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Comparison of LARS-WG and AAFC-WG stochastic weather generators for diverse Canadian climates

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ABSTRACT: Two weather generators — LARS-WG, developed at Long Ashton Research Station (UK), and AAFC-WG, developed at Agriculture and Agri-Food Canada — were compared in order to gauge their capabilities of reproducing probability distributions, means and variances of observed daily precipitation, maximum temperature and minimum temperature for diverse Canadian climates. Climatic conditions, such as wet and dry spells, interannual variability and agroclimatic indices, were also used to assess the performance of the 2 weather generators. AAFC-WG performed better in simulating temperature-related statistics, while it did almost as well as LARS-WG for statistics associated with daily precipitation. Using empirical distributions in AAFC-WG for daily maximum and minimum temperatures helped to improve the temperature statistics, especially in cases where local temperatures did not follow normal distributions. However, both weather generators had overdispersion problems, i.e. they underestimated interannual variability, especially for temperatures. Overall, AAFC-WG performed better.

KEY WORDS: Weather generators · Climate scenarios · Impact studies · Agriculture · Canada

1. INTRODUCTION

Stochastic weather generators are statistical models that mostly generate synthetic daily weather series, usually precipitation, maximum and minimum temperatures, and solar radiation (Richardson 1981, Richardson & Wright 1984, Semenov et al. 1998, Hayhoe 2000). Other weather series, such as wind speed and dewpoint, can also be modelled (Parlange & Katz 2000). Weather generators, sometimes, are also applied on an hourly time step. For example, Katz & Parlange (1995) described the generation of hourly precipitation. Precipitation is always the most important component in a weather generator, because it deals with the occurrence of a wet day and the amount of precipitation on a wet day. Other weather variables are usually conditional on the occurrence of a wet day or a dry day. Therefore, some weather generators only generate synthetic daily precipitation sequences (e.g. Bardossy & Plate 1992, Corte-Real et al. 1999b). Most weather generators are designed for simulating weather series at a single site, but multisite weather generators are also under development (Wilks 1998, 1999, Qian et al. 2002), because it is important to maintain spatial correlations in synthetic weather series in applications such as hydrology.

Generated synthetic weather series can be input to hydrological and agricultural models such as Erosion-Productivity Impact Calculator (EPIC; Williams 1995) and The Decision Support System for AgroTechnology (DSSAT; Jones et al. 2003) to make long-term risk assessment, because the observed historical weather series are often too short to allow for a good estimation of the probability of extreme weather events. The probability distributions of synthetic weather series are very important in such applications, because the extreme values often determine the interpretation of the model's output. It is therefore essential to evaluate whether or not the synthetic weather series follow the same probability distribution as the observed series. Weather generators can also be used to extend the simulation of

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weather series to locations where no observed weather data are available, by interpolating weather generator parameters obtained from nearby stations to the required locations (Carter et al. 1995, Hutchinson 1995, Semenov & Brooks 1999). In recent years stochastic weather generators have received attention for their application in climate-change studies, where they are used as a statistical downscaling technique for developing daily climate scenarios (Wilks 1992, Semenov & Barrow 1997). The use of weather generators in downscaling and climate scenario development is also covered in short reviews in the Intergovernmental Panel on Climate Change (IPCC) Third Assessment Report (Giorgi et al. 2001, Mearns et al. 2001).

Stochastic weather generators can be conditional based on large-scale atmospheric circulation. For example, input parameters are conditional on daily circulation patterns or weather types (Wilson et al. 1991, Bogardi et al. 1993, Schubert 1994, Goodess & Palutikof 1998, Corte-Real et al. 1999b, Qian et al. 2002) and the modes of atmospheric variability such as the North Atlantic Oscillation and El Niño/Southern Oscillation (Mearns et al. 2001, Katz et al. 2003). Conditional weather generators can be used in developing climate scenarios from GCM (general circulation model or global climate model)-simulated large-scale atmospheric circulation, which is more reliable than GCM predictions of surface climate variables on a regional scale (Corte-Real et al. 1999a, Giorgi et al. 2001). However, this relies on the assumption that the observed relationships between large-scale atmospheric circulation and a weather variable remain valid in a changing/changed climate. Moreover, this assumption is not guaranteed, although a case study from a GCM simulation gave positive prospects (Corte-Real et al. 1999a). Stochastic weather generators, which are unconditional on large-scale atmospheric circulation, can also be applied to generate future climate scenarios by adjusting weather-generator parameters for a changing/changed climate (Wilks 1992, Semenov & Barrow 1997). For instance, statistics of weather variables for the current climate and the future climate from GCM outputs can be used to construct climate-change scenarios, which can then be applied to perturb weather-generator parameters.

Weather generators can be grouped according to their structure into 2 categories: the Richardson-type (Richardson 1981)—such as WGEN (Richardson & Wright 1984), WXGEN (Williams 1995) and CLIGEN (Zhang & Garbrecht 2003)—and the series weather generator—such as LARS-WG (Racsko et al. 1991, Semenov & Barrow 1997). The Richardson-type weather generators use a Markov chain (first-order, second-order or hybrid) to simulate the occurrence of wet days and a skewed probability distribution (such as a skewed normal distribution, gamma distribution or mixed exponential distribution) to generate precipitation amount on a wet day. Then, they apply a first-order multivariate autoregressive model to simulate other weather variables, such as temperature and radiation, conditioned on the precipitation status (wet or dry). Weather generators that use the serial approach differ from the Richardson-type mainly in how they simulate the occurrence of wet days. Empirical distributions of wet and dry spells are used instead of a Markov chain. The empirical distribution $Emp = \{a_0, a_i; h_i, i = 1,\ldots,10\}$ used in LARS-WG is a histogram with 10 intervals, $[a_{i-1}, a_i)$, where $a_{i-1} < a_i$ and h_i denotes the number of events from the observed data in the ith interval. Random variables from empirical distributions are chosen by first selecting one of the intervals (using the proportion of events in each interval as the selection probability), and then selecting a value within that interval from the uniform distribution. The simulation of other variables is also somewhat different. The different probability distributions used in weather generators become important in a highly diverse climate where the same weather variable may follow a different probability distribution.

LARS-WG, a series weather generator developed at the Long Ashton Research Station (UK), uses empirical distributions of wet and dry spells, precipitation amounts and solar radiation. The use of empirical distributions makes it more flexible for application in diverse climates around the world. Semenov et al. (1998) compared LARS-WG and WGEN, a version of the Richardson-type weather generator, and found that LARS-WG tended to match the observed data more closely than WGEN, although there were certain characteristics (such as interannual variability) of the data that neither generator reproduced accurately. A weather generator developed at Agriculture and Agri-Food Canada (AAFC) was designed to keep the Richardson-type structure because of its advantage of maintaining the relationships between weather variables, while introducing the flexibility of empirical distributions for the diverse Canadian climates (Hayhoe 2000). This weather generator will be named AAFC-WG hereafter.

The objectives of this paper are to compare the most critical features of LARS-WG and AAFC-WG that relate to their ability to reproduce observed statistical properties including probability distributions and agroclimatic characteristics of observed weather series across Canada.

2. AAFC-WG COMPARISON WITH LARS-WG

The Richardson-type weather generators are widely used in research, and some software packages, such as

WGEN, WXGEN and CLIGEN, are available to the public. Hayhoe & Stewart (1996) and Hayhoe (1998) found that synthetic weather data from WGEN and WXGEN poorly represent some important statistics of observed weather series, such as regional and seasonal differences in the relationship between weather variables, for Canadian climates. This was not surprising because the software packages were designed and calibrated for climates in the US, and important parameters, such as correlation matrices and temperature differences on wet and dry days, in these software packages were simplified and preset for US climatic conditions. Consequently, mismatches in simulations with these weather generators are, at least partly, due to these simplified and preset parameters. The Richardson-type weather generators may perform better if all the parameters are calibrated in accordance with local observations.

