SENSITIVITY OF CERES-MAIZE YIELDS TO STATISTICAL STRUCTURE OF DAILY WEATHER SERIES

MARTIN DUBROVSKÝ [1], ZDENĚK ŽALUD [2] and MILADA ŠŤASTNÁ [2]
[1] *Institute of Atmospheric Physics, AS CR, Husova 456, 50008 Hradec Králové, Czech Republic*
E-mail: dub@ufa.cas.cz
[2] *Mendel University of Agriculture and Forestry, Brno, Czech Republic*

Abstract. To study impacts of climate variations on crop production, the growth models are used to simulate yields in present vs. changed climate conditions. Met&Roll is a four-variate (precipitation amount, solar radiation, minimum and maximum temperatures) stochastic weather generator used to supply synthetic daily weather series for the crop growth model CERES-Maize. Three groups of experiments were conducted in this study: (1) Validation of Met&Roll reveals some discrepancies in the statistical structure of synthetic weather series, e.g., (i) the frequency of occurrence of long dry spells, extreme values of daily precipitation amount and variability of monthly means are underestimated by the generator; (ii) correlations and lag-1 correlations among weather characteristics exhibit a significant annual cycle not assumed by the model. On the whole, the best fit of the observed and synthetic weather series is experienced in summer months. (2) The Wilcoxon test was employed to compare distributions of maize yields simulated with use of observed vs. synthetic weather series. As no statistically significant differences were detected, it is assumed that the generator imperfections in reproducing the statistical structure of weather series negligibly affect the model yields. (3) The sensitivity of model yields to selected characteristics of the daily weather series was examined. Emphasis was placed on the characteristics not addressed by typical GCM-based climate change scenarios: daily amplitude of temperature, persistence of the weather series, shape of the distribution of daily precipitation amount, and frequency of occurrence of wet days. The results indicate that some of these characteristics may significantly affect crop yields and should therefore be considered in the development of climate change scenarios.

1. Introduction

In view of the climate change anticipated in the near future, ever increasing efforts are being made to study the possible impact of this change on various fields of human activity and to identify strategies for adapting to it. Agriculture is among the most prominent endeavours potentially endangered by the climate change, as it is significantly dependent on weather variability. The impacts of climate variations on crop production can be studied with the use of crop models (Bacsi and Hunkár, 1994; Mearns et al., 1992, 1996, 1997; Maytín et al., 1995; Semenov and Barrow, 1997; Semenov and Porter, 1995). To simulate crop growth in daily steps, the crop models take into account cultivar characteristics, field and soil characteristics, planting details, management factors and daily weather conditions. The weather conditions are typically represented by maximum and minimum temper-

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ature, precipitation amount and total solar radiation. These parameters are required for simulations by the crop model CERES, which has recently been employed in many studies (e.g., Bacsi and Hunkár, 1994; Eitzinger and Dirmhirn, 1994; Makadho, 1996; Maytín et al., 1995; Mearns et al., 1992, 1996, 1997). Some crop models, e.g., MACROS (Penning de Vries et al., 1989), consider additional weather characteristics, such as wind speed and water vapour pressure.

An assessment of the climate change impacts is based on a comparison of crop model simulations with present-climate weather series and changed-climate weather series. The weather data representing present climate conditions may be taken from the archived records of observational data. Problems arise in securing data representing changed climate conditions. Various techniques have been suggested to complete this task; most of which rely on the output from General Circulation Model (GCM) simulations. Since the state-of-the-art GCMs do not satisfactorily reproduce the temporal variability of surface weather conditions on a local scale (Beersma, 1992; Gates et al., 1990; Kalvová and Nemešová, 1998; Mearns et al., 1990), several techniques have been developed to construct time series of weather elements at the desired spatial and temporal resolutions from a larger-scale GCM output. These techniques include:

(i) Nested mesoscale model (Giorgi, 1990; Giorgi et al., 1992; Jones et al., 1995; Russo and Zack, 1994);
(ii) Statistical downscaling of GCM-simulated upper-air circulation patterns to surface weather characteristics (Bárdossy and Plate, 1992; Bogardi et al., 1993; Wilby, 1994; Wilson et al., 1992);
(iii) Direct modification of observed weather series in accordance with a GCM-based climate change scenario (Bacsi and Hunkár, 1994; Mearns et al., 1992);
(iv) Stochastic weather generator with parameters modified in accordance with a GCM-based climate change scenario (Semenov and Barrow, 1997). Mearns et al. (1997) used a regional climate model nested within a GCM to specify changes of the generator parameters.

In the latter two approaches, the climate change scenario consists of the increments based on a comparison of GCM simulations of present-day and changed climate conditions. In the direct modification approach, (iii), the modified series, $x'(t)$, is obtained from the original series, $x(t)$, with use of the formula:

$$x'(t) = x(t) \odot \delta_i(d)\,, \tag{1}$$

where $\delta_i(d)$ is an increment related to day d (Julian day) and the symbol $\odot$ stands for either additive or multiplicative operator. Additive modifications are typically used for changing temperature characteristics and multiplicative modifications are used for changes in precipitation and solar radiation (Wilks, 1992). The variance of the series may also be changed in the direct modification approach. The above equation allows for modification of monthly precipitation totals through multiplying daily precipitation amounts by a given factor on all wet days. A more sophisticated method has been designed (Maytín et al., 1995) to change monthly precipitation amounts by modifying frequency of occurrence of wet days. This ‘direct modification’ technique has some limitations, however. First, the method cannot be used for locations for which there are no historical records. Second, the length of the synthetic series is limited by the length of the observed series (if available), which may be insufficient for a detailed sensitivity analysis. Third, the technique gives only limited possibilities for consistent adjustment of the statistical structure of the series. All these limitations are overcome if a weather generator is used.

The purpose of the weather generator is to produce a weather series whose statistical structure is similar to the observed series. In developing the generator, a suitable model is selected to represent the distribution of weather variables, relations between those variables (if more than one variable is treated by the generator) and the temporal variability of the time series. Autoregressive models and Markov chains of first or higher (less frequent) order are mostly used for this purpose (e.g., Gabriel and Neumann, 1962; Gates and Tong, 1976; Gregory et al., 1993; Katz, 1977; Richardson, 1981). The parameters of the generator are derived from an observed series of sufficient length, or may be deduced from the geographical distribution of relevant climatic characteristics (for stations without historical records). Once the parameters are determined, an arbitrarily long series may be generated using a random number generator and the equations of the model. If a generated series is intended to represent the changed climate conditions, the generator parameters are modified in accordance with a climate change scenario. The scenario may be based on the comparison of GCM-simulated present and changed climates. The nested limited-area model was recently used to determine mean and variability changes of daily climatic characteristics (Mearns et al., 1997).

Several critical points are encountered while developing and using the weather generator. The first point concerns the choice of the generator’s model which must satisfactorily portray the statistical structure of the weather series. Regarding the effect on crop yields (Mearns et al., 1996, 1997; Riha et al., 1996; Semenov and Barrow, 1997), not only the means, but also the variances and frequencies of extreme event occurrence should be reproduced. An estimation of the model parameters is the second point. A multi-parameter model may generally better conform to the structure of the data. However, the more parameters must be estimated from the observed data sample of a limited size, the greater is the error of the estimates. Consequently, when a sufficiently long weather series is not available, it may be more advantageous to calculate only selected parameters from the observed weather series and to estimate remaining parameters using empirical relationships. This approach is employed in the SIMMETEO weather generator (Geng and Auburn, 1986; Geng et al., 1986, 1988). The third problem is faced if the generator is used to produce synthetic data for changed climate conditions. Climate change scenario is often given in terms of only few characteristics and the task is to project the scenario into parameters of the generator. For example, a typical GCM-based climate change scenario specifies changes in monthly mean temperature and precipitation sums. However, the scenario does not provide answers to the following questions: Will the daily temperature amplitude remain the same? Will the variance of the temperature remain the same? Will the change in precipitation sums be due to changes in number of wet days or due to changes in distribution of daily precipitation amount, or both? Will the relations between individual weather characteristics change? Will the persistence of the weather series change? These questions may be avoided if the surface weather characteristics are downscaled from GCM-simulated circulation patterns, or if the changes of the generator parameters are based on nested limited-area model simulations. Unfortunately, these latter approaches are accompanied by other serious problems concerning the reliability of GCM-simulated atmospheric circulation, magnitude of correlation between the circulation and surface weather and the reliability of surface weather regime simulated by limited-area models. It is therefore desirable to know the sensitivity of crop model simulations to the climatic characteristics not explicitly addressed by typical GCM-based climate change scenarios.

