Assessment and Improvement of Stochastic Weather Generators in Simulating Maximum and Minimum Temperatures

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

Abstract. *Stochastic weather generators are commonly used to generate time series of weather variables to drive agricultural and hydrologic models. One of their most appealing features is the ability to rapidly generate the very long time series used in agricultural and hydrological impact studies. However, they also have various problems, such as the inability to represent the interannual variability of the climate system, and it is difficult for them to accurately preserve the auto- and cross-correlation of maximum and minimum temperatures (T_{max} and T_{min}). This research aims to merge two widely used weather generators (CLIGEN (v5.22564) and WGEN) into a hybrid method that combines the strengths of each (referred to as the conditional method) for generating T_{max} and T_{min} and apply an approach to correct the interannual variability of T_{max} and T_{min} (referred to as the spectral correction method). The results show that CLIGEN reproduced mean daily T_{max} and T_{min} very well. WGEN also produced mean daily T_{max} reasonably well but slightly underestimated mean daily T_{min}. Moreover, CLIGEN was better than WGEN at producing standard deviations of daily T_{max} and T_{min}. The conditional and spectral correction methods resulted in a weather generator that accurately produced means, standard deviations, and extremes of daily T_{max} and T_{min}. The auto- and cross-correlations of and between daily T_{max} and T_{min} were well reproduced and much better than those of CLIGEN- and WGEN-generated data. Moreover, the spectral correction approach successfully reproduced the observed interannual variability of T_{max} and T_{min}.*

Keywords. *CLIGEN, Climate variability, Stochastic weather generator, Temperature, WGEN.*

With the growing use of physically based response models such as hydrological and agricultural models, there has been a more frequent requirement for weather generators to generate long meteorological time series to simulate the long-term effects of climate variability. Over the past three decades, several weather generators have been developed to meet this requirement, such as Weather Generator (WGEN) (Richardson, 1981; Richardson and Wright, 1984), USCLIMATE (Hanson et al., 1994), Climate Generator (CLIGEN) (Nicks et al., 1995), Climate Generator (ClimGen) (Stockle et al., 1999), and the Long Ashton Research Station Weather Generator (LARS-WG) (Semenov and Barrow, 2002). The main reason for the development of weather generators is their ability to generate long-term synthetic daily weather data that statistically resemble the observed historical record. Weather generators can also be used to generate weather data for ungauged basins by interpolating model parameters from adjacent gauged sites. More recently, another application of weather generators is to use them as a downscaling tool to generate climate projections at the daily time scale to quantify the impacts of future climate change (Semenov and Barrow, 1997; Wilks, 1992, 1999; Pruski and Nearing, 2002; Zhang et al., 2004; Zhang, 2005; Zhang and Liu, 2005). This use is achieved by perturbing the weather generator parameters according to relative changes projected by a climate model (Chen et al., 2011). Of all the aforementioned weather generators, WGEN and CLIGEN are arguably the most widely used for simulating daily weather time series including precipitation, maximum and minimum temperatures (T_{max} and T_{min}), and solar radiation.

Over the past few decades, numerous studies have been conducted to evaluate, improve, and compare the performance of weather generators (Qian et al., 2004; Semenov et al., 1998; Zhang and Garbrecht, 2003; Hayhoe, 2000, Chen et al., 2009). Weather generators are good at reproducing precipitation occurrence and quantity (Semenov et al., 1998; Chen et al., 2008, 2009), but have difficulties dealing with interannual variability. Several methods have been presented to correct this problem (Hansen and Mavromatis, 2001; Dubrovsky et al., 2004; Wang and Nathan, 2007; Chen et al., 2010). Compared to precipitation, the simulation of temperatures has been given less attention in the literature. Weather generators also significantly underestimate the monthly and annual variability of temperatures (Dubrovsky et al., 2004). Dubrovsky et al. (2004) applied a monthly generator (based on a first-order linear autoregressive model) to adjust the low-frequency variability of T_{max} and T_{min} based on a WGEN-like weather genera-

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Table 1. Comparison of the WGEN, CLIGEN, and conditional method algorithms at generating maximum and minimum temperatures (T_{max} and T_{min})

No.	WGEN	CLIGEN	Conditional Method
1	T_{max} and T_{min} are conditioned on wet and dry states.	T_{max} and T_{min} are not conditioned on wet and dry states.	T_{max} and T_{min} are conditioned on wet and dry states.
2	The time series of observed data is reduced to a time series of residual elements. (daily basis).	Parameters are calculated for each month (monthly basis).	The time series of observed data is reduced to a time series of residual elements (daily basis).
3	Residual elements are analyzed to determine the auto- and cross-correlation of and between T_{max} and T_{min}.	Two random numbers are used to generate the standard normal deviate. The second number for one day is reused as the first number for the following day.	Residual elements are analyzed to determine the auto- and cross-correlation of and between T_{max} and T_{min}.
4	Generating residual series of T_{max} and T_{min} is based on a first-order linear autoregressive model. The daily values of T_{max} and T_{min} are found by multiplying the residuals by the standard deviation and adding the mean.	The smaller standard deviation of T_{max} or T_{min} is used as a base, and the other parameter is generated conditioned on the chosen parameter.	The smaller standard deviation of T_{max} or T_{min} is used as a base, and the other parameter is generated conditioned on the chosen parameter.
5	T_{max} and T_{min} are generated unconditionally, resulting in several cases in which T_{min} is larger than T_{max} on a given day. A range-check scheme is imposed to force T_{min} to be smaller than T_{max}.	T_{min} is generated conditioned on T_{max} to ensure that it is less than T_{max} on a given day. The range check scheme is unnecessary.	T_{min} is generated conditioned on T_{max} to ensure that it is less than T_{max} on a given day. The range check scheme is unnecessary.

tor. The results demonstrated that conditioning a daily weather generator on a monthly model has positive effects. However, this model was still unable to accurately reproduce yearly variances and autocorrelations of observed temperatures because it did not specifically consider the interannual variability. To date, no other approaches have been proposed to correct the underestimation of monthly and annual temperature variability. One of the explanations for this lacuna may be that temperatures are not considered as important as precipitation in some practical applications, such as hydrological studies.

