HIGH-FREQUENCY AND LOW-FREQUENCY VARIABILITY IN STOCHASTIC DAILY WEATHER GENERATOR AND ITS EFFECT ON AGRICULTURAL AND HYDROLOGIC MODELLING

MARTIN DUBROVSKÝ [1], JOSEF BUCHTELE [2] and ZDENĚK ŽALUD [3]

[1] *Institute of Atmospheric Physics, Husova 456, 50008 Kradec Králové, Czech Republic*
E-mail: dub@ufa.cas.cz
[2] *Institute of Hydrodynamics AS CR, Praha, Czech Republic*
[3] *Mendel University of Agriculture and Forestry, Brno, Czech Republic*

Abstract. The high-frequency and low-frequency variabilities, which are often misreproduced by the daily weather generators, have a significant effect on modelling weather-dependent processes. Three modifications are suggested to improve the reproduction of the both variabilities in a four-variate daily weather generator Met&Roll: (i) inclusion of the annual cycle of lag-0 and lag-1 correlations among solar radiation, maximum temperature and minimum temperature, (ii) use of the 3rd order Markov chain to model precipitation occurrence, (iii) applying the monthly generator (based on a first-order autoregressive model) to fit the low-frequency variability. The tests are made to examine the effects of the three new features on (i) a stochastic structure of the synthetic series, and on (ii) outputs from CERES-Wheat crop model (crop yields) and SAC-SMA rainfall-runoff model (monthly streamflow characteristics, distribution of 5-day streamflow) fed by the synthetic weather series. The results are compared with those obtained with the observed weather series. Results: (i) The inclusion of the annual cycle of the correlations has rather ambiguous effect on the temporal structure of the weather characteristics simulated by the generator and only insignificant effect on the output from either simulation model. (ii) Increased order of the Markov chain improves modelling of precipitation occurrence series (especially long dry spells), and correspondingly improves reliability of the output from either simulation model. (iii) Conditioning the daily generator on monthly generator has the most positive effect, especially on the output from the hydrological model: Variability of the monthly streamflow characteristics and the frequency of extreme streamflows are better simulated. (iv) Of the two simulation models, the improvements related to the three modifications are more pronounced in the hydrological simulations. This may be also due to the fact that the crop growth simulations were less affected by the imperfections of the unmodified version of Met&Roll.

1. Introduction

Stochastic weather generators are often used in climate change impact studies to provide synthetic weather series representing present and changed climate conditions. The weather series are used as an input to the simulation models (e.g., crop growth models, rainfall-runoff models) and the impacts are thereafter assessed by comparing the results obtained with the weather series representing present and changed climates.

Climatic Change **63:** 145–179, 2004.

The generators employ statistical models to generate arbitrarily long synthetic weather series which resemble (in terms of the statistical characteristics) the real-world weather series. Parameters of the generator use to be derived from the observed weather series or they may be interpolated from the surrounding stations (Guenni, 1994). To generate series representing the changed climate, the parameters of the generator are modified according to the GCM-based climate change scenario or according to the user's choice. As the generators use to have only modest demands on computer resources, one may generate a set of long synthetic weather series representing a broad range of climate scenarios. This makes the generators helpful not only in evaluating a response of the weather-dependent processes to anticipated climate change, but also in performing detailed sensitivity analysis to changes in individual climate variables.

Depending on the processes being modelled, weather generators differ in time resolution (daily step, hourly step, continuous in time), spatial resolution (single site, multiple sites, continuous in space) and number of variables (single-variate, multi-variate). The choice of the underlying statistical model aims to achieve the best fit between the stochastic structure of the observed and synthetic weather series.

Single-site multivariate daily generators are typically used to provide weather series for the crop models (Semenov and Porter, 1995; Riha et al., 1996; Mearns et al., 1997; Semenov and Barrow, 1997; Dubrovský et al., 2000 – hereafter referred to as DZS2000; Tubiello et al., 2000). These generators are frequently based on the Richardson's (1981) WGEN generator: Precipitation occurrence is modelled by the first-order Markov chain, precipitation amount on a wet day is approximated by Gamma distribution, and solar radiation, maximum temperature and minimum temperature are modelled by the tri-variate first-order autoregressive model. The detailed description of this type of the generator may be found, e.g., in Wilks (1992), Katz (1996) and Mearns et al. (1996, 1997). Other generators differ from WGEN either in model formulation, or only in methodology of estimating parameters of the generator and representing their annual cycle. The greatest number of papers is being devoted to modelling precipitation, which appears one of the most important as well as one of the most difficult (to be modelled) weather elements dealt with in weather generators. Precipitation occurrence series may be alternatively modelled by higher-order Markov chain (Gates and Tong, 1976; Chin, 1977; Moon et al., 1994; Jones and Thornton, 1997; Lana and Burgueño, 1998; Wilks, 1999a), hybrid-order Markov chain (Stern and Coe, 1984 (cited by Wilks, 1999a); Wilks, 1999b) or by a serial-approach model (Racsko et al., 1991; Semenov and Barrow, 1997; Semenov et al., 1998). Precipitation amount may be alternatively modelled by other distribution function (Todorovic and Woolhiser, 1975; Hansen and Mavromatis, 2001) and the parameters of the distribution function may be conditioned on the rank of the day within the wet spell (Chin and Miller, 1980). Katz and Parlange (1996) allowed the precipitation intensities within a given wet spell to be autocorrelated. Comparison of various precipitation models (both occurrence and amount) may be found, e.g., in Wilks (1999a). The non-precipitation weather characteristics are modelled by the higher-order autoregressive model in Gutry-Korycka et al. (1994). In other approaches, Peiris and McNicol (1996) generate precipitation conditionally on the non-precipitation variables, and Young (1994) employs the nearest-neighbours resampling technique to simulate maximum and minimum temperatures and daily precipitation amounts. The WGEN-like generators may differ from WGEN in handling the parameters of the underlying model: only some parameters are determined from the observed data in SIMMETEO generator and the other ones are estimated using parameterisations (Geng et al., 1988). Annual cycles may be represented using smoothed curves of daily statistics (Dubrovský, 1997), Fourier series (Spirkl and Ries, 1986; Semenov and Barrow, 1997), high-degree polynom (Gutry-Korycka et al., 1994) or by a simple harmonic wave (Peiris and McNicol, 1996). The generators involving additional variables (wind and humidity) required in some crop growth models are described in Peiris and McNicol (1996) and Wallis and Griffiths (1997).

The surface weather variables may be conditioned on a larger-scale circulation, which is characterised either using a limited set of the circulation or weather types (Bárdossy and Plate, 1992; Bogardi et al., 1993; Wilson et al., 1992; Wilby, 1994; Wallis and Griffiths, 1997; Stehlík and Bárdossy, 2002) or by several continuous variables (Dubrovský, 1997). In the latter case, the circulation was characterised by the modes of the variability determined by the principal components analysis (Huth, 1997). The conditioning of the surface weather on circulation allows to account for the possible changes in atmospheric circulation regime by taking the circulation series from GCM simulations or by modifying parameters of the circulation generator.

In assessing the weather effects of elevated CO_2 on crops, the increasing attention is given to changes in variability and occurrences of extreme events, such as droughts, frosts, and heat waves. Many studies (e.g., Riha et al., 1996; Mearns et al., 1997; DZS2000; Mavromatis and Hansen, 2001) show that an 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. As the generators often underestimate the interannual variability (Johnson et al., 1996; Katz and Parlange, 1996; Wilks, 1989, 1999a, DZS2000; Mavromatis and Hansen, 2001), at least two approaches were suggested to reduce this insufficiency: (i) conditioning the daily generator on circulation indices (Katz and Parlange, 1993; Katz, 1996) or on monthly averages of the weather characteristics (Wilks, 1989), and (ii) perturbing the monthly parameters using the low-frequency generator (Hansen and Mavromatis, 2001).

For the purpose of modelling rainfall-runoff processes in river catchments, the multisite weather generators were developed using various approaches. For example, the nearest neighbours resampling technique is employed by Buishand and Brandsma (2001), and the extension of the WGEN generator by parameterising the interstation correlations was developed by Wilks (1998, 1999b). The multisite generators are often conditioned on the circulation (Bárdossy and Plate, 1992; Wilson et al., 1992; Bogardi et al., 1993; Kiely et al., 1998; Katz and Parlange, 1993; Bellone et al., 2000), which may be either stochastically generated, observed or modelled (e.g., by GCM). For small river-catchment modelling, the single-site generators may be used, too (Buchtele et al., 1999).

Quality of the weather generator may be assessed by direct and indirect validation tests.

In the *direct validation*, we ask: How do the synthetic weather series resemble the observed series? The direct validation experiments are usually focused on reproduction of characteristics representing the distribution of the variables (means, standard deviations and higher-order moments), their interdiurnal variability, and correlations among them. The differences between the characteristics derived from the observed and synthetic series should not differ statistically significantly. However, no generator may obviously fit all characteristics of the observed series. Unfortunately, some of the characteristics, which are not reproduced with satisfactory accuracy, may crucially affect output from the models fed by the synthetic weather series. For example, the above mentioned low-frequency variability, which is often underestimated by the generators, has an effect on the crop yields. Generally, nearly any insufficiency of the generator in reproducing stochastic structure of the weather series may be reduced by suitable modification of the underlying model. However, this usually leads to greater complexity of the model (with more parameters), and thereby to lower accuracy of parameters derived from the learning sample of given limited size (lower 'stability' of the model). Before modifying the model of the generator, it is therefore reasonable to perform the indirect validation, which may show whether the generator is applicable in a given application.

The question to be answered in the *indirect validation* stands: How do the generator's imperfections affect output from the model (crop growth model, rainfall-runoff model) fed by the synthetic weather series? The indirect validation is made by comparing statistical properties of output characteristics (crop yields, streamflows) simulated with observed vs. synthetic weather series. The results of the indirect validation may show that the weather series created by a simpler generator, which fails in some direct validation tests, serves satisfactorily as an input for some simulation models. For example, DZS2000 found that the grain maize yields simulated by CERES-Maize model with use of synthetic weather series generated by Met&Roll had the same means and variability as the yields simulated with observed weather series. Similarly, Semenov and Porter (1995), who used AFRCWHEAT2 crop model (Porter, 1993) and their serial-approach weather generator, found no statistically significant difference between characteristics (grain yield, day of anthesis) simulated with observed and synthetic weather series.

A 'statistical' note may be added to both direct and indirect validation. In comparing statistical characteristics derived from the observed and synthetic weather series, or in comparing outputs from the simulation models fed by the observed and synthetic weather series, a great number of tests may be done. In this situation, even having a perfect weather generator, a small percentage of statistically significantly differences usually occurs due to the randomness involved in the generator. In these cases (the percentage corresponds to the significance level of the tests), we reject the hypothesis on equality and thereby commit a type I error. On the other hand, each test has only a limited power and it may fail to detect the difference: we accept the hypothesis on equality although we should have rejected (type II error). Therefore, one should be very careful when assessing results of the multiple tests.

Met&Roll (Dubrovský, 1997) is a WGEN-like four-variate single-site stochastic weather generator. Although it was designed to provide synthetic weather series mainly for crop growth modelling (DZS2000; Žalud and Dubrovský, 2002), its simplified two-variate version was also used to generate weather series for rainfall-runoff model SAC-SMA in assessing impacts of climate change on a hydrological regime in the relatively small river-catchment (Buchtele et al., 1999). Despite some insufficiencies revealed in the direct validation tests (Dubrovský, 1997), the indirect validation (DZS2000) proved an applicability of the generator in grain maize modelling. However, as the results obtained in the indirect validation are not transferable to other crops and/or models, the imperfections (listed in Section 2.1.1) in reproducing some features of the stochastic structure of the weather series are a good motivation for further improving the generator.

In the present paper, three modifications of Met&Roll are suggested (Section 2.1.2) to improve reproduction of the high-frequency (interdiurnal) and the low-frequency (intermonthly) variability of the weather series. The direct (Section 3) and indirect (Section 4) validation experiments are made to show the effects of the three modifications on a stochastic structure of the synthetic weather series and on simulations made by two weather-dependent models. The crop growth model CERES-Wheat and rainfall runoff model SAC-SMA are used in the indirect validation experiments. We preferred CERES-Wheat to CERES-Maize (used in DZS2000) here as we expected the wheat simulations to be more sensitive to the imperfections of the generator: In contrast with the maize, which is the spring crop, the winter wheat is exposed to weather during a longer period including the winter, when the generator performs worse than in summer.