In 1993–1995, the Czech Republic’s Country Study, supported by the U.S. Environmental Protection Agency, was conducted (Brázdil and Rožnovský, 1996; Moldan and Sobíšek, 1996). One project goal was the estimation of impacts of potential climate change on crop production with the use of the DSSAT3 (Decision Support System for Agrotechnology Transfer, version 3) software package (Tsuji et al., 1994), which includes two weather generators, WGEN (Richardson and Wright, 1984) and SIMMETEO (Geng et al., 1988). As some parameters of the two generators were optimised for the territory of the U.S.A., and could not be modified by a program user, the analogous generator, Met&Roll, was developed for the purpose of the Country Study project (Dubrovský, 1996a,b; Dubrovský, 1997).

This paper deals with the description and validation of Met&Roll, verifies its applicability in crop growth simulations, and demonstrates its use in assessing climate change impacts. Section 2 gives a brief description of the generator and reviews the results of tests validating the statistical structure of the synthetic series produced by the generator. Specifications of the experiments made with the crop model are given in Section 3. Applicability of the generator for crop growth simulation is examined in Section 4. Synthetic weather series are used as an input to the CERES-Maize model and the sample distributions of grain yields simulated for 17 Czech stations are compared with the distributions obtained from simulations with observed weather series. Section 5 deals with the sensitivity of model grain yields to various characteristics of the statistical structure of the weather series. The collection of characteristics being considered in this analysis includes also those, which are not explicitly treated by the typical GCM-based scenario, but which can be controlled by the generator, such as daily temperature amplitude, persistence of the weather series, and shape of the distribution of daily precipitation amount. In the experiments, parameters of Met&Roll are first modified to reflect changes of desired characteristics. Then, the synthetic series is generated and used as an input to the CERES-Maize model simulation. The results of this analysis are expected to give insight into possible errors, which may result from inaccuracy of GCM-based climate change scenarios and from ambiguities in projecting the climate change scenarios into parameters of the weather generator.

2. Weather Generator

2.1. MODEL

Met&Roll is a stochastic weather generator dealing with four daily weather characteristics: RAIN = daily precipitation amount, SRAD = daily sum of global solar radiation, TMIN = daily temperature minimum, TMAX = daily temperature maximum. The model of the generator is based on the scheme adopted from Wilks (1992):

- Precipitation occurrence forms a primary series which is modelled by a two-state first-order Markov chain

  $$\Pr(\mathrm{RAIN}(t) > 0) = \begin{cases} \pi_{01}(m) & \text{if } \mathrm{RAIN}(t-1) = 0 \\ \pi_{11}(m) & \text{if } \mathrm{RAIN}(t-1) > 0\,, \end{cases} \tag{2}$$

  where $\pi_{01}(m)$ and $\pi_{11}(m)$ are transition probabilities and m is an index for month. Unconditional probability of wet day occurrence will be denoted as π_1. It holds: $\pi_1 = \pi_{01}/(1 + \pi_{01} - \pi_{11})$.
- Precipitation amount on a wet day is represented by the Gamma distribution

  $$f(\mathrm{RAIN};\ \alpha,\ \beta) = \left(\frac{\mathrm{RAIN}}{\beta}\right)^{\alpha-1} \frac{e^{\mathrm{RAIN}/\beta}}{\beta\Gamma(\alpha)}\,, \tag{3}$$

  where α is the shape parameter, β is the scale parameter and $\Gamma(\bullet)$ is a Gamma function. The mean daily precipitation amount on a wet day is $\alpha\beta$.
- Standardised deviations of SRAD, TMAX and TMIN from their mean annual cycles are modelled by a first-order autoregressive (AR) model

  $$\boldsymbol{x}^*(t) = \boldsymbol{A}\boldsymbol{x}^*(t-1) + \boldsymbol{B}\boldsymbol{\varepsilon}(t)\,, \tag{4}$$

  where $\boldsymbol{A}$ and $\boldsymbol{B}$ are 3×3 matrices, $\boldsymbol{\varepsilon}(t)$ is three-dimensional white noise, and $\boldsymbol{x}^* = (x_1^*,\ x_2^*,\ x_3^*)$ is a vector of the three standardised daily weather characteristics

  $$x_i^*(t) = \frac{x_i(t) - \mu_{ij}(d)}{\sigma_{ij}(d)}\,, \tag{5}$$

  where x_i, $i = 1, 2, 3$, stands for SRAD, TMAX and TMIN, respectively, and $\mu_{ij}(d)$ and $\sigma_{ij}(d)$ are conditional means and standard deviations of x_i for day d of the year, which is either dry ($j = 0$) or wet ($j = 1$).

TABLE I

Parameters of the model of the weather generator Met&Roll

Parameter	Description	Annual cycle is represented by
π_1, π_{01}	Parameters of the first-order Markov chain: unconditional probability of a wet day occurrence, transition probability of a wet day following a dry day	Monthly values
α, β	Shape and scale parameters of the Gamma distribution for daily precipitation amount	Monthly values
$m(x \mid \text{dry}),\ s(x \mid \text{dry}),$ $m(x \mid \text{wet}),\ s(x \mid \text{wet}),$ $x \in \{\text{SRAD, TMAX, TMIN}\}$	Means and standard deviations of SRAD, TMAX and TMIN; defined separately for dry and wet days	Daily values
$\boldsymbol{A}, \boldsymbol{B}$	Matrices of the first-order autoregressive model for interdiurnal variability of standardised values of SRAD, TMAX and TMIN	One value per year

Met&Roll calculates all parameters of the model (Table I) from the observed series. Parameters of the precipitation model (parameters of the Gamma distribution, α and β, and parameters of the Markov chain model, π_1 and π_{01}) are calculated on a monthly basis. Means and standard deviations – defined separately for wet and dry days – of SRAD, TMAX and TMIN are determined for each day of the year. Annual cycles are smoothed by robust locally weighted regression (Solow, 1988). Matrices of the AR model are assumed to be constant throughout the year. Overall, the most important difference between Met&Roll and the other two generators mentioned above (WGEN and SIMMETEO) is that no empirical relationships are used in Met&Roll to calculate any parameters of the model from the others.

2.2. VALIDATION

The purpose of the weather generator is to produce a weather series which is statistically similar to the observed series. In other words, statistical characteristics representing the distribution of the variables, their interdiurnal variability, and correlations between them, should all be the same if derived from either series. Since a detailed validation of Met&Roll was published recently (Dubrovský, 1996b, 1997), we will only review the main results here. In the validation tests, the characteristics derived from the observed series (30-yr series from 17 Czech stations listed in Table II and displayed in Figure 1) were compared with characteristics derived from the synthetic series or with values valid for the model assumed.

Some features of the statistical structure of the daily weather series were found to be well preserved by Met&Roll:

TABLE II

Selected characteristics of the reference climatic stations. Legend: Ind. = station index number; ALT = altitude (meters above the sea level); R(y) = total annual precipitation; P(y) = annual mean probability of occurrence of the wet day; R(7) = precipitation sum for July; TA(y) = mean annual temperature (= annual mean of the daily mean temperature, which is defined here as an average of daily minimum and daily maximum temperatures); TX(7) = mean daily maximum temperature in July; SR(y) = annual mean of daily sum of global solar radiation; SR(6) = mean daily sum of global solar radiation in June. See Figure 1 for the location of the stations

Ind.	Station	ALT [m.a.s.l.]	R(y) [mm]	P(y) [%]	R(7) [mm]	TA(y) [°C]	TX(7) [°C]	SR(y) [MJ/m^2]	SR(6) [MJ/m^2]
– [a]	Žabčice	179	480	31	57.1	9.1	25.2	10.8	20.2
11518	Ruzyně	380	526	46	66.2	8.1	23.2	9.9	18.5
11523	Hostomice	345	543	50	64.7	8.5	24.5	10.0	18.9
11561	Semčice	234	579	53	72.0	8.8	23.9	9.9	18.6
11563	Stará Boleslav	179	576	42	69.3	9.2	24.8	9.5	17.9
11572	Ondřejov	526	675	45	82.9	7.7	22.4	10.4	18.8
11627	Čechtice	490	716	51	84.9	7.8	22.3	10.5	19.0
11636	Kostelní Myslová	569	583	48	73.2	7.2	22.1	10.5	19.6
11649	Hradec Králové	278	617	46	71.1	8.6	23.8	10.6	19.7
11659	Přibyslav	530	677	48	81.3	6.9	21.8	10.3	19.1
11687	Velké Meziříčí	452	594	47	67.7	7.2	23.1	10.4	19.9
11698	Kuchařovice	334	471	41	60.3	8.7	24.4	11.0	20.3
11723	Brno – Tuřany	241	490	39	63.7	8.9	24.5	10.8	20.1
11754	Staré Město	235	536	39	63.3	9.1	24.6	10.3	19.1
11755	Strážnice	176	537	36	59.9	9.0	24.8	10.9	20.0
11774	Holešov	224	613	45	78.0	8.6	24.0	10.7	19.8
11779	Strání	421	799	47	72.6	7.9	23.1	10.5	19.3

[a] Not included in the network of meteorological stations.