Different probability distributions, for example the 2-parameter gamma distribution, the exponential distribution and the mixed exponential distribution have been used to simulate daily precipitation amounts on wet days. This reflects the fact that observed daily precipitation amounts may follow different types of probability distributions in different climates. Therefore, it will be preferable to use an empirical distribution to simulate daily precipitation amounts, as LARS-WG does, rather than a simple standard distribution that introduces the problem of selecting the correct probability distribution. Palutikof et al. (2002) sampled an observed daily precipitation time series to avoid the distribution problem. This sampling procedure was applied to a multisite simulation, but a potential limitation is that the generated scenarios do not have values beyond the data pool.

Other weather variables involved in weather generators are usually assumed to follow a normal distribution or can be transformed to a normal distribution. Daily temperatures are assumed to follow a normal distribution in LARS-WG. However, daily maximum and minimum temperatures do not always follow a normal distribution for most months at stations across Canada (Hayhoe 2000). 'Standardized' daily temperatures, or residuals from their long-term means, which are usually simulated first in weather generators rather than the original daily series, also do not follow normal distributions.

An attempt has been made to improve the Richardson-type weather generator with the flexibility of empirical distributions, in order to adapt the weather generator to highly diverse climates. Hayhoe (2000) used the structure of the Richardson-type weather generators but replaced the simple standard probability distributions in the random-number generation with empirical distributions. The developed weather generator, AAFC-WG, has the advantages of the Richardson-type weather generators in maintaining autocorrelations and inter-variable relationships, while the flexibility to model a variety of probability distributions is introduced by using empirical distributions. Detailed descriptions of AAFC-WG can be found in Hayhoe (2000). Table 1 summarizes some technical details of how AAFC-WG generates weather series in comparison with LARS-WG.

AAFC-WG generates 4 weather variables: daily precipitation (P), daily maximum temperature (T_x), daily minimum temperature (T_n) and radiation (R). Other variables such as humidity or dewpoint may be easily integrated into the model using the same procedure for T_x, T_n and R because of the flexibility to accommodate different types of probability distributions. There are major differences between AAFC-WG and LARS-WG. Firstly, AAFC-WG uses a second-order 2-state Markov chain to simulate wet and dry day sequences, while LARS-WG applies empirical distributions for wet and dry sequences. It is necessary to check whether the second-order Markov chain can simulate wet and dry spells as well as LARS-WG. Secondly, empirical distributions are used for daily T_x and T_n in AAFC-WG, whereas normal distributions are assumed for daily T_x and T_n in LARS-WG. This may result in AAFC-WG simulating temperature-related statistics better than LARS-WG, especially the probability distributions. Thirdly, AAFC-WG has kept the structure of the Richardson-type weather generators; it uses the first-order multivariate autoregressive model to simulate all other weather variables except precipitation. Lag-0 and Lag-1 correlation matrices are estimated bimonthly. Actual autocorrelations maintain the serial structure of the observed weather series, which may also be helpful in reducing overdispersion problems (Katz & Parlange 1998). Serial correlations may also be important in reproducing dates, such as the last frost day in spring and the first frost day in fall. Cross-correlations may also lead to a reasonable reproduction of the relationships among the involved weather variables.

It should be noted that the use of the first-order multivariate autoregressive model in AAFC-WG implies that the residuals of T_x, T_n and R are normally distributed. However, as has been mentioned before, this assumption may not be valid for all locations or for every month. The normal score transformation (Johnson 1987) is used in AAFC-WG to overcome this problem. The version of LARS-WG used for this comparison is a software package running in a Windows environment (LARS-WG Stochastic Weather Generator 3.0; available for download from http://www.rothamsted.bbsrc.ac.uk/mas-models/larswg.html). Technical details of LARS-WG can be referred to in the accompanying user's manual.

Table 1. AAFC-WG in comparison with LARS-WG

Weather variable	LARS-WG	AAFC-WG
Weather status (wet or dry)		
Definition of wet day	Daily precipitation ≥ 0.1 mm	Daily precipitation ≥ 0.2 mm
Determination of weather status	Lengths of alternate wet and dry sequences chosen from an empirical distribution fitted to the observed series. Separate parameters are calculated for each month	Transition probabilities of a second-order 2-state Markov chain applied to the previous 2 days' status. Separate transition probabilities estimated monthly from observations
Precipitation amount on a wet day (P)	Empirical distribution with 10 intervals from observed daily precipitation amounts on wet days for each month. Amount on a wet day independent from previous weather status or amounts	Similar to LARS-WG, but empirical distribution estimated from logarithm-transformed precipitation amounts on wet days bimonthly. Random numbers generated from empirical distribution then converted to precipitation amounts
Maximum temperature (T_x)	Normal distribution. Mean and standard deviation of the normal vary daily, by fitting Fourier series to means and standard deviations of observed data throughout year. Separate Fourier series fitted for wet and dry days. Constant Lag-1 autocorrelation and preset cross-correlation between maximum and minimum temperature	Empirical distribution estimated from the residual series. Mean and standard deviation of the normal vary daily, by interpolating monthly values of means and standard deviations of observed daily data with a spline interpolation procedure. Separate means and standard deviations calculated for wet and dry days. Lag-0 and Lag-1 correlation matrices estimated from residuals of T_x, T_n and R bimonthly
Minimum temperature (T_n)	Same procedure as for maximum temperature	Same procedure as for maximum temperature
Radiation (R)	Empirical distribution. Separate parameters estimated for wet and dry days for each month. Constant Lag-1 autocorrelation	Same procedure as for T_x and T_n

3. DATA AND METHODS

3.1. Canadian stations used

Canada is a country with diverse climates with probability distributions of weather variables that can be very different at different locations. For example, normal distributions can be good candidates for daily T_x and/or T_n at some locations, but poor representatives at other sites across the country. Therefore, in order to ensure a valid comparison, it is important to examine various stations across the country. Agriculture is mostly found in the southern parts of Canada, and stations in this study were selected from the AAFC's archived weather database using representative locations across the country. Nine stations, mainly from south of 60° N (see Fig. 1), were used in this study. The selection of the stations was also affected by the available years of the historical weather records. These weather series were almost complete, with only 2 days missing at Regina. Climate statistics for 1971–2000, including 30 yr mean maximum temperatures, minimum temperatures, monthly precipitation totals and numbers of wet days for the coldest and warmest months are listed in Table 2. The coldest month is January at all 9 stations, while the warmest month is July, an exception being Vancouver, where the latter is August. Climate characteristics shown in Table 2 represent a variety of climates including a mild maritime climate on the west coast (Vancouver) and a semi-arid continental climate on the Canadian Prairies (Regina).

3.2. Comparison of simulations

3.2.1. Statistical properties of concern

Weather generators are supposed to generate synthetic weather series which have statistical properties similar to the observed series. Some common statistical properties need to be satisfied for most applications, although additional statistical properties may be important for specific applications. Means and variances of daily synthetic weather data are usually required to be not significantly different from those calculated from observed series. It is also important that synthetic weather series

Fig. 1. Location of the Canadian stations for weather-generator comparisons

Table 2. Mean maximum temperature (T_x), minimum temperature (T_n), monthly precipitation total (P) and number of wet days (NWD) for the coldest (C) and warmest (W) months at Canadian stations for 1971–2000

Stn	T_x (°C)		T_n (°C)		P (mm)		NWD	
	C	W	C	W	C	W	C	W
Beaverlodge	−8.2	21.5	−17.4	9.0	31.0	70.6	10.6	13.5
Fredericton	−4.4	25.4	−14.6	13.2	104.4	89.7	13.1	13.8
Goose	−12.9	20.9	−23.3	9.7	64.8	113.8	16.3	18.8
Ottawa	−6.1	26.4	−14.8	15.5	64.2	88.9	16.6	12.4
Regina	−10.7	25.6	−21.6	11.8	14.6	64.4	10.8	10.9
Toronto	−1.1	26.4	−7.3	17.9	61.2	67.5	15.3	10.3
Truro	−1.4	23.9	−12.2	12.6	117.3	90.5	16.3	13.0
Vancouver	6.1	21.9	0.5	13.4	153.6	39.1	18.5	6.8
Winnipeg	−12.8	25.7	−22.8	13.2	19.6	70.9	11.9	11.5

follow a probability distribution which is not statistically different from the observations. Furthermore, monthly values of the weather variables can be obtained from their corresponding daily values; thus, means and variances of monthly values are also statistics of concern.