The preservation of the auto- and cross-correlations for and between T_{max} and T_{min} is an important criterion for assessing the ability of a weather generator to simulate temperatures, but very few approaches have tried to address this problem. For example, CLIGEN uses two random numbers to generate the standard normal deviate. The second number for one day is reused as the first number for the following day. This method has limited effects, however, especially for evaluating day-to-day persistence (Zhang, 2004; Chen et al., 2008). WGEN uses a first-order linear autoregressive model to generate the residual series of T_{max} and T_{min}. According to this scheme, the lag 0 and lag 1 correlations are derived from the observed data, and lag k's correlation coefficient is given by the kth power of the lag 1 correlation. This approach is thus effective at reproducing lag 0 and lag 1 correlations, but lags greater than one day are not well preserved (Richardson, 1981).

The objectives of this work were to merge two widely used weather generators (CLIGEN (v5.22564) and WGEN) into a hybrid method that combines the strengths of each for generating T_{max} and T_{min} and apply an approach to correct the interannual variability of T_{max} and T_{min}.

Methodology

Stochastic Weather Generators

The two weather generators compared here, CLIGEN and WGEN, are arguably the ones most commonly used. They generate synthetic daily weather data using statistics derived from observed data based on a normal distribution, combined with a random number generator. Table 1 briefly summarizes the differences between the two weather generators at producing T_{max} and T_{min}. More details are presented below.

WGEN

WGEN is a four-variate (precipitation, T_{max}, T_{min} and solar radiation), single-site, stochastic weather generator (Richardson, 1981; Richardson and Wright, 1984). It 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 mean and dividing by the standard deviation. The means and standard deviations are conditioned on the wet or dry status (Richardson 1981). The residual series are then generated by:

$$x_{p,i}(j) = Ax_{p,i-1}(j) + B\varepsilon_{p,i}(j) \tag{1}$$

where $x_{p,i}(j)$ 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; and 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:

$$A = M_1 M_0^{-1} \tag{2}$$

$$BB^T = M_0 - M_1 M_0^{-1} M_1^T \tag{3}$$

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 and adding the mean using the following equations:

$$T_{max} = \mu_{max} + \sigma_{max} \cdot x_{p,i} \tag{4}$$

$$T_{min} = \mu_{min} + \sigma_{min} \cdot x_{p,i} \tag{5}$$

Because T_{max} and T_{min} are generated unconditionally using equations 4 and 5, there are several cases in which the generated T_{min} is larger than T_{max} on a given day. To resolve this problem, a range check is imposed, forcing T_{min} to be smaller than T_{max} (e.g., T_{min} may be set to T_{max} - 1). However, this has an undesirable effect on the mean and standard deviation of T_{min}.

CLIGEN

The CLIGEN weather generator generates daily values of T_{max}, T_{min}, dewpoint temperature, solar radiation, and wind velocity and direction, as well as precipitation-related variables such as precipitation occurrence, quantity, duration, peak storm intensity, and time to peak intensity, based on long-term monthly statistical parameters (Nicks et al., 1995). This article only focuses on the generation of T_{max} and T_{min}.

Daily T_{max} and T_{min} are generated using normal distributions. The long-term monthly statistical parameters, including the mean and standard deviation, are used to run CLIGEN to generate daily weather series. Specifically, for CLIGEN (v5.22564), the temperature with the smaller standard deviation between T_{max} and T_{min} is computed first, 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}, then daily temperatures are generated by equations 6 and 7:

$$T_{min} = \mu_{min} + \sigma_{min} \cdot \chi \tag{6}$$

$$T_{max} = T_{min} + \left(\mu_{max} - \mu_{min}\right) + \sqrt{\sigma_{max}{}^2 - \sigma_{min}{}^2} \cdot \chi \tag{7}$$

If the standard deviation of T_{max} is less than that of T_{min}, then daily temperatures are generated by equations 8 and 9:

$$T_{max} = \mu_{max} + \sigma_{max} \cdot \chi \tag{8}$$

$$T_{min} = T_{max} - \left(\mu_{max} - \mu_{min}\right) - \sqrt{\sigma_{min}{}^2 - \sigma_{max}{}^2} \cdot \chi \tag{9}$$

where μ is the monthly mean of the daily temperatures, σ is the standard deviation of daily temperatures, and χ is a generated standard normal deviate, which is obtained for each day using two random numbers. A T_{min} value generated using this scheme is always less than T_{max}, which eliminates any need for the range check that must be used in WGEN to ensure that T_{min} is less than T_{max}.

Conditional Method

The main motivation for this work was to combine the most desirable properties of both weather generators into a hybrid method to maximize the strengths and minimize the drawbacks of each. To achieve this, WGEN is used as the basic weather generator. The residual series of T_{max} and T_{min} conditioned on wet and dry states are generated by a first-order linear autoregressive model (eqs. 1 through 3). But instead of using equations 4 and 5, the conditional equations 6 through 9 derived from CLIGEN are used, to ensure that T_{min} is always less than T_{max} on a given day. The residual series developed in equations 1 through 3 were further used in equations 6 through 9 as normal variates rather than using two random numbers. Thus, the range check is no longer necessary. Throughout this article, this is referred to as the conditional method. More details are presented in table 1.

Correction of InterAnnual Variability

An important goal of this work was to specifically correct the interannual variability of T_{max} and T_{min} using the power spectra of observed time series at the yearly scale. The power spectra are computed using fast Fourier transforms (FFT). This approach was proposed by Chen et al. (2010) for correcting the low-frequency variability of precipitation for weather generators.

The use of FFT is widespread in engineering and signal processing, and it stems from the concept that any discrete signal (such as yearly averaged T_{min} at a station) can be exactly represented by a summation of sine waves with magnitude S and phase ϕ. Following the FFT, each sine wave component is expressed as a complex number:

$$\mathrm{C} = X + i * Y \quad \left(i = \sqrt{-1}\right) \tag{10}$$

from which the magnitude S and phase ϕ can be extracted with the following equations:

$$S = \left|C\right| = \sqrt{X^2 + Y^2} \tag{11}$$

$$\varphi = \tan^{-1}\left(Y/X\right) \tag{12}$$

The variance and phase of each component can be modified and returned back in complex form with the following equation, and then returned back to the time domain with an inverse FFT:

$$C = S * e^{(i*\varphi)} \tag{13}$$

By modifying the phase of each component and reverting to the time domain, a new signal with an identical power spectrum (and variance) can be created. As such, low-frequency components (such as decadal variability) will be preserved in the new signal. This property is used to modify the daily sequences from the weather generator in order to correct for the underestimated variances at the interannual scale. Throughout this article, this procedure is referred to as the spectral correction method, and it is comprised of three steps:

1. Daily T_{max} and T_{min} time series are generated by WGEN with the conditional method using parameters derived from the observed daily temperature series. In this study, the length of the generated series was 20 times that of the observed series in order to obtain the true expectancy of a weather generator. Using short time series could result in biases due to the random nature of the stochastic process.