- Annual cycles of the weather generator parameters, except for the shape parameter of the Gamma distribution, are well reproduced (Figures 2 and 3). The discrepancies in the case of the shape parameter are due to the rounding error (the values of RAIN are stored with one decimal place precision), which deforms the distribution of RAIN in the near-zero area.
- TMAX and TMIN are approximately normally distributed (assumption of the AR model) during summer months.
- Distribution of the length of wet periods is satisfactorily modelled by the two-state first-order Markov chain.
- Daily precipitation amount may be represented by the Gamma distribution during summer months. It should be noted, however, that the approximated Gamma distribution underestimates frequency of occurrence of both extremely high and low precipitation amounts for most months at most stations.

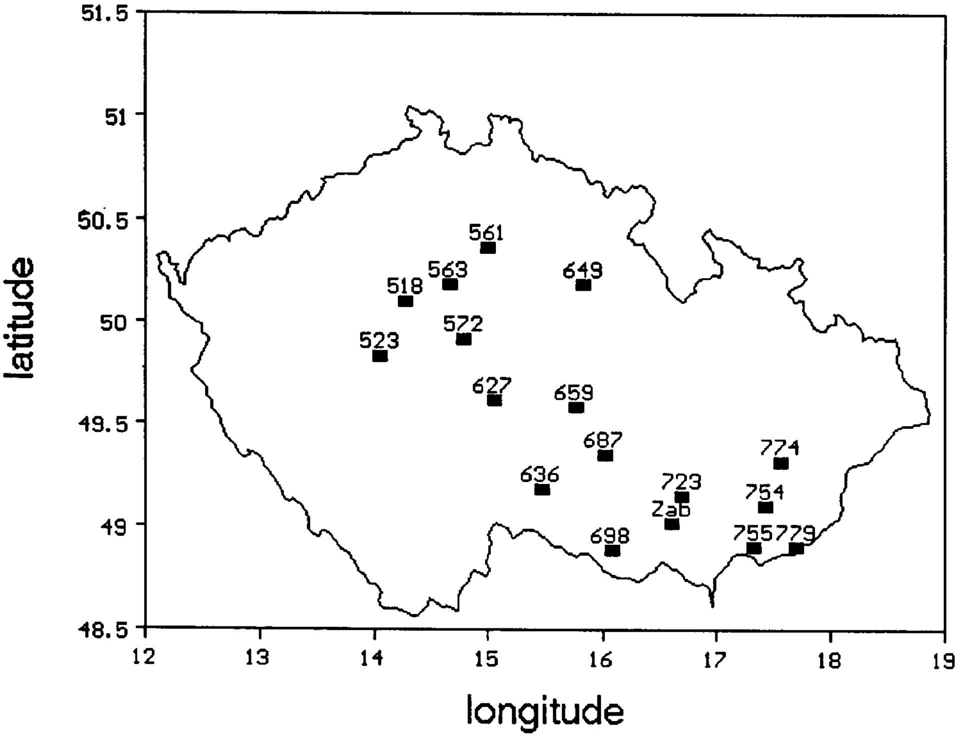

Figure 1. Locations of the agricultural experimental site Žabčice (Zab) and the meteorological stations (marked by the last three digits of their station index – see Table II for the list).

On the other hand, some features (including those listed above in winter months) are not well modelled by the generator:

- SRAD does not follow the normal distribution, as assumed by the AR model.
- Correlations (Figure 4) and lag-1 correlations among SRAD, TMAX and TMIN vary throughout the year, which contradicts the use of annual-cycle-free matrices in the autoregressive model.
- Variability of monthly means of solar radiation and variability of monthly sums of precipitation are underestimated during the entire year. Variability of monthly means of extreme temperatures is underestimated in winter and overestimated in summer (Figure 5).
- 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 by the generator.

Some modifications of the generator's model were suggested in Dubrovský (1997) to improve the reproduction of the statistical structure of an observed series.

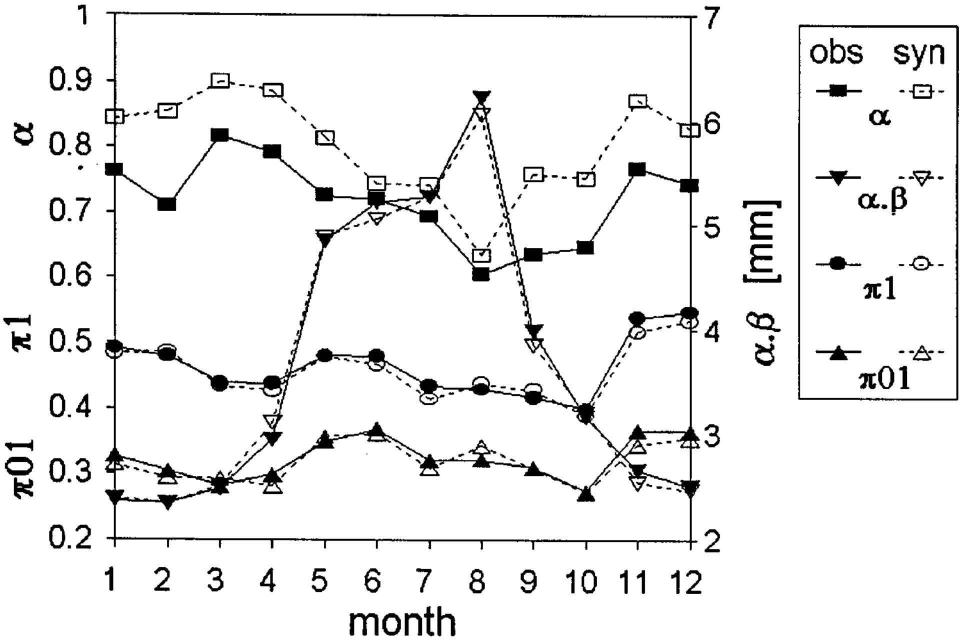

Figure 2. Annual cycle of parameters of the precipitation model derived from the observed series (solid lines with filled symbols) and synthetic series (dashed lines with empty symbols). Note that the product of the two parameters of the Gamma distribution, $\alpha\beta$, represents the mean precipitation sum on a wet day.

3. Specifications of the Crop Growth Model Simulations

The CERES-Maize model, version 3.0, included in the DSSAT3 software package was used to simulate crop growth. CERES-Maize is a mechanistic process-based model which increments crop growth in daily steps. The model incorporates the following processes (Hunkár, 1994):

- phenological development,
- extension of leaves, stems and roots,
- biomass accumulation and partitioning,
- soil water balance and water use by crop,
- soil nitrogen transformation, uptake by the crop, and partitioning among plant parts.