As has been mentioned before, AAFC-WG uses a second-order Markov chain in simulating the sequences of wet and dry days, while empirical distributions of wet and dry spells are used in LARS-WG. It is essential to verify whether AAFC-WG can simulate wet and dry spells reasonably well in comparison to LARS-WG, in terms of probability distributions of the lengths of wet and dry spells and corresponding mean lengths, since wet and dry spells are important for agricultural applications.

3.2.2. Agroclimatic indices

Agroclimatic indices are also used to test the capability of the weather generators for agricultural applications. Nine agroclimatic indices are computed from observed weather series and synthetic weather series generated by LARS-WG and AAFC-WG. Most are relevant to heat units and the lengths of growing season for crops, but a water-related index is also included. The agroclimatic indices are as follows: last date of frost ($T_n \geq 0$°C) in spring (FS), first date of frost in fall (FF), last date of killing frost ($T_n \geq -2$°C) in spring (KFS), first date of killing frost in fall (KFF), frost-free days (FFD), growing degree-days (GDD), effective growing degree-days (EGDD), corn heat units (CHU) and precipitation deficit/surplus (PDS). The dates related to frost are calculated as day of the year. GDD, EGDD and CHU are computed based on the findings of the Agronomics Interpretations Working Group (1995) and Bootsma et al. (1999). PDS is calculated on a daily basis by subtracting precipitation (P) from the potential evapotranspiration (PE) and accumulating values over the same period as EGDD. PE is determined using the Baier & Robertson (1965) method to compute latent evaporation (LE) from T_x, T_n and solar radiation at the top of the atmosphere and subsequently LE is converted to PE (Baier 1971).

3.2.3. Statistical tests

Observed daily T_x, T_n and P series for 1971–2000 at 9 stations are used as inputs to the 2 weather generators and then synthetic weather series of 300 yr length are generated for each site. A long synthetic series will provide stable statistical properties to ensure that any significant difference between the observed series and the synthetic series is not a result of sampling, as the observed series is only a short part of the 'real' stochastic process.

The 2-sample Kolmogorov-Smirnov (K-S) test is performed to check whether the differences are small enough not to reject the null hypothesis that the synthetic series comes from the same probability distribution as the observed series. The 2-sample K-S test is used because it detects the maximum difference between the probability distribution functions of the 2 samples, without the weakness of the χ^2 test of depending on grouping the samples.

Quantile–quantile (Q–Q) plots are also used to demonstrate visually how well the synthetic series followed the probability distribution of the observed series for daily T_x, T_n and P in January and July at

Beaverlodge and Truro. Relative frequencies of wet or dry spells for different lengths in synthetic sequences of wet and dry days are plotted against those from the observed sequences to show the goodness-of-fit in simulating wet and dry spells, besides the 2-sample K-S test.

The unequal variance *t*-test is used to test the statistical significance of differences in means between synthetic series and observations. The *F*-test is performed to test the statistical significance of differences in variances. Using *t*- and *F*-tests usually assumes that the series in question are normally distributed, although daily precipitation series on wet days may not follow such a distribution. Hayhoe (2000) has explained this problem and its solution: precipitation amounts on wet days from observations and simulations produced by both LARS-WG and AAFC-WG are transformed using the logarithmic function before applying the *t*- and *F*-tests. All statistical tests are conducted at the 0.05 significance level on a monthly basis.

4. RESULTS AND DISCUSSION

4.1. Wet and dry spells

Because LARS-WG uses empirical distributions to simulate wet and dry spells, it is reasonable to question whether the AAFC-WG, which models wet and dry spells indirectly using a second-order 2-state Markov chain, can calculate these spells with similar accuracy. It was found that AAFC-WG was able to simulate the relative frequencies of the lengths of wet and dry spells as well as LARS-WG in all instances. Results from the K-S test (not shown) indicate that the probability distributions of wet and dry spells from synthetic daily precipitation are not significantly different from the corresponding observed ones in all months at all stations, for both LARS-WG and AAFC-WG.

Fig. 2 displays relative frequencies of wet and dry spells in the synthetic weather series from LARS-WG and AAFC-WG against those observed for January and July at 2 sites, Toronto and Vancouver. These 2 stations were chosen because Vancouver experiences a wet period in winter and a dry period in summer, while seasonal variation of precipitation in Toronto is not so distinct. The relative frequency of the duration of dry or wet spells is the ratio of the number of dry or wet spells with a given duration to the total number of dry or wet spells of all different durations started in the month. As a dry or wet spell can span calendar months, the length (duration) of a dry or wet spell in a calendar month is counted for a spell starting in the month regardless of when it ends.

Both LARS-WG and AAFC-WG are capable of simulating dry and wet spells, and the second-order 2-state Markov chain in AAFC-WG performed as well as LARS-WG with its empirical distributions. Both weather generators give a much smoother curve for the relative frequencies of dry spells in July at Vancouver when the observed data show that it is very variable, although LARS-WG usually reproduces the fluctuations slightly better than AAFC-WG. This may be associated with intervals of the durations of wet or dry spells used for the empirical distribution, as LARS-WG tends to use larger intervals when some long dry spells exist in a very dry month. Some fluctuations in the relative frequencies may be the result of the short observation period and therefore in reality the curves may be smoother. If this is true, then using the second-order 2-state Markov chains may have the advantage in generating future climate scenarios, because the transition probabilities can be easily modified to accommodate climate change. It may not be feasible to modify the empirical distributions of dry and wet spells, since only mean lengths of dry or wet spells are modified in LARS-WG.

Since wet and dry spells are not directly simulated in AAFC-WG, it needs to be verified whether AAFC-WG is able to simulate mean lengths of wet and dry spells as well as LARS-WG (Fig. 3). Because there are 9 stations and 12 months involved, a total of 108 data points are shown in Fig. 3, as is the case for the remaining figures related to means and standard deviations. AAFC-WG reproduced the mean lengths of wet and dry spells equally as accurate as LARS-WG, and the RMSE (root-mean squared error; Qian et al. 2002) values also indicated similar simulation results to LARS-WG. Results from the *t*-test (not shown) did not indicate a significant difference between synthetic data and observations for all months and stations.

4.2. Daily values

The results for LARS-WG and AAFC-WG simulations from the K-S test are listed in Table 3, together with results from *t*- and *F*-tests. The AAFC-WG simulations had fewer months and stations which failed to pass the test than LARS-WG, for both temperatures and precipitation amounts on wet days. As large values in Table 3 imply a poor simulation with the weather generator, AAFC-WG showed a much better performance than LARS-WG in simulating temperature probability distributions, although some lack-of-fit was still detected, notably in the probability distributions of T_x and T_n. The better simulation of daily P on wet days by AAFC-WG may be related to the technique used in this weather generator whereby empiri-

