A VERSATILE WEATHER GENERATOR FOR DAILY PRECIPITATION AND TEMPERATURE

J. Chen, F. P. Brissette, R. Leconte, A. Caron

ABSTRACT. *Stochastic daily weather generators are often used to generate long time series of weather variables to drive hydrological and agricultural models. More recently, they have also been used as a downscaling tool for studying the impacts of climate change. This article describes a versatile stochastic weather generator (WeaGETS) for producing daily precipitation, and maximum and minimum temperatures (T_{max} and T_{min}). WeaGETS regroups several options of other weather generators into one package, such as three Markov models to produce precipitation occurrence, four distributions to generate wet day precipitation amount, and two methods to simulate T_{max} and T_{min}. More importantly, a spectral correction approach is included in WeaGETS for correcting the underestimation of interannual variability, which is a problem common to all weather generators. The performance of WeaGETS is demonstrated through a comparison against two well-known weather generators (WGEN and CLIGEN) with respect to the generation of precipitation, T_{max}, and T_{min} for two Canadian meteorological stations. The results show that the widely used first-order Markov model is adequate for producing precipitation occurrence, but it underestimates the longest dry spell for the low-precipitation station. The higher-order models have positive effects. The mixed exponential and skewed normal Pearson III distributions are consistently better than the exponential and gamma distributions at generating precipitation amounts. The two-component mixed exponential distribution is better at representing extreme precipitation events than the other three distributions. WeaGETS is consistently better than WGEN and CLIGEN at producing T_{max} and T_{min}. Both WGEN and CLIGEN underestimate the monthly and interannual variances of precipitation and temperatures. However, WeaGETS successfully preserves the observed low-frequency variability and autocorrelation functions of precipitation and temperatures. Overall, WeaGETS is consistently better than the other two weather generators (WGEN and CLIGEN) for producing precipitation, T_{max}, and T_{min}. The Matlab freeware allows for easy modification of all routines, making it easy to add additional weather variables to simulate.*

Keywords. *Matlab, Precipitation, Stochastic weather generator, Temperature.*

Weather generators are computer algorithms that produce long time series of weather variables that have statistical properties comparable to those of existing records. They are also able to generate weather data at ungauged sites through the interpolation of model parameters from adjacent gauged sites (Baffault et al., 1996). Weather generators can generate weather data at various temporal scales, but the daily scale is the one that has received the most attention. Over the past decade, weather generators have been widely used in climate change studies as downscaling tools by perturbing their parameters to account for expected changes in precipitation and temperature (Semenov and Barrow, 1997; Wilks, 1992; Pruski and Nearing, 2002; Zhang et al., 2004; Zhang, 2005; Zhang and Liu, 2005; Kilsby et al., 2007, Chen et al., 2011a). Appealing properties of downscaling weather generator parameters are their ability to rapidly produce long series of daily weather data that are not available from observations and their use in investigating potential impacts of climate change. Over the past three decades, several weather generators have been developed to meet those requirements, such as WGEN (Richardson, 1981; Richardson and Wright, 1984), USCLIMATE (Hanson et al., 1994), CLIGEN (Nicks et al., 1995), WGENAL (Skiles and Richardson, 1998), ClimGen (Stockle et al., 1999), and LARS-WG (Semenov and Barrow, 2002). The generation of precipitation and maximum and minimum temperatures ($T_{\max}$ and $T_{\min}$) are the usual main components of these weather generators, especially for climate change impact studies. However, these weather variables are often generated based on different schemes. For example, daily precipitation amount is generated using a gamma distribution in WGEN, while a skewed normal Pearson III distribution is used in CLIGEN. Most weather generators use a first-order Markov model to generate precipitation occurrence. This model has been shown to be adequate in temperate climates, but in wet or dry areas the use of higher-order Markov chains may be necessary

Submitted for review in August 2011 as manuscript number SW 9338; approved for publication by the Soil & Water Division of ASABE in May 2012.

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  ISSN 2151-0032

(Wilks, 1999). To circumvent this problem, LARS-WG uses empirical histograms of dry/wet series (Racsko et al., 1991; Semenov and Barrow, 2002). A one-parameter exponential distribution is the simplest method used to generate daily precipitation amount (Todorovic and Woolhiser, 1974; Richardson, 1981), but the two-parameter gamma distribution is more widely used due to its better performance. A three-parameter Pearson III distribution is used to generate daily precipitation amount in CLIGEN. Compared to precipitation, temperatures are much simpler to produce, since they often approximately follow a normal distribution. However, daily T_{max} and T_{min} are correlated with each other, and this correlation varies depending on whether a day is dry or wet. Thus, the preservation of these correlations is an important criterion to assess the performance of a weather generator. Moreover, one problem with currently available daily weather generators is the underestimation of low-frequency variations, such as monthly and interannual variances, because weather generators do not take into account the low-frequency component of climate variability (Buishand, 1978; Johnson et al., 1996; Wilks, 1989, 1999; Gregory et al., 1993; Katz and Parlange, 1993, 1998; Hansen and Mavromatis, 2001; Zhang and Garbrecht, 2003; Chen et al, 2009). Surface weather variables such as precipitation and temperature are partly conditioned on the larger-scale atmospheric circulation (Dubrovsky et al., 2004), whose behavior is dictated by the chaotic nature of the climate system. Patterns such as the El Niño Southern Oscillation (ENSO) are a dominant mode of climate variability at the interannual timescale (Cibot et al., 2005). Weather generators simply assume that the daily weather process is stationary and do not explicitly take into account low-frequency variability such as decadal oscillations, and thus underestimate monthly and yearly variances (Chen et al., 2010). Several methods have been presented to correct the low-frequency variability of precipitation (Hansen and Mavromatis, 2001; Dubrovsky et al., 2004; Wang and Nathan, 2007; Chen et al., 2010, 2011b). The spectral correction approach of Chen et al. (2010, 2011b) is arguably the best available method for dealing with the low-frequency problem.

All of the weather generators currently available only provide a single scheme to generate each climate variable, such as the first-order Markov model for precipitation occurrence and exponential or gamma distribution for wet day precipitation amount. Users have little choice in selecting appropriate options for generating weather variables according to their specific study. Moreover, there is no scheme incorporated into weather generators to deal with their underestimation of interannual variability.

This article describes a Matlab-based software package for the stochastic weather generation of precipitation and temperatures (T_{max} and T_{min}) for individual sites at a daily time scale. For climate change impact studies, changes in future precipitation and temperature predicted by general circulation models (GCM) can be incorporated by adding the changes in mean temperature to the baseline date and multiplying the ratio of precipitation change to the chosen precipitation frequency distribution. The Weather Generator of École de Technologie Supérieure (WeaGETS) software regroups several options of other weather generators into one package, and allows for correction of the underestimation of interannual variability. More importantly, users can easily tailor WeaGETS to their specific needs with simple modifications, since the software is open source and freely available on the Matlab Central file exchange site.

This article first presents the algorithm for the generation of precipitation and temperatures. Two Canadian meteorological weather stations are then selected to demonstrate the typical performance of WeaGETS. Results are compared against those produced by the commonly used weather generators WGEN and CLIGEN. Discussion and conclusions are presented in the last section.

Model Description

WeaGETS provides three options to generate precipitation occurrence, four options to produce precipitation amount, and two options to simulate T_{max} and T_{min}. There is also an option of smoothing the precipitation parameters with Fourier harmonics following Richardson's approach (1981) and to correct for the low-frequency variability of precipitation and temperature following the spectral correction method of Chen et al. (2010, 2011b).