The input data required for the simulations include:

- cultivar characteristics (given in terms of genetic coefficients),
- field attributes (slope, drains, longitude, latitude),
- soil characteristics (texture, bulk density),
- planting details (date of seeding, seeding population, row spacing, planting depth),

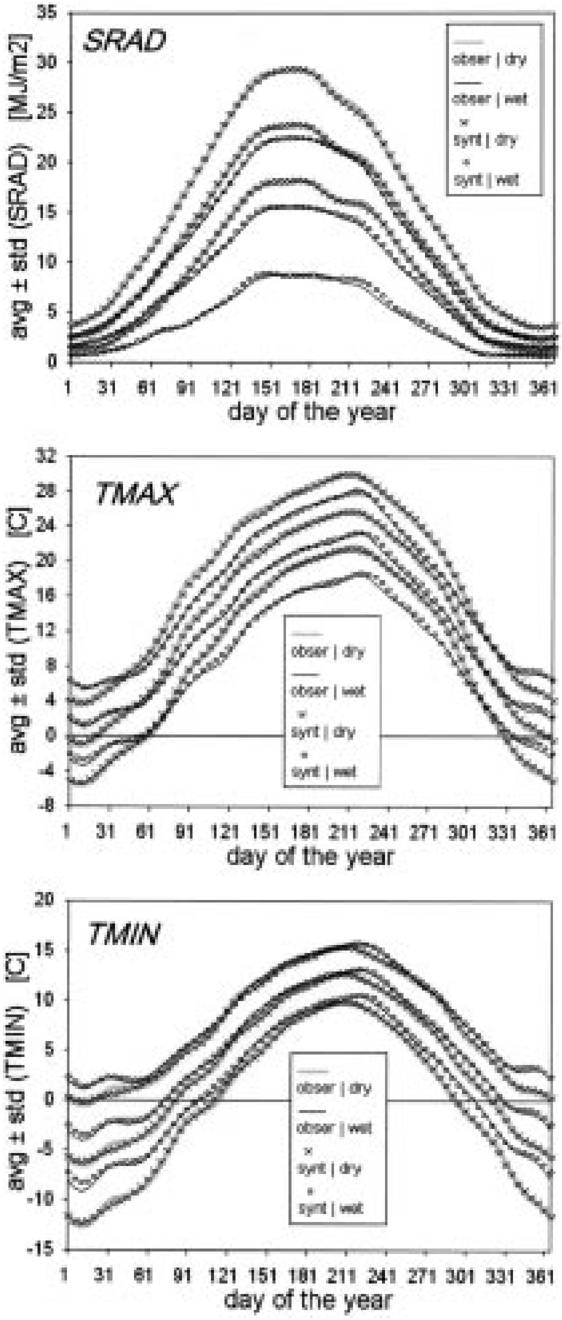

Figure 3. Annual cycle of variability (average, and average ± standard deviation) of SRAD, TMAX and TMIN. The curves were smoothed by robust locally weighted regression. Heavy and thin lines represent characteristics derived from dry and wet days of the observed series (Hradec Králové, 1961–1990). Crosses and circles represent the same characteristics but derived from the synthetic series generated by Met&Roll.

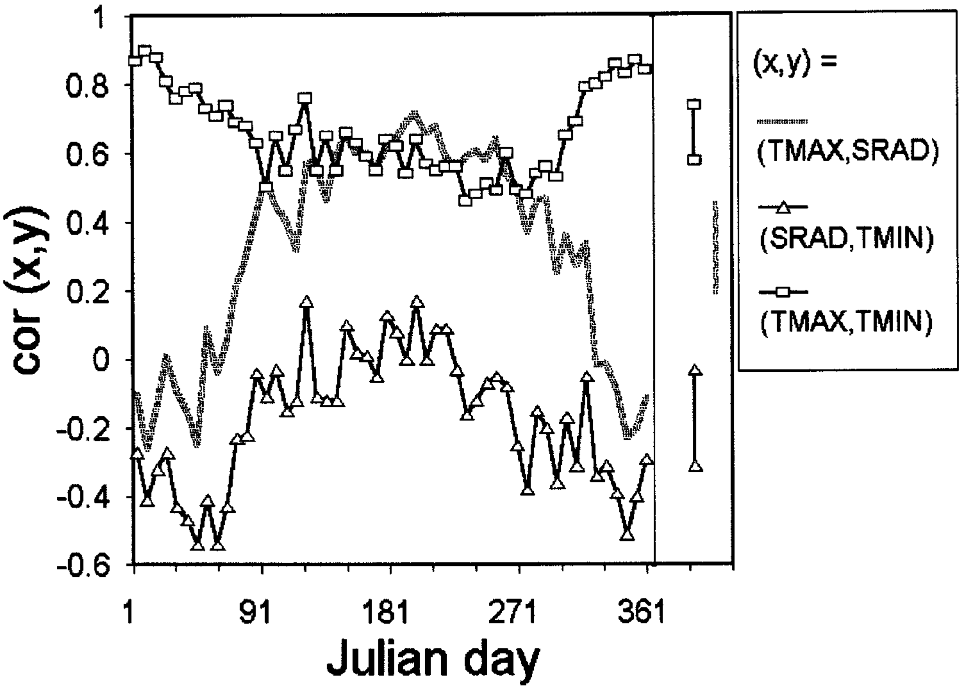

Figure 4. Annual cycle of lag-0 correlations among SRAD, TMAX and TMIN. The sample correlation coefficients for individual weeks were calculated from the 30-year observed series. The vertical bars at the right part of the graph indicate the 95% confidence intervals of the all-year correlations used as parameters of the weather generator's model.

- management factors (tillage, irrigation, fertilisation),
- series of daily weather characteristics (sum of global solar radiation, maximum and minimum air temperatures and precipitation amount).

In this study, the model input data were based on the field experiments made in Žabčice (in the southeast of the Czech Republic [49°01′ N, 16°37′ E], 179 m above sea level; more detailed climatic characteristics are given in Table III). The cultivar is DEA (FAO 300, origin PIONEER 3839, licensed from 1982) and the soil type is Oxyaquic Cryofluvents according to the classification of the U.S. Department of Agriculture (Soil Survey Staff, 1975). Planting details, management factors and fertilisation regime were set to be the same for all stations, climate scenarios and simulation years. No irrigation was applied. Two types of weather data were used:

(i) In experiments referred in Sec. 4: Observed and synthetic series related to 17 locations (including Žabčice) in the Czech Republic were used. The synthetic series were generated by Met&Roll with use of the present-climate parameters derived from the observed series. The selected climatic characteristics (derived from the observed series) of individual stations are given in Table II.

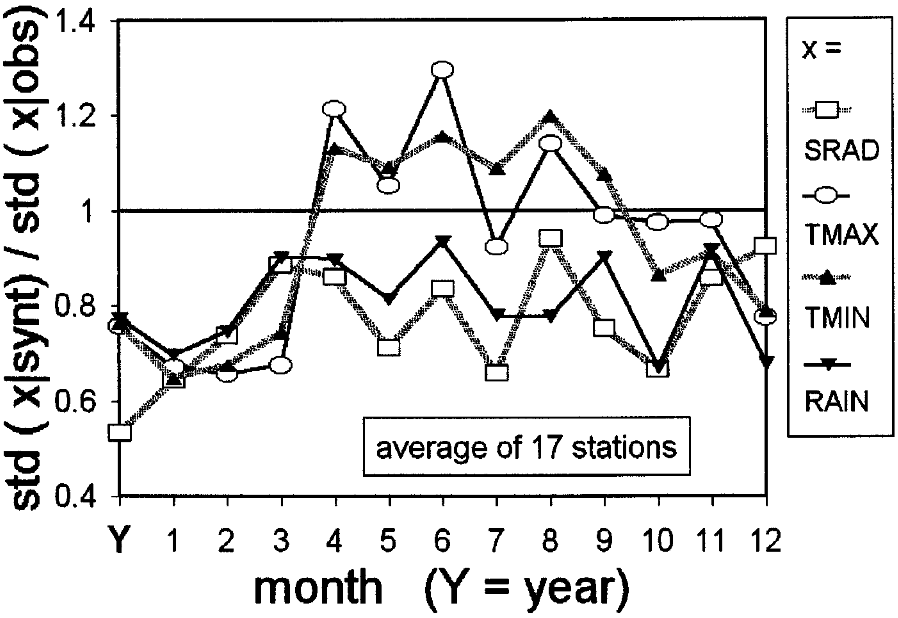

Figure 5. Reproduction of the variability of monthly and annual means by Met&Roll. The figure displays the ratios of synthetic to observed sample standard deviations of monthly and annual means of SRAD, TMAX, TMIN and RAIN. These ratios were averaged over 17 stations.

(ii) In experiments referred in Sec. 5: Single-station synthetic series for present climate and changed climate conditions were used. The series were generated by Met&Roll with use of the parameters derived from the Žabčice observed data and modified in accordance with individual scenarios.

