and related characteristics (e.g. the occurrence of frosts in spring and heat stress in summer) may have a significant effect, among others, on the growth and development of crops (e.g. Chmielewski and Köhn, 1999; Fowler *et al.*, 1999; Bencze *et al.*, 2004). Validation of weather generators should focus on such characteristics that are important from the point of view of impact studies. Therefore, it is desirable to test whether the misreproduction of the characteristics evaluated above has an effect on crop characteristics simulated by a crop model fed by a stochastically generated weather series. In the case where discrepancies are found one may either modify an existing weather generator (e.g. by applying suitable transformations to the daily weather characteristics) or use a different type of model (e.g. a generator based on a resampling procedure, a more comprehensive time-series model, or a more realistic treatment of the residuals in the model).

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