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WeaGETS – a Matlab-based daily scale weather generator for generating precipitation and temperature

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Abstract

This paper describes a versatile stochastic daily weather generator (WeaGETS) for producing daily precipitation, maximum and minimum temperatures (Tmax and Tmin). The performance of WeaGETS is demonstrated with respect to the generation of precipitation, Tmax and Tmin 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 dry station. The higher-order models have positive effects. The gamma distribution is consistently better than the exponential distribution at generating precipitation quantity. The conditional scheme is good at simulating Tmax and Tmin. The spectral correction approach built in WeaGETS successfully preserves the observed low-frequency variability and autocorrelation functions of precipitation and temperatures.

Keywords: Stochastic weather generator; precipitation; temperature; Matlab.

1. Introduction

Weather generators are computer algorithms that produce long time series of weather variables that have statistical properties comparable to those of existing records. They also have been widely used as a downscaling tool in climate change studies [1-7]. Consequently, several weather generators have been developed over the past three decades, such as WGEN [8-9], USCLIMATE [10], CLIGEN [11], ClimGen

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[12] and LARS-WG [13]. All of the weather generators currently available only provide a single scheme to generate each climate variable. 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 the well-known underestimation of inter-annual variability, even though several approaches were presented to deal with this problem [14-17].

This paper describes a Matlab-based versatile stochastic daily weather generator (WeaGETS) for producing daily precipitation, maximum and minimum temperatures (Tmax and Tmin). The WeaGETS is available on the public domain (http://www.mathworks.com/matlabcentral/fileexchange/). First, second and third-order Markov models are provided to generate precipitation occurrence, and exponential and gamma distributions are available to produce wet day precipitation quantity. A conditional scheme is available to simulate Tmax and Tmin. Finally, a spectral correction approach is included to correct the well-known underestimation of monthly and inter-annual variability associated with weather generators. WeaGETS has the 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 inter-annual 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.

2. Model description

WeaGETS provides three options to generate precipitation occurrence, two options to produce precipitation quantity and a conditional scheme to simulate Tmax and Tmin. There is an option of smoothing the precipitation parameters with Fourier harmonics following Richardson's approach [8] and to correct for the low-frequency variability of precipitation and temperature following the spectral correction method of Chen et al. [17].

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.

2.1. Smoothing scheme

The precipitation occurrence parameters include the transition probabilities of first, second and third-order Markov chains. For precipitation quantity, there is one parameter for the exponential distribution, and two parameters for the gamma distribution. 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 other will not be smooth, and the true yearly distribution of the parameter value will be party 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 than the observed precipitation. One to four Fourier harmonics built in WeaGETS can be used to smooth the yearly parameters distribution. The smoothing process eliminates sharp parameter transitions between computing periods that may occur due to outliers, especially for short time series.

2.2. Generation of precipitation occurrence

WeaGETS provides three options including first, second and third-order Markov models to produce precipitation occurrence. The first-order Markov process is the simplest and most widely used. 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:

$$P01 = P\{\text{precipitation on day } t \mid \text{no precipitation on day } t\text{-}1\} \qquad (1)$$

$$P11 = P\{\text{precipitation on day } t \mid \text{precipitation on day } t\text{-}1\} \qquad (2)$$

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.

A generalization of the first-order Markov model is to consider higher-order Markov models such as the second and third-order models. Letting $R_t = 0$ if day t is dry, and $R_t = 1$ if day t is wet, Equations (1) and (2) can be extended to the second and third-order Markov chains following equations 3 and 4:

$$P_{ijk} = P\{ R_t = k \mid R_t = j \mid R_t = i \} \qquad (3)$$

$$P_{hijk} = P\{R_t = k \mid R_t = j \mid R_t = i \mid R_t = h\} \qquad (4)$$

where h, i, j and k =0 or 1, respectively.

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. According to previous study [18], first-order

Markov chains may not be adequate for generating long dry or wet spells. Higher-order Markov models perform better, but more parameters must be determined. Since a minimum number of rainfall events need to be present to adequately estimate transition probabilities, second and third-order parameter estimation requires longer time series of observed precipitation.