The basic input data include an observed weather data filename, a filename to store the subsequently generated data, a precipitation threshold value (minimum rainfall amount in mm for a day to be considered wet), and the number of years of data to generate. Figure 1 presents the WeaGETS structure.

Smoothing Scheme

The precipitation occurrence parameters include the transition probabilities of first-, second-, and third-order Markov chains. For precipitation amounts, there is one parameter for the exponential distribution, two parameters for the gamma distribution, and three parameters for the skewed normal Pearson III and mixed exponential distributions. These parameters are computed on a biweekly basis (26 estimations over the whole year). Because of climate variability and the finite length of the historical records, the variation from one 2-week period to the next will not be smoothed, and the true yearly distribution of the parameter value will be partly hidden. The user can decide to accept sudden variations (keeping constant parameters values for the 2-week period) or to smooth the computed distribution to allow for smooth transitions of the parameters on a daily basis. In the latter case, WeaGETS will try to reproduce the precipitation characteristics of the smoothed line and not of the original observed values. In this case, generated precipitation may be slightly different from the observed precipitation. One to four Fourier harmonics can be used to smooth the yearly parameter distribution. The smoothing process eliminates sharp parameter transitions between computing periods that may occur due to outliers, especially for short time series. Figure 2 presents a dry day following a wet day (P10) parameter smoothed by Fourier harmonics. A first-order Fourier harmonic is clearly inadequate in this case. However, a higher number of harmonics will better fit the

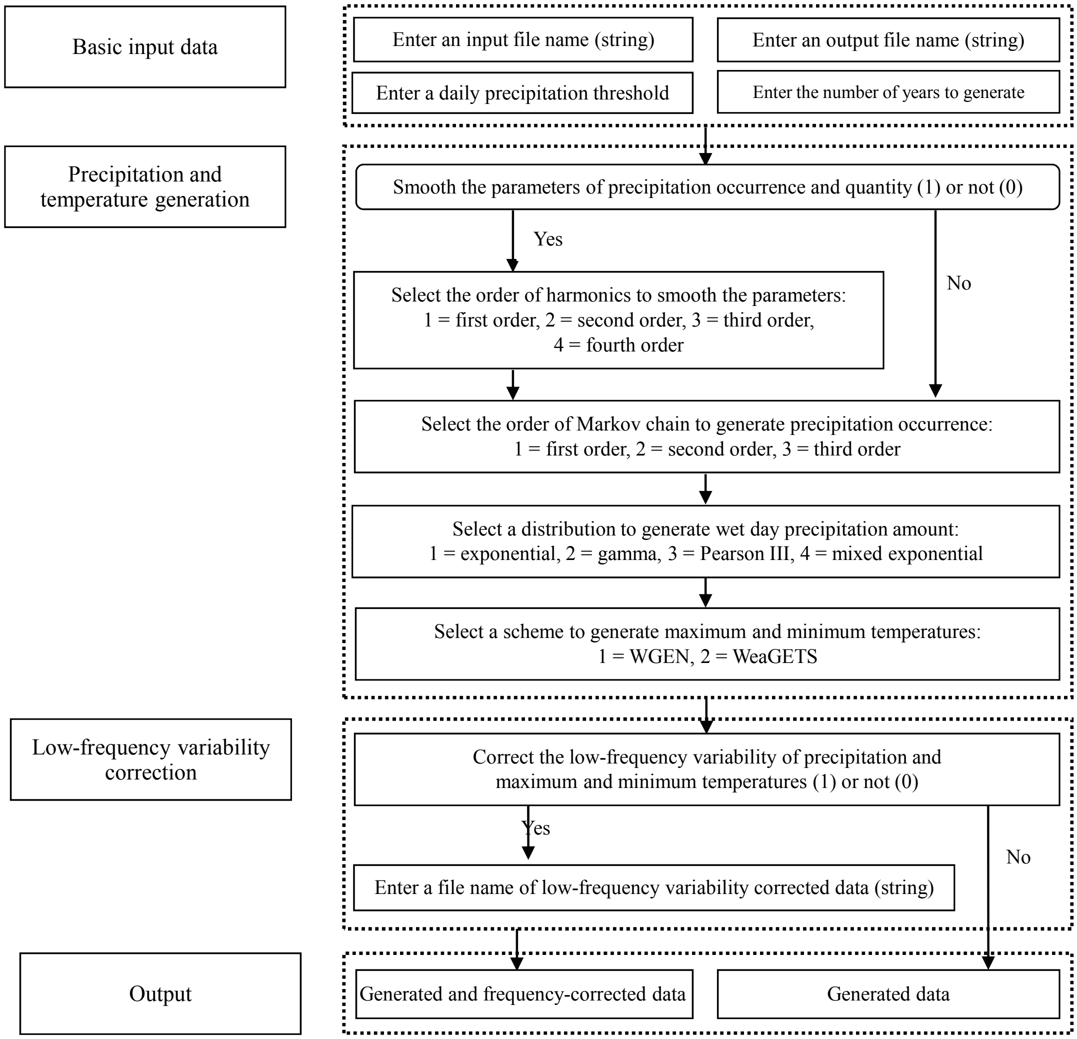

Figure 1. Structure of the stochastic weather generator WeaGETS.

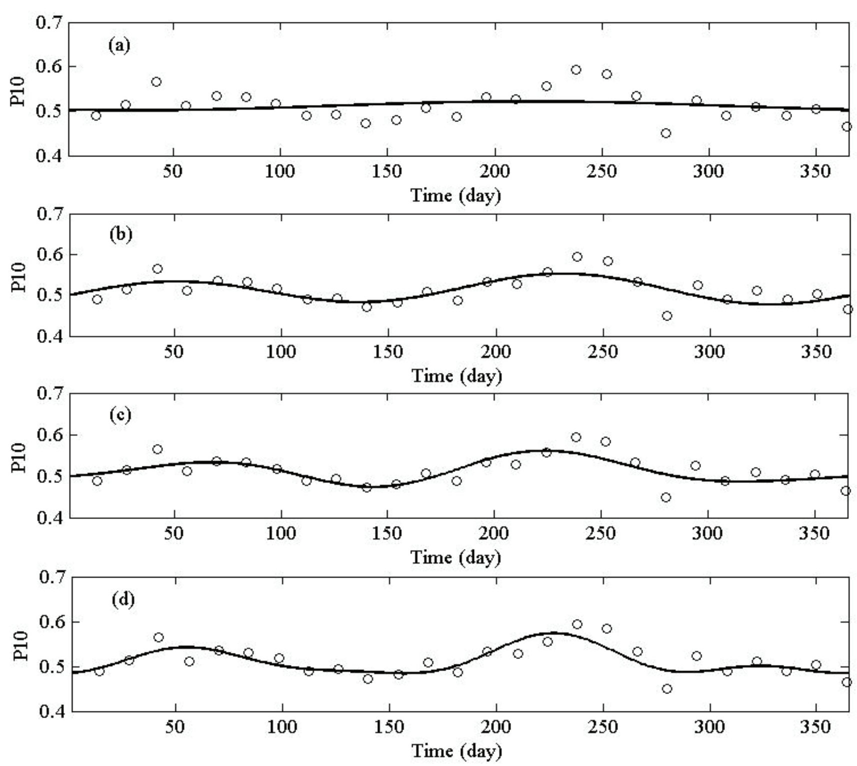

Figure 2. A dry day following a wet day (P10) calculated at a two-week scale and smoothed by (a) first-order, (b) second-order, (c) third-order, and (d) fourth-order Fourier harmonics.

data at the potential expense of reproducing trends that may not exist. The choice of smoothing or not, and how much smoothing is needed, is partly a philosophical debate and will depend on the experience of the modeler. In most cases, the use of two harmonics is adequate for representing seasonal trends in the precipitation-generating parameters, but this depends on local climatology.