4. Sufficiency of the Weather Generator for Crop Growth Simulations

One might ask: What is the effect of the generator imperfections (discussed in Section 2.2) on crop yields simulated by the growth model? To give the answer, the model grain yields simulated with use of observed weather data were compared with yields simulated with synthetic weather data. The synthetic series of daily weather characteristics were generated by Met&Roll. Parameters of the weather generator were derived from the 30-year series of observed daily weather characteristics. To increase a sample size for model yield validation and to expand the spectrum of climatic conditions for which the applicability of the weather generator is approved, the simulations were made for 17 sites in the Czech Republic (Table II), for which the relevant climatic observations were available. Since the primary goal of these experiments was to validate applicability of the weather generator in crop growth simulations and since the non-meteorological data (including cultivar and soil characteristics) required for the simulations were available

TABLE III

Climatic characteristics of Žabčice. AVG and STD are means and standard deviations calculated from DRY and WET days, respectively; α and β are parameters of the Gamma distribution; π_1 and π_{01} are parameters of the Markov chain model; TAMP is daily temperature amplitude ($\equiv$ TMAX – TMIN)

Month	SRAD				RAIN			
	DRY		WET		α	$\alpha \cdot \beta$	π_1	π_{01}
	AVG	STD	AVG	STD				
January	2.8	1.2	2.5	1.1	1.00	2.80	0.29	0.25
April	15.0	4.6	11.7	4.4	0.89	3.63	0.31	0.23
July	21.4	4.8	16.9	5.2	0.86	5.25	0.35	0.28
October	7.1	2.8	5.3	2.5	0.76	4.06	0.25	0.17
Year	11.4	8.0	9.6	6.9	0.85	4.20	0.31	0.24

Month	TMAX				TMIN				AVG(TAMP)	
	DRY		WET		DRY		WET		DRY	WET
	AVG	STD	AVG	STD	AVG	STD	AVG	STD		
January	0.8	4.7	1.9	4.6	–5.9	6.0	–4.2	5.2	6.6	6.1
April	16.0	5.0	13.3	4.5	3.7	3.7	3.9	3.2	12.3	9.4
July	26.2	4.1	23.3	4.2	12.2	3.4	12.7	3.1	14.0	10.6
October	15.3	4.4	14.0	3.7	4.0	4.5	5.4	3.6	11.4	8.5
Year	14.3	10.1	13.8	8.8	3.6	7.6	5.3	6.9	10.7	8.5

only for one site (Žabčice), the input data sets for individual site-specific simulations differed only in weather data. For each site, a 30-year synthetic series was generated and the multi-year crop growth experiment was run. Selected statistical characteristics calculated from the sets of 30 values (one value per year) of grain yield are graphically displayed in Figure 6.

The figure shows that the characteristics obtained using synthetic weather data are very similar to those obtained using observed data. This rather subjective judgement is supported by the results of the Wilcoxon test (Figure 7). The values of the test statistic indicate that the differences between the distributions of the grain yields simulated with the two types of weather series are not statistically significant. It is therefore concluded that the imperfections of the generator in reproducing the statistical structure of daily weather series have only a negligible effect on the summary crop growth characteristics simulated by the CERES-Maize model.

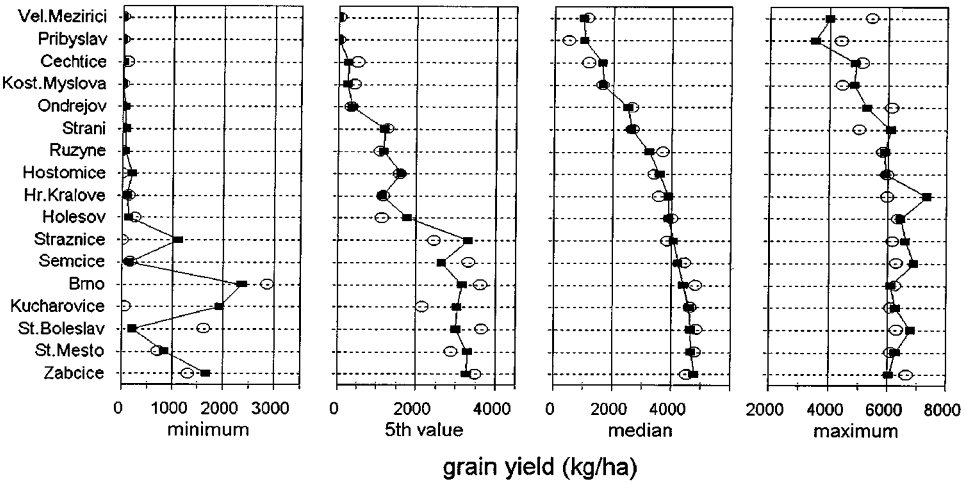

Figure 6. Extreme values, medians and the 5th values from the set (sorted in ascending order) of grain yields obtained in the 30-year CERES-Maize simulations with use of observed (lines + rectangles) and synthetic (circles) weather series. The synthetic series were generated by Met&Roll.

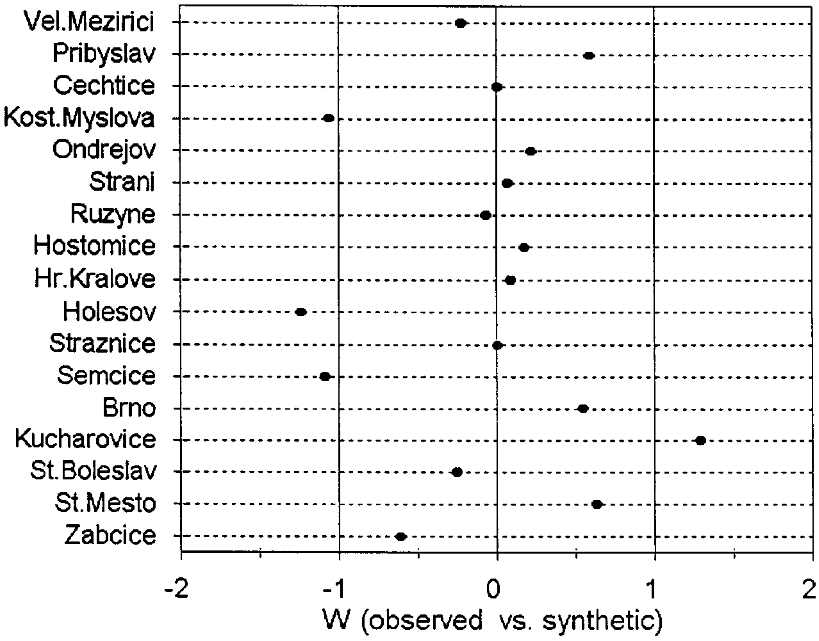

Figure 7. Standardised values of the Wilcoxon statistics for testing the hypothesis that the distribution of grain yields simulated with the observed weather series is the same as the distribution obtained using the synthetic weather series. The synthetic series were generated by Met&Roll.

5. Sensitivity of Model Yields to Statistical Structure of Daily Weather Series

As earlier introduced, ambiguities exist in projecting the climate change scenarios into the set of weather generator's parameters. The crucial question stands: what is the sensitivity of the crop growth to various projections allowed by these ambiguities. To suggest an answer, several scenarios of changes in statistical structure of weather series (see Table IV for the list of the scenarios) are assumed in the following sensitivity analysis. The scenarios represent (i) changes of monthly averages/totals assumed by typical GCM-based climate change scenarios, e.g., changes of the mean temperature (scenarios of type A) or precipitation amount (scenarios E, F and G), and (ii) changes which have no effect on the means but may modify frequency of undesirable extreme weather conditions. The scenarios of the latter type include the following: changes in the daily temperature amplitude (scenario B), changes in the standard deviations of daily weather characteristics (scenario C), decrease/increase in the daily precipitation amounts with simultaneous increase/decrease in the number of wet days (scenarios I and J), changes in the shape of distribution of daily precipitation amounts (scenario H), and changes in the persistence of the series (scenarios D and K).

All characteristics which may take only positive values (probabilities of precipitation occurrence, π_1 and π_{01}; mean daily precipitation amount, $\alpha\beta$; daily sum of global solar radiation, SRAD; standard deviations of SRAD, TMAX and TMIN) were modified with the use of a multiplicative operator. Monthly means of TMAX and TMIN were modified additively. In changing parameters of the precipitation model, the following considerations were incorporated:

(a) If the probability of wet day occurrence, π_1, is changed (scenarios F, G, I and J), some statistical characteristics of solar radiation and extreme temperatures series, which are modelled conditionally on precipitation occurrence, are also changed (Katz, 1996). Specifically, the unconditional mean of X ($\mathrm{X} \in \{\mathrm{SRAD}, \mathrm{TMAX}, \mathrm{TMIN}\}$), which is calculated from both dry and wet days, changes as follows:

$$\Delta\mathrm{X} \equiv m(\mathrm{X})' - m(\mathrm{X}) = (\pi_1' - \pi_1) \cdot [m(\mathrm{X} \mid \mathrm{wet}) - m(\mathrm{X} \mid \mathrm{dry})]\,, \tag{6}$$

where the prime indicates the modified parameters. Consequently, if we change π_1 and require that the unconditional mean of X remains the same, the dry and wet means of X, $m(\mathrm{X} \mid \mathrm{dry})$ and $m(\mathrm{X} \mid \mathrm{wet})$, must be changed adequately. This may be achieved by simultaneous modification of the two conditional means of X according to the formula:

$$m(\mathrm{X} \mid \bullet)' = m(\mathrm{X} \mid \bullet) - \Delta\mathrm{X}\,, \tag{7}$$

where $\Delta\mathrm{X}$ is defined in Equation (6) and $\bullet$ stands for 'wet' and 'dry', respectively. This correction is applied in the cases of scenarios G and J.