2.3. Generation of precipitation quantity

For a predicted rainy day, two probability distribution functions are available to produce the daily precipitation quantity. The first is the one-parameter exponential distribution, which has a probability density function given by

$$f(x) = \lambda e^{-\lambda x} \tag{5}$$

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

$$f(x) = \frac{(x/\beta)^{\alpha-1} \exp[-x/\beta]}{\beta \Gamma(\alpha)} \tag{6}$$

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 quantity. It would be very easy to add other distribution functions, such as the mixed exponential (a three-parameter distribution) that has also been used in the literature.

2.4. Generation of maximum and minimum temperatures

Similarly to the WGEN [8-9], the WeaGETS uses a first-order linear autoregressive model to generate Tmax and Tmin. 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

$$\chi_{p,i}(j) = A\chi_{p,i-1}(j) + B\varepsilon_{p,i}(j) \tag{7}$$

where $x_{p,i}(j)$ is a (2×1) matrix for day i of year p whose elements are the residuals of Tmax (j=1) and Tmin (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

$$A = M_1 M_0^{-1} \tag{8}$$

$$BB^T = M_0 - M_1 M_0^{-1} M_1^T \qquad (9)$$

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.

A conditional scheme is available to generate Tmax and Tmin on top of the generated residual series. The temperature with the smallest standard deviation between Tmax and Tmin is first computed, followed by the others [19]. If the standard deviation of Tmax is larger than or equal to the standard deviation of Tmin, daily temperatures are generated by equations (10) and (11):

$$T_{min} = \mu_{min} + \sigma_{min} \times \chi_{p,i} \qquad (10)$$

$$T_{max} = T_{min} + (\mu_{max} - \mu_{min}) + \sqrt{\sigma_{max}^2 - \sigma_{min}^2} \times \chi_{p,i} \qquad (11)$$

If the standard deviation of Tmax is less than that of Tmin, daily temperatures are generated by equations (12) and (13):

$$T_{max} = \mu_{max} + \sigma_{max} \times \chi_{p,i} \qquad (12)$$

$$T_{min} = T_{max} - (\mu_{max} - \mu_{min}) - \sqrt{\sigma_{min}^2 - \sigma_{max}^2} \times \chi_{p,i} \qquad (13)$$

Using this scheme, Tmin is always less than Tmax and no range check is necessary.

2.5. Correction of low-frequency variability

Weather generators underestimate the monthly and inter-annual variance, because they do not take into account the low-frequency component of climate variability. WeaGETS provides an approach (spectral correction approach) to correct for this underestimation, for both precipitation and temperature.

Low-frequency variability is first modeled using a Fast Fourier Transform (FFT) based on the power spectra of the 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, which 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 inter-annual variability for precipitation follows the approach of Chen et al. [17]. Their results show that this approach performs very well in preserving the low-frequency variability of precipitation and temperatures.

3. An illustration of model performance

Two Canadian meteorological stations are used to illustrate the performance of WeaGETS. The basic information, including average annual precipitation, Tmax and Tmin, longitude, latitude, elevation and record duration for the two stations is given in Table 1. WeaGETS has been used and tested

extensively at several other locations under various climates [17, 20-21]. These two stations were selected simply to outline the typical outputs and results.

Table 1. Location, record period, average annual precipitation, maximum and minimum temperatures (Tmax and Tmin) for Ottawa and Churchill stations

Station name	Latitude (N)	Longitude (E)	Elevation (m)	Records of data	Annual precipitation (mm)	Annual Tmax (C)	Annual Tmin (C)
Ottawa	45.26	-75.74	93	1891-2008 (118)	882	10.98	0.79
Churchill	58.73	-94.05	29	1947-2006 (60)	439.1	-2.71	-10.91

The observed daily precipitation, Tmax and Tmin, were used to run WeaGETS 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 generated time series for each meteorological variable.

3.1. Precipitation occurrence

The precipitation occurrences are produced using first, second and third-order Markov chains. Each Markov model produces a good replication of the mean of both dry and wet spells for both stations (Table 2). 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 and 75th percentiles of both dry and wet spells for both stations. 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 relative dry station and Ottawa is much wetter. The third-order Markov model is, not surprisingly the best. Wilks [18] 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.