Table 2. Diagnostics for comparing each method.

No.	Diagnostics
1	Mean and standard deviation of daily T_{max} and T_{min}
2	Averaged yearly maximum T_{max} and minimum T_{min}
3	Auto- and cross-correlations of and between T_{max} and T_{min}
4	Autocorrelation of averaged yearly T_{max} and T_{min}
5	Mean and standard deviation of averaged yearly T_{max} and T_{min}

Table 3. Location, record period, and average annual maximum and minimum temperature for six stations.

Region	Station	Latitude (°N)	Longitude (°W)	Elevation (m)	Records of Daily Data	Averaged Yearly T_{max} (°C)	Averaged Yearly T_{min} (°C)
Vancouver Island	Victoria	48.65	123.32	19	1941-2006 (66)	14.10	5.38
Queen Charlotte Islands	Langara	54.25	133.05	14	1937-2006 (70)	9.86	5.55
Okanagan River basin	VGR[a]	50.23	119.20	482	1907-1996 (90)	12.70	1.92
Mackenzie	Yellowknife	62.47	114.43	206	1945-2002 (58)	-0.57	-9.34
Nelson and Churchill River basin	Churchill	58.73	94.05	29	1947-2006 (60)	-2.72	-10.91
Middle St. Lawrence River basin	Dorval	45.47	73.75	36	1943-1994 (52)	11.08	1.59

[a] VGR = Vernon Goldstream Ranch.

2. Interannual variability is modeled based on a power spectrum using FFT. The generation of a new power spectrum for T_{max} is achieved by assigning random phases to each spectral component represented by a complex number, as mentioned above, and then transferring back to the time domain using the inverse FFT. Random phases were chosen from a uniform distribution over the range [0, 2π]. To be sure not to perturb the cross-correlation between T_{max} and T_{min}, the random phases used to generate the power spectrum of T_{max} were reused to generate that of T_{min}.

3. The daily T_{max} and T_{min} series generated in step 1 are adjusted incrementally. The series of yearly averaged T_{max} and T_{min} calculated from the daily series generated in step 1 are adjusted to the yearly averaged T_{max} and T_{min} series generated in step 2. In other words, the differences of the two yearly time series (one calculated from the daily time series generated in step 1, and the other generated in step 2 using FFT) are added to the daily time series generated in step 1 for every year.

Validation of Each Method

The diagnostics listed in table 2 were used to compare the observed and synthesized T_{max} and T_{min}. Two tailed *t*-tests and F-tests were conducted to test the equality of the mean and standard deviation between observed and synthesized T_{max} and T_{min} time series, respectively. A significance level of $p = 0.05$ was used for these tests.

Meteorological Data

Meteorological data, including daily T_{max}, T_{min}, and precipitation for six stations dispersed across Canada, were used to drive the weather generators. To be consistent with a previous study, the chosen meteorological stations are the same stations used by Chen et al. (2010) to verify the spectral correction method for correcting low-frequency preci–pitation variability. Basic information, including longitude, latitude, elevation, record duration, and averaged yearly T_{max} and T_{min} for these stations is given in table 3. Averaged yearly temperatures at these stations varied from -2.72°C at Churchill to 14.10°C at Victoria for T_{max}, and from -10.91°C at Churchill to 5.55°C at Langara for T_{min}, adequately representing the natural climate variability in Canada.

Results

Relationship Between Averaged Yearly Precipitation and Temperatures

One of the goals of this article is to apply a method to correct the interannual variability of T_{max} and T_{min} for weather generators. In order to do this, correlations between averaged yearly temperatures and precipitation were looked at. If averaged yearly temperatures are strongly correlated with precipitation, then the correlation may be perturbed by correction schemes.

Table 4. Correlation between averaged yearly T_{max} (T_{min}) and precipitation for six stations.

Station	T_{max} vs. Precipitation R[a]	T_{max} vs. Precipitation p-Value	T_{min} vs. Precipitation R[a]	T_{min} vs. Precipitation p-Value
Victoria	0.120	0.338	0.191	0.125
Langara	0.207	0.085	0.207	0.058
VGR	0.152	0.093	0.022	0.835
Yellowknife	0.176	0.187	0.237	0.074
Churchill	0.270	0.037	0.256	0.048
Dorval	0.183	0.193	0.126	0.374

[a] R = Correlation coefficient.

The correlation between averaged yearly temperatures and precipitation was tested for six stations (table 4). The results showed that there is no significant correlation between the averaged yearly T_{max} (T_{min}) and precipitation at the $p = 0.05$ level, with the exception of the Churchill station where the correlation is nevertheless small. Therefore, it was assumed that the interannual variability of T_{max} and T_{min} may be corrected independently of precipitation.

Power Spectra of Mean Yearly Temperature Time Series

Figures 1a and 1b show the time series and power spectra of the mean observed yearly T_{min} at the Yellowknife station. Figure 1b clearly shows that warmer and colder years are not randomly distributed and display patterns associated with natural climate variability. In this case, there are strong 3- and 10-year oscillations. By assigning random phases to each component of the power spectrum and reverting to the time domain, a new signal (mean yearly T_{min}) with an identical power spectrum (and thus showing the same variability) can be created. This mean yearly T_{min} time series (fig. 1c) has a power spectrum (fig. 1d) that is almost identical to the one shown in figure 1b.