(b) The first-order Markov chain model is defined by two parameters; π_1 and π_{01} are used in Met&Roll. The other three transition probabilities can be expressed

TABLE IV

The list of scenarios used to modify paameters of the weather generator (the acronyms of the scenarios refer to Figure 8; k stands for a variable parameter)

Scenario		Explanation
(***A***)	$\mathrm{T} + k$	the means of TMAX and TMIN are additively modified by $k \in \{-2, -1, +1, +2, +4\,^{\circ}\mathrm{C}\}$[a,b], (temperature means are changed, daily temperature amplitudes are preserved)
(***B***)	$\mathrm{T}_{\mathrm{max}} + k$; $\mathrm{T}_{\mathrm{min}} - k$	k is added to $m(\mathrm{TMAX} \mid \bullet)$ and subtracted from $m(\mathrm{TMIN} \mid \bullet)$, where $\bullet$ stands for ‘wet’ or ‘dry’ [a]; $k \in \{-2, -1, 1, 2\}$; (daily temperature amplitudes are changed, daily temperature means are preserved)
(***C***)	$s(\mathrm{X}) \times k$	standard deviations of TMAX, TMIN and SRAD are multiplied by $k \in \{0.1, 0.5, 0.75, 1.25, 1.5\}$[a]; the means are preserved
(***D***)		lag-1 correlations among SRAD, TMAX and TMIN are set to:
	no persist	– zero
	high persist	– about 90% of the lag-0 correlations
(***E***)	Gsc × k	the scale parameter of Gamma distribution, β, is multiplied by $k \in \{0.5, 0.75, 1.25, 1.5\}$; mean daily precipitation amount is multiplied by k, number of wet days is preserved)
(***F***)	(P1,P01) × k	parameters of the Markov chain model, π_1 and π_{01}, are multiplied by $k \in \{0.5, 0.75, 1.25, 1.5\}$; (monthly sums of precipitation are multiplied by k; mean daily precipitation amount on a wet day is preserved)
(***G***)	(P1,P01) × k	the same as scenario ***F*** but the means of daily extreme temperatures and solar radiation are additively modified according to Equation (7)[a,b] to preserve the monthly means [see note (a) in Section 5]
(***H***)	Gsh × k	parameters of the Gamma distribution are modified: shape parameter α is multiplied by k, scale parameter β is divided by k; $k \in \{16, 4, 0.25, 0.06\}$; (mean daily precipitation sums are preserved)
(***I***)	Gsc × k; P × $1/k$	scale parameter β of the Gamma distribution is multiplied by k, parameters π_1 and π_{01} of the Markov chain are multiplied by $1/k$; $k \in \{0.67, 1.5\}$; (mean daily precipitation amount on a wet day and frequency of wet days are changed; monthly sums of precipitation are preserved)
(***J***)	Gsc × k; P × $1/k$	the same as scenario ***I*** but the means of daily extreme temperatures and solar radiation are additively modified according to Equation (7)[a,b] to preserve the monthly means [see note (a) in Section 5]
(***K***)		persistence of the wet day occurrence is modified:
	P01 × k	– π_{01} is multiplied by $k \in \{0.1, 0.25, 0.5\}$
	P01 = P11 = P1	– π_{01} is set to π_1 (lag-1 correlation of wet day occurrence, Equation (9), is zeroed)
	P11 = 0	– maximum persistence is set up

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[a] the characteristics related to dry and wet days are modified in a same manner.

[b] TMIN and TMAX are modified in a same manner.

as: $\pi_{11} = 1 - \pi_{01}(1/\pi_1 - 1)$, $\pi_{00} = 1 - \pi_{01}$, $\pi_{10} = 1 - \pi_{11}$. Since precipitation occurrence on two successive days is positively correlated, it holds that $\pi_{01} < \pi_1 < \pi_{11}$. If the scenario prescribes a change in π_1 (scenarios F, G, I and J), one might also consider a modification of π_{01} to assure that

$$\pi'_{01} < \pi'_1 < \pi'_{11} < 1\,. \tag{8}$$

A possible criterion for consistent modification of Markov chain parameters may be based on a conservation of the lag-1 correlation of precipitation occurrence, which reads:

$$\mathrm{cor}(\mathrm{X}_t, \mathrm{X}_{t-1}) = \frac{\pi_{11} - \pi_1}{1 - \pi_1} = \frac{\pi_{00} - \pi_0}{1 - \pi_0} = 1 - \frac{\pi_{01}}{\pi_1}\,. \tag{9}$$

Apparently, the lag-1 correlation, as well as the condition expressed in Equation (8) are both preserved if both π_1 and π_{01} are changed by the same multiplier, the value of which is positive and less than $1/\pi_1$.

(c) If the monthly precipitation sums are to be changed by modifying the distribution of daily totals (scenario E), the simplest way to achieve this is to modify only the scale parameter of the Gamma distribution. Since the mean of the Gamma distributed variable is $\mathrm{E}(\mathrm{X} \mid \alpha, \beta) = \alpha\beta$, multiplication of the scale parameter by k (a new value reads $\beta' = k\beta$) implies a multiplicative change of the mean daily totals by k.

(d) If the shape of the Gamma distribution is to be modified but the mean daily totals are to be preserved (scenario H), we apply $\alpha' = k\alpha$ and $\beta' = \beta/k$.

For each scenario, the parameters of Met&Roll were adequately modified and the 99-year synthetic series was generated. The synthetic series was then used as an input to the CERES-Maize multi-year simulation. The parameters of crop model simulations from Section 4 were preserved, and only the daily weather series was varied. The characteristics of distributions of grain yields obtained in the 99-year simulations are graphically displayed in Figure 8. The horizontal bars represent variability of the grain yields (5th, 25th, 50th, 75th and 95th values are marked from the set of 99 values sorted in ascending order) for the individual scenarios. The numbers appearing to the right of each bar are values of the standardised Wilcoxon statistic, W, which was employed to test the hypothesis that the distribution of the grain yields for a given scenario does not differ from the reference distribution. The reference distribution relates to the ‘no change’ scenario, for which the synthetic series was generated with use of the unmodified set of weather generator parameters. Because the test statistic W approximately follows a normal distribution, N(0,1), the null hypothesis (‘no effect’ hypothesis) is rejected at the 5% (or 1%) significance level if $|\mathrm{W}| > 1.96$ (or 2.58).

Scenario A: Modification of the Mean Temperature

The results suggest that the present-climate daily mean temperatures should increase by about 1 °C to maximise grain yields. Further increase of the temperature