Table 2. Statistics of dry and wet spells for the Ottawa and Churchill stations (OBS=observed data, Order 1= first-order Markov chain, Order 2= second-order Markov chain, Order 3= third-order Markov chain, and Stdev = standard deviation)

Station	Source	Dry spell				Wet spell			
		OBS	Order 1	Order 2	Order 3	OBS	Order 1	Order 2	Order 3
Ottawa	Mean	3.0	3.0	3.0	3.0	2.0	2.0	2.0	2.0
	Stdev	2.6	2.4	2.5	2.5	1.3	1.4	1.3	1.3
	25th percentile	1	1	1	1	1	1	1	1
	50th percentile	2	2	2	2	2	1	2	2
	75th percentile	4	4	4	4	2	2	2	2
	Longest	25	29	30	28	16	17	14	14

Churchill	Mean	3.2	3.2	3.2	3.2	2.2	2.2	2.2	2.2
	Stdev	3.0	2.8	2.8	2.9	1.7	1.7	1.6	1.7
	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	3	3	3	3
	Longest	43	32	31	39	17	26	19	23

3.2. Precipitation quantity

To compare the exponential and gamma distributions in terms of accurately producing precipitation quantity, two time series of precipitation occurrence are generated using the first-order Markov model, and then the wet day precipitations are simulated with exponential and gamma distributions, respectively. The results show that both the exponential and gamma distributions reproduce the mean daily precipitation very well (Table 3). However, they both underestimate the standard deviations of daily precipitation. This indicates that both distributions underestimate the high-frequency variability of precipitation. Both distributions overestimate the 25th, 50th and 75th percentiles of daily precipitation for both stations, while underestimating the all-time maximum daily precipitations. This is understandable because neither the exponential nor the gamma distribution is tailed to generated extreme precipitation events. It is well-documented that extreme precipitation values follow different distribution functions. Both distributions, however, perform well in producing monthly and annual mean precipitation, while they underestimate the standard deviation of monthly precipitation. The standard deviation of annual precipitation is also considerably underestimated for both. As discussed earlier, this indicates that the exponential and gamma distributions underestimate the inter-annual and intra-annual variability of precipitation. Both distributions generate the percentiles of monthly and yearly precipitations very well for the Ottawa station. In contrast, for the Churchill station, both distributions overestimate the lower percentiles of monthly and yearly precipitations, and underestimate the higher percentiles. This indicates (again) that weather generators generally perform better when simulating precipitation for wetter regions than for dry regions. Moreover, the gamma distribution is consistently better than the exponential distribution at simulating precipitation.

Table 3. Statistics of daily, monthly and yearly precipitation quantities for Ottawa and Churchill stations (OBS=observed data, Exp=exponential distribution, Gam=gamma distribution and Std ev=standard deviation)

Station	Source	Daily			Monthly			Yearly		
		OBS	Exp	Gam	OBS	Exp	Gam	Obs	Exp	Gam
Ottawa	Mean	6.1	6.1	6.1	73.5	73.3	73.6	882.0	879.1	882.8
	Stdev	7.6	6.2	6.9	33.9	30.2	31.9	112.9	97.7	99.2
	25th percentile	1.3	1.8	1.4	48.7	51.8	50.7	814.1	813.8	816.5
	50th percentile	3.3	4.2	3.8	69.5	69.2	69.4	872.5	880.1	881.9
	75th percentile	8.1	8.4	8.2	94.5	91.5	91.5	961.6	939.4	943.8
	Maximum	108.6	84.1	95.0	250.2	261.7	242.2	1159.2	1273.0	1183.4

	Mean	2.9	2.9	2.9	36.6	36.4	36.7	439.1	436.9	440.6
	Stdev	4.8	3.3	3.9	29.1	23.0	24.1	102.5	52.0	55.3
Churchill	25th percentile	0.5	0.8	0.6	15.0	18.0	18.0	361.9	400.2	403.3
	50th percentile	1.2	1.8	1.6	28.5	31.0	30.9	426.2	434.7	437.6
	75th percentile	3.2	3.8	3.7	50.3	50.9	50.8	503.3	469.1	476.6
	Maximum	62.3	44.3	84.2	247.0	166.1	183.5	748.5	587.1	644.7

A main advantage of WeaGETS over most other stochastic weather generators is that an approach to correct for the underestimation of the low-frequency variability for both precipitation and temperature is built in. Table 4 presents the mean and standard deviations of monthly and annual precipitations generated by WeaGETS and derived from the observed series for two stations. With a spectral correction, WeaGETS reproduces mean and standard deviations of monthly and annual averaged very well for both stations. Mean absolutely relative errors (MAREs) of mean are 1.25% at the monthly scale and 0.88% at the yearly scale over two stations and MAREs of standard deviation are 1.09% at the monthly scale and 0.59% at the yearly scale.