Statistics of Maximum and Minimum Temperatures

All of the methods, including CLIGEN, WGEN, and the conditional and spectral correction approaches, reproduced the mean daily T_{max} very well (table 5). In particular, the mean daily T_{max} was exactly produced by the spectral correction method. The *t*-tests showed that there is no significant difference between observed and the method-generated T_{max} at the $p = 0.05$ level. WGEN somewhat underestimated the standard deviation of daily T_{max}. The

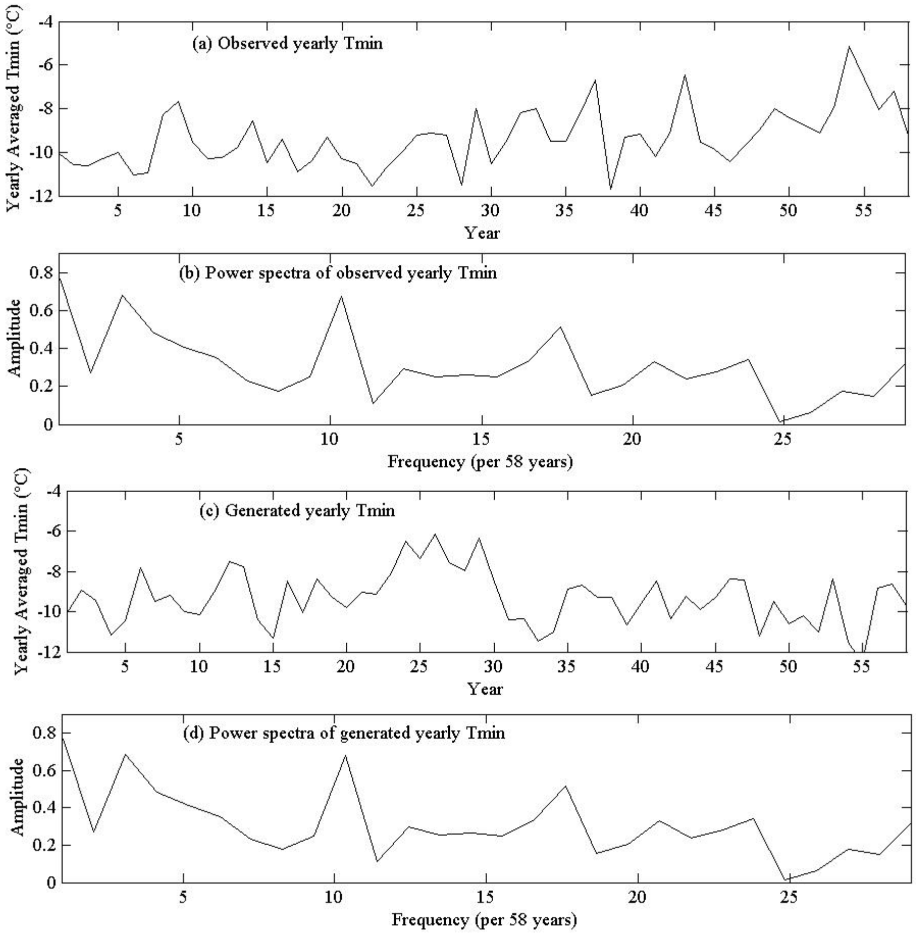

Figure 1. (a and c) Time series and (b and d) their power spectra of observed and generated averaged yearly T_{min} at the Yellowknife station.

Table 5. Statistics (°C) of daily T_{max} by location and source.[a]

Station	Statistic	OBS	WGEN	CLIGEN	CON	SPC
Victoria	Mean	14.10	14.09	14.10	14.10	14.10
	SD	6.36	6.06*	6.36	6.25*	6.26*
	Averaged yearly max.	30.75	28.05	29.85	29.55	29.51
Langara	Mean	9.86	9.86	9.86	9.87	9.86
	SD	4.43	4.35*	4.43	4.39	4.43
	Averaged yearly max.	20.70	19.64	20.00	19.90	19.89
VGR	Mean	12.70	12.72	12.70	12.68	12.70
	SD	11.28	10.73*	11.28	11.04*	11.07*
	Averaged yearly max.	34.81	33.22	37.45	36.43	36.46
Yellowknife	Mean	-0.57	-0.56	-0.57	-0.59	-0.57
	SD	16.77	15.80*	16.76	16.55*	16.67
	Averaged yearly max.	28.46	24.04	29.95	28.56	28.59
Churchill	Mean	-2.71	-2.72	-2.70	-2.76	-2.71
	SD	15.46	14.47*	15.48	15.37	15.40
	Averaged yearly max.	30.35	23.38	31.58	26.13	26.19
Dorval	Mean	11.08	11.07	11.08	11.05	11.08
	SD	12.55	11.77*	12.54	12.35*	12.36*
	Averaged yearly max.	32.79	30.15	34.50	34.40	34.43

[a] Asterisk (*) indicates value is different from observed time series at p = 0.05. OBS = observed T_{max}, CON = conditional method generated T_{max}, SPC = spectral correction method corrected T_{max}, SD = standard deviation, and Averaged yearly max. = averaged yearly maximum T_{max}.

F-tests showed that observed and WGEN-generated T_{max} are significantly different for all six stations. The standard deviations of CLIGEN generated-data virtually matched those from observation in all cases. All of the F-tests between observed and CLIGEN-generated data were insignificant at p = 0.05. Standard deviations of daily T_{max} produced by the conditional and spectral correction methods were better than those generated by WGEN but worse than those generated by

Table 6. Statistics (°C) of daily T_{min} by location and source.[a]

Station	Statistic	OBS	WGEN	CLIGEN	CON	SPC
Victoria	Mean	5.38	5.30*	5.38	5.38	5.38
	SD	4.72	4.86*	4.72	4.69	4.71
	Averaged yearly min.	-8.09	-8.60	-8.30	-7.11	-7.06
Langara	Mean	5.55	5.38*	5.55	5.56	5.55
	Std. dev	4.21	4.20	4.21	4.21	4.21
	Averaged yearly min.	-7.90	-6.63	-6.77	-7.23	-7.25
VGR	Mean	1.92	1.69*	1.90	1.86	1.91
	SD	8.23	8.51*	8.24	8.14*	8.18
	Averaged yearly min.	-25.57	-24.66	-25.28	-21.53	-21.47
Yellowknife	Mean	-9.34	-10.27*	-9.35	-9.42	-9.34
	SD	17.02	17.89*	17.01	16.97	17.01
	Averaged yearly min.	-44.62	-57.34	-51.10	-54.51	-54.43
Churchill	Mean	-10.91	-11.65*	-11.00	-10.97	-10.91
	SD	14.97	15.52*	14.98	15.29*	15.32*
	Averaged yearly min.	-40.84	-49.86	-46.89	-49.45	-49.38
Dorval	Mean	1.59	1.17*	1.59	1.54	1.59
	SD	11.74	12.34*	11.73	11.69	11.70
	Averaged yearly min.	-28.87	-34.34	-31.62	-26.48	-26.43

[a] Asterisk (*) indicates value is different from observed time series at p = 0.05. OBS = observed T_{min}, CON = conditional method generated T_{min}, SPC = spectral correction method corrected T_{min}, SD = standard deviation, and Averaged yearly min. = averaged yearly minimum T_{min}.