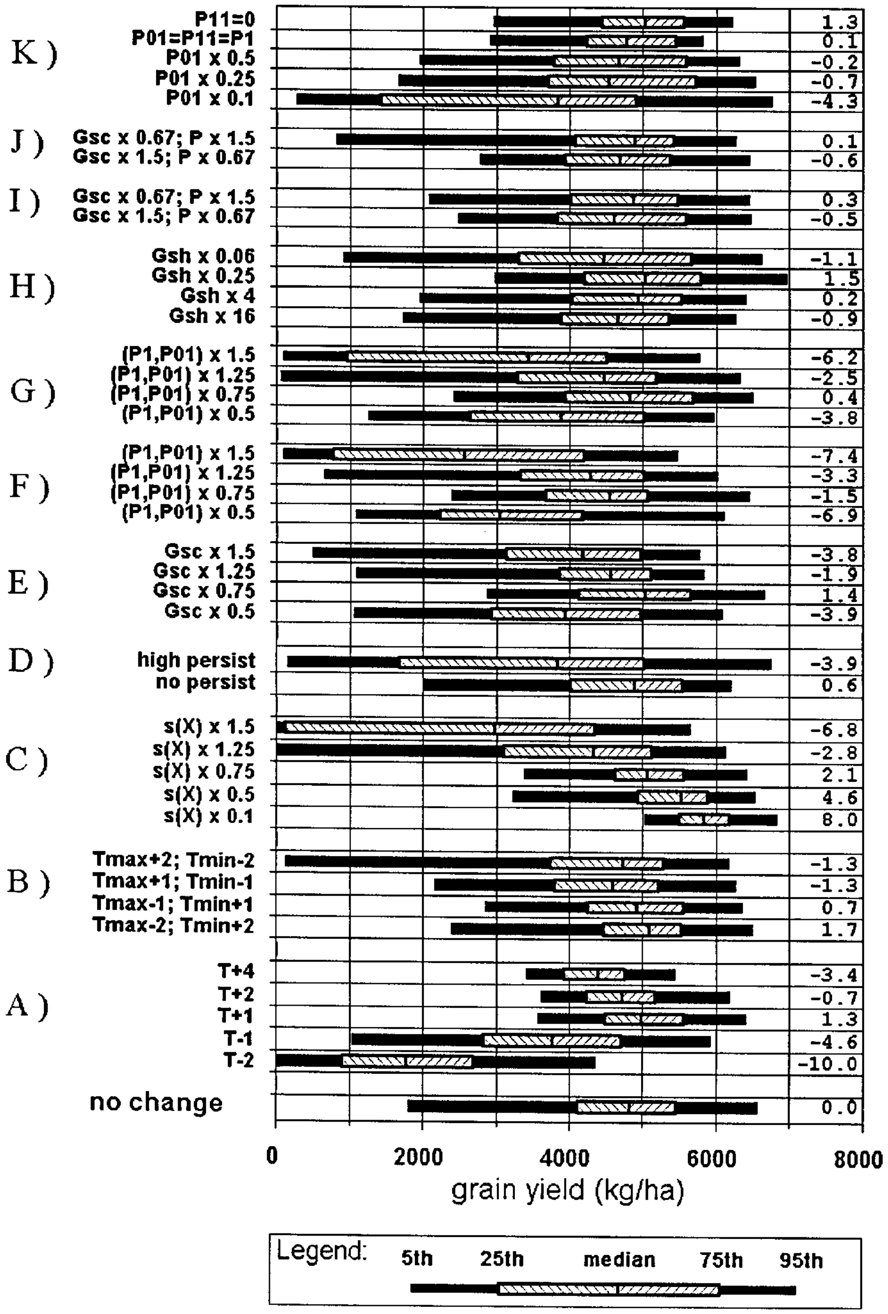

Figure 8. Quantiles of the sets of grain yields obtained in the 99-year crop growth simulation for various climate change scenarios (see Table IV for the list). The numbers to the right of each bar are values of the standardised Wilcoxon statistic for testing the hypothesis that the distribution of grain yields under a given scenario does not differ from the reference distribution related to present-climate conditions (‘no change’ scenario).

would, however, reduce grain yields due to shortening of a growing season (its average length is 154, 157, 154, 144, 130 and 113 days for T – 2, T – 1, no change, T + 1, T + 2 and T + 4 scenarios). Simultaneously with increasing temperature, variability of growing season length and variability of grain yields decreases. Water stress, which could decrease crop yields at higher temperature conditions, was not revealed in the model output.

Scenario B: Modification of the Daily Temperature Amplitude
Although the changes of grain yields are not statistically significant for the scenarios displayed, the yields tend to decrease with increasing daily temperature amplitude. Note the significant decrease of the 5% quantile of grain yields related to a 2 °C decrease of TMIN. This decrease is explained by an increasing probability of occurrence of temperatures below the minimum growth temperature at the beginning of the vegetation period. The minimum growth temperature takes value of 8–10 °C for maize.

Scenario C: Variability of Temperature and Solar Radiation Is Changed
Increased temperature and solar radiation variability results in lower mean and higher variance in grain yields. As with scenario B, we assume that this effect is mainly due to the increased frequency of occurrence of too low temperatures at the beginning of the vegetation period. This finding is in agreement with Mearns et al. (1996, 1997) and Riha et al. (1996) who studied the impact of temperature and precipitation variability on crop yields.

Scenario D: Modification of the Persistence of the Autoregressive Model
The correlation and autocorrelation matrices were modified so that the lag-1 correlations were set either to zero (scenario ‘no persist’) or to the values close to the lag-0 correlations (scenario ‘high persist’). While the grain yields in the ‘no persist’ scenario are not statistically significantly different from the present climate situation, there is a significant decrease in grain yields under the ‘high persist’ scenario, due to the occurrence of long hot and long cold spells.

Scenario E: Modification of the Mean Daily Precipitation Amount
The CERES-Maize simulations indicate that the precipitation sums should decrease by some amount (by less than 25%) to maximise grain yields under present-climate temperature conditions. Similar results were obtained for scenarios F and G. A reduction in yields related to increased precipitation sums is contrary to initial expectations: Because present-climate precipitation sums are generally considered deficient in the region studied, it was expected that an increase in precipitation would stimulate maize yields. Instead, however, it was found that increased precipitation sums induced more intensive nitrogen leeching, leading to a decrease in yields due to nitrogen stress.

Scenarios F and G: Modification of Probability of Wet Day Occurrence

As in the previous case, the results suggest that the present-climate frequency of wet day occurrence should be slightly decreased to maximise grain yields. Interestingly, the decreases in grain yields related to individual changes of precipitation sums are mostly larger than the yield decreases induced by corresponding changes in daily precipitation amounts (scenario E). In order to preserve unconditional means of daily temperature extremes and solar radiation, corrections defined by Equation (7) were applied in scenario G. For example, if the probability of wet day occurrence is increased/decreased by 25%, the conditional means (i.e., means for wet and dry days, respectively) of temperature extremes are increased/decreased by +0.1 °C and the means of solar radiation are increased/decreased by 2%. Figure 8 shows that the corrections have an effect: regardless of an increase or decrease in the precipitation totals, the grain yields are always higher compared to the simulations with no corrections applied. The following reasons are suggested to explain this effect: (a) an increase in the number of wet days reduces the mean temperature and solar radiation (in the case of no corrections being made), which could contribute to the water surplus in the models, and (b) a decrease in the number of wet days increases the mean temperature and solar radiation (in the case of no corrections being made), which may deepen the drought stress.

Scenario H: Distribution of the Daily Precipitation Amount is Modified (Long-Term Precipitation Totals Are Preserved)

The observed values of the shape parameter of the Gamma distribution, α, vary between 0.75 and 1.11 for Žabčice (see Table III for the values in selected months). In this scenario, the values of α were multiplied by factor k, which ranged from 0.06 (implying a highly asymmetrical distribution) to 16 (nearly normal distribution is obtained). The shape of the Gamma distribution for selected values of α is displayed in Figure 9. The two lowest values of α (0.05 and 0.2) produce a rather distorted distribution of generated daily precipitation amounts, since a non-negligible probability exists that the below-threshold precipitation amount (0.1 mm) is generated for a day with precipitation occurrence. To preserve the number of the wet days, the value of 0.1 mm is assigned to such days. This deforms the distribution of daily precipitation amounts in the near-zero area and slightly (but not significantly) increases precipitation totals. The results displayed in Figure 8 show that the shape of the distribution of daily precipitation amount does not affect the model grain yields significantly.

Scenarios I and J: Simultaneous Change of Number of Wet Days and Mean Daily Precipitation Amount (Long-Term Precipitation Totals Are Preserved)

Although the results displayed in Figure 8 suggest that the grain yields tend to be higher if the given monthly precipitation total is supplied in smaller daily amounts distributed over more days, the values of the Wilcoxon test do not indicate that this effect is statistically significant.

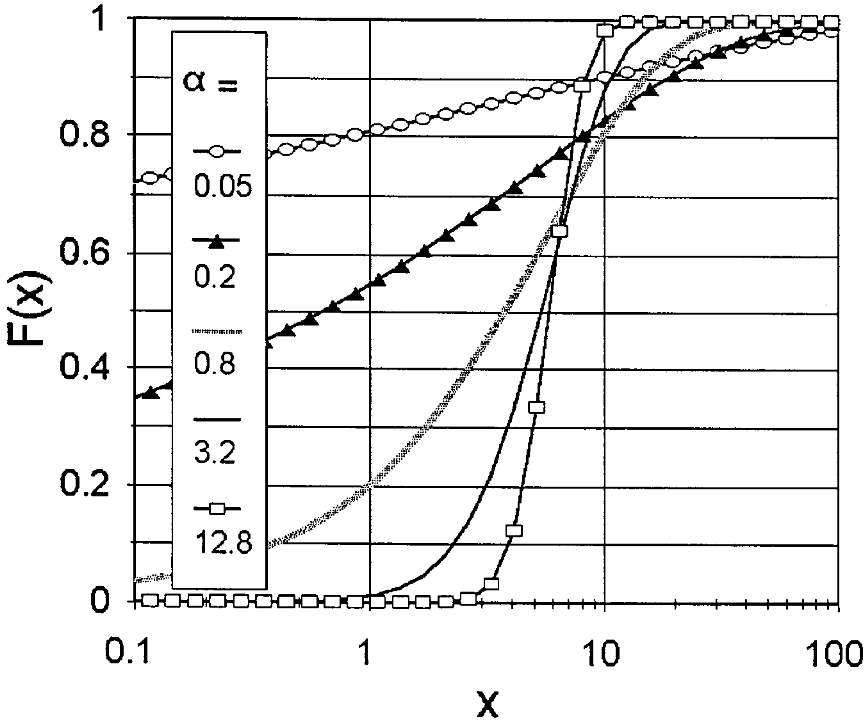

Figure 9. Cumulative probability function of the Gamma distribution, $\Gamma(\alpha, \beta)$ [frequency function is defined by Equation (3)]. The values of α are given in the legend box, and $\beta = 6/\alpha$, which implies that $E(x) = 6$ for each case.