Generation of Precipitation Occurrence

A first-order, two-state Markov chain is one of the most widely used methods to generate the occurrence of wet and dry days. Both WGEN and CLIGEN use this scheme. The probability of precipitation on a given day is based on the wet or dry status of the previous day, which can be defined in terms of two transition probabilities, P01 and P11:

$$\mathrm{P01} = \Pr\left\{\text{precip. on day } t \,\middle|\, \text{no precip. on day } t-1\right\} \tag{1a}$$

$$\mathrm{P11} = \Pr\left\{\text{precip. on day } t \,\middle|\, \text{precip. on day } t-1\right\} \tag{1b}$$

Since precipitation either occurs or does not occur on a given day, the two complementary transition probabilities are: P00 = 1 − P01, and P10 = 1 − P11.

In addition to providing the first-order, two-state Markov chain to generate precipitation occurrence, WeaGETS provides two more options including second- and third-order, two-state Markov models to produce precipitation occurrence.

Letting $R_t = 0$ if day t is dry, and $R_t = 1$ if day t is wet, equations 1a and 1b can be extended to the second- and third-order Markov chains following equations 2 and 3:

$$P_{ijk} = \Pr\left\{R_t = k \,\middle|\, R_{t-1} = j \,\middle|\, R_{t-2} = i\right\} \tag{2}$$

$$P_{hijk} = \Pr\left\{R_t = k \,\middle|\, R_{t-1} = j \,\middle|\, R_{t-2} = i \,\middle|\, R_{t-3} = h\right\} \tag{3}$$

where h, i, j, and k = 0 or 1. The number of parameters required to characterize precipitation occurrence increase exponentially with the order of Markov process. This means that two, four, and eight parameters must be estimated for first-, second-, and third-order Markov models, respectively.

Generation of Precipitation Amount

In WGEN, a one-parameter exponential distribution and a two-parameter gamma distribution are used to generate daily precipitation amount for wet days. CLIGEN uses a three-parameter skewed normal Pearson III distribution to produce the wet day precipitation. The mixed exponential distribution usually offers a better representation of precipitation extremes. In WeaGETS, all four probability distribution functions are available to produce the daily precipitation amount for a wet day.

The first is the one-parameter exponential distribution, which has a probability density function given by:

$$f(x) = \lambda e^{-\lambda x} \tag{4}$$

where x is the daily precipitation intensity, and λ is the distribution parameter (equal to the inverse of the mean).

The other function is the two-parameter gamma distribution. The probability density function for this distribution is given by:

$$f(x) = \frac{(x/\beta)^{\alpha-1}\exp[-x/\beta]}{\beta\Gamma(\alpha)} \tag{5}$$

where α and β are the two distribution parameters, and $\Gamma(\alpha)$ indicates the gamma function evaluated at α. This method is easy to compute and performs better than the exponential distribution. Therefore, it is widely used to generate daily precipitation amount.

The third option is the three-parameter skewed normal Pearson III distribution (Nicks and Lane, 1989; Nick et al., 1995):

$$\lambda = \frac{6}{g}\left\{\left[\frac{g}{2}\left(\frac{x-\mu}{s}\right)\right]^{1/3} - 1\right\} + \frac{g}{6} \tag{6}$$

where λ is the standard normal deviate, and μ, s, and g are the mean, standard deviation, and skewness coefficient of daily precipitation amount, respectively.

The last option is the three-parameter mixed exponential distribution (Wilks, 1999) with a probability density function of:

$$f(x) = \frac{\alpha}{\beta_1}\exp\left(\frac{-x}{\beta_1}\right) + \frac{1-\alpha}{\beta_2}\exp\left(\frac{-x}{\beta_2}\right) \tag{7}$$

This distribution is a probability mixture of two one-parameter exponential distributions. The parameter α is the mixing probability, which determines the weights given to the two exponential distributions with scale parameters β_1 and β_2.

Generation of Maximum and Minimum Temperatures

WGEN uses a first-order linear autoregressive model to generate $T_{\max}$ and $T_{\min}$. The observed time series is first reduced to residual elements by subtracting the daily means and dividing by the standard deviations. The means and standard deviations are conditioned on the wet or dry status. The residual series are then generated by:

$$\chi_{p,i}(j) = A\chi_{p,i-1}(j) + B\varepsilon_{p,i}(j) \tag{8}$$

where $\chi_{p,i}(j)$ is a (2×1) matrix for day i of year p whose elements are the residuals of $T_{\max}$ (j = 1) and $T_{\min}$ (j = 2); $\varepsilon_{p,i}(j)$ is a (2×1) matrix of independent random components that are normally distributed with a mean of zero and a variance of unity. A and B are (2×2) matrices whose elements are defined such that the new sequences have the desired auto- and cross-correlation coefficients. The A and B matrices are determined by:

$$A = M_1 M_0^{-1} \tag{9}$$

$$BB^T = M_0 - M_1 M_0^{-1} M_1^T \tag{10}$$

where the superscripts -1 and T denote the inverse and transpose of the matrix, respectively, and M_0 and M_1 are the lag 0 and lag 1 covariance matrices. The daily values of T_{max} and T_{min} are found by multiplying the residuals by the standard deviation (σ) and adding the mean (μ) (eqs. 11 and 12):

$$T_{max} = \mu_{max} + \sigma_{max} \times \chi_{p,i} \tag{11}$$

$$T_{min} = \mu_{min} + \sigma_{min} \times \chi_{p,i} \tag{12}$$

Because T_{max} and T_{min} are generated unconditionally of each other based on equations 11 and 12, there are a number of cases in which T_{min} is larger than T_{max}. Thus, a range check is imposed to force T_{min} to be less than T_{max}. For example, if T_{min} is greater than T_{max}, then T_{min} is set equal to T_{max} minus 1.

T_{max} and T_{min} are generated based on a normal distribution for the latest version of CLIGEN (version 5.22564). T_{max} and T_{min} are conditioned on each other but are not conditioned on the wet and dry states. The temperature with the smallest standard deviation between T_{max} and T_{min} is first computed, followed by the others (Chen et al., 2008). If the standard deviation of T_{max} is larger than or equal to the standard deviation of T_{min}, daily temperatures are generated by equations 13 and 14:

$$T_{min} = \mu_{min} + \sigma_{min} \times \chi_{p,i} \tag{13}$$

$$T_{max} = T_{min} + \left(\mu_{max} - \mu_{min}\right) + \sqrt{\sigma_{max}^2 - \sigma_{min}^2} \times \chi_{p,i} \tag{14}$$

If the standard deviation of T_{max} is less than that of T_{min}, daily temperatures are generated by equations 15 and 16:

$$T_{max} = \mu_{max} + \sigma_{max} \times \chi_{p,i} \tag{15}$$

$$T_{min} = T_{max} - \left(\mu_{max} - \mu_{min}\right) - \sqrt{\sigma_{min}^2 - \sigma_{max}^2} \times \chi_{p,i} \tag{16}$$

Using this scheme, T_{min} is always less than T_{max} and no range check is necessary.