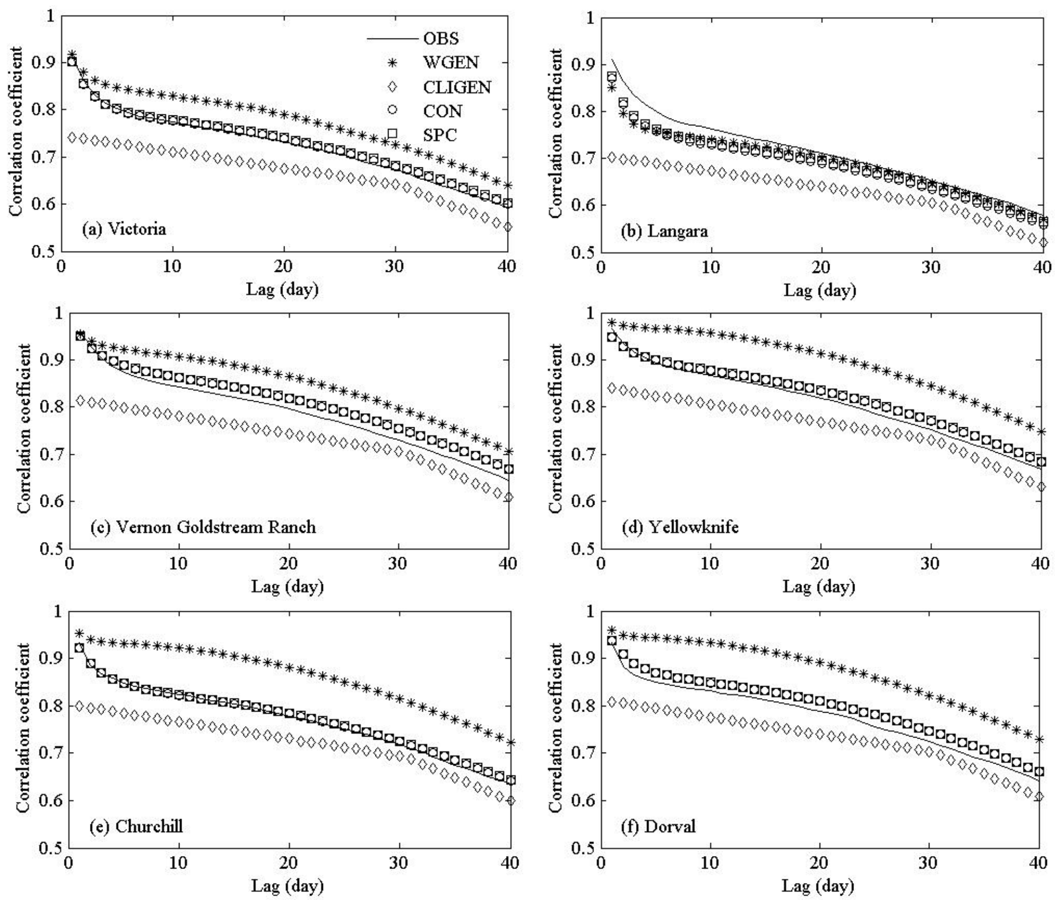

Figure 2. 40 days of lagged autocorrelation for observed (OBS), CLIGEN generated, WGEN generated, conditional method generated (CON), and spectral correction method corrected (SPC) daily T_{max} for the six stations.

CLIGEN. The F-tests showed that the observed standard deviations of generated data were significantly different for the conditional method (four of the six stations) and for the spectral correction method (three of the six stations). Looking at extremes, WGEN was the worst at preserving the averaged yearly maximum temperature, with a mean absolute error (MAE) of 3.23°C. CLIGEN and the conditional and spectral correction methods were all better, with MAEs of 1.44°C, 1.59°C, and 1.60°C, respectively.