Scenario K: Modification of the Persistence of Wet Day Occurrence

Under this scenario, the unconditional probability of wet day occurrence, π_1, is preserved and the transition probabilities of the Markov chain model are changed. In this situation, the mean monthly precipitation totals remain unchanged but the persistence of wet day occurrence varies. Figure 10 shows three pairs of sample distribution functions (derived from the 99-year synthetic series) of length of wet and dry periods considered in scenarios of type K:

(i) the present climate situation,

(ii) the climate with high persistence of wet day occurrence (values of π_{01} are multiplied by 0.1, which implies a significant increase in the length of wet and dry periods),

(iii) the climate with high interdiurnal variability of wet day occurrence [π_{11} is set to zero, which implies that wet periods are never longer than 1 day. Dry periods may, however, last longer because the number of dry days is higher than the number of wet days. This is indicated by values of parameter π_1, which are lower than 0.5 in all months of the year (see Table III for selected months)].

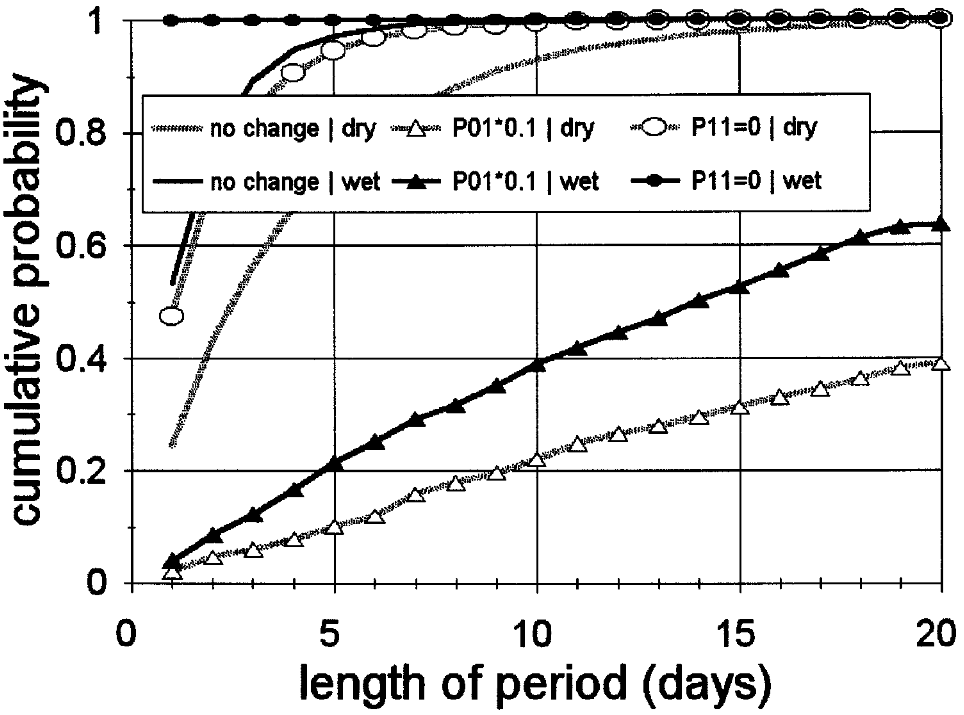

Figure 10. Distribution of the length of dry and wet periods for 3 versions of the Markov chain model. Lines with no symbols: present climate conditions ('no change' scenario); triangles: as previous but the values of π_{01} are multiplied by 0.1 (implies higher persistence of wet day occurrence); circles: π_{11} is set to 0 (this forces π_{01} and π_{10} to increase to their maximum values). The frequency functions were derived from 99-year synthetic series generated by Met&Roll.

Increasing persistence of wet day occurrence results in an increasing probability of drought stress occurrence, which is accompanied by decreased mean and increased variance of the grain yields (Figure 8). This result is analogous to the outcomes achieved through modifying persistence in the autoregressive model (scenario D).

6. Conclusions

The present paper aimed to (i) verify applicability of the stochastic weather generator Met&Roll for crop growth modelling, and (ii) study the sensitivity of simulated grain yields to variations in selected characteristics of the statistical structure of daily weather series.

Met&Roll is a weather generator based on the Richardson's (1981) model WGEN. It was designed to stochastically generate a series of 4 daily weather characteristics (precipitation amount, sum of global solar radiation and minimum and maximum temperatures) which are inputs to the crop growth model CERES-Maize.

The tests performed here were intended to examine the generator's ability to reproduce the statistical structure of daily weather series. It was found that the model of the generator better fits the observed series during summer months. Discrepancies between observed and generated data were revealed in the shape of the distributions of radiation sum and precipitation amount, in length of dry spells and in variability of monthly averages of the four daily weather characteristics. Furthermore, the correlations and lag-1-correlations among radiation and extreme temperatures exhibit a significant annual cycle, which is not assumed by the autoregressive model. More details on validation of Met&Roll as well as discussion on possible improvements of the generator's model can be found in Dubrovský (1996b, 1997). Although some modifications to the model have already been implemented in the latest version of Met&Roll, the experiments referred to in Sections 4 and 5 were aimed to examine the applicability of the present version of the generator to crop growth simulation.

In Section 4, the grain yields simulated by the CERES-Maize model with the use of observed weather series and synthetic weather series, generated by Met&Roll, were compared. The quantile characteristics displayed in Figure 6 and the results of the Wilcoxon test (Figure 7) indicate that the variability of the grain yields is about the same for both the observed and synthetic weather series. It is inferred from this that the imperfections in the statistical structure of the synthetic weather series do not significantly affect the model grain yields.

In Section 5, the sensitivity of the model grain yields to various characteristics of the statistical structure of the daily weather series was studied. The scenarios (Table IV) included in the sensitivity analysis represent (i) changes of monthly means or totals, and (ii) changes affecting the weather variability and frequency of occurrence of undesirable extreme weather conditions. The scenarios of the latter type are given greater attention for two reasons. First, these scenarios represent changes of those parameters of the weather generator which are not explicitly treated by the typical GCM-based climate change scenarios. The magnitude of the possible changes of these parameters may thus become a subject of speculation. Second, some of the characteristics addressed by these scenarios are not satisfactorily modelled by the generator and the results of the sensitivity analysis help to identify possible errors due to the imperfections of the generator's model. It is seen in Figure 8 that some characteristics of the daily weather series have a pronounced effect on grain yields. In some cases (e.g., scenario K which modifies persistence of precipitation occurrence), the change of the characteristic would have to be too great in order to produce a statistically significant effect on grain yields. In other cases, e.g., in scenario H, in which the shape of the distribution of daily precipitation amount is modified, the effect on grain yields is not statistically significant. Overall, it can be concluded that the obtained results support the findings of other recent studies addressing the impact of weather variability on crop yields.

In conclusion, two important circumstances should be mentioned. First, the results obtained are closely related to given set of input parameters used in the crop model simulations. In other words, the findings concerning the applicability of the weather generator and the sensitivity of model yields to variations in statistical structure of the daily weather series are not generally transferable to other cultivars, climates or growing conditions. Second, regarding the main aims of the present study, some settings in the CERES-Maize multi-year experiments were somewhat simplified. As a result, the model yields simulated for present climate conditions do not necessarily fit the observed yields. This deficiency will be avoided in forthcoming experiments already underway. In these experiments, the observed yields will be compared with simulated ones, and the most recent GCM-based climate change scenarios will be employed to estimate impacts on the yields.

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