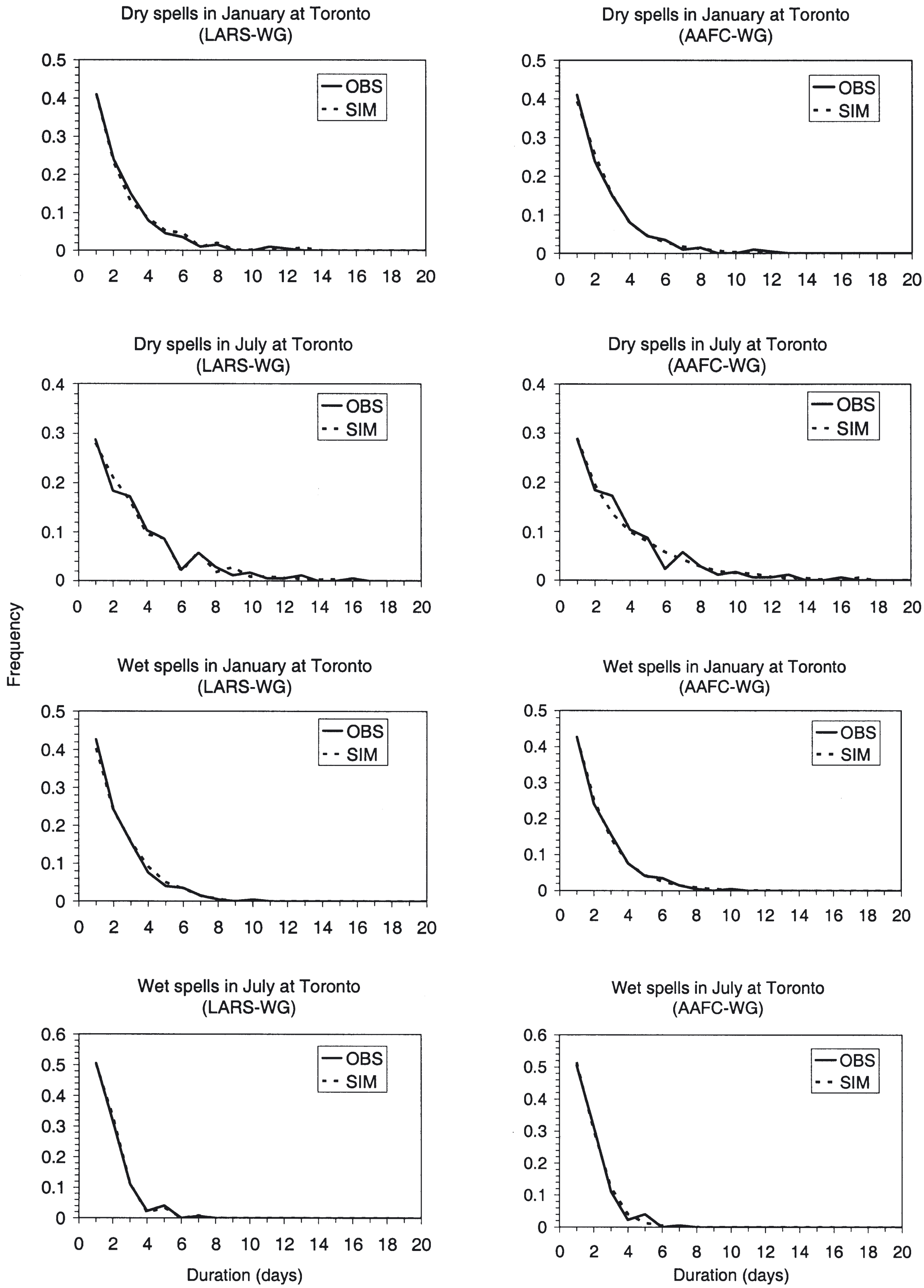
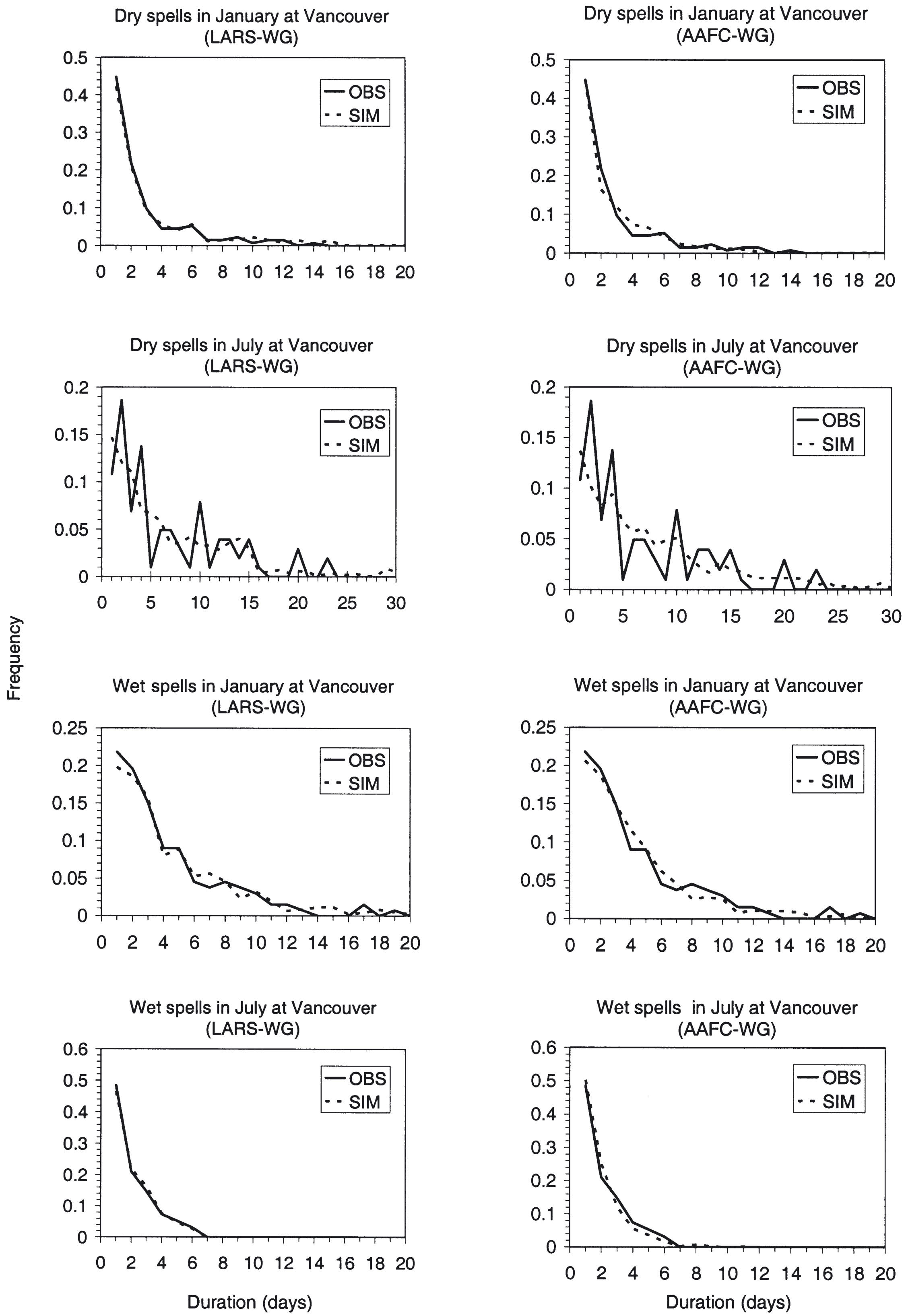


Fig. 2. (Above and following page.) January and July relative frequencies of dry and wet spells in synthetic daily precipitation series respectively from LARS-WG (left panels) and AAFC-WG (right panels) in comparison with observations at Toronto and Vancouver. Observed (OBS) and simulated (sim) means are shown



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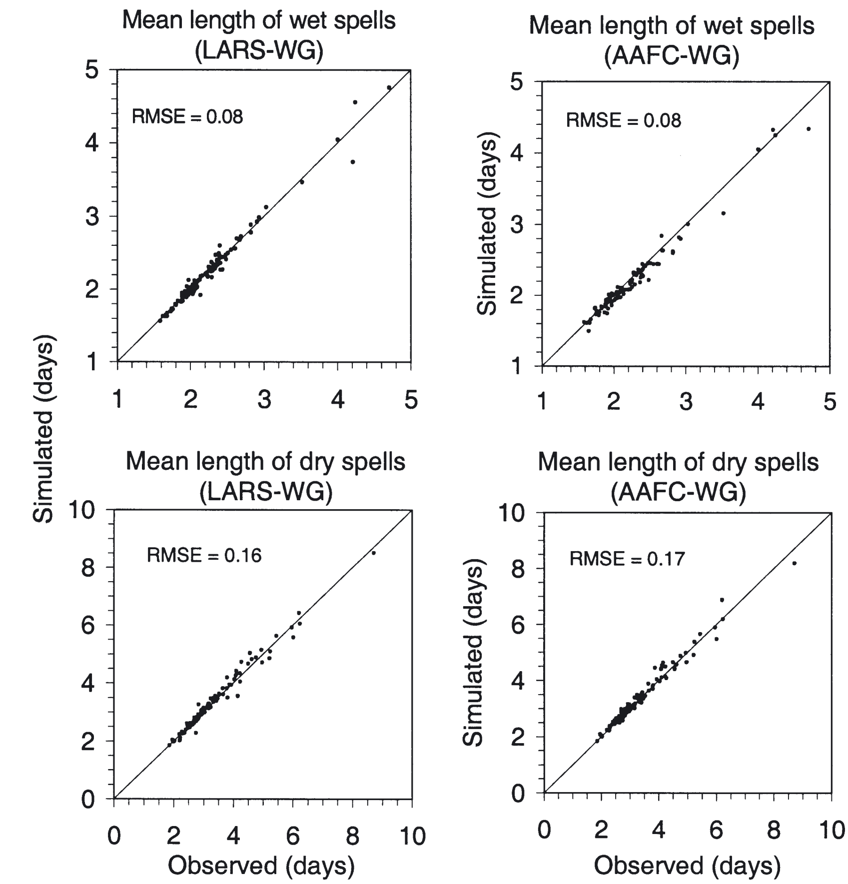