2. Methods and Data

2.1. STOCHASTIC WEATHER GENERATOR MET&ROLL

2.1.1. *Basic Version*

Met&Roll (Dubrovský, 1997) is a WGEN-like (Richardson, 1981) four-variate daily weather generator. The equations of the model were based primarily on Wilks (1992). The four variables are daily sum of global solar radiation (*SRAD*), daily precipitation amount (*PREC*), daily maximum temperature (*TMAX*) and daily minimum temperature (*TMIN*). Precipitation occurrence is modelled by a first-order

Markov chain, M(1), which is completely determined by two transition probabilities, P_{01} and P_{11}. Precipitation amount on a wet day is modelled by Gamma distribution, $\Gamma(\alpha, \beta)$. Parameters of the precipitation model (P_{01}, P_{11}, α, β) are defined for individual months. Standardised deviations of *SRAD*, *TMAX* and *TMIN* from their mean annual cycles are modelled by a first-order autoregressive model, AR(1). The means and standard deviations, which are used to standardise the three variables, are determined separately for wet and dry days and depend on a day of the year. In this case, we will talk about conditionally standardised variables. In contrast, the unconditionally standardised variables will refer to the product of standardisation, in which the means and standard deviations are determined from both dry and wet days. The annual cycles of the means and standard deviations are smoothed by robust locally weighted regression (Solow, 1988), which was found very useful in smoothing the annual cycle of total ozone (Kalvová and Dubrovský, 1995). Matrices of the AR(1) model, which are derived from the lag-0 and lag-1 correlations among the three conditionally standardised variables, are constant throughout the year.

The above version of the generator (hereafter referred to as the basic version) was validated in detail using 30-year observed series from 16 Czech stations (Dubrovský, 1996, 1997). Some features of the stochastic structure of the daily weather series were found to be well reproduced by Met&Roll, but imperfections were revealed in reproducing other features:

- *SRAD* does not follow the normal distribution assumed by the AR model. Also *TMAX* and *TMIN* do not follow the normal distribution – especially in winter – but the misfit is not so crucial as for *SRAD*.
- Correlations and lag-1 correlations among conditionally standardised values of *SRAD*, *TMAX* and *TMIN* may significantly vary throughout the year (Figure 1), which contradicts the use of constant matrices in the autoregressive model.
- Variability of monthly averages of *SRAD* and *PREC* is underestimated during the entire year. (Note that the monthly average is considered here to be an average value of the variable over all days of a given single month, not the long-term monthly mean.) Variability of monthly averages of *TMAX* and *TMIN* is underestimated only in winter. In January and February, the standard deviation of monthly averages of each of the four daily weather characteristics in the synthetic series is by about 30% lower (average from the 16 Czech stations) than the standard deviation of the observed monthly averages. Variability of annual averages of all four weather characteristics is underestimated.
- Distribution of the length of dry periods is not satisfactorily modelled by the two-state first-order Markov chain – the frequency of occurrence of long dry spells is underestimated (especially in winter) by the generator.

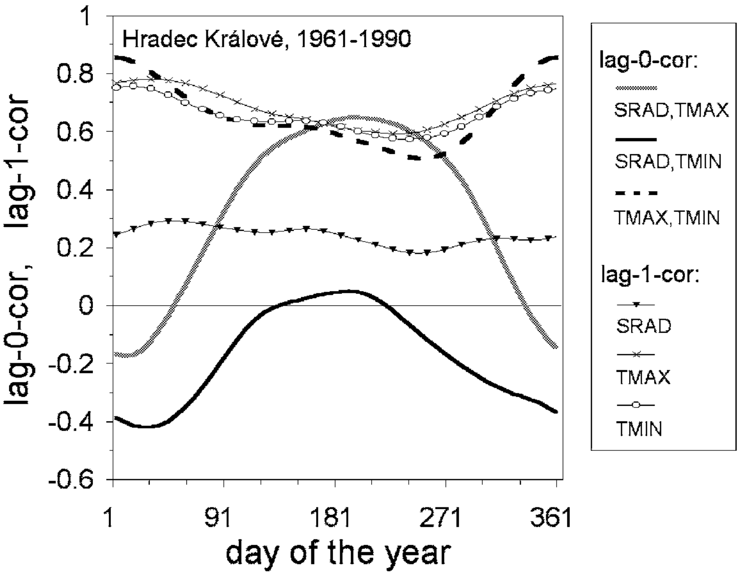

Figure 1. Lag-0 correlations (lag-0-cor) among conditionally standardised values of *SRAD*, *TMAX* and *TMIN* and lag-1 autocorrelations (lag-1-cor) of conditionally standardised *SRAD*, *TMAX* and *TMIN*.

2.1.2. *Modifications*

Various modifications may be considered to reduce the above imperfections. Here, the stress is put on improving the temporal structure of the weather series, i.e., the latter three items of the list given at the end of the previous paragraph will be dealt with. Three adjustments are suggested in the following paragraphs.

(a) Inclusion of the annual cycle of lag-0 and lag-1 correlations among SRAD, TMAX and TMIN. In the generator, the high-frequency (interdiurnal) variability of *SRAD*, *TMAX* and *TMIN* is determined by the lag-1 correlations among the three variables. The most straightforward adjustment to the generator, which should lead to better reproduction of the high-frequency variability, is made by allowing lag-0 and lag-1 correlations among *SRAD*, *TMAX* and *TMIN* to vary during the year. The values of the correlations vary in 14-day steps, annual cycle is smoothed by robust locally weighted regression (Solow, 1988). Note, that the annual cycle of correlations and lag-correlations among the weather variables was recently introduced into the weather generator also by Hayhoe (2000).

(b) Higher-order Markov chain. There exists a great number of papers dealing with modelling daily precipitation occurrence by Markov chains. Some authors suggest that the first-order Markov chain is satisfactory for some locations (Tel Aviv data analysed by Gabriel and Neumann, 1962; Katz, 1977; the central and eastern U.S. stations tested by Wilks, 1999a). Harrison and Waylen (2000) found that the zero-order or first-order Markov chain gives the best results in modelling precipitation occurrence in Costa Rica. On the other hand, higher-order Markov

chains should be used to improve the reproduction of the long wet or dry spells in some cases (Tel Aviv data – the same as those analysed by Gabriel and Neumann – examined by Gates and Tong, 1976; Chin, 1977; South Korean stations analysed by Moon et al., 1994; Lana and Burgueño, 1998; western U.S. stations used in Wilks, 1999a). It appears, that the optimum order of the Markov chain vary between zero and three 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. In Met&Roll, the transition probabilities of the higher-order Markov chain (3rd order is used in the present analysis) are defined separately for the four seasons of the year.

(c) Monthly weather generator. It was mentioned in the Introduction that the variability of monthly and annual averages of the weather variables is usually underestimated by the generators. This may be related to the fact, that the common types of the generators (including the basic version of Met&Roll) do not explicitly consider low-frequency variability which might be responsible for this underestimation. To improve the reproduction of the low-frequency variability, the monthly weather generator is used in this paper to produce time series of the monthly averages with realistic intermonthly correlations. Since the monthly averages of the four weather variables are mutually correlated as well as the correlations among the monthly averages in consecutive months are non-zero, the four-variate first-order autoregressive model ($\Delta t = 1$ month) was chosen to model the time series of the monthly averages. Unlike the daily generator, the precipitation in monthly generator is modelled by a single continuous variable being one of the four variables modelled by AR(1) model. As the distributions of the monthly solar radiation and especially of monthly precipitation are highly skewed, the transformations are applied to these characteristics. The fourth root transformation was found optimal for the precipitation. In case of the solar radiation, the logarithmic transformation is used as it implies slightly better (compared to the fourth root transformation) reproduction of the tails of probability distribution of monthly radiation. In result, the four variables used in the monthly generator are $y_1 = \ln\langle SRAD\rangle$, $y_2 = \langle PREC\rangle^{0.25}$, $y_3 = \langle TMAX\rangle$, $y_4 = \langle TMIN\rangle$, where $\langle X\rangle$ denotes the monthly average of X. As in the daily generator, standardised variables are modelled by the first order autoregressive model:

$$\boldsymbol{y}^*(t) = \boldsymbol{C}\boldsymbol{y}^*(t - \Delta t) + \boldsymbol{D}\boldsymbol{e}(t), \tag{1}$$

where $\Delta t = 1$ month, $\boldsymbol{C}$ and $\boldsymbol{D}$ are 4×4 matrices, $\boldsymbol{e}(t)$ is a four-dimensional white noise, and $\boldsymbol{y}^* = (y_1^*, y_2^*, y_3^*, y_4^*)$ is a vector of the four standardised monthly characteristics:

$$y_i^*(t) = \frac{y_i(t) - \mu_i(m)}{\sigma_i(m)} \qquad (i = 1, \ldots, 4),$$

where $m \in \langle 1, 12\rangle$ is an index of the running month of the year, and $\mu_i(m)$ and $\sigma_i(m)$ are the mean and standard deviation of y_i in the m-th month. Matrices $\boldsymbol{C}$ and

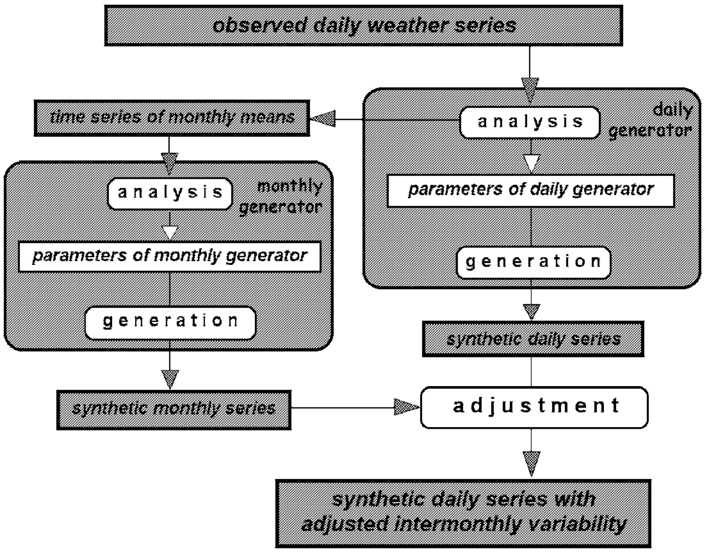

Figure 2. Linkage of the daily weather generator with the monthly weather generator. The adjustment procedure is graphically displayed in Figure 3.

D are determined from the observed monthly series (= series of monthly averages derived from the daily weather series) separately for the four seasons of the year. When generating the monthly series, the standardised deviations of individual variables are generated using Equation (1) and then destandardised using the means and standard deviations appropriate for given month and variable. Note that, in contrast to the daily generator, the (de)standardisation of the monthly variables is made unconditionally on the precipitation which is now one of the four variables modelled by the autoregressive model. The monthly generator is linked with the daily generator in a following way (Figures 2 and 3):

(i) The daily weather series is generated by the daily weather generator whose parameters were derived from the observed daily weather series.
(ii) The monthly series is generated by the monthly generator whose parameters were derived from the observed monthly series.
(iii) The daily series generated in the first step is adjusted by increments, so that the series of the monthly averages derived from the daily series fits the monthly series generated in the second step (Figure 3). Daily extreme temperatures are adjusted additively, precipitation amounts and solar radiation sums are adjusted multiplicatively.

In the basic version of the adjustment procedure (step (iii)), the value of the increment applied to the daily series is the same for all days within a month. For each single month and each of the four variables, the increment equals the difference (in case of the additive modification) or the ratio (in case of the multiplicative modification) between the monthly average generated by the monthly generator

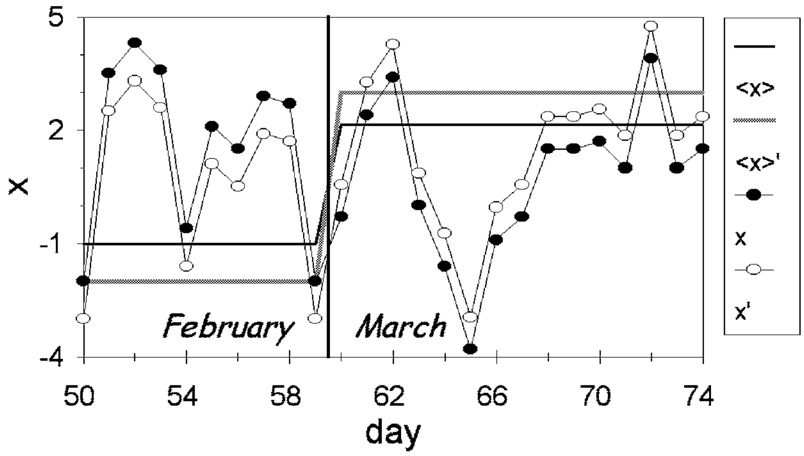

Figure 3. Adjustment of the daily weather series to the monthly averages (only 25-day segment from the daily series is shown). $\langle x \rangle$ is the series of monthly averages derived from the daily series, $\langle x \rangle'$ is the series of monthly averages generated by monthly generator, x is daily series generated by daily generator, x' is the daily series modified to fit $\langle x \rangle'$.

and monthly average calculated from the daily series generated in step (i). The month-to-month steps in the increments (caused by applying different values of the increments on the last day of the month and the first day of the following month) applied to the daily series may be optionally smoothed by a procedure, which preserves the monthly averages. This smoothing procedure was, however, rejected due to two reasons: Firstly, the variability of the interdiurnal changes of individual variables is several times higher compared to the variability of the intermonthly changes so that the basic (without smoothing) adjustment procedure only insignificantly affects the overall interdiurnal and diurnal variability. Secondly, smoothing of the intermonthly steps may superimpose an additional within-month trend to the daily series, and thereby artificially increase the interdiurnal correlations (compare results in Figure 4 obtained with using (curves marked as WG-AMs) and not-using (WG-AM) the smoothing procedure).