WeaGETS provides two options to generate T_{max} and T_{min}. The first is to use the WGEN scheme. The other option is to combine the most desirable properties of WGEN and CLIGEN (referred to as the conditional method). WGEN is used as the basic weather generator. The residual series of T_{max} and T_{min} conditioned on the wet and dry states are generated by a first-order linear autoregressive model (eqs. 8 through 10). But instead of using equations 11 and 12, the conditional equations 13 through 16 derived from CLIGEN are used to ensure that the T_{min} is always less than the T_{max} on a given day.

Correction of Low-Frequency Variability

Weather generators such as WGEN and CLIGEN underestimate the monthly and interannual variance because they do not take into account the low-frequency component of climate variability. WeaGETS provides an approach to correct for this underestimation for both precipitation and temperatures.

Low-frequency variability is first modeled using a fast Fourier transform (FFT) based on the power spectra of the monthly and annual time series of precipitation and temperature. Generations of monthly and yearly precipitation and yearly average temperatures data are achieved by assigning random phases for each spectral component that preserve the power spectrum and variances as well as the autocorrelation function. The link to daily parameters is established through linear functions. The correction of monthly and interannual variability for precipitation follows the approach of Chen et al. (2010, 2011b). Their results show that this approach performs very well in preserving the low-frequency variability of precipitation and temperatures.

Example of Model Performance

Three weather generators (WGEN, CLIGEN, and WeaGETS) are compared in terms of producing precipitation and temperatures for two Canadian meteorological stations to illustrate the advantages of WeaGETS. The basic information, including average annual precipitation, T_{max} and T_{min}, longitude, latitude, elevation, and record duration for the two stations is given in table 1. All three weather generator have been used and tested extensively at several other locations under various climates (Semonev et al., 1998; Zhang and Garbrecht, 2003; Zhang, 2004; Taulis and Milke, 2005; Caron, 2006; Chen et al., 2008, 2009, 2010, 2011b). These two stations were selected simply to outline the typical outputs and results.

The observed daily precipitation, T_{max}, and T_{min} data (118 years for Ottawa and 60 years for Churchill) were used to run the three weather generators to generate synthetic time series without parameter smoothing. The length of the generated series is 10 times that of the observed series. Statistics including mean, standard deviation, percentiles, and extreme values are calculated for both observed and synthetic time series for each meteorological variable.

Precipitation Occurrence

Both WGEN and CLIGEN use the first-order Markov chain to produce the precipitation occurrence, while WeaGETS also provides the options of using second- or third-order Markov chains. The statistics of dry and wet spells calculated from those time series are presented in table 2. Each Markov model produces a good replication of

Table 1. Location, period of record, averaged annual precipitation, and maximum and minimum temperatures (T_{max} and T_{min}) for the Ottawa and Churchill stations.

Station	Latitude (° N)	Longitude (° W)	Elevation (m)	Period of Record	Annual Precipitation (mm)	Averaged Annual T_{max} (°C)	Averaged Annual T_{min} (°C)
Ottawa	45.26	75.74	93	1891-2008 (118 years)	882.0	10.98	0.79
Churchill	58.73	94.05	29	1947-2006 (60 years)	439.1	-2.71	-10.91

Table 2. Statistics of dry and wet spells for the Ottawa and Churchill stations.[a]

		Ottawa				Churchill			
	Source	Obs.	1st	2nd	3rd	Obs.	1st	2nd	3rd
Dry spell	Mean	3.0	3.0	3.0	3.0	3.2	3.2	3.2	3.2
	Std	2.6	2.4	2.5	2.5	3.0	2.8	2.8	2.9
	25th percentile	1	1	1	1	1	1	1	1
	50th percentile	2	2	2	2	2	2	2	2
	75th percentile	4	4	4	4	4	4	4	4
	95th percentile	8	8	8	8	9	9	9	9
	99th percentile	13	12	12	12	14	14	14	14
	Longest	25	29	30	28	43	32	31	39
	p-value of K-S test	-	0.862	0.775	0.994	-	0.112	0.478	0.968
Wet spell	Mean	2.0	2.0	2.0	2.0	2.2	2.2	2.2	2.2
	Std	1.3	1.4	1.3	1.3	1.7	1.7	1.6	1.7
	25th percentile	1	1	1	1	1	1	1	1
	50th percentile	2	1	2	2	2	2	2	2
	75th percentile	2	2	2	2	3	3	3	3
	95th percentile	5	5	4	4	5	6	5	6
	99th percentile	7	7	7	7	9	8	8	9
	Longest	16	17	14	14	17	26	19	23
	p-value of K-S test	-	0.000	1.000	1.000	-	0.119	0.328	1.000

[a] Obs. = observed data, 1st = first-order Markov chain, 2nd = second-order Markov chain, 3rd = third-order Markov chain, and Std = standard deviation.

the mean of both dry and wet spells for both stations. However, the standard deviation of dry spells is slightly underestimated by each model, while the two higher-order models perform somewhat better than the first-order model. Each Markov model reproduced the 25th, 50th, 75th, 95th, and 99th percentiles of both dry and wet spells for both stations. Kolmogorov-Smirnov (K-S) tests show that the distributions of wet and dry day spells are not different at p = 0.01 for all Markov models and both stations, with the exception of wet day spells using the first-order Markov chain for Ottawa. The longest dry spells are overestimated for the Ottawa station and underestimated for the Churchill station. Overall, the performance at the Ottawa station is slightly better that at the Churchill station. The differences between stations are due to the different climate zones they belong to. Churchill is a low-precipitation station, and Ottawa is much wetter. The third-order Markov model is, not surprisingly, the best. Wilks (1999) observed that the first-order Markov model may be inadequate at generating long dry spells in very wet and or dry regions. Here, the replication of long wet spells is better than for long dry spells, especially for the Ottawa station. Even though the higher-order Markov chains are better than the first-order in reproducing the statistics of precipitation occurrence, more parameters need to be determined. Thus, they may be not practical for climate change studies. Moreover, higher-order parameter estimation requires longer time series of observed precipitation, since a minimum number of rainfall events needs to be presented to adequately estimate transition probabilities. The longer the duration, the more likely the stationarity hypothesis will be violated by the stochastic weather generation.

PRECIPITATION AMOUNT

To compare the exponential, gamma, Pearson III, and mixed exponential distributions in terms of accurately producing precipitation amount, four time series of precipitation occurrence are generated using the first-order Markov model, and then the wet day precipitations are simulated with exponential, gamma, Pearson III, and mixed exponential distributions. The results show that all four distributions reproduce the daily precipitation mean very well (table 3). The Pearson III and mixed exponential distributions reproduce the standard deviation of daily precipitation reasonably well for both stations. However, both the exponential and gamma distributions underestimate the standard deviations of daily precipitation, with mean relative errors (MREs) of -25.8% and -14.6% for Ottawa and Churchill, respectively. This indicates that these two distributions underestimate the high-frequency variability of precipitation. The 25th, 50th, 75th, 95th, and 99th percentiles are well reproduced by the Pearson III and mixed distributions for both stations. This indicates that the Pearson III and mixed distributions may be capable of preserving the distribution

Table 3. Statistics of daily precipitation for the Ottawa and Churchill stations.[a]