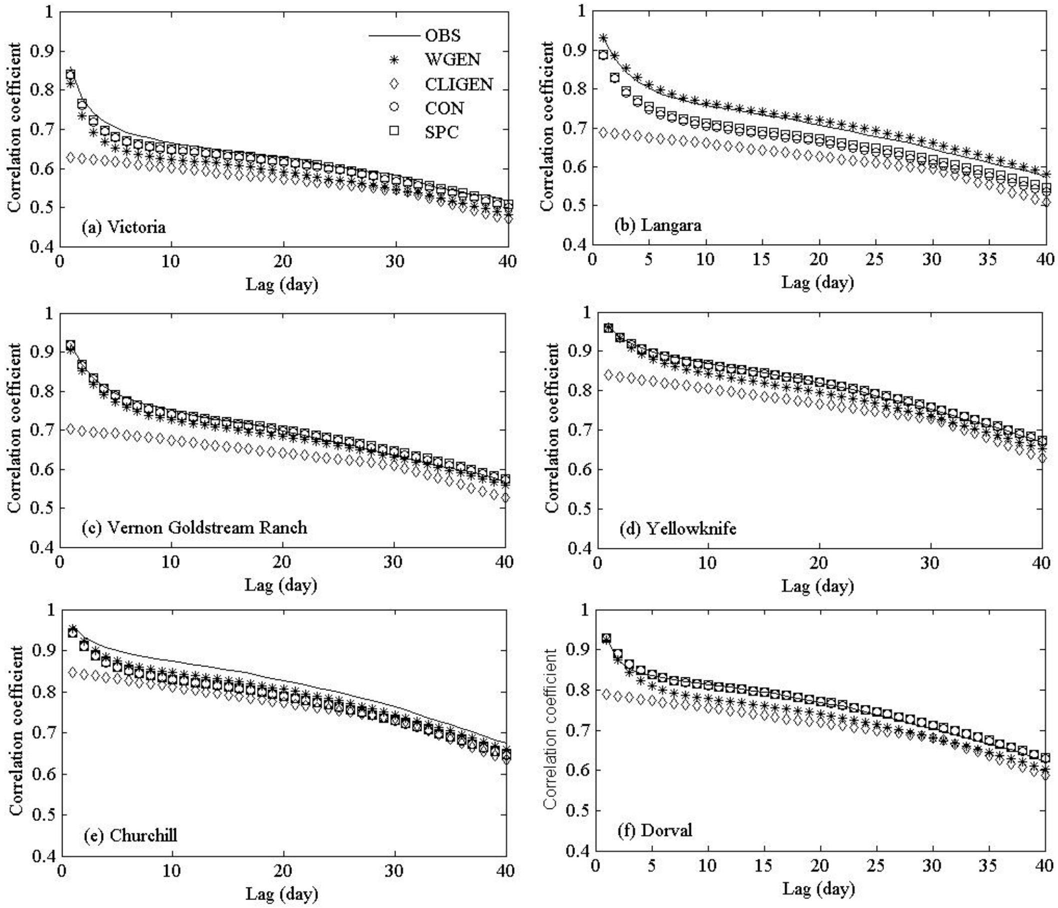

Figure 3. 40 days of lagged autocorrelation for observed (OBS), CLIGEN generated, WGEN generated, conditional method generated (CON) and spectral correction method corrected (SPC) daily T_{min} for the six stations.

Table 6 shows that WGEN performed the poorest at reproducing T_{min}, with MAEs of mean, standard deviation, and averaged yearly minimum T_{min} of 0.43°C, 0.41°C, and 4.98°C, respectively. The *t*-tests and F-tests showed that the means and standard deviations of the observed data were significantly different from those generated with WGEN at p = 0.05 for all stations and for five of the six stations, respectively. This is essentially because of the range check imposed in WGEN to ensure that the daily T_{min} is less than T_{max} on any given day. CLIGEN reproduced the mean and the standard deviation of T_{min} very well for all six stations. Both the conditional and spectral correction methods reproduced T_{min} reasonably well, although there were significant differences for standard deviations for two stations and for one station, respectively. For extreme T_{min}, WGEN again fared less well, with an MAE of 4.98°C for the averaged yearly T_{min}. CLIGEN performed the best, with an MAE of 2.82, while the conditional and spectral correction methods had the same MAE (4.43°C).

Auto- and Cross-Correlation of Daily Temperatures

Auto- and cross-correlations of and between daily T_{max} and T_{min} were computed for unfiltered observed and synthesized data sets. Figure 2 shows the results for T_{max}. The observed data show a clear day-to-day persistence. WGEN predictably reproduced the observed lag 1 autocorrelation, but lags greater than one day were consistently greater than those of the observed data with the exception of the wettest station (Langara). This indicates that WGEN may preserve the autocorrelation correctly for very wet stations. CLIGEN consistently underestimated day-to-day persistence. The conditional and spectral correction methods reproduced not only the day-to-day persistence but also the month-to-month persistence, as shown by the 30-day lag results.

Similarly to its results for T_{max}, CLIGEN consistently underestimated the autocorrelation of T_{min}, especially at the day-to-day persistence (fig. 3). The other three methods worked well, although WGEN was systematically inferior to the conditional and spectral correction methods. The range check imposed in WGEN has little effects on the autocorrelation of T_{min}.

Cross-correlation persistence between T_{max} and T_{min} is shown in figure 4. CLIGEN data underestimated the cross-correlations between T_{max} and T_{min}. Once again, WGEN showed better performance than CLIGEN, while the conditional and spectral correction methods were the most successful at reproducing the observed cross-correlations.

Autocorrelation of Averaged Yearly Temperatures

Figure 5 displays the autocorrelation function of the observed averaged yearly T_{min}. It clearly indicates that warmer and cooler years are not random, but rather come in series, as was shown by the power spectra of averaged yearly T_{min} series (fig. 1). Since similar results were obtained with