The implementation of the monthly generator may be compared with the procedure suggested by Hansen and Mavromatis (2001). Both their and our methods add the low-frequency variability to daily weather series by applying multivariate first-order autoregressive model to monthly statistics. Hansen and Mavromatis uses 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 paper are generated by the daily generator with unperturbed monthly parameters and postprocessed thereafter to fit the monthly series generated by the monthly generator. In this approach, the intermonthly variability (characterised by lag-1 correlations among the monthly averages) in the resultant daily series exactly equals the intermonthly

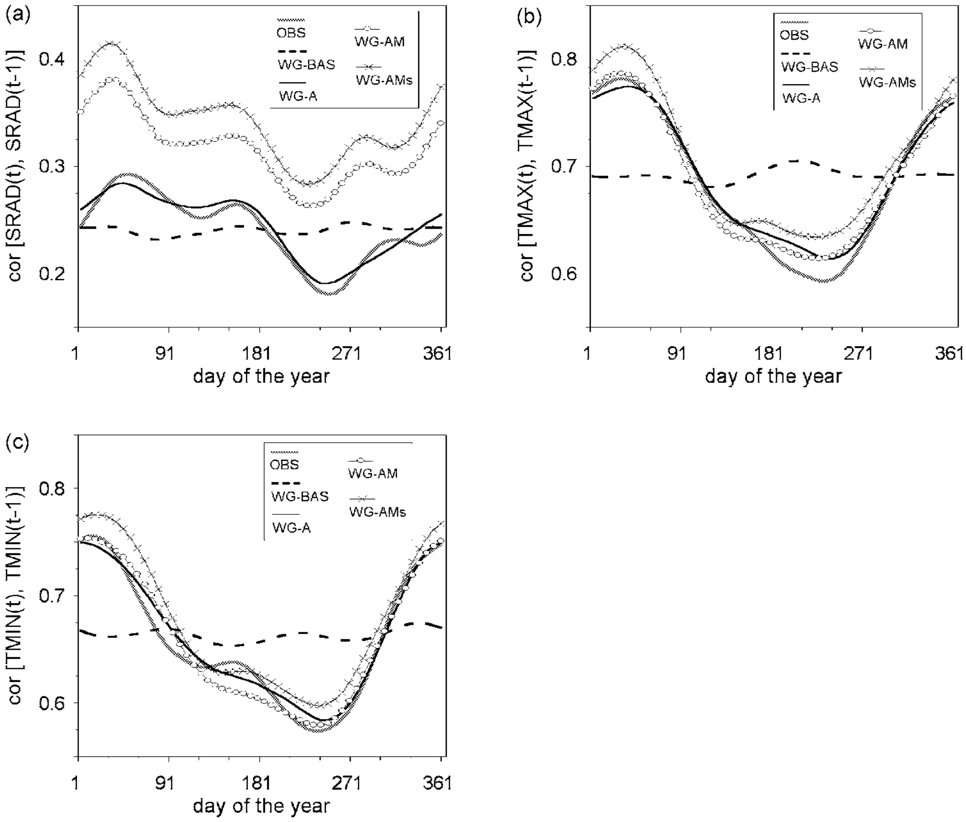

Figure 4. Lag-1 autocorrelations of conditionally standardised *SRAD* (a), *TMAX* (b), and *TMIN* (c). The autocorrelations were calculated from the 30-year observed series (OBS; station = Hradec Králové, 1961–1990) and 100-year synthetic series generated by three versions of the generator (see Table I for the acronyms). WG-A3 and WG-A3M are not shown as the curves are the same as for WG-A and WG-AM, respectively. WG-AMs is the same as WG-AM but the intermonthly steps in the increments added in the adjustment procedure (Figure 3) are smoothed as described in the text.

variability of the series produced by the monthly generator. The final effect of both approaches on the daily weather series should be very similar.

2.1.3. *Two-Variate Version*

Only daily precipitation sum and daily average temperature (*TAVG*) are used as the input weather data for simulations made with SAC-SMA model. The two-variate synthetic series are generated by Met&Roll similarly as the four-variate series, with the exception that the one-dimensional AR(1) model is used to model time series of *TAVG*.

2.2. CROP GROWTH MODEL CERES-WHEAT

The CERES-Wheat model, version 3.0, included in the DSSAT (Tsuji et al., 1994) software package (CERES = Crop Estimation through Resource and Environment Synthesis; DSSAT = Decision Support System for Agrotechnology Transfer) was used to simulate winter wheat growth. CERES-Wheat is a mechanistic process-based model which increments crop growth and development of individual parts of the plants in daily steps. The input data required for the simulations include: cultivar characteristics (given in terms of genetic coefficients), field attributes (slope, drains, longitude, latitude), soil characteristics (e.g., texture and bulk density), planting details (date of seeding, seeding population, row spacing, planting depth), management factors (e.g., tillage, irrigation and fertilisation), and the series of daily weather characteristics. The obligatory weather characteristics are sum of global solar radiation, maximum and minimum air temperatures and precipitation amount; wind speed and air humidity are optional and were not used in the present simulations. The model input data were based on the field experiments made in Žabčice (49°01′ N, 16°37′ E, 179 m above sea level) which belongs to the warmest and driest regions of the Czech Republic. The 1961–1990 means of the annual temperature and annual precipitation sum in Žabčice are 9.1 °C and 480 mm, respectively. More detailed climatic characteristics of the site are given in Rožnovský and Svoboda (1995) and DZS2000. The crop sown in the experimental field was the semi-dwarf hard-red winter wheat cultivar Hana, which is considered to have slight tillering capacity, good resistance to lodging, medium resistance to diseases, high yield potential, and very high baking quality. The soil type can be described as Oxyaquic Cryofluvent with topsoils of clay loam and silty clay textures. Planting details, management factors and fertilisation regime were set to be the same for all stations, all versions of the generator and all simulation years. No irrigation was applied. The CERES-Wheat model was validated by Šťastná et al. (2002) for the conditions of the Czech Republic.

The CERES-Wheat model is one of the most prominent crop growth models and has been used in a great number of studies (e.g., Mearns et al., 1992; Bacsi and Hunkár, 1994; Chipanshi et al., 1997; Mearns et al., 1997; Landau et al., 1998; Cuculeanu et al., 1999; Mavromatis and Jones, 1999; Mearns et al., 1999; Šťastná and Žalud, 1999; Alexandrov and Hoogenboom, 2000). CERES-Wheat was compared with other wheat models by Wolf et al. (1996) and Jamieson (1998).

2.3. HYDROLOGICAL RAINFALL-RUNOFF MODEL SAC-SMA

Sacramento soil moisture accounting (SAC-SMA) model (Burnash, 1995) was used to simulate rainfall-runoff processes in the Malše river basin (48°50′ N, 14°30′ E; 495 km^2 catchment area) in the Czech Republic. SAC-SMA is the water balance model coupled with the snow sub-model. It considers the basin as a system of vertically and horizontally interconnected zones ('reservoirs'), for which six runoff components are generated: (i) direct runoff from temporally impervious areas (after saturation), (ii) runoff from the permanently impervious part of the basin, (iii) surface runoff, (iv) interflow, (v) supplementary baseflow, i.e., essentially a seasonal component, and (vi) primary baseflow, i.e., a long term part of the baseflow. The model is usually run with a daily step and uses spatially averaged inputs and parameters for the whole basin. However, the model may be implemented also in a semidistributed mode (space variability of the inputs and/or parameters is considered), and a shorter time step may be used, too. The flexibility of the model is given by its 12 parameters, which characterise geomorphology, soils, geology and land-use in the given basin. Moreover, the snow sub-model includes 16 additional parameters. Besides that, the SAC-SMA model allows to take into account some other important phenomena, e.g., vertical gradient of air-temperature and correction factor for adjusting the disagreement between the measured and real precipitation amounts.

The model has been applied to several tens of Central-European basins (Buchtele et al., 1996, 1998) as well as to basins in other regions of the world (Burnash, 1995). Recently, the model was used to assess impacts of climate change on runoff regime of several small (100–500 km^2) river catchments (Buchtele et al., 1999).

3. Direct Validation of the Generator

The crucial question to be answered by the direct validation experiments stands: How do the synthetic weather series resemble the observed series? Or more specifically: What is the fit between the statistical characteristics derived from the synthetic series and those derived from the observed series?

Herein, the stress is put on the characteristics, which portray high-frequency (interdiurnal) and low-frequency (intermonthly) variability and are affected by the three suggested modifications of the underlying model. The direct validation of the generator is made here in terms of (i) lag-1 autocorrelations of both conditionally and unconditionally standardised values of *SRAD*, *TMAX* and *TMIN* (Figures 4 and 5), (ii) variability of monthly and annual means (Figure 6), and (iii) characteristics of dry and wet spells (Table II; Figure 7). The figures (except for Figure 7) show the results of the tests, in which the characteristics of the 100-year synthetic weather series generated using various settings of the generator (Table I) were compared to those derived from the 30-year observed series (station Hradec Králové). In testing the reproduction of the dry and wet spells, thirty 30-year synthetic series were generated and compared with 30-year observed series for each of the 14 Czech stations (a subset of the stations used in Dubrovský (1996) and DZS2000).

The effects of the three modifications are discussed below.

(a) Inclusion of the annual cycle of lag-0 and lag-1 correlations among SRAD, TMAX and TMIN.

(a1) It follows from the definition of the model, that this modification has no effect on the precipitation model as well as on the marginal distributions of *SRAD,*

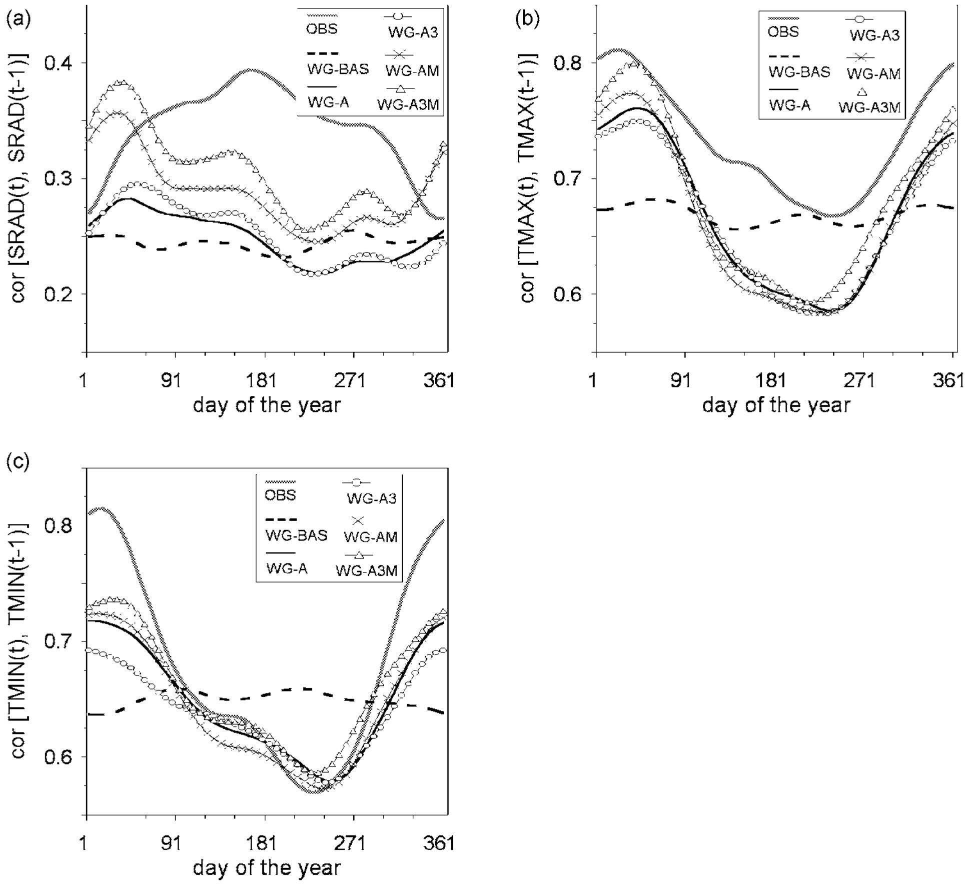

Figure 5. Lag-1 autocorrelations of unconditionally standardised *SRAD* (a), *TMAX* (b), and *TMIN* (c). OBS = observed series from Hradec Králové, 1961–1990; see Table I for the acronyms of the versions of the weather generator.