	Ottawa					Churchill				
Source	Obs.	Exponential	Gamma	Pearson III	Mixed Exponential	Obs.	Exponential	Gamma	Pearson III	Mixed Exponential
Mean	6.1	6.1	6.1	6.1	6.1	2.9	2.9	2.9	2.8	2.9
Std	7.6	6.2	6.9	7.5	7.5	4.8	3.3	3.9	4.7	4.6
25th percentile	1.3	1.8	1.4	1.3	1.2	0.5	0.8	0.6	0.5	0.5
50th percentile	3.3	4.2	3.8	3.4	3.3	1.2	1.8	1.6	1.0	1.2
75th percentile	8.1	8.4	8.2	8.0	8.1	3.2	3.8	3.7	2.9	3.1
95th percentile	21.0	18.3	19.7	20.5	21.2	11.7	9.4	10.4	11.2	11.9
99th percentile	35.8	28.8	32.5	35.4	35.3	23.8	15.5	18.7	23.3	22.3
Maximum	108.6	84.1	95.0	147.1	109.7	62.3	44.3	84.2	112.5	83.9

[a] Obs. = observed data, Std = standard deviation, and Maximum = all-time maximum daily precipitation. The Kolmogorov-Smirnov (K-S) tests between observed and each distribution generated daily precipitation are significant at p = 0.01.

of daily precipitation. However, both the exponential and gamma distributions overestimate the 25th, 50th, and 75th percentiles of daily precipitation and underestimate the 95th and 99th percentiles for both stations. The K-S tests rejected the null hypothesis that the observed and generated data are from the same population for all four distribution and both stations at very significant levels ($p < 0.01$). This might be a result of the large sample size ($n > 100{,}000$ for generated data, and $n > 10{,}000$ for observed data). When sample size is very large, as is the case here, the K-S test becomes extremely stringent and powerful. The use of a small precipitation threshold (0.25 mm in this case) for the wet day status also makes it much harder to fit distributions, as the data become even more skewed. The exponential distribution underestimates the all-time maximum daily precipitation for the two stations, while the Pearson III distribution overestimates it. The use of the gamma distribution results in an underestimation of the all-time maximum daily precipitation for Ottawa and an overestimation for Churchill. This is understandable because these three distributions are not tailed to generated extreme precipitation events. However, the mixed exponential distribution is much better at generating extreme precipitation than other distributions, especially for the Ottawa station.

All four distributions perform very well in producing monthly and annual mean precipitation (tables 4 and 5). However, all of them underestimate the standard deviations of monthly and annual precipitation for Churchill. The exponential and gamma distributions also underestimate the standard deviations of monthly and annual precipitation for Ottawa. As discussed earlier, this indicates that these two distributions underestimate the interannual and intra-annual variability of precipitation. However, the Pearson III and mixed exponential distributions reproduce the standard deviations of monthly and annual precipitation very well. This indicates that the three-parameter Pearson III and mixed exponential distributions are much better at reproducing both interannual and intra-annual variability of precipitation. All four distributions generate the percentiles of monthly and yearly precipitations well for the Ottawa station. In contrast, for the Churchill station, all of them overestimate the lower percentiles of monthly and yearly precipitations, and underestimate the higher percentiles. The K-S tests show that the distributions of observed and generated monthly and annual precipitation are significantly different ($p = 0.01$) for both the exponential and gamma distributions for Ottawa. The distributions of monthly precipitation are also significantly different between the observed and generated data for the exponential distribution ($p = 0.01$) for both stations. From the p-values of the K-S tests, it seems that the weather generators perform better at the Churchill station than at the Ottawa station, but it should be noted that the sample size is larger for Ottawa than for Churchill (1180 vs. 600 years). Overall, the Pearson III and mixed exponential distributions are consistently better than the exponential and gamma distribution at simulating precipitation.

Both WGEN and CLIGEN do not take into account the low-frequency component of precipitation. A main advantage of WeaGETS over most other stochastic weather generators is that an approach (the spectral correction method of Chen et al., 2010, 2011b) to correct for the underestimation of low-frequency variability for both precipitation and temperature is built in. The mean and standard deviations of monthly and annual precipitation and autocorrelations of annual precipitation generated by the three weather generators are compared for the two stations.

Figure 3 presents the ratios of the mean and standard deviations of monthly and annual precipitations derived from the synthetic weather series to those derived from the

Table 4. Statistics of monthly precipitation for the Ottawa and Churchill stations.[a]

	Ottawa					Churchill				
Source	Obs.	Exponential	Gamma	Pearson III	Mixed Exponential	Obs.	Exponential	Gamma	Pearson III	Mixed Exponential
Mean	73.5	73.3	73.6	72.8	73.2	36.6	36.4	36.7	35.0	36.1
Std	33.9	30.2	31.9	35.0	33.7	29.1	23.0	24.1	26.5	25.4
25th percentile	48.7	51.8	50.7	47.8	48.9	15.0	18.0	18.0	15.8	16.9
50th percentile	69.5	69.2	69.4	67.0	68.6	28.5	31.0	30.9	27.5	29.1
75th percentile	94.5	91.5	91.5	90.9	92.5	50.3	50.9	50.8	47.0	49.5
95th percentile	135.5	126.7	133.5	137.8	135.3	93.9	80.5	83.5	88.2	86.7
99th percentile	171.4	161.2	165.4	184.0	171.5	129.3	104.1	107.3	125.1	114.9
Maximum	250.2	261.7	242.2	305.3	270.4	247.0	166.1	183.5	281.8	192.2
p-value of K-S test	-	0.000	0.000	0.227	0.027	-	0.009	0.119	0.065	0.720

[a] Obs. = observed data, Std = standard deviation, and Maximum = all-time maximum monthly precipitation.

Table 5. Statistics of annual precipitation for the Ottawa and Churchill stations.[a]

	Ottawa					Churchill				
	Obs.	Exponential	Gamma	Pearson III	Mixed Exponential	Obs.	Exponential	Gamma	Pearson III	Mixed Exponential
Mean	882.0	879.1	882.8	873.5	878.0	439.1	436.9	440.6	420.4	433.7
Std	112.9	97.7	99.2	111.7	114.9	102.5	52.0	55.3	69.4	64.9
25th percentile	814.1	813.8	816.5	794.9	801.2	361.9	400.2	403.3	371.8	388.1
50th percentile	872.5	880.1	881.9	865.1	870.7	426.2	434.7	437.6	416.5	433.0
75th percentile	961.6	939.4	943.8	937.1	951.7	503.3	469.1	476.6	462.8	472.5
95th percentile	1060.6	1044.6	1057.3	1078.7	1087.8	610.7	527.1	534.5	546.6	540.4
99th percentile	1154.3	1122.8	1141.9	1159.6	1177.5	742.9	562.9	583.5	615.5	603.5
Maximum	1159.2	1273.0	1183.4	1259.6	1260.5	748.5	587.1	644.7	683.6	726.9
p-value of K-S test	-	0.004	0.005	0.111	0.092	-	0.265	0.413	0.156	0.611

[a] Obs. = observed data, Std = standard deviation, and Maximum = all-time maximum annual precipitation.