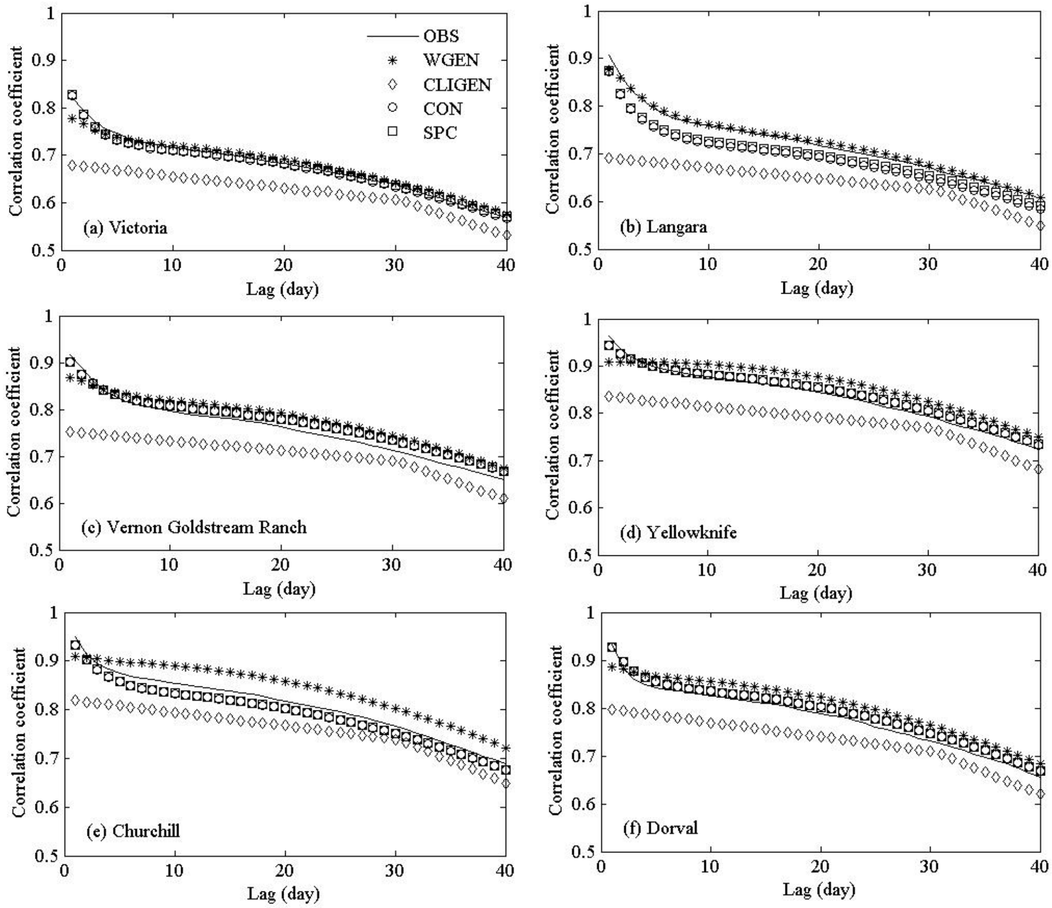

Figure 4. 40 days of lagged cross correlation between observed (OBS), CLIGEN generated, WGEN generated, conditional method generated (CON) and spectral correction method corrected (SPC) daily T_{max} and those of daily T_{min} for the six stations.

T_{max}, only the results of T_{min} are shown in figure 5. WGEN, CLIGEN, and the conditional method could not preserve the autocorrelation function for temperatures because they do not take into account the low-frequency component of climate variability. Instead, they try to reproduce the average year, every year. The spectral correction method successfully reproduced the observed autocorrelation for all six stations.

Interannual Variability of Maximum and Minimum Temperature

All methods reproduced the mean yearly T_{max} and T_{min} very well (table 7), with the exception of WGEN, which had some problems with T_{min}. The *t*-tests showed that mean yearly T_{min} values generated by WGEN were significantly different at p = 0.05 for five out of six stations. As mentioned earlier, this occurs because a range check is used with WGEN to ensure that T_{min} is less than T_{max} on any given day, thereby perturbing the statistics of T_{min}.

CLIGEN, WGEN, and the conditional method under-estimated the interannual variability of averaged yearly T_{max} and T_{min}, as represented by their standard deviations (table 8). The F-tests showed that there is a statistically significant difference between the observed data and that generated from the three methods for all six stations at the p = 0.05 level. The conditional method somewhat improved the simulation of yearly T_{max}. This was because equation 7 was used to generate T_{max} if the standard deviation of T_{max} was larger than or equal to the standard deviation of T_{min}, which implies that the standard deviation of T_{max} was conditioned on the standard deviation of T_{min} in some cases. The spectral correction method preserved the standard deviations of averaged yearly T_{max} and T_{min} very well for all stations. All the F-tests between the standard deviations of observed data and the spectral correction method corrected data were insignificant at the p = 0.05 level.

Discussion and Conclusions

Two weather generators, CLIGEN and WGEN, were compared with respect to the generation of minimum and maximum temperatures (T_{max} and T_{min}). Both generate T_{max} and T_{min} based on a normal distribution; the main differences are that unlike WGEN, CLIGEN generates T_{max} and T_{min} conditioned on each other, and the two weather generators use different schemes to preserve the auto- and cross-correlation of and between T_{max} and T_{min}. The results showed that CLIGEN reproduced the mean and standard deviation of daily T_{max} and T_{min} very well, and better than WGEN. This is because WGEN's unconditional generation of T_{max} and T_{min} resulted in a large number of cases where T_{min} is larger than T_{max} in a day, and any scheme forcing T_{min} to be smaller than T_{max} perturbs the statistics of T_{min}. WGEN reproduced the observed lag 1 autocorrelation very well, but its performance deteriorated rapidly for greater lags, with the exception of the wettest station (Langara). The autocorrela-