Table I

Specifications of the five versions of the generator used in the experiments

	Version of the weather generator (acronym)				
	WG-BAS	WG-A	WG-A3	WG-AM	WG-A3M
Annual cycle of matrices of AR(1) model included	NO	YES	YES	YES	YES
Markov chain order	1	1	3	1	3
Monthly generator used	NO	NO	NO	YES	YES

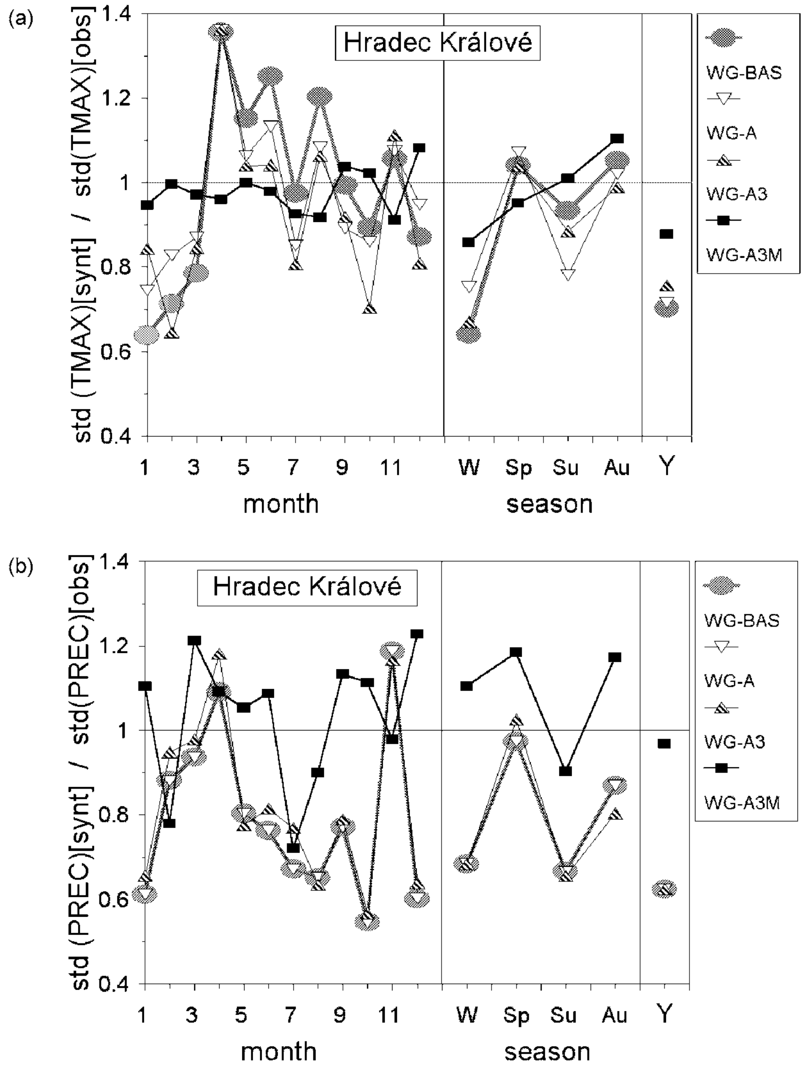

Figure 6. The ratios of the standard deviations of monthly, seasonal and annual means of (a) daily maximum temperature and (b) daily precipitation sum derived from the synthetic weather series to the standard deviations derived from the observed series. The synthetic series were generated using four settings of the generator (see Table I for the acronyms).

TMAX and *TMIN*. Therefore, the means, standard deviations, and the coefficients of skewness and kurtosis of individual daily weather characteristics are not affected.

(a2) Lag-1 autocorrelations of the three conditionally standardised variables are fitted during the whole year (Figure 4). The slight differences between the annual cycles derived from the observed and synthetic series are due to sample errors and smoothing procedure. Inclusion of the annual cycle has much less vivid effect on the lag-1 autocorrelations of unconditionally standardised variables (Figure 5) as

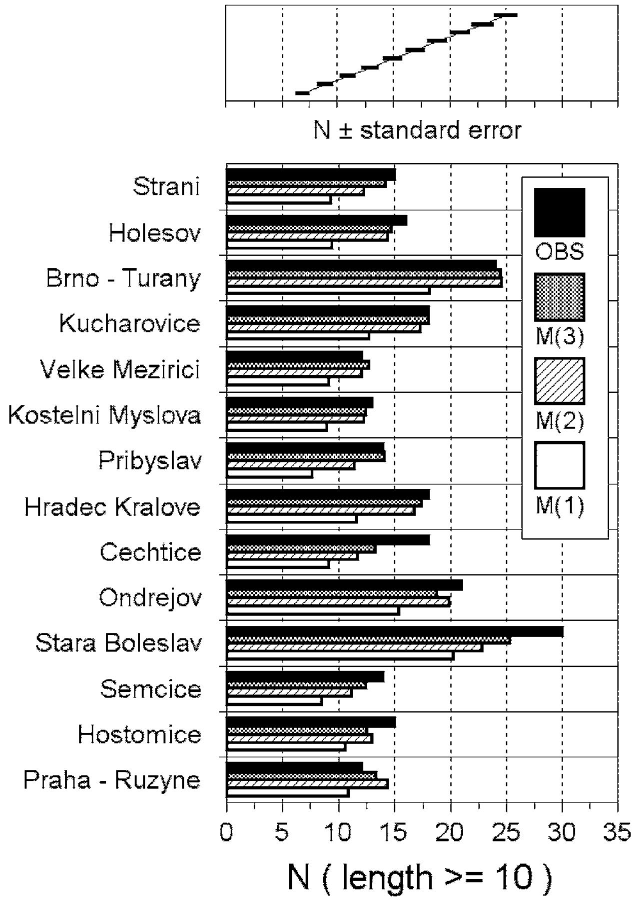

Figure 7. Number of dry spells (length $\geq$10 days) in winter in 30-year observed precipitation series (OBS; 14 stations in the Czech Republic) and in synthetic precipitation series generated by 1st, 2nd and 3rd order Markov chain model [M(1), M(2), M(3)]. The values related to the synthetic series are averages from 30 realisations of the 30-year series. The standard error of these averages is displayed in the upper part of the graph in terms of the horizontal bars related to a specific value of N.

these correlations are significantly affected by the interdiurnal variability in precipitation occurrence series. It should be noted here, that the misreproduction of the unconditional lag-1 correlations may affect modelling of those characteristics, which are related to the interdiurnal weather variability. For example, Huth et al. (2001) and Kyselý et al. (2001) found that the inclusion of the annual cycle of the correlations into the generator improves reproduction of the cold waves characteristics in winter but deteriorates hot waves characteristics in summer. The latter, rather paradoxical result follows from the comparison of the annual cycles of unconditional lag-1 autocorrelations in observed, WG-BAS and WG-A series: inclusion of the annual cycle improves the fit of lag-1 autocorrelation of *TMIN* in winter (Figure 5c), but deteriorates the fit of lag-1 autocorrelation of *TMAX* in summer (Figure 5b).

(a3) No (or possibly only slight) effect on the variability of the monthly averages is detected (Figure 6). The following explanation may be suggested: Variability of the monthly averages is affected by the low-frequency variability, which is not satisfactorily reproduced by the tested version of the daily weather generator. Moreover, the ambiguous effect of including the annual cycle of AR matrices on the lag-1 correlations among unconditionally standardised daily weather characteristics (see the previous paragraph, a2) may also play a role.

(b) Higher-order Markov chain.

(b1) In assessing impacts of the higher-order Markov chain on precipitation occurrence series, the stress was put on reproducing long dry and long wet spells. The observed and synthetic precipitation series in 14 Czech stations were compared in terms of (i) the distribution functions of length of dry and wet spells (Wilcoxon test); (ii) the number of spells longer than 10 days, and (iii) the maximum length of the spells. Summary of the selected statistics is shown in Table II, frequencies of long dry spells in observed and synthetic series are displayed in Figure 7. Parameters of the Markov chain model were defined separately for individual seasons in the tests. When using the first-order Markov chain, it was found:

(i) The Wilcoxon test indicates (characteristic D in Table II), that the distribution of the length of dry spells is misreproduced (level of significance: $\alpha = 0.05$) by M(1) model in most of the stations in autumn and in 8 stations in winter. No rejection (characteristic C in Table II) is indicated in spring and summer and for wet spells.

(ii) Number of long spells (characteristic B in Table II), whether dry or wet, is underestimated; the only exception is the number of long wet spells in spring. Number of long dry spells is underestimated more significantly than the number of long wet spells. The greatest underestimation is exhibited in autumn (by 32%) and winter (by 33%) dry spells.

(iii) The maximum length of both dry and wet spells (characteristic A in Table II) is always underestimated; the greatest underestimation occurs for wet spells in winter (by 28%). However, except for the winter, the maximum length of the dry spells is more underestimated than the maximum length of the wet spells.

(iv) Overall, the tests indicate that the wet spells are generally better modelled than the dry spells. The dry spells are worst reproduced in autumn and winter, when the Wilcoxon test suggests to reject M(1) model. Except for the winter, wet spells are satisfactorily modelled by the 1st order Markov chain.

If the higher-order Markov chain is used, the similarity between the observed and the synthetic precipitation occurrence series is improved. The improvement is mainly experienced if the order of the chain is increased from 1 to 2. Further increase of the order (to value 3) brings only slight benefit. The positive effect of the increased order manifests itself especially in better reproduction of dry spells in autumn and winter (Figure 7). Although the Wilcoxon test does not indicate any statistically significant ($\alpha = 0.05$) difference between distributions derived from the synthetic and observed series, the number of long dry spells and the maximum length of the dry spells in all seasons are underestimated by the 2nd order Markov chain. The same holds for wet spells in winter. Although being slighter, this underestimation is apparent even for the 3rd order chain. Unfortunately, further increase of the order of the Markov chain would imply further increase of the number of parameters to be estimated from the observed series and thereby an increasing error in estimating these parameters. Therefore, one should rather consider other approaches to modelling alternation of wet and dry days (see the Introduction for the references) if a more accurate reproduction of the long wet and dry spells is required.

(b2) It follows from the definition of the model, that the order of the Markov chain has no effect on the precipitation amount model.

(b3) An effect on the lag-1 autocorrelations of unconditionally standardised variables (Figure 5) is very small compared to the error (difference between the characteristics derived from observed and synthetic weather series) in reproducing this characteristic. This means, that we cannot expect any significant improvement in reproducing heat and cold waves, in contrast with a hope expressed by Huth et al. (2001). They hypothesised that the temporal structure of the synthetic temperature series generated conditionally on the precipitation occurrence might be improved if the precipitation occurrence series was better modelled.

(b4) Order of the Markov chain has no effect on the variability of the monthly precipitation (Figure 6). It is assumed that the underestimated variability of the monthly precipitation is related partly to the limited ability of the Markov chain model to reproduce the long dry and wet spells (see paragraph b1), and partly to the low frequency variability, which is expected to be improved by linking the daily generator with the monthly generator.

(c) Monthly generator.

(c1) It follows from the method of linking the monthly and daily generators, that employment of the monthly generator has no effect on the precipitation occurrence series as well as on the means of the four variables.

(c2) On the other hand, standard deviations of daily values are increased by 1% on average. The highest increase (but not higher than by 5%) occurs in winter. This may be explained by the fact that the variability of the monthly averages is most significantly underestimated in winter by the daily generator (Figure 6), and therefore the additional variability contributed by the monthly generator is the greatest in this season. However, the systematic overestimation of the daily variability is considered insignificant – also because of the good results obtained by the monthly generator in the indirect validation tests (chapter 4).