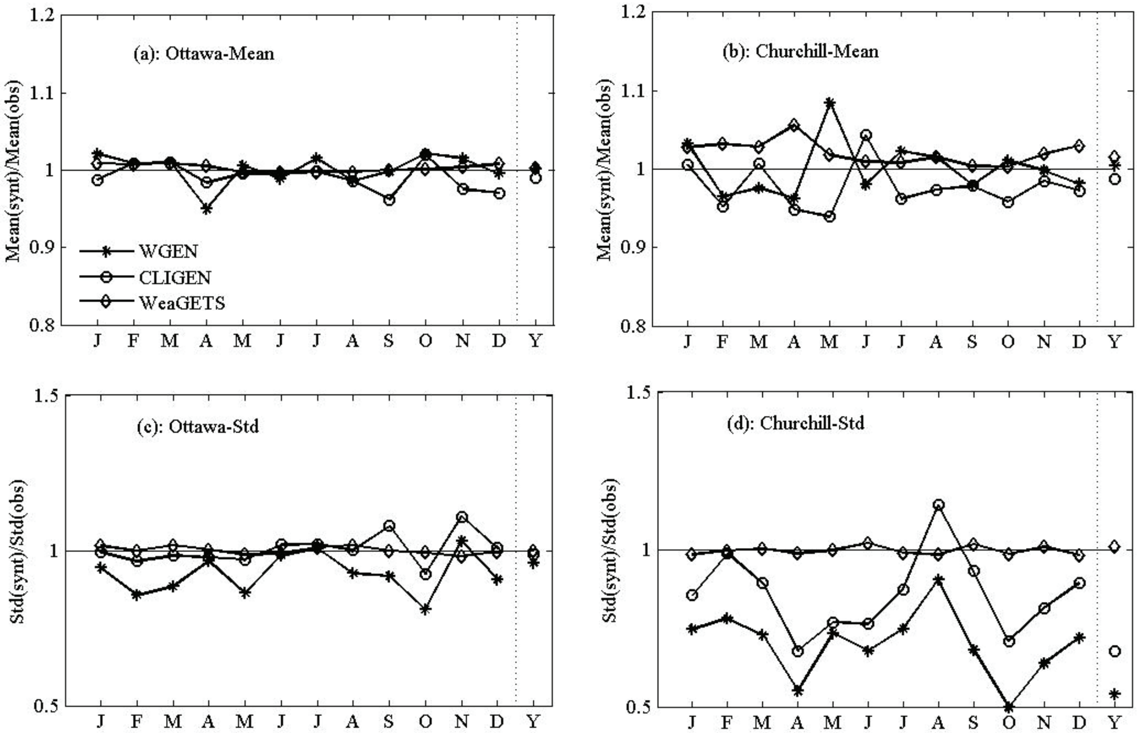

Figure 3. Ratios of the mean and standard deviation (Std) of monthly and annual precipitations derived from the synthetic weather series (synt) to the mean and standard deviations derived from the observed series (obs) for the Ottawa and Churchill stations. The synthetic precipitation is generated by WGEN, CLIGEN, and WeaGETS.

observed series. All three weather generators reproduce monthly and annual averaged precipitations well (figs. 3a and 3b). The slight fluctuations result from the stochastic nature of precipitation generation. However, WGEN and CLIGEN underestimate the variance of monthly and yearly precipitation, as shown in figures 3c and 3d, especially those produced by WGEN for Churchill. WeaGETS reproduces very well the low-frequency variability of precipitation at both month and annual scales.

The annual autocorrelation functions of observed annual precipitation presented in figure 4 display clear trends, indicating that dryer and wetter years do not occur in random order. Both WGEN and CLIGEN simply aim to reproduce the same mean climatology year after year, as shown in figure 4. WeaGETS successfully reproduces the observed autocorrelation of precipitation for both stations because it specifically takes into account the interannual variability.

MAXIMUM AND MINIMUM TEMPERATURES

WGEN and WeaGETS generate T_{max} and T_{min} conditioned on wet and dry states simulated with a first-order Markov model. CLIGEN, on the other hand, generates T_{max}

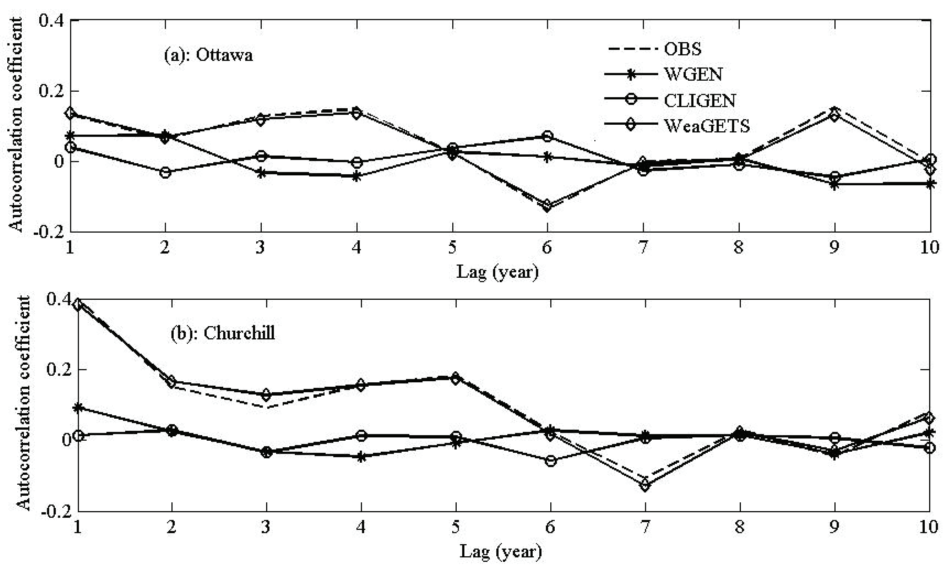

Figure 4. Ten-year lagged autocorrelation of observed (OBS) and averaged annual precipitation produced by three weather generators (WGEN, CLIGEN, and WeaGETS) for the Ottawa and Churchill stations.

Table 6. Statistics of maximum and minimum temperatures (T_{max} and T_{min}) for the Ottawa and Churchill stations.[a]

	Source	Ottawa Obs.	Ottawa WGEN	Ottawa CLIGEN	Ottawa WeaGETS	Churchill Obs.	Churchill WGEN	Churchill CLIGEN	Churchill WeaGETS
T_{max}	Mean	11.0	11.0	11.0	11.0	-2.7	-2.7	-2.7	-2.7
	Std	13.0	12.3	13.0	12.7	15.5	14.5	15.5	15.3
	25th percentile	1.0	-0.2	0.3	-0.7	-15.2	-15.4	-15.2	-14.9
	50th percentile	11.7	12.1	12.1	12.0	-1.4	-2.4	-1.9	-2.2
	75th percentile	22.2	22.5	22.4	22.4	9.3	10.8	9.7	11.0
	95th percentile	29.4	27.7	29.3	29.2	21.9	18.0	20.9	19.3
	99th percentile	32.8	30.0	32.8	32.8	27.4	21.0	26.7	23.3
	Max or Min	37.8	35.5	43.5	38.7	36.9	30.0	45.5	36.3
T_{min}	Mean	0.8	0.4	0.8	0.8	-10.9	-11.7	-11.1	-10.9
	Std	12.0	12.5	12.0	11.9	15.0	15.5	14.9	15.2
	25th percentile	-7.2	-8.8	-7.9	-8.8	-24.6	-24.5	-24.2	-23.6
	50th percentile	1.8	2.2	2.4	2.3	-8.0	-10.3	-8.8	-9.5
	75th percentile	10.6	10.6	10.7	11.0	1.9	2.5	2.2	2.8
	95th percentile	17.2	17.6	17.2	17.1	9.0	9.5	9.2	9.8
	99th percentile	20.0	21.3	20.4	20.9	13.3	12.4	12.4	13.1
	Max or Min	-38.9	-51.6	-50.1	-47.4	-45.4	-70.3	-59.8	-65.4

[a] Obs. = observed data, Std = standard deviation, and Max or Min = all-time maximal T_{max} or all-time minimal T_{min}. The Kolmogorov-Smirnov (K-S) tests between observed and each weather generator generated daily T_{max} and T_{min} are significant at p = 0.01.