Fig. 3. Mean lengths of wet and dry spells simulated by LARS-WG (left panels) and AAFC-WG (right panels) in comparison with observations (n = 108). RMSE: root-mean squared error

cal distributions for generating synthetic precipitation data are constructed from logarithm-transformed daily precipitation amounts on wet days, since intervals for empirical distributions can be determined more smoothly after transformation.

The mean from a synthetic series can be very close to the observed one, but still comes from a different population, and a statistical test may identify such cases. Results from the t- and F-tests for means and variances computed from daily values are listed in Table 3. For means and variances of daily T_x and T_n, there is no significant difference detected for AAFC-WG, while quite a few cases are found different from observations for LARS-WG. For precipitation amounts on wet days, significant differences are found in some cases for LARS-WG, which further implies a better performance of AAFC-WG.

Fig. 4 shows Q–Q plots of daily P on wet days, T_x and T_n for January at Beaverlodge and July at Truro. In these Q–Q plots, quantiles for 1 to 99% are plotted. It is clear that synthetic temperatures from AAFC-WG match the observations better than LARS-WG, although in some cases LARS-WG is also able to reproduce the observed distributions well.

Fig. 5 shows visual comparisons of means and standard deviations computed from synthetic series of daily P, T_x and T_n against observations, using all stations combined. AAFC-WG performs better in simulating means and standard deviations of daily T_x and T_n, resulting in significant lower RMSE values than those of LARS-WG. While the means of daily P are calculated with similar RMSE values, the RMSE of standard deviations of daily P is twice as high for AAFC-WG compared to LARS-

Table 3. Number of months showing significant differences between observed and simulated daily maximum temperature (T_x), minimum temperature (T_n) and precipitation (P) on wet days by LARS-WG (L) and AAFC-WG (A), using various statistical tests

Variable:	P						T_x						T_n					
Test:	Distribution K-S		Mean t		Variance F		Distribution K-S		Mean t		Variance F		Distribution K-S		Mean t		Variance F	
Stn	L	A	L	A	L	A	L	A	L	A	L	A	L	A	L	A	L	A
Beaverlodge	1	0	3	0	10	0	8	1	7	0	3	0	9	5	4	0	3	0
Fredericton	2	0	0	0	2	0	9	3	4	0	1	0	8	3	5	0	4	0
Goose	6	0	0	0	2	0	7	2	4	0	4	0	12	1	6	0	8	0
Ottawa	2	0	0	0	3	0	5	3	5	0	2	0	9	3	5	0	4	0
Regina	5	3	0	0	2	0	9	1	7	0	1	0	10	1	6	0	6	0
Toronto	1	0	0	0	1	0	2	1	4	0	3	0	5	0	2	0	2	0
Truro	4	0	0	0	3	0	5	2	2	0	0	0	12	5	4	0	5	0
Vancouver	1	0	0	0	1	0	6	1	2	0	2	0	5	0	4	0	0	0
Winnipeg	8	1	0	0	0	0	9	3	6	0	2	0	8	3	3	0	7	0

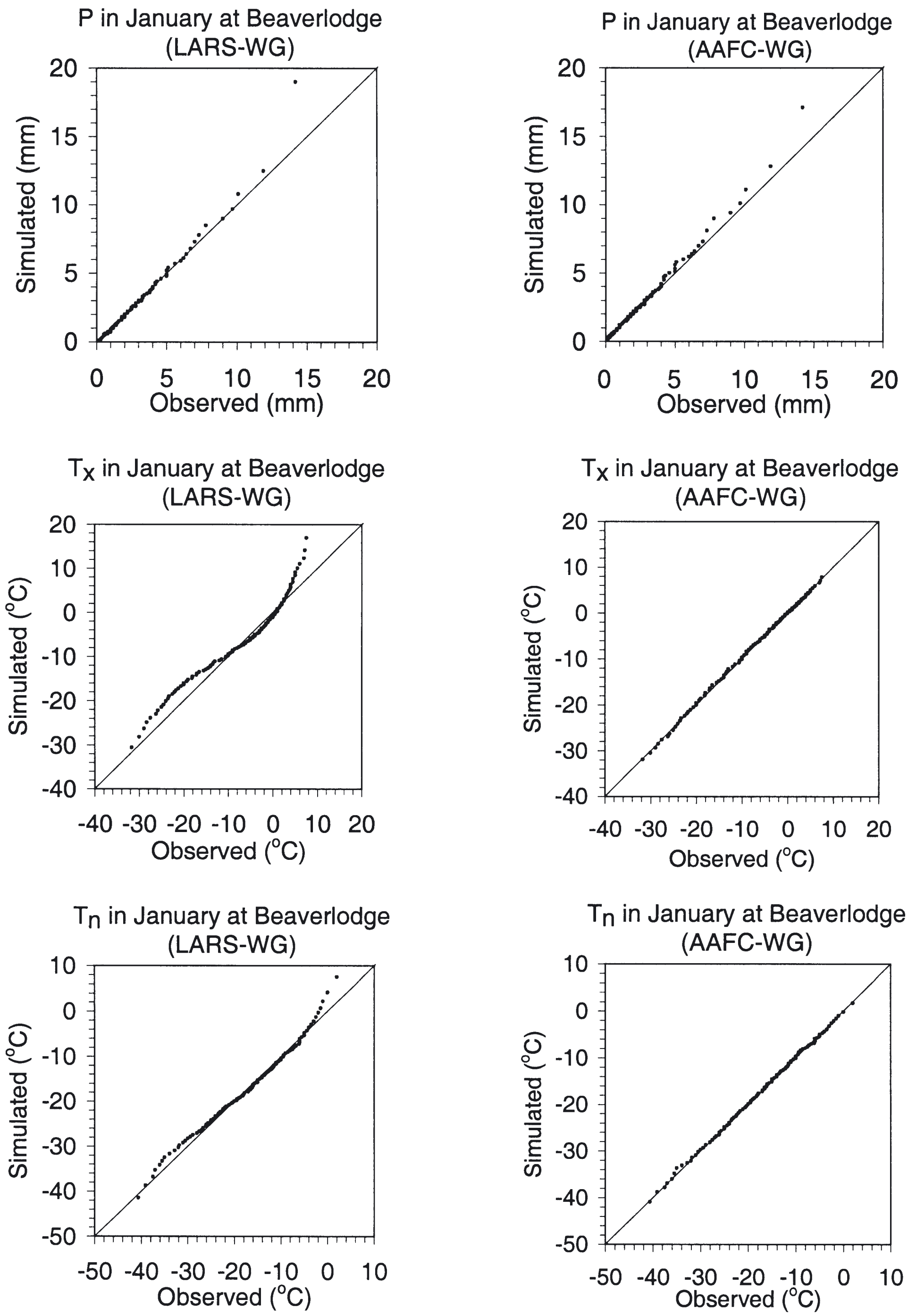

Fig. 4. (Above and facing page.) Quantile–quantile plots of synthetic daily precipitation (P) on wet days, maximum (T_x) and minimum temperatures (T_n) in January at Beaverlodge and July at Truro, from LARS-WG (left panels) and AAFC-WG (right panels) in comparison with observations

WG, indicating a slightly better performance of LARS-WG, although the RMSE values are small for both weather generators. Nevertheless, no significant difference is found between observed variances and simulated values from AAFC-WG, using the *F*-test.