Table II

Summary statistics of testing the performance of the Markov chain in modelling alternation of dry and wet spells in 14 Czech stations. A = ratio[a] of the maximum lengths of the spells in synthetic and observed series; B = ratio[b] of the numbers of spells longer than 10 days in synthetic and observed series; C = number of rejections (of 14 stations) of the hypothesis that the distribution functions of the length of spells in synthetic and observed series are the same (Wilcoxon test[c], 0.05 significance level); D = average value (over 14 stations) of the Wilcoxon statistic[c] used to test the fit of the two distributions; r = order of the Markov chain

	A = Max(syn)/ Max(obs)[a]			B = Sum[N10(synt)]/ Sum[N10(obs)][b]			C = number of rejections[c]			D = Avg(WILC)[c]		
r =	1	2	3	1	2	3	1	2	3	1	2	3
(a) Dry spells												
Year	0.79	0.84	0.87	0.75	0.89	0.95	14	0	0	–2.87	–0.85	–0.51
Spring	0.76	0.79	0.80	0.83	0.97	0.98	0	0	0	–0.90	–0.50	–0.25
Summer	0.80	0.83	0.86	0.84	0.96	1.04	0	0	0	–0.68	–0.25	–0.33
Autumn	0.83	0.91	0.96	0.68	0.81	0.88	12	0	0	–2.21	–0.53	–0.19
Winter	0.77	0.83	0.87	0.67	0.89	0.93	8	0	0	–1.98	–0.41	–0.23
(b) Wet spells												
Year	0.79	0.81	0.84	0.87	0.92	1.01	0	0	0	–0.72	–0.63	–0.25
Spring	0.98	0.96	0.98	1.04	0.98	0.99	0	0	0	–0.02	–0.10	–0.16
Summer	0.94	0.93	0.96	0.98	0.91	1.08	0	0	0	–0.12	–0.15	0.20
Autumn	0.92	0.95	0.99	0.91	1.02	1.11	0	0	0	–0.61	–0.52	–0.31
Winter	0.72	0.74	0.78	0.74	0.84	0.94	0	0	0	–0.67	–0.49	–0.24

[a] Average over 14 stations. The statistic for individual station was obtained by averaging the ratios related to thirty realisations of 30-year synthetic series.
[b] The numbers of spells in synthetic and observed series were summed over the 14 stations. Numbers of spells in synthetic series for given station were averaged over thirty realisations of 30-year series.
[c] The Wilcoxon test was used to compare 900-year synthetic series (aggregation of thirty 30-year series) with 30-year observed series for each of the 14 stations.

(c3) Employment of the monthly generator tends to inflate lag-1 autocorrelations of the daily weather variables (compare WG-AM vs. WG-A in Figures 4 and 5, and WG-A3M vs. WG-A3 in Figure 5). The inflation increases as the ratio of monthly variability to daily variability increases. The highest inflation (by 32% if averaged over the whole year) is detected in the case of lag-1 autocorrelation of *SRAD* (Figure 5a). The inflation is negligible with respect to the sampling errors in case of *TMAX* and *TMIN*.

(c4) As expected, inclusion of the monthly generator improves reproduction of variability of monthly, seasonal and annual means (Figure 6).

4. Indirect Validation of the Weather Generator

The question to be answered in the indirect validation of the weather generator stands: How do the imperfections of the generator affect results obtained with model fed by the synthetic weather series? Ideally, the probability distributions of model output characteristics obtained with the synthetic series should be the same as those obtained with the observed series. In the following two experiments, impacts of the three modifications of the generator on outputs from the crop growth model CERES-Wheat and the hydrological rainfall-runoff model SAC-SMA are analysed. It should be stressed here, that the discrepancies between the model outputs obtained with the observed and synthetic weather series are due to sensitivity of the models to some of those climatic characteristics, which are not perfectly reproduced by the weather generator. However, as the main role is played by the weather generator in this paper and the two simulation models are treated here as black boxes, the above mentioned discrepancies will not be related to individual processes simulated by the models.

4.1. CROP GROWTH MODELLING

CERES-Wheat model simulations were run for 17 Czech stations with 30-year observed weather series and 100-year synthetic weather series. As the single-year crop simulation starts in the autumn and ends in the summer of the consecutive year, the output of the multi-year simulation comprises 29 and 99 values of the crop yield, respectively. The non-meteorological input parameters (cultivar characteristics, soil properties, planting details, fertilisation regime) were the same for all sites and all years and reflect the typical values applied in the real crop experiments made in Žabčice. This approach is justifiable, as the purpose of the experiment is the indirect validation of the weather generator in various climate conditions and not the crop yield forecasting.

The model yields simulated with synthetic weather series were compared to those simulated with the observed series using Wilcoxon test (comparison of the distributions of the yields), t-test (comparison of the means) and F-test (comparison of the standard deviations). The ratios of statistics (means or standard deviations) related to the two types of input weather series are displayed in Figure 8, and the summary of the indirect validation analysis is given in Table III. The results of the Wilcoxon test are not shown as the test was not found sufficiently sensitive – the differences between the distribution functions of the yields simulated with the five versions of the weather generator were found statistically insignificant in all stations.

The results show:

(i) WG-BAS: The mean yields simulated with the weather series produced by the basic version of the generator are by 3.0% higher (averaged over all 17 stations) than the means simulated with the observed weather series, which vary between

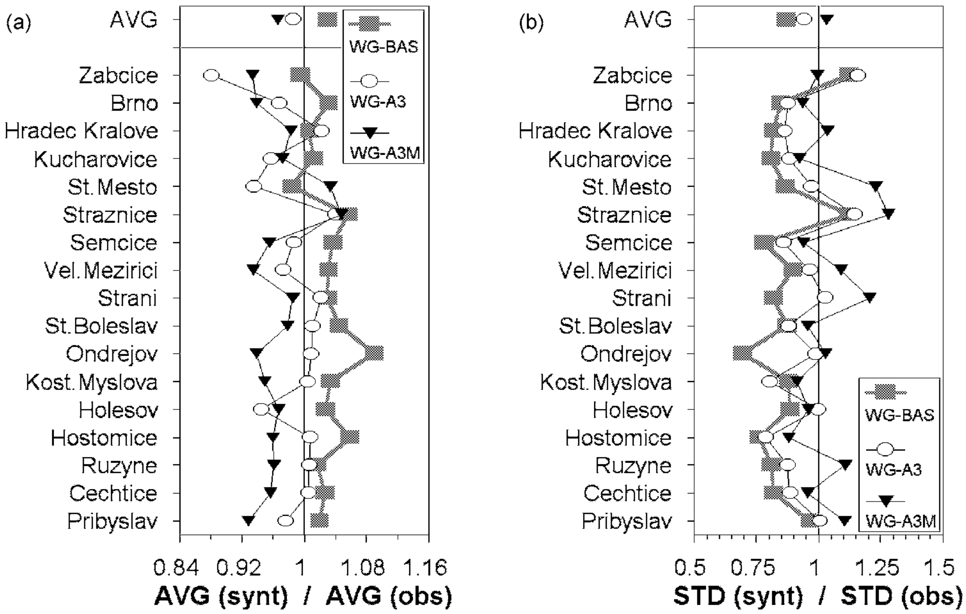

Figure 8. The ratios of the (a) averages and (b) standard deviations of the 99-year model wheat yields simulated with synthetic weather series to the averages and standard deviations, respectively, of the 29-year model wheat yields simulated with observed weather series. The synthetic weather series were generated with three settings of the generator (see Table I for the specifications) and for 17 Czech stations (AVG relates to the statistics averaged over all 17 stations).

Table III

The fit between the wheat yields simulated with synthetic and observed weather series for 17 Czech stations. See Figure 8 for the graphical representation of the results related to individual stations

	Version of the weather generator[a]				
	WG-BAS	WG-A	WG-A3	WG-AM	WG-A3M
Bias in the mean[b] [%]	+3.0	+2.8	–1.5	–2.8	–3.5
Bias in the standard deviation[b] [%]	–13.0	–15.1	–6.0	+2.9	+3.2
Number of stations rejected by t-test ($\alpha = 0.05$)	1	1	0	0	0
Number of stations rejected by F-test ($\alpha = 0.1, 0.05$)	3, 1	5, 2	1, 0	1, 0	1, 0

[a] See Table I for the acronyms.
[b] The mean (averaged over 17 stations) deviation of the statistic obtained with the synthetic weather series from the statistic obtained with the observed series.

4600 and 5900 kg/ha. The t-test shows that the means simulated with the two weather series are statistically significantly different (significance level: $\alpha = 0.05$) only in one station (Ondrejov). On the other hand, the standard deviation of the yields simulated with the synthetic series is on average by 13.0% lower than the standard deviation of the yields simulated with the observed weather series, and the F-test indicates that the standard deviations of the yields simulated with the two types of the weather series are significantly different ($\alpha = 0.05$) at one station and several other stations are close to the rejection area.

(ii) WG-A (the curves are not shown in Figure 8 as they closely resemble the WG-BAS curves): The inclusion of the annual cycle of lag-0 and lag-1 correlations has no apparent effect on the model yields. On the contrary, the fit of the standard deviations of the yields simulated with the observed and synthetic series appears slightly, but insignificantly, worse: The mean yields simulated with observed weather series are overestimated by 2.8% and the standard deviations underestimated by 15.1%. The insignificant effect of the annual cycle of AR matrices supports a practice of Mearns et al. (1996), who used the Richardson's WGEN generator with matrices generalised for entire year and entire territory of the U.S.A.

(iii) WG-A3: Increasing order of the Markov chain improves the fit between the statistics of the yields simulated with observed and synthetic weather series. The ratios of the averages as well as of the standard deviations of the yields simulated with the two types of the weather series are closer to 1 than for the previous versions of the generator. If averaged over all stations, the means and the standard deviations of the model yields simulated with synthetic weather series underestimate the yields simulated with observed series by 1.5% and 6.0%, respectively. Both t-test and F-test indicate statistically significant difference in no station (0.05 significance level).

(iv) WG-AM and *WG-A3M* (the curves for WG-AM are not shown in Figure 8 as the results are very similar to WG-A3M): Inclusion of the monthly weather generator increases the variability of the monthly weather characteristics (Figure 6). We assume that this is the reason for the decrease in the mean yields and increase in their variability. These trends are in good concordance with the earlier results of Mearns et al. (1997) and Mavromatis and Hansen (2001). The results for WG-AM are slightly, but insignificantly, better than for WG-A3M: On average, the means of the yields simulated with observed weather series are underestimated by 2.8% (WG-AM) and 3.5% (WG-A3M), and the standard deviations are overestimated by 2.9% (WG-AM) and 3.2% (WG-A3M). No rejection is indicated by t-test and F-test ($\alpha = 0.05$) for both WG-AM and WG-A3M. Although the quality of the reproduction of the mean yields is comparable with the basic version of the generator (and even worse than the quality related to WG-A3), the variability of the yields is reproduced best of all versions of the generator.

Overall, two of the three modifications of the weather generator slightly improve its performance in crop simulation experiments. Only the inclusion of the annual cycle of the correlations has no effect on the model yields. Two explanations may be suggested for this no effect: Firstly, the crop model may be rather insensitive to changes in interdiurnal weather variability. Secondly, the inclusion of the annual cycle of lag-1 correlations among conditionally standardised weather characteristics does not imply unambiguous improvement in reproducing the temporal structure of the weather series (see paragraph a2 in Section 3). Specifically, the hot spells, which might have a significant effect on the crop yields, are reproduced worse by WG-A than by WG-BAS due to poorer reproduction of the lag-1 autocorrelation of unconditionally standardised maximum temperature in summer (Figure 5b). On the other hand, an improved reproduction of the dry and wet spells related to the increased order of the Markov chain has a positive effect on the simulated yields. The use of the monthly weather generator significantly improves the reproduction of the variability of the yields.

4.2. HYDROLOGICAL MODELLING

The indirect validation of the generator was based on the 39-year simulations of rainfall-runoff processes in the Malše river basin using the SAC-SMA model. Similarly as in the crop model simulations, the hydrological model was run with the observed weather series and the synthetic weather series generated by the five versions of the generator (Table I). Regarding the small size of the river catchment, the weather conditions in the whole area were represented by the single station (České Budějovice, 15° E 49° N) series of daily average temperature and daily precipitation amount. The synthetic series were generated by the two-variate version of Met&Roll (Section 2.1.3). The outputs from SAC-SMA model run with individual weather series were assessed using (i) the averages and standard deviations of monthly averages and monthly maxima of daily streamflows (Figures 9 and 10; Table IV), and (ii) the probability distributions of the 5-day average streamflow (Figure 11). The distributions of the 5-day streamflows simulated with the synthetic weather series were compared with the distributions related to the observed weather series in terms of (i) the standardised statistic of the Wilcoxon test and (ii) the quantiles expressing extremely low or high streamflows (Table V). It should be noted here, that the Wilcoxon test, which compares the fit of the two sample distributions, is not much affected by few occurrences of extreme values. Consequently, the quantiles or the frequencies of extremely low or high streamflows may be better indicators of the generator's performance if one is interested in reproduction of the extreme values.