Table 7. Mean and standard deviation (Std) of yearly maximum and minimum temperatures (T_{max} and T_{min}) derived from the synthesized and observed series for the Ottawa and Churchill stations. The synthesized precipitation series are generated by WGEN, CLIGEN, and WeaGETS.

	Ottawa				Churchill			
	T_{max}		T_{min}		T_{max}		T_{min}	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Observed	10.98	0.84	0.79	1.09	-2.71	1.25	-10.91	1.18
WGEN	11.00	0.43	0.44	0.51	-2.70	0.66	-10.90	0.71
CLIGEN	10.98	0.29	0.76	0.30	-2.71	0.34	-11.05	0.29
WeaGETS	10.98	0.83	0.79	1.08	-2.71	1.21	-10.91	1.12

and T_{min} independently of the wet and dry states. Table 6 presents the statistics of T_{max} and T_{min} as observed and reproduced by the three weather generators. The results show that both CLIGEN and WeaGETS reproduce the mean of daily temperatures very well. In particular, WeaGETS exactly reproduces the mean of both T_{max} and T_{min}. WGEN slightly underestimates the mean T_{min} because T_{max} and T_{min} are generated unconditionally, resulting in several cases in which T_{min} is greater than T_{max} in a single day. Thus, a range check is imposed to force the generated T_{min} to be less than T_{max}. This procedure affects the statistics of T_{min}. Both CLIGEN and WeaGETS reproduce the standard deviations of T_{max} and T_{min} well. WGEN slightly underestimates the standard deviation of T_{max} and somewhat overestimates the standard deviation of T_{min}. Generally, all three weather generators provide good simulations of all percentiles, even though there are some biases. However, the K-S tests rejected the null hypothesis that the observed and generated data are from the same population for all three weather generator and both stations at a very significant level ($p < 0.01$). As mentioned earlier, this may be a result of the large sample size. Both WGEN and CLIGEN poorly reproduce the all-time maximum and minimum temperatures, especially for the Churchill station. WeaGETS reproduces the all-time maximum T_{max} reasonably well but underestimate the all-time minimum T_{min}. Overall, WeaGETS is consistently better than the other two weather generators for all statistics.

Auto- and cross-correlations of and between daily T_{max} and T_{min} are computed for observed and generated time series (fig. 5). The autocorrelation is a measure of the persistence of temperature trends, and it is an important characteristic to reproduce. CLIGEN consistently underestimates the autocorrelation of both T_{max} and T_{min}. WGEN reproduces the observed lag 1 autocorrelation of T_{max} well, but for larger lags its values are consistently greater than those of the observed data for both stations. WeaGETS reproduces the day-to-day persistence much better. A similar conclusion can also be drawn when looking at cross-correlation, which indicates that the conditional method (combining WGEN and CLIGEN) used in WeaGETS is able to reproduce the auto- and cross-correlation of and between T_{max} and T_{min}.

The means of yearly T_{max} and T_{min} are reproduced very well by all three weather generators for both stations (table 7). As was the case for precipitation, WGEN and CLIGEN underestimate the interannual variability of temperature data, as represented by the standard deviation for both stations. WGEN is somewhat better than CLIGEN. In contrast, WeaGETS preserves the standard deviations of yearly T_{max} and T_{min} very well.

Similar to precipitation, the annual autocorrelation functions of observed T_{max} and T_{min}, presented in figure 6, display clear trends, indicating that warmer and cooler years do not occur in random order. Both WGEN and CLIGEN could not preserve the autocorrelation function for temperatures because they do not take into account the low-frequency component of climate variability. However, WeaGETS successfully reproduces the observed autocorrelation for both stations.

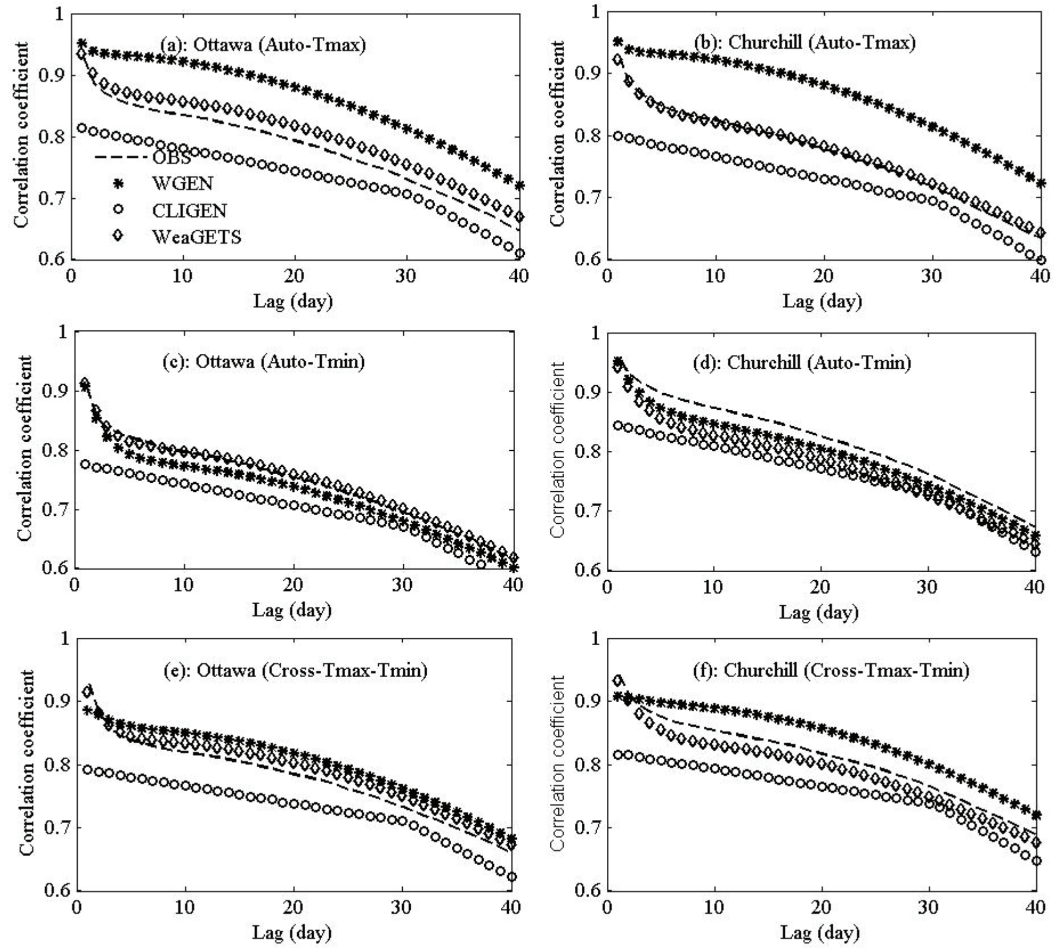

Figure 5. Forty days of lagged auto- and cross-correlation of and between observed (OBS) and WGEN, CLIGEN, and WeaGETS generated data for maximum and minimum temperatures (T_{max} and T_{min}) for the Ottawa and Churchill stations.