4.3. Monthly values

Monthly means of T_x and T_n, as well as monthly P totals, can be calculated from daily values. Results from statistical tests indicate no significant difference

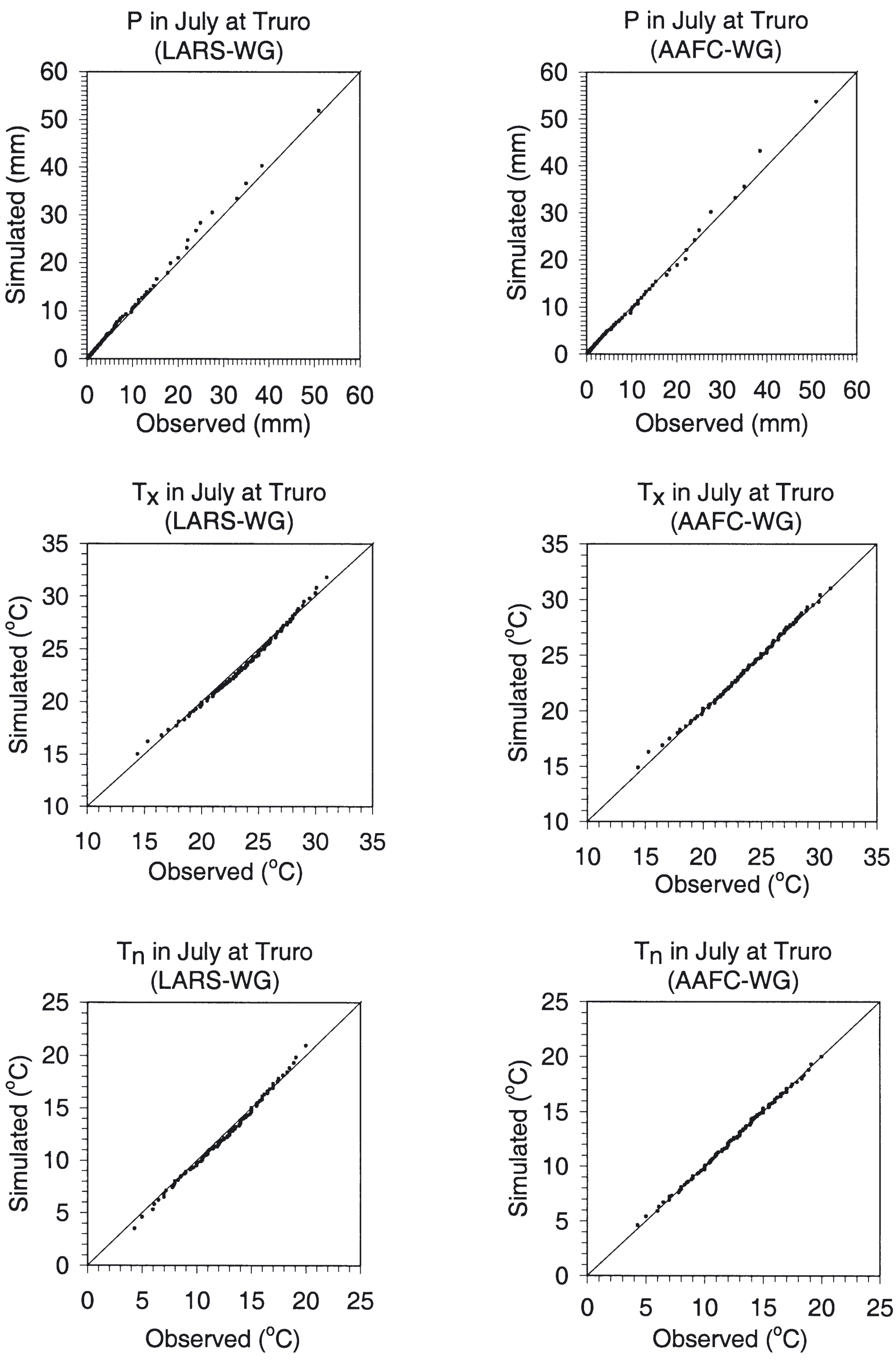

Fig. 4 (continued)

in means of the simulated monthly P totals compared to the observations, for both LARS-WG and AAFC-WG (Table 4). However, significant differences are detected for some cases in means of monthly mean T_x and T_n simulated by LARS-WG against the observed values, but simulations from AAFC-WG can pass the t-test for all months at all stations.

One of the challenges for weather generators is how well they can simulate interannual variability. Standard deviations of the monthly values computed from synthetic data are displayed in Fig. 6 in comparison with the observed values. Both LARS-WG and AAFC-WG simulate interannual variability of monthly P totals quite well, although some overdispersion is observed for some

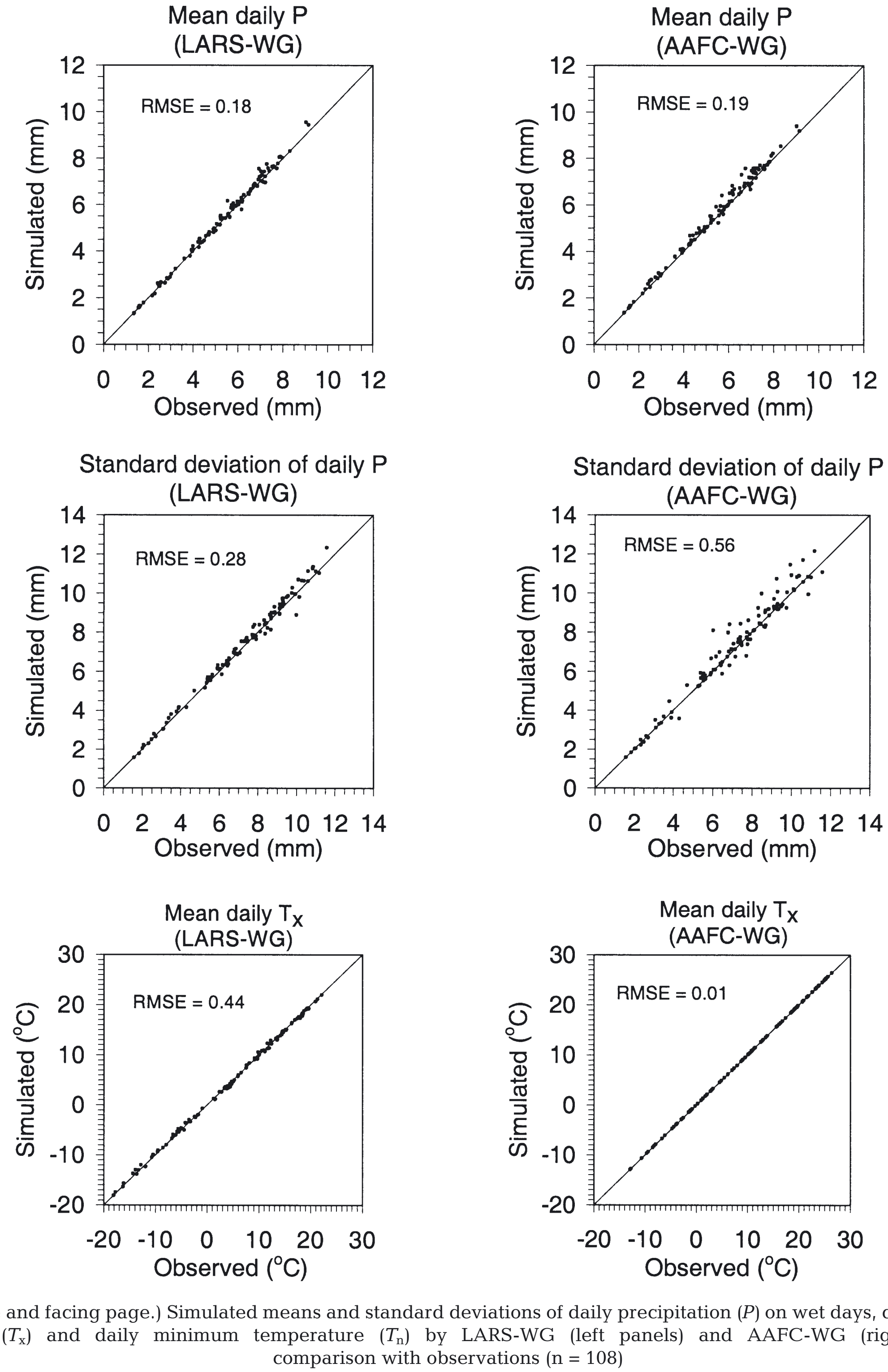

Fig. 5. (Above and facing page.) Simulated means and standard deviations of daily precipitation (P) on wet days, daily maximum temperature (T_x) and daily minimum temperature (T_n) by LARS-WG (left panels) and AAFC-WG (right panels) in comparison with observations (n = 108)