(i) WG-BAS: The results for the basic version of the generator show:

- Average streamflows simulated with the synthetic weather series slightly underestimate the streamflows simulated with the observed weather series (Figure 9a) in April to June.
- Average monthly maxima are underestimated more vividly and during greater part of the year (Figure 10a).
- Variability of monthly averages (Figure 9b) and monthly maxima (Figure 10b) is underestimated during a whole year, by 50% in spring.
- Frequency of high streamflows is underestimated; the greatest underestimation occurs in spring (Figure 11; Table V).
- Except for the spring, the Wilcoxon test indicates significant differences between the distributions of the streamflows simulated with the synthetic and observed weather series (Table V). We may note that the positive values of the

Table IV

The fit of the averages and standard deviations of monthly streamflow characteristics simulated using the synthetic weather series with those simulated using the observed series (Figures 9 and 10). Each cell contains numbers of the statistically significantly different averages (t-test, 0.05 significance level) or standard deviations (F-test, 0.05 significance level) of the monthly characteristics, tested separately for each month of the year (m; max. value = 12), each season of the year (s; max. value = 4) and for the whole year (y; value = 0 or 1). See Table I for the acronyms of the generators

	Version of the weather generator				
	WG-BAS	WG-A	WG-A3	WG-AM	WG-A3M
	$m/s/y$	$m/s/y$	$m/s/y$	$m/s/y$	$m/s/y$
(a) Average monthly streamflow:					
AVG; rejected by t-test	0/0/0	0/0/0	0/0/0	0/0/0	0/0/0
STD; rejected by F-test	3/3/1	4/3/1	4/3/1	4/1/0	3/1/0
(b) Maximum monthly streamflow:					
AVG; rejected by t-test	2/2/1	1/2/1	1/1/1	1/0/0	0/1/0
STD; rejected by F-test	9/3/1	8/3/1	6/3/1	5/2/0	2/2/0

Wilcoxon statistic indicate that the streamflows simulated with the synthetic series are somewhat larger than the streamflows simulated with the observed series. These trends, however, need not correlate with the lower ($Q_{0.01}$ and $Q_{0.05}$) and upper ($Q_{0.95}$ and $Q_{0.99}$) quantiles, since the Wilcoxon statistic is not so affected by rare occurrences of extreme values.

- The differences between the observed and WG-BAS weather series in the lower quantiles are only slight. Noteworthy, the lower two quantiles are less affected by the three modifications of the generator than the upper two quantiles.
- The upper quantiles are mostly lower than those simulated with the observed weather series. The greatest underestimation occurs in spring.

(ii) WG-A: Inclusion of the annual cycle of lag-1 correlation of *TAVG* has nearly no effect on the monthly streamflow characteristics as well as on the distribution of the 5-day average streamflows. Similarly to the crop modelling, this may be attributed to the following conflict: The generator preserves lag-correlation of the conditionally standardised *TAVG* but the processes simulated by the SAC-SMA model are rather affected by the temporal structure of the unconditionally standardised temperature. In the present case, however, another explanation may be also suggested: The temperature correlations exhibit almost no annual cycle (Figure 1). This means that the inclusion of the annual cycle of lag-1 autocorrelation of *TAVG*

Table V

Comparison of the distribution functions of the 5-day streamflows simulated by SAC-SMA with observed weather series (OBS) and with synthetic series generated by five versions of the generator (see Table I for the specifications). WILC = standardised Wilcoxon statistic for comparing distributions obtained with the synthetic vs. observed weather series. Q_x = quantiles ($x = 0.01, 0.05, 0.5$ (=median), 0.95, 0.99) of the model 5-day streamflows

Season	Weather series	WILC [a]	$Q_{0.01}$	$Q_{0.05}$	$Q_{0.5}$	$Q_{0.95}$	$Q_{0.99}$
Year	OBS		0.91	1.18	3.27	10.45	18.59
	WG-BAS	6.30	0.97	1.23	3.54	8.78	12.91
	WG-A	4.97	0.96	1.22	3.49	9.05	13.33
	WG-A3	1.65	0.95	1.16	3.41	9.18	13.86
	WG-AM	–0.53	0.92	1.17	3.22	10.44	17.67
	WG-A3M	–0.44	0.91	1.19	3.20	10.15	17.43
DJA [b]	OBS		0.93	1.09	3.28	7.91	11.53
	WG-BAS	6.36	0.99	1.20	3.62	7.73	10.09
	WG-A	3.12	0.97	1.18	3.47	7.67	10.54
	WG-A3	–1.41	1.00	1.12	3.26	6.94	9.23
	WG-AM	–3.11	1.04	1.20	2.98	7.53	12.19
	WG-A3M	–3.47	1.02	1.32	2.98	7.57	10.89
MAM [b]	OBS		1.20	1.97	4.84	12.66	20.76
	WG-BAS	–0.82	1.79	2.34	4.87	9.42	12.00
	WG-A	–0.17	1.65	2.26	4.86	9.93	12.86
	WG-A3	1.50	1.81	2.32	4.92	11.00	14.44
	WG-AM	3.15	1.69	2.28	4.98	13.03	20.47
	WG-A3M	3.93	1.63	2.16	5.20	12.52	19.91
JJA [b]	OBS		1.08	1.35	3.34	12.89	23.01
	WG-BAS	2.46	0.98	1.34	3.64	11.14	17.61
	WG-A	2.68	0.98	1.35	3.66	11.13	17.61
	WG-A3	–2.32	0.97	1.27	3.29	10.91	18.50
	WG-AM	–6.11	0.92	1.21	3.06	11.24	18.20
	WG-A3M	–6.17	0.93	1.23	3.06	10.69	18.41
SON [b]	OBS		0.83	1.07	1.92	7.21	12.92
	WG-BAS	4.38	0.90	1.06	2.06	5.93	8.23
	WG-A	4.42	0.91	1.07	2.06	6.02	8.28
	WG-A3	5.00	0.86	1.03	2.21	5.69	7.58
	WG-AM	1.23	0.77	1.00	1.93	7.99	13.45
	WG-A3M	1.99	0.78	1.01	1.99	8.59	13.63

[a] The statistic has approximately normal distribution, $N(0, 1)$, if the two samples have the same distributions. The positive values indicate that the streamflows simulated with the synthetic series are 'larger' than the streamflows simulated with observed series.

[b] DJF = DEC + JAN + FEB, MAM = MAR + APR + MAY, JJA = JUN + JUL + AUG, SON = SEP + OCT + NOV.

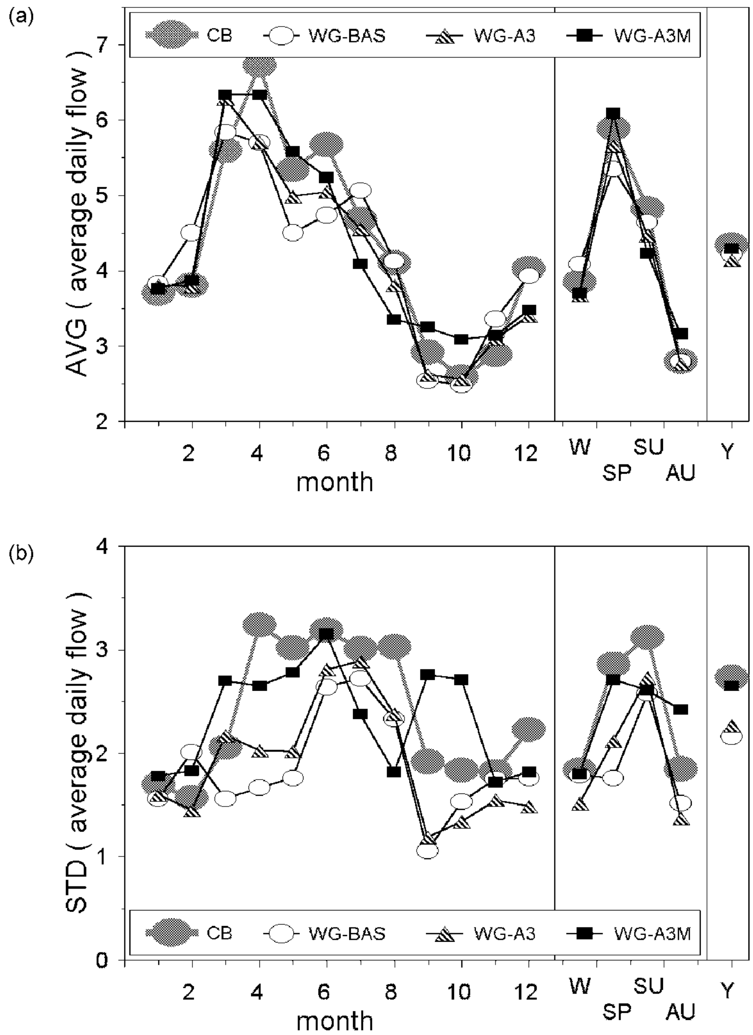

Figure 9. (a) Averages and (b) standard deviations of monthly average streamflow simulated by SAC-SMA model using 39-year observed weather series (CB; station = České Budějovice) and 39-year synthetic series generated with three settings of the generator (see Table I for the specifications; the results for WG-A and WG-AM are not shown as they are very similar to WG-BAS and WG-A3M, respectively). The averages and standard deviations for seasons (W = DEC + JAN + FEB, SP = MAR + APR + MAY, SU = JUN + JUL + AUG, AU = SEP + OCT + NOV) and the whole year (Y) are calculated from all monthly average streamflows within given season or within the whole year, respectively. Summary of the t-test and F-test made to compare the averages and the standard deviations is in Table IV.

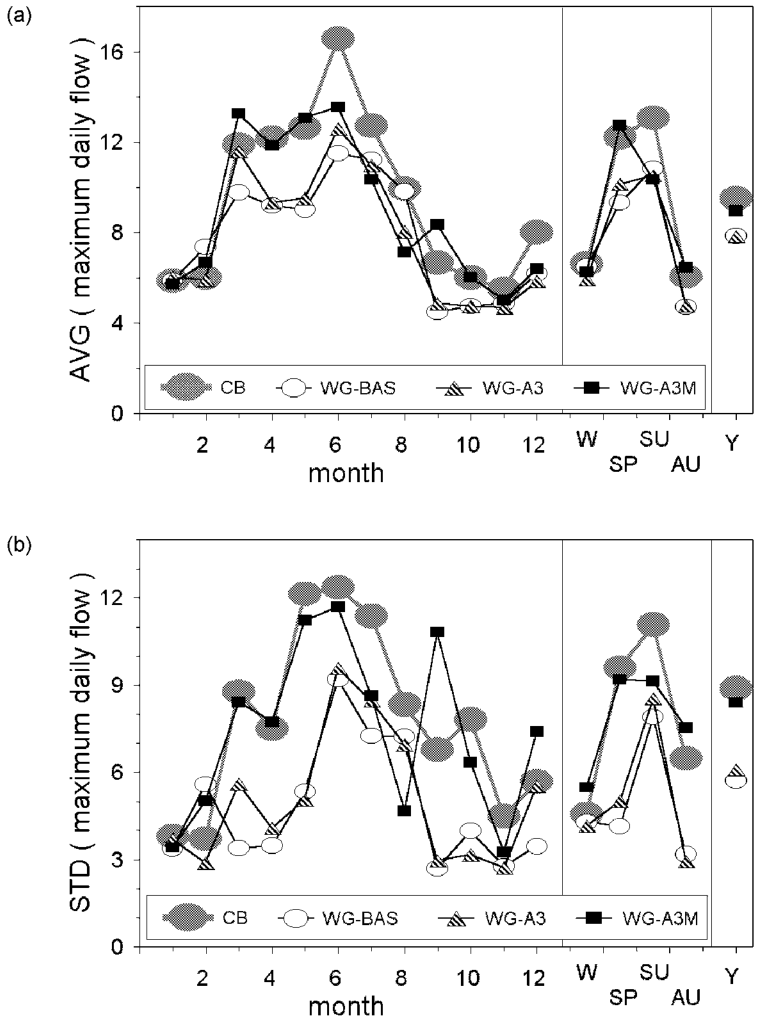

Figure 10. As the previous figure but for the averages and standard deviations of monthly maxima of daily streamflow.

will have only little effect on the temperature series produced by the generator, as well as on the hydrological series modelled with use of this temperature series.

(iii) WG-A3: Increased order of the Markov chain appears to improve only slightly the generator's performance in hydrological modelling. Specifically, some improvement is detected in fitting the averages and standard deviations of the monthly streamflow characteristics (Table IV), and the Wilcoxon test indicates improvement for the spring and the whole year (Table V).