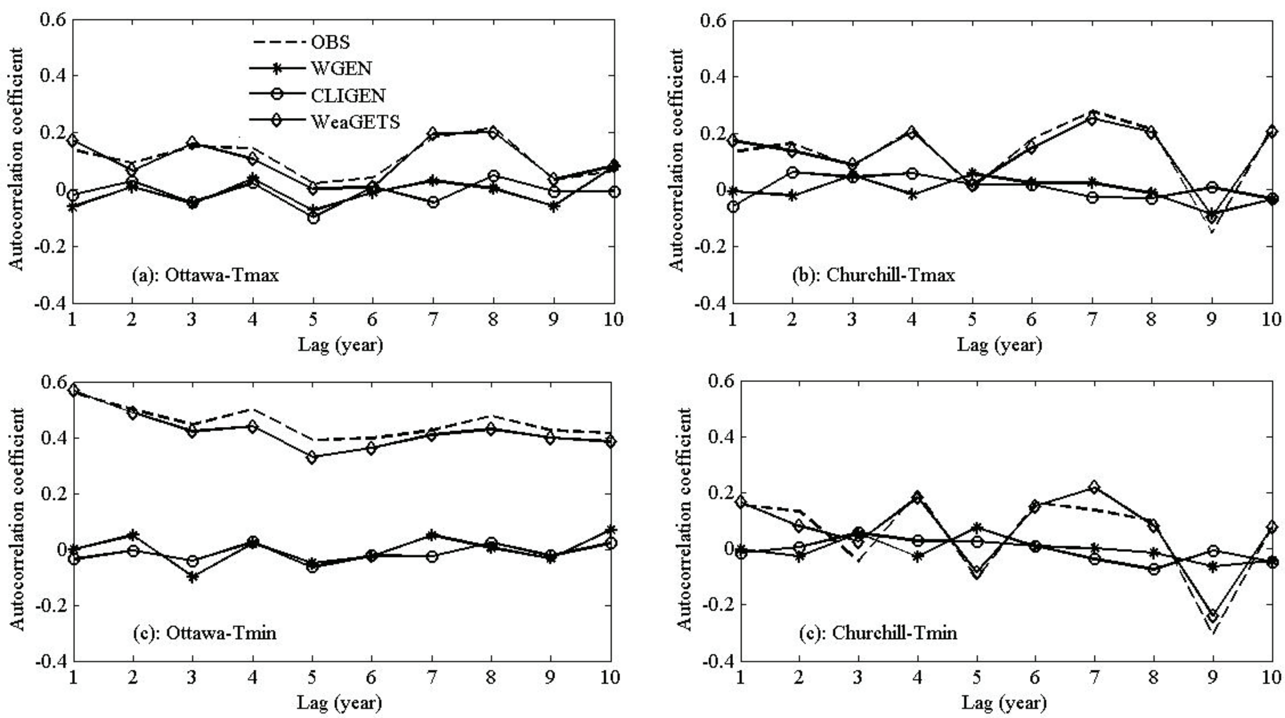

Figure 6. Ten-year lagged autocorrelation of observed (OBS) and averaged annual maximum and minimum temperatures (T_{max} and T_{min}) produced by three weather generators (WGEN, CLIGEN, and WeaGETS) for the Ottawa and Churchill stations.

DISCUSSION AND CONCLUSION

Similar to other weather generators, such as WGEN and CLIGEN, WeaGETS is a daily stochastic weather generator that can generate precipitation, T_{max}, and T_{min} time series of unlimited length for use in agricultural and hydrological impact studies. Furthermore, by perturbing its parameters according to changes projected by climate models, WeaGETS can be used as a downscaling tool for climate change studies. WeaGETS has the unique advantage of incorporating the computational schemes of other well-known weather generators, as well as offering unique options, such as correction of the underestimation of interannual variability and the ability to use Markov chains of varying orders. More importantly, the use of Matlab allows for easy modification of the source code to suit the specific needs of users. It would be very easy, for example, to add additional precipitation distribution functions. Finally, Matlab offers an integrated environment to further analyze the data generated by WeaGETS.

Two Canadian stations were selected to compare the performance of WeaGETS to other two well-known weather generators: WGEN and CLIGEN. The results demonstrate that the most widely used model, a first-order Markov model, is adequate at producing precipitation occurrence, but it underestimates the longest wet and especially dry spells. The higher-order models have positive effects, at the expense of having more parameters to be determined. Since a minimum number of rainfall events needs to be presented to adequately estimate transition probabilities, second- and third-order parameter estimation requires longer time series of observed precipitation. If the goal is to use WeaGETS as a downscaling tool for climate change studies, the first-order process is usually more practical because it only requires the perturbation of two parameters. The mixed exponential and skewed normal Pearson III distributions are consistently better than the exponential and gamma distributions in generating precipitation amount. In particular, the mixed exponential distribution is the best at reproducing the extreme precipitation events. This is because precipitation extremes are known to have a different distribution compared to the daily precipitation observations to which the distribution is mostly fitted (Wilks, 1999). Thus, the two-component distribution (one component for extremes, and the other component for the other precipitation events) is more suitable at representing precipitation extremes. WeaGETS is better than WGEN and CLIGEN at simulating temperatures, especially at preserving autocorrelations of T_{max} and T_{min} and cross-correlation between T_{max} and T_{min}. Both WGEN and CLIGEN underestimate the monthly and interannual variances of precipitation and temperatures. The included spectral correction approach option in WeaGETS is very successful in resolving this underestimation problem.

Although WeaGETS is more flexible than other available weather generators in generating precipitation, T_{max}, and T_{min}, it does have a few limitations. The first limitation is linked to the spectral correction approach that keeps the precipitation occurrence process constant. Ongoing work shows that the transition probabilities also display interannual variability. However, a relatively simply approach to adjust the low-frequency variability of precipitation occurrence remains elusive. Secondly, the low-frequency variability of temperatures is only corrected at the yearly scale. Consequently, the monthly variability is improved, but it is not as good as that at the yearly scale (results not shown). This is because the correction of interannual variability has a limited effect at the monthly scale (Chen et al., 2010). Thus, it may be necessary to correct the monthly variability at the same time, but this may bring along overfitting problems, resulting in cases in which T_{min} is greater than T_{max} on a given day. Therefore, this type of correction is not incorporated into this version of WeaGETS. Thirdly, when working with weather generators, there is always the danger that more complex schemes dealing with secondary statistics may have a negative impact on the more fundamental distribution properties of the generated variables. Finally, only two stations were used to demonstrate and compare the performances of the three weather generators. The performances may be different for other regions with different climates. For example, the distribution of extreme precipitation can vary quite drastically on a regional basis, and it is no simple task to find a distribution that is suitable for all climate zones. However, as mentioned earlier, both WGEN and CLIGEN have been used and tested extensively at other locations under various climates (Semonev et al., 1998; Zhang and Garbrecht, 2003; Zhang, 2004; Taulis and Milke, 2005; Chen et al., 2008, 2009). WeaGETS can also be considered as having been extensively tested, since it shares the same major components. Previous versions of WeaGETS have also been used extensively in Canada over the past ten years in various climate zones (Caron, 2006; Chen et al., 2010, 2011b). Additional evaluations will be conducted for future WeaGETS versions.

ACKNOWLEDGEMENTS

This work was partly supported by the Natural Science and Engineering Research Council of Canada (NSERC), Hydro-Québec, Manitoba Hydro, and the Ouranos Consortium on Regional Climatology and Adaptation to Climate Change.

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