places. Results of the F-test showed only a few cases which were different from observed variances (Table 4). The overdispersion problem, i.e. underestimation of interannual variability, seemed more serious for T_x and T_n as more cases were significantly different from observed variances (Table 4). AAFC-WG performed slightly better in simulating interannual variability of monthly mean T_x and T_n than LARS-WG. The RMSE value for the standard deviations of monthly mean T_n was 0.41°C for AAFC-WG and 0.58°C for LARS-WG.

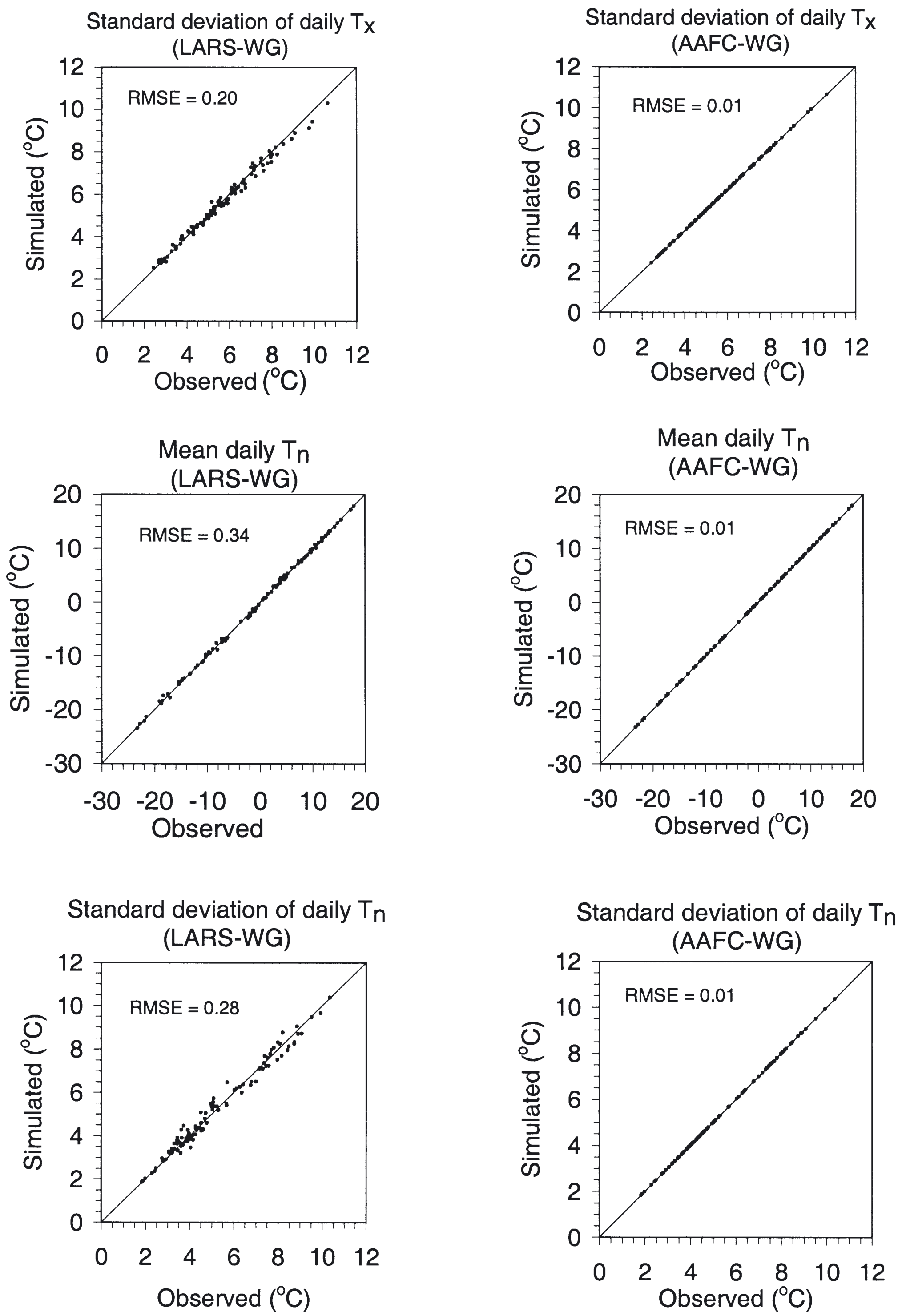

Fig. 5 (continued)

4.4. Mean values of agroclimatic indices

A statistical t-test was conducted to verify whether there are significant differences between observed values of selected agroclimatic indices and simulated values computed from synthetic weather data. Results are listed in Table 5. Both weather generators simulate these agroclimatic indices reasonably well, although some differences can be identified. AAFC-WG appears to do a better job than LARS-WG, since AAFC-WG only fails in 5 cases, while LARS-WG fails in 14 cases. Most cases that are not well reproduced by the weather generators are those associated with daily T_n.

Table 4. Number of months showing significant differences between observed and simulated means and variances of monthly precipitation totals (*P*) and monthly mean maximum (T_x) and minimum (T_n) temperatures by LARS-WG (L) and AAFC-WG (A), using various statistical tests

Variable:	P				T_x				T_n			
	Mean		Variance		Mean		Variance		Mean		Variance	
Test:	*t*		*F*		*t*		*F*		*t*		*F*	
Stn	L	A	L	A	L	A	L	A	L	A	L	A
Beaverlodge	0	0	4	5	0	0	2	6	3	0	5	2
Fredericton	0	0	0	0	1	0	1	1	0	0	1	3
Goose	0	0	0	0	0	0	3	1	0	0	4	3
Ottawa	0	0	1	0	0	0	1	3	0	0	1	1
Regina	0	0	0	3	1	0	7	5	1	0	4	1
Toronto	0	0	0	0	0	0	2	1	0	0	1	1
Truro	0	0	0	1	0	0	5	3	0	0	3	3
Vancouver	0	0	0	1	0	0	5	5	0	0	4	5
Winnipeg	0	0	2	0	1	0	3	2	0	0	5	0

The *F*-test was also applied to check whether the variances of agroclimatic indices from synthetic weather data are significantly different from observations. Results (not shown) indicate a reasonable reproduction as no significant differences are found for most indices at most stations.