(iv) WG-AM and *WG-A3M*: When the monthly weather generator is used, the Wilcoxon test (Table V) indicates poorer reproduction of the distribution of the 5-day streamflows in spring and summer. This is probably due to the worse repro-

duction of the middle part of the distribution function, as indicated by the median of the 5-day streamflows (column $Q_{0.5}$ in Table V). The error in reproducing the median is lower than approximately 10%. On the other hand, the frequency of occurrence of high 5-day streamflows is now better reproduced, especially in spring (Figure 11) and autumn, as indicated by better fit of the two upper quantiles ($Q_{0.95}$ and $Q_{0.99}$). This positive effect of the monthly generator is considered to be of greater importance than the insufficiency in reproducing the middle part of the distribution function of the streamflows, since the high 5-days streamflow may be a significant indicator of a flood occurrence. As for the averages and standard deviations of the monthly streamflow statistics, an employment of the monthly generator significantly improves their reproduction, even in spring (Figures 9 and 10; Table IV).

5. Conclusions

The paper addressed the interdiurnal and intermonthly variability in stochastic daily weather generator Met&Roll, whose basic version followed the 'classical' Richardson's WGEN generator. Three modifications of the generator aiming to better reproduce the two types of the temporal variability have been suggested and tested: (i) inclusion of the annual cycle of lag-0 and lag-1 correlations among *SRAD*, *TMAX* and *TMIN*, (ii) use of the 3rd order Markov chain to model precipitation occurrence, (iii) applying the monthly generator (based on the first-order autoregressive model) to fit the intermonthly variability of the monthly averages. The direct and indirect validation experiments were made to examine the effects of the three modifications. In the direct validation experiments, the statistics derived from the synthetic weather series were compared with those derived from the observed series. In the indirect validation experiments, the outputs from CERES-Wheat crop growth model and SAC-SMA rainfall-runoff model fed by the observed and synthetic weather series were examined.

The results of the direct validation may be summarised in following points:

(i) The inclusion of the annual cycle of lag-0 and lag-1 correlations among *SRAD*, *TMAX* and *TMIN* has an ambiguous effect on the lag-1 autocorrelations of unconditionally standardised weather characteristics (Figure 5). Precipitation series, shape of the distribution of *SRAD*, *TMAX* and *TMIN*, and intermonthly variability are not affected.

(ii) Higher-order Markov chain improves modelling of long dry spells, especially in autumn and winter (Table II; Figure 7). Lag-1 autocorrelations of unconditionally standardised *SRAD*, *TMAX*, and *TMIN* (Figure 5), as well as the variability of the monthly averages of the weather characteristics (Figure 6) are only slightly affected.

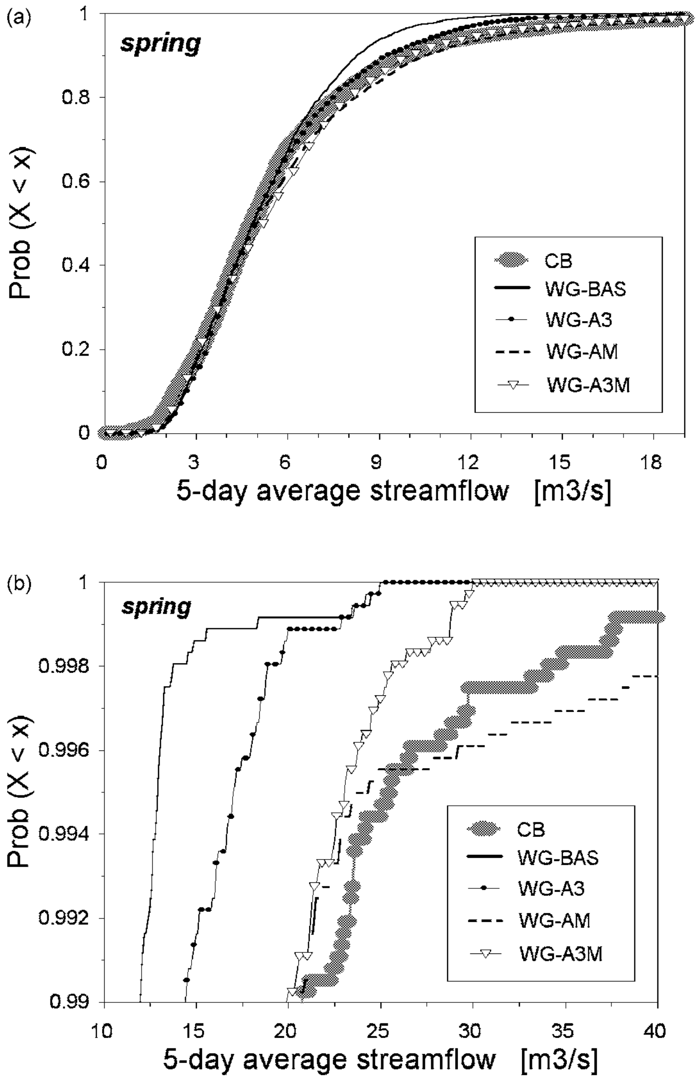

Figure 11. Probability distribution of the 5-day average streamflow in spring simulated by SAC-SMA model with observed weather series (CB) and synthetic weather series generated with four settings of the generator (see Table I for the specifications; curves for WG-A are not shown as they are very similar to WG-BAS). Graph (b) shows the upper tails of the distributions displayed in graph (a). See Table V for the tests of the fit of the distribution functions.

(iii) Employment of the monthly generator significantly improves the reproduction of the variability of monthly, seasonal and annual means of the weather characteristics (Figure 6). The manner, in which the monthly and daily generators are linked, implies that the monthly generator has no effect on the precipitation occurrence model and on the means of *SRAD*, *TMAX* and *TMIN*. On the contrary, the standard deviations of the three variables are slightly increased (by 1% on average), and their lag-1 autocorrelations also tend to be inflated (Figure 5). The lag-1 autocorrelation of *SRAD* is increased by 32% (average over the whole year) but the inflation of autocorrelations of *TMAX* and *TMIN* is negligible with respect to the sampling errors. The insufficiencies are, however, considered insignificant – also because of the good results obtained by the monthly generator in the indirect validation tests. Moreover, the linkage of the daily and monthly generators allows one interesting possibility: to generate daily weather series with precisely specified monthly averages. Specifically, one might generate daily weather series, which conform with, e.g., the monthly averages simulated by GCM (representing either present or changed climate) or the long-term forecast given in terms of the monthly averages.

The results of the indirect validation may be summarised in the following points:

(i) Inclusion of the annual cycle of correlations among *SRAD*, *TMAX* and *TMIN* has no apparent effect on the results obtained by both CERES-Wheat and SAC-SMA models. This may be related to the fact that fitting the annual cycle of lag-1 correlations among conditionally standardised daily weather characteristics does not imply unambiguous improvement in reproducing the temporal structure of the weather series. Two additional explanations were also suggested: Firstly, the crop model may be rather insensitive to changes in interdiurnal weather variability. Secondly, annual cycle of autocorrelation of *TAVG* is insignificant (this applies in case of the rainfall-runoff model).

(ii) Increased order of the Markov chain improves reliability of output from the two simulation models. This is probably related to the fact that the simulated processes are sensitive to the persistence in precipitation occurrence series, especially to occurrences of long wet or dry periods.

(iii) Conditioning the daily generator on monthly generator improves the statistical properties of the output from both simulation models, especially from the rainfall-runoff model. In the crop model, the variability of the model wheat yields is slightly better simulated. In the rainfall-runoff model, the variability of the monthly average streamflow and the average and variability of the monthly maxima of the daily streamflows are better reproduced, especially in spring. The frequency of occurrence of the extreme 5-day streamflows is also better simulated, especially in spring and autumn.

Overall, the results of the indirect validation indicate that the suggested modifications of the generator improve the reliability of the statistics derived from the output of the two simulation models. Of the three modifications, the greatest improvement (in both simulation models) is related to the monthly generator. On the other hand, an inclusion of the annual cycle of lag-0 and lag-1 correlations among *SRAD*, *TMAX* and *TMIN* brings no improvement in either simulation model. Of the two models, the positive effect of the two modifications of the generator is more pronounced in SAC-SMA model simulations. On the other hand, one may find that even the basic version of the generator performs reasonably well in crop growth modelling. This finding suggests that the crop growth model is less sensitive to the imperfections of the generator's basic version.

The paper might be concluded by a rather general note on the roles of the direct and indirect validation of the weather generator. The direct validation allows to examine any feature of the stochastic structure of the weather series, and thereby helps to suggest improvements of the generator, whatever is its further use. However, the improvements are often redeemed by increased number of parameters of the generator. This may lead to lower accuracy of estimating the parameters from a given observed series of a limited length. In this situation, the indirect validation allows one to concentrate on the performance of the generator in its specific application: The obtained results show whether the insufficiencies in reproducing the stochastic structure of the observed series have an effect on the output from the simulation model fed by the synthetic weather series. If the effect on the model output is insignificant, the improvement of the generator is not necessary. In any case, one should bear in mind that the results of the indirect validation of the weather generator are generally valid only for the model, location and experimental settings being used in the tests, and are not directly transferable to other simulation models, other locations or other experimental settings.

Acknowledgements

The study was sponsored by Grant Agency of the Czech Republic, contract 205/99/1561. The agricultural part was also made within the frame of research project 432100001 supported by the Ministry of Education, Youth and Sports of the Czech Republic, and the hydrological part was co-sponsored by the Grant Agency of the Czech Academy of Sciences, contract A3-060-002. The first author is grateful to his colleagues J. Kyselý and R. Huth for their help in making the text more intelligible.

References

Alexandrov, V. A. and Hoogenboom, G.: 2000, 'The Impact of Climate Variability and Change on Crop Yield in Bulgaria', *Agric. For. Meteorol.* **104**, 315–327.

Bacsi, Z. and Hunkár, M.: 1994, 'Assessment of the Impacts of Climate Change on the Yields of Winter Wheat and Maize, Using Crop Models', *Idöjárás* **98**, 119–134.

Bárdossy, A. and Plate, E. J.: 1992, 'Space-Time Model for Daily Rainfall Using Atmospheric Circulation Patterns', *Water Resour. Res.* **28**, 1247–1259.

Bellone, E., Hughes, J. P., and Guttorp, P.: 2000, 'A Hidden Markov Model for Downscaling Synoptic Atmospheric Patterns to Precipitation Amounts', *Clim. Res.* **15**, 1–12.

Bogardi, I., Matyasovszky, I., Bárdossy, A., and Duckstein, L.: 1993, 'Application of a Space-Time Stochastic Model for Daily Precipitation Using Atmospheric Circulation Patterns', *J. Geophys. Res.* **D98**, 16653–16667.

Buchtele, J., Buchtelová, M., Fořtová, M., and Dubrovský, M.: 1999, 'Runoff Changes in Czech River Basins – the Outputs of Rainfall-Runoff Simulations Using Different Climate Change Scenarios', *J. Hydrol. Hydromech.* **47**, 180–194.

Buchtele, J., Herrmann, A., Maraga, F., and Bajracharya, O. T.: 1998, 'Simulations of Effects of Land-Use Changes on Runoff and Evapotranspiration', in *Hydrology, Water Resources and Eco-hydrology in Headwaters*, Procceedings of Conf. HeadWater '98, Merano, April 1998, IAHS Publ. No. 248, pp. 99–106.

Buchtele, J., Kesl, J., and Cissé, Y.: 1996, 'Evaluation of Dynamics of Groundwater Storages Using the Water Balance Simulation', *J. Hydrol. Hydromech.* **44**, 376–395.

Buishand, T. A. and Brandsma, T.: 2001, 'Multisite Simulation of Daily Precipitation and Temperature in the Rhine Basin by Nearest-Neighbor Resampling', *Water Resour. Res.* **37**, 2761–2776.

Burnash, J. C. R.: 1995, 'The NWS River Forecast System – Catchment Modelling', in Singh, V. P. (ed.), *Computer Models of Watershed Hydrology*, Water Resources Publications, Colorado, pp. 311–366.

Chin, E. H.: 1977, 'Modelling Daily Precipitation Occurrence Process with Markov Chain', *Water Resour. Res.* **13**, 949–956.

Chin, E. H. and Miller, J. F.: 1980, 'On the Conditional Distribution of Daily Precipitation Amounts', *Mon. Wea. Rev.* **108**, 1462–1464.

Chipanshi, A. C., Ripley, E. A., and Lawford, R. G.: 1997, 'Early Prediction of Spring Wheat Yields in Saskatchewan from Current and Historical Weather Data Using the CERES-Wheat Model', *Agric. For. Meteorol.* **84**, 223–232.

Cuculeanu, V., Marica, A., and Simota, C.: 1999, 'Climate Change Impact on Agricultural Crops and Adaptation Options in Romania', *Clim. Res.* **12**, 153–160.

Dubrovský, M.: 1996, 'Validation of the Stochastic Weather Generator Met&Roll', *Meteorol. Zpr.* **49**, 129–138 (in Czech).

Dubrovský, M.: 1997, 'Creating Daily Weather Series with Use of the Weather Generator', *Environmetrics* **8**, 409–424.