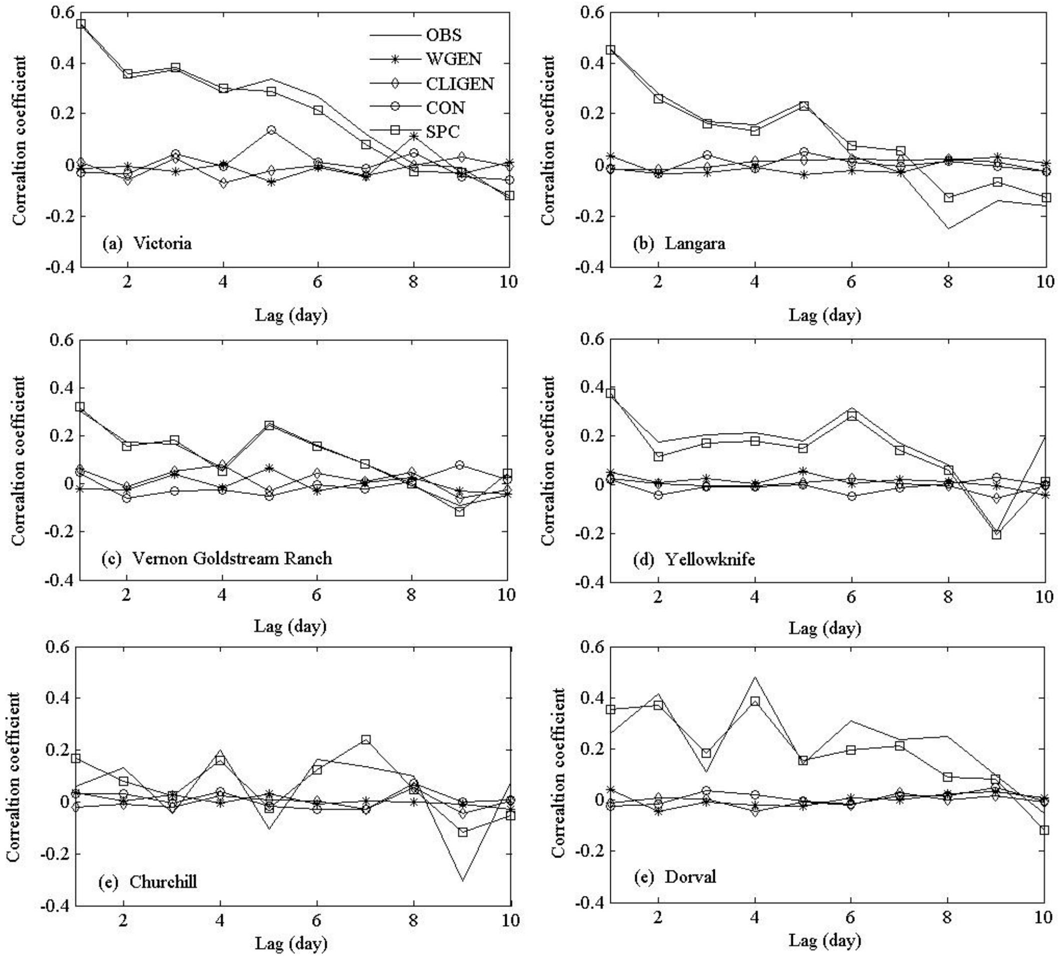

Figure 5. 10 years of lagged autocorrelation of observed (OBS), CLIGEN generated, WGEN generated, conditional method generated (CON) and spectral correction method corrected (SPC) averaged yearly T_{min} for the six stations.

Table 7. Means of yearly T_{max} and T_{min} derived from the synthesized and observed series for six stations. The synthesized T_{max} and T_{min} series include the data generated by CLIGEN, WGEN, the conditional method (CON), and corrected using the spectral correction method (SPC).[a]

Station	T_{max}					T_{min}				
	OBS	WGEN	CLIGEN	CON	SPC	OBS	WGEN	CLIGEN	CON	SPC
Victoria	14.10	14.09	14.10	14.10	14.10	5.38	5.30	5.38	5.39	5.38
Langara	9.86	9.86	9.86	9.87	9.86	5.55	5.38*	5.55	5.56	5.55
VGR	12.70	12.72	12.70	12.68	12.70	1.92	1.69*	1.90	1.86	1.92
Yellowknife	-0.57	-0.56	-0.57	-0.59	-0.57	-9.34	-10.27*	-9.35	-9.42	-9.34
Churchill	-2.71	-2.72	-2.70	-2.76	-2.71	-10.91	-11.65*	-11.00	-10.97	-10.91
Dorval	11.08	11.07	11.08	11.05	11.08	1.59	1.17*	1.59	1.54	1.59

[a] Asterisk (*) indicates value is different from observed time series at p = 0.05.

Table 8. Standard deviations of yearly T_{max} and T_{min} derived from the synthesized and observed series for six stations. The synthesized precipitation series include the data generated by CLIGEN, WGEN, the conditional method (CON), and corrected using the spectral correction method (SPC).[a]

Station	T_{max}					T_{min}				
	OBS	WGEN	CLIGEN	CON	SPC	OBS	WGEN	CLIGEN	CON	SPC
Victoria	0.67	0.22*	0.16*	0.29*	0.67	0.59	0.27*	0.15*	0.27*	0.59
Langara	0.66	0.19*	0.13*	0.24*	0.65	0.72	0.26*	0.12*	0.26*	0.71
VGR	0.88	0.29*	0.24*	0.47*	0.88	0.95	0.55*	0.22*	0.52*	0.94
Yellowknife	1.16	0.17*	0.35*	0.64*	1.13	1.35	0.98*	0.35*	0.79*	1.33
Churchill	1.25	0.23*	0.37*	0.66*	1.21	1.18	0.70*	0.30*	0.70*	1.12
Dorval	0.66	0.18*	0.28*	0.49*	0.64	0.82	0.65*	0.27*	0.55*	0.79

[a] Asterisk (*) indicates value is different from observed time series at p = 0.05.

tion coefficients of the CLIGEN-generated temperatures were consistently less than those of the observed data. The CLIGEN scheme of using two uniform random numbers for inducing additional dependency between two consecutive days is clearly inadequate, even for the lag 1 autocorrelation coefficient. Zhang (2004) and Chen et al. (2008) obtained similar results with respect to CLIGEN. WGEN proved better than CLIGEN in producing the cross-correlation between T_{max} and T_{min}. Neither weather generator could preserve the autocorrelation of averaged yearly T_{max} and T_{min}, nor preserve their interannual variability.

The autocorrelation of yearly T_{max} and T_{min} and their interannual variability are important for many applications, such as agriculture and hydrology. For example, it is important to be able to reproduce successions of warmer or cooler years for drought studies, which are directly related to fluctuations in agricultural yield. For river basin streamflow prediction, it is also important to preserve the interannual variability of historical temperature, since temperatures are closely linked to snowmelt and evapotranspiration.

The conditional and spectral correction methods presented in this article resulted in weather generators that produced accurate means, standard deviations, and extremes of daily T_{max} and T_{min}. Moreover, when compared to WGEN and CLIGEN, the conditional and spectral correction method improved the simulations of auto- and cross-correlations for and between daily T_{max} and T_{min}. However, similarly to both WGEN and CLIGEN, the conditional method was unable to preserve the autocorrelation function of averaged yearly T_{max} and T_{min}, because, as mentioned earlier, it does not take into account the low-frequency variability of climate. The spectral correction approach successfully reproduced the observed autocorrelation of averaged yearly T_{max} and T_{min}, and successfully preserved the interannual variability of T_{max} and T_{min}.

Overall, coupling the conditional method with the spectral correction method results in a weather generator that not only accurately preserves basic statistics including means, standard deviations, and extremes of T_{max} and T_{min} but also preserves the auto- and cross-correlations for and between T_{max} and T_{min}. Even more importantly, this coupled method preserves the autocorrelation functions and interannual variability. The monthly variability was also improved along with the correction of interannual variability (results not shown), but it was not as good as that at the yearly scale, indicating that the scheme for correcting interannual variability has a limited effect at the monthly scale. Thus, it might be necessary to add monthly or seasonal variability into the correction scheme. However, this step may lead to overfitting problems, resulting in too many cases where T_{min} is greater than T_{max}. This article only validated the applied methods directly, rather than linking them to practical applications. A more comprehensive assessment, including linking these methods with agricultural and hydrological models, for example, may be required in further studies.

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