5. CONCLUSIONS

The second-order 2-state Markov chain used by AAFC-WG can simulate durations of wet and dry spells as well as the empirical distributions of wet and dry spells used in LARS-WG. As mentioned in Section 4, using the second-order 2-state Markov chain may be preferable to the approach used in LARS-WG in applications for developing future climate scenarios, because modifying

Table 5. Mean values of agroclimatic indices computed from synthetic weather data generated by LARS-WG (L) and AAFC-WG (A) in comparison with observed values (O). *Values significantly different from observed ones at the 0.05 significance level as determined by a *t*-test. Remark: Goose is not in an agricultural region. Agroclimatic indices: FS, last date of frost in spring; FF, first date of frost in fall; KFS, last date of killing frost in spring; KFF, first date of killing frost in fall; FFD, frost free days; GDD, growing degree-days; EGDD, effective growing degree-days; CHU, corn heat units; PDS, precipitation deficit/surplus

Indices		Beaverlodge	Fredericton	Goose	Ottawa	Regina	Toronto	Truro	Vancouver	Winnipeg
FS	O	143	135	158	118	139	106	147	81	143
	L	141	139	161	124*	141	111*	147	85	143
	A	140	135	160	122	140	109	145	84	142
FF	O	253	273	264	277	256	304	269	311	266
	L	254	270	256*	281*	261*	303	266	307	267
	A	252	273	262	279	259	306	269	309	263*
KFS	O	129	121	145	109	130	98	130	51	131
	L	128	126	148	116*	131	102*	135*	66*	135
	A	129	123	147	113*	130	100	134	63*	134
KFF	O	267	282	275	289	267	318	282	314	272
	L	269	281	274	292	270	315	278	317	275
	A	264	282	272	290	266	319	281	320	273
FFD	O	109	137	105	158	116	196	121	229	122
	L	112	130*	94*	156	119	191	118	221	123
	A	110	137	101	157	118	197	122	224	120
GDD	O	1240	1792	948	2097	1681	2401	1609	2007	1761
	L	1213	1772	958	2054	1650	2399	1602	1989	1731
	A	1233	1783	971	2091	1679	2412	1625	2008	1765
EGDD	O	1127	1659	921	1955	1517	2336	1460	1964	1658
	L	1104	1619*	883*	1953	1519	2335	1410*	1932	1616
	A	1117	1656	943	1978	1532	2357	1456	1954	1636
CHU	O	1427	2404	1012	2887	2215	3435	2176	2527	2442
	L	1454	2382	1054	2942	2182	3491	2112	2561	2402
	A	1445	2466	1117*	2980*	2181	3506	2195	2609	2435
PDS	O	193	107	–33	122	328	81	79	–130	241
	L	177	99	–24	104	334	65	78	–113	238
	A	194	95	–40	107	332	72	74	–103	239

the mean lengths of wet and dry spells may not be sufficient to incorporate changes in frequency distributions of wet and dry spells associated with climate change.

LARS-WG assumes that daily T_x and T_n follow normal distributions, while AAFC-WG applies empirical distributions. The advantages and disadvantages of using simple standard distributions or empirical dis-

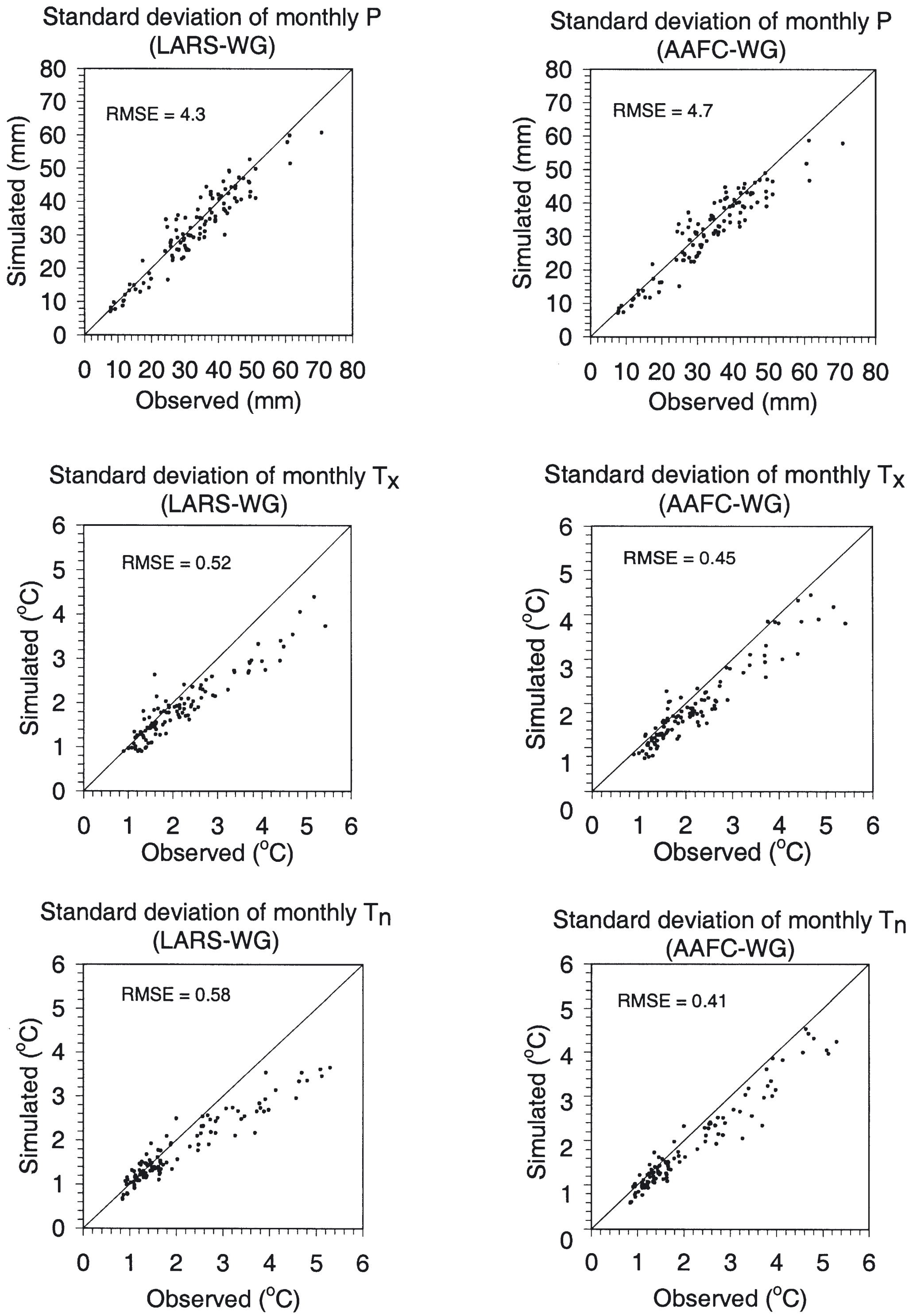

Fig. 6. Standard deviations of monthly precipitation (*P*) totals and monthly mean maximum (T_x) and minimum temperatures (T_n) of synthetic data from LARS-WG (left panels) and AAFC-WG (right panels) in comparison with observations (n = 108)

tributions have been discussed by Semenov et al. (1998). It appears that empirical distributions can improve capabilities of weather generators in simulating more realistic weather series when a simple standard distribution does not fit the observations. The improvement is not only in the probability distributions of the synthetic weather series, but also in the corresponding means, variances and relevant agroclimatic indices computed from the synthetic weather data.

The 2 weather generators simulate daily P better than T_x and T_n in relation to the overdispersion problem. Although AAFC-WG performs better in terms of both the probability distributions and the means and variances related to daily T_x and T_n, it will still be useful to investigate if the underestimation of interannual variability can be remedied. Using higher-order multivariate regressive models may possibly improve the overdispersion problem, but will create more numerical difficulties in the complex models. However, the causes of the overdispersion problem are still not very clear, and AAFC-WG reproduces interannual variability reasonably well. The overdispersion problem should not seriously affect results from climate-change impact studies unless the application is very sensitive to interannual variability.

It is also of concern to climate-change impact researchers whether weather generators have the capability of reproducing extremes. This aspect is not directly assessed in this paper; however, a reasonable simulation can be expected if a weather generator can simulate the probability distributions well. From the Q–Q plots in Fig. 4 for AAFC-WG, it can be seen that extreme values are usually very close to the observed values, such as 95% quantiles, if the synthetic series follows the same probability distribution as the observed series. This implies that AAFC-WG can be expected to better reproduce temperature extremes than LARS-WG.

The agroclimatic indices computed from the synthetic weather data are not significantly different from observed ones. This implies that it is appropriate to use synthetic data from weather generators in agricultural applications. Climate-change impacts on Canadian agriculture can be evaluated partly through studying the potential changes in agroclimatic indices, which can provide insight into possible changes in crop distribution or adaptation strategies.

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