Dubrovský, M., Žalud, Z., and Šťastná, M.: 2000, 'Sensitivity of CERES-Maize Yields to Statistical Structure of Daily Weather Series', *Clim. Change* **46**, 447–472.

Gabriel, K. R. and Neumann, J.: 1962, 'A Markov Chain Model for Daily Rainfall Occurrence at Tel Aviv', *Quart. J. Roy. Meteorol. Soc.* **88**, 90–95.

Gates, P. and Tong, H.: 1976, 'On Markov Chain Modelling to Some Weather Data', *J. Appl. Meteorol.* **15**, 1145–1151.

Geng, S., Auburn, J. S., Brandsetter, E., and Li, B.: 1988, *A Program to Simulate Meteorological Variables: Documentation for SIMMETEO*, Agronomy Progress Report No. 204, Dept. of Agronomy and Range Sci., University of California, Davis, CA.

Guenni, L.: 1994, 'Spatial Interpolation of the Parameters of Stochastic Weather Models', in Paoli, G. (ed.), *Climate Change, Uncertainty and Decision Making*, Institute for Risk Research, University of Waterloo, Ontario and IGBP-BAHC, Berlin, pp. 61–79.

Gutry-Korycka, M., Werner, P., and Jakubiak, B.: 1994, 'Generation of Time Series of the Meteorological Values in Changing Climatic Conditions', *Geographia Polonica* **62**, 23–45.

Hansen, J. W. and Mavromatis, T.: 2001, 'Correcting Low-Frequency Variability Bias in Stochastic Weather Generators', *Agric. For. Meteorol.* **109**, 297–310.

Harrison, M. and Waylen, P.: 2000, 'A Note Concerning the Proper Choice for Markov Model Order for Daily Precipitation in the Humid Tropics: A Case Study in Costa Rica', *Int. J. Clim.* **20**, 1861–1872.

Hayhoe, H. N.: 2000, 'Improvements of Stochastic Weather Data Generators for Diverse Climates', *Clim. Res.* **14**, 75–87.

Huth, R.: 1997, ‘Continental-Scale Circulation in the UKHI GCM’, *J. Climate* **10**, 1545–1561.

Huth, R., Kyselý, J., and Dubrovský, M.: 2001, ‘Time Structure of Observed, GCM-Simulated, Downscaled, and Stochastically Generated Daily Temperature Series’, *J. Climate* **14**, 4047–4061.

Jamieson, P. D., Porter, J. R., Goudriaan, J., Ritchie, J. T., van Keulen, H., and Stol, W.: 1998, ‘A Comparison of the Models AFRCWHEAT2, CERES-Wheat, Sirius, SUCROS2 and SWHEAT with Measurements from Wheat Grown under Drought’, *Field Crops Res.* **55**, 23–44.

Johnson, G. L., Hanson, C. L., Hardegree, S. P., and Ballard, E. B.: 1996, ‘Stochastic Weather Simulation: Overview and Analysis of Two Commonly Used Models’, *J. Appl. Meteorol.* **35**, 1878–1896.

Jones, P. G. and Thornton, P. K.: 1997, ‘Spatial and Temporal Variability of Rainfall Related to a Third-Order Markov Model’, *Agric. For. Meteorol.* **86**, 127–138.

Kalvová, J. and Dubrovský, M.: 1995, ‘Assessments of the Limits Between which Daily Average Values of Total Ozone Can Normally Vary’, *Meteorol. Zpr.* **48**, 9–17 (in Czech).

Katz, R. W.: 1977, ‘Precipitation as a Chain-Dependent Process’, *J. Appl. Meteorol.* **16**, 671–676.

Katz, R. W.: 1996, ‘Use of Conditional Stochastic Models to Generate Climate Change Scenarios’, *Clim. Change* **32**, 237–255.

Katz, R. W. and Parlange, M. B.: 1993, ‘Effects of an Index of Atmospheric Circulation on Stochastic Properties of Precipitation’, *Water Resour. Res.* **29**, 2335–2344.

Katz, R. W. and Parlange, M. B.: 1996, ‘Overdispersion Phenomenon in Stochastic Modeling of Daily Precipitation’, in *13th Conf. on Prob. & Stat.*, San Francisco, American Meteorol. Soc., Boston, pp. 291–294.

Kiely, G., Albertson, J. D., Parlange, M. B., and Katz, R. W.: 1998, ‘Conditioning Stochastic Properties of Daily Precipitation on Indices of Atmospheric Circulation’, *Meteorol. Appl.* **5**, 75–87.

Kyselý, J., Huth, R., and Dubrovský, M.: 2001, ‘Simulation of Extreme Temperature Events Using General Circulation Models, Statistical Downscaling and Stochastic Generator’, *Meteorol. Zpr.* **54**, 73–82 (in Czech).

Lana, X. and Burgueño, A.: 1998, ‘Daily Dry-Wet Behaviour in Catalonia (NE Spain) from the Viewpoint of Markov Chains’, *Int. J. Clim.* **18**, 793–815.

Landau, S., Mitchell, R. A. C., Barnett, V., Colls, J. J., Craigon, J., Moore, K. L., and Payned, R. W.: 1998, ‘Testing Winter Wheat Simulation Models, Predictions Against Observed U.K. Grain Yields’, *Agric. For. Meteorol.* **89**, 85–100.

Mavromatis, T. and Jones, P. D.: 1999, ‘Evaluation of HadCM2 and Direct Use of Daily GCM Data in Impact Assessment Studies’, *Clim. Change* **41**, 583–614.

Mavromatis, T. and Hansen, J. W.: 2001, ‘Interannual Variability Characteristics and Simulated Crop Response of Four Stochastic Weather Generators’, *Agric. For. Meteorol.* **109**, 283–296.

Mearns, L. O., Mavromatis, T., Tsvetsinskaya, E., Hays, C., and Easterling, W.: 1999, ‘Comparative Responses of EPIC and CERES Crop Models to High and Low Spatial Resolution Climate Change Scenarios’, *J. Geophys. Res.* **D104**, 6623–6646.

Mearns, L. O., Rosenzweig, C., and Goldberg, R.: 1992, ‘Effect of Changes in Interannual Climatic Variability on CERES-Wheat Yields: Sensitivity and $2\times$ CO_2 General Circulation Model Studies’, *Agric. For. Meteorol.* **62**, 159–189.

Mearns, L. O., Rosenzweig, C., and Goldberg, R.: 1996, ‘The Effect of Changes in Daily and Interannual Climatic Variability on CERES-Wheat: A Sensitivity Study’, *Clim. Change* **32**, 257–292.

Mearns, L. O., Rosenzweig, C., and Goldberg, R.: 1997, ‘Mean and Variance Change in Climate Scenarios: Methods, Agricultural Applications, and Measures of Uncertainty’, *Clim. Change* **35**, 367–396.

Moon, S.-E., Ryoo, S.-B., and Kwon, J. G.: 1994, ‘A Markov Chain Model for Daily Precipitation Occurrence in South Korea’, *Int. J. Clim.* **14**, 1009–1016.

Peiris, D. R. and McNicol, J. W.: 1996, 'Modelling Daily Weather with Multivariate Time Series', *Agric. For. Meteorol.* **79**, 219–231.

Porter, J. R.: 1993, 'AFRCWHEAT2: A Model of the Growth and Development of Wheat Incorporating Responses to Water and Nitrogen', *Eur. J. Agron.* **2**, 69–82.

Racsko, P., Szeidl, L., and Semenov, M.: 1991, 'A Serial Approach to Local Stochastic Weather Models', *Ecol. Modelling* **57**, 27–41.

Richardson, C. W.: 1981, 'Stochastic Simulation of Daily Precipitation, Temperature, and Solar Radiation', *Water Resour. Res.* **17**, 182–190.

Riha, S. J., Wilks, D. S., and Simoens, P.: 1996, 'Impact of Temperature and Precipitation Variability on Crop Model Predictions', *Clim. Change* **32**, 293–311.

Rožnovský, J. and Svoboda, J.: 1995, 'Agroclimatological Characterization of Zabcice Field', *Folia Universitatis Agriculturae et Silviculturae*, MZLU Brno, Czech Republic, 49 pp. (in Czech).

Semenov, M. A. and Barrow, E. M.: 1997, 'Use of a Stochastic Weather Generator in the Development of Climate Change Scenarios', *Clim. Change* **35**, 397–414.

Semenov, M. A., Brooks, R. J., Barrow, E. M., and Richardson, C. W.: 1998, 'Comparison of the WGEN and LARS-WG Stochastic Weather Generators for Diverse Climates', *Clim. Res.* **10**, 95–107.

Semenov, M. A. and Porter, J. R.: 1995, 'Climatic Variability and the Modelling of Crop Yields', *Agric. For. Meteorol.* **73**, 265–283.

Solow, A. R., 1988: 'Detecting Changes through Time in the Variance of a Long-Term Hemispheric Temperature Record: an Application of Robust Locally Weighted Regression', *J. Climate* **1**, 290–296.

Spirkl, W. and Ries, H.: 1986, 'Non-Stationary Markov Chains for Modelling Daily Radiation Data', *Q. J. R. Meteorol. Soc.* **112**, 1219–1229.

Šťastná, M., Trnka, M., Křen, J., Dubrovský, M., and Žalud, Z.: 2002, 'Evaluation of the CERES Models in Different Production Regions of the Czech Republic', *Rostlinná Výroba* **48**, 125–132.

Šťastná, M. and Žalud, Z.: 1999, 'Sensitivity Analysis of Soil Hydrologic Parameters for Two Crop Simulation Models', *Soil and Tillage Res.* **50**, 305–318.

Stehlík, J. and Bárdossy, A.: 2002, 'Multivariate Stochastic Downscaling Model for Generating Daily Precipitation Series Based on Atmospheric Circulation', *J. Hydrol.* **256**, 120–141.

Stern, R. D. and Coe, R.: 1984, 'A Model Fitting Analysis of Daily Rainfall Data', *J. Roy. Statist. Soc.* **A147**, 1–34.

Todorovic, P. and Woolhiser, D. A.: 1975, 'A Stochastic Model of n-Day Precipitation', *J. Appl. Meteorol.* **14**, 17–24.

Tubiello, F. N., Donatelli, M., Rosenzweig, C., and Stockle, C. O.: 2000, 'Effects of Climate Change and Elevated CO_2 on Cropping Systems: Model Predictions at Two Italian Locations', *Eur. J. Agron.* **13**, 179–189.

Tsuji, G. Y., Uehara, G., and Balas, S.: 1994, *DSSAT v3.*, University of Hawaii, Honolulu, Hawaii.

Wallis, T. W. R. and Griffiths J. F.: 1997, 'Simulated Meteorological Input for Agricultural Models', *Agric. For. Meteorol.* **88**, 241–258.

Wilby, R. L.: 1994, 'Stochastic Weather Type Simulation for Regional Climate Change Impact Assessment', *Water Resour. Res.* **30**, 3395–3403.

Wilks, D. S.: 1989, 'Conditioning Stochastic Daily Precipitation Models on Total Monthly Precipitation', *Water Resour. Res.* **25**, 1429–1439.

Wilks, D. S.: 1992, 'Adapting Stochastic Weather Generation Algorithms for Climate Change Studies', *Clim. Change* **22**, 67–84.

Wilks, D. S.: 1998, 'Multisite Generalization of a Daily Stochastic Precipitation Generation Model', *J. Hydrol.* **210**, 178–191.

Wilks, D. S.: 1999a, 'Interannual Variability and Extreme-Value Characteristics of Several Stochastic Daily Precipitation Models', *Agric. For. Meteorol.* **93**, 153–169.

Wilks, D. S.: 1999b, 'Simultaneous Stochastic Simulation of Daily Precipitation, Temperature and Solar Radiation at Multiple Sites in Complex Terrain', *Agric. For. Meteorol.* **96**, 85–101.

Wilson, L. L., Lettenmaier, D. P., and Skyllingstad, E.: 1992, 'A Hierarchical Stochastic Model of Large-Scale Atmospheric Circulation Patterns and Multiple Station Daily Precipitation', *J. Geophys. Res.* **D97**, 2791–2809.

Wolf, J., Evans, L. G., Semenov, M. A., Eckersten, H., and Iglesias, A.: 1996, 'Comparison of Wheat Simulation Models under Climate Change. I. Model Calibration and Sensitivity Analyses', *Clim. Res.* **7**, 253–270.

Young, K. C.: 1994, 'A Multivariate Chain Model for Simulating Climatic Parameters from Daily Data', *J. Appl. Meteorol.* **33**, 661–671.

Žalud, Z. and Dubrovský, M.: 2002, 'Modelling Climate Change Impacts on Maize Growth and Development in the Czech Republic', *Theor. Appl. Climatol.* **72**, 85–102.

(Received 20 March 2002; in revised form 4 April 2003)