Table 4. Mean and standard deviations (Stdev) of monthly and annual precipitation observed (OBS) at Ottawa and Churchill stations and generated (GEN) by WeaGETS for both stations.

Station	Source		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual
Ottawa	Mean	OBS	66.1	55.8	65.4	64.8	73.9	86.2	89.5	80.9	80.5	72.5	73.2	73.2	882.0
		GEN	66.7	56.2	65.9	65.1	73.7	85.9	89.2	80.6	80.6	72.6	73.5	73.8	883.9
	Stdev	OBS	26.1	25.9	30.1	28.2	35.6	36.5	38.7	39.6	35.4	36.8	28.0	27.9	112.9
		GEN	26.5	25.9	30.6	28.3	35.2	36.1	39.1	40.3	35.3	36.6	27.5	27.8	112.6
Chur-chill	Mean	OBS	16.6	14.8	17.8	23.2	31.1	44.1	55.9	65.9	60.6	49.4	39.1	20.5	439.1
		GEN	17.1	15.3	18.3	24.5	31.7	44.5	56.4	66.9	60.8	49.6	39.9	21.1	445.9
	Stdev	OBS	9.3	8.3	11.5	19.5	22.1	29.7	31.5	28.3	31.9	33.9	20.8	11.1	102.5
		GEN	9.1	8.2	11.6	19.3	22.0	30.3	31.2	27.8	32.5	33.4	21.0	10.9	103.5

The autocorrelation functions of observed annual precipitation in Fig. 1 display clear trends, indicating that dryer and wetter years do not occur in random order. The spectral correction method successfully reproduces the observed autocorrelation of precipitation for both stations.
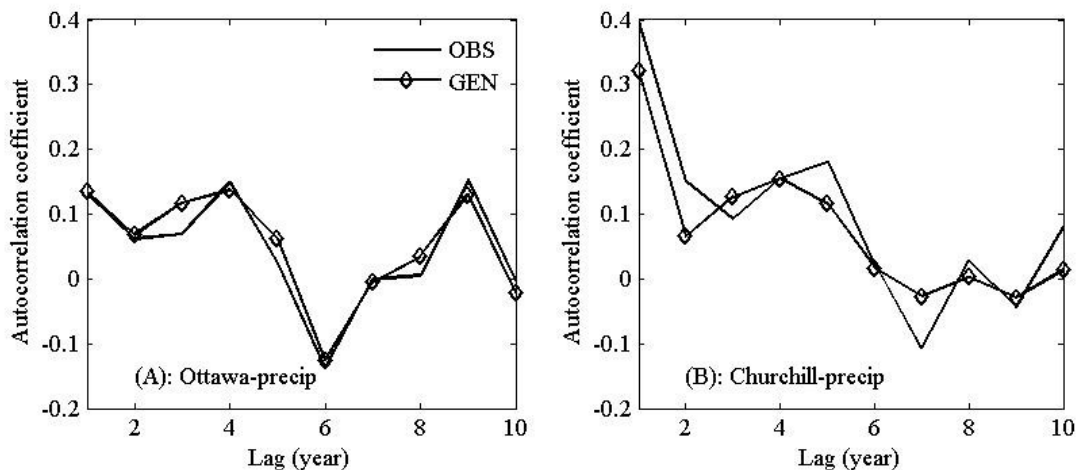

Fig. 1. 10-year lagged autocorrelation of observed (OBS), WeaGETS-generated (GEN) yearly precipitation for the Ottawa and Churchill stations.

3.3. Maximum and minimum temperatures

Tmax and Tmin are generated using a conditional scheme, conditioned on wet and dry states simulated with first-order Markov model. Table 5 presents the statistics of observed and WeaGETS-generated Tmax and Tmin. Overall, WeaGETS provides good simulations of mean standard deviations of Tmax and Tmin,

even though there are some biases. However, it poorly reproduces the all-time minimum temperatures, especially for the Churchill station.

Table 5. Statistics of maximum and minimum temperatures for Ottawa and Churchill stations (Stdev = standard deviation and Max or Min = all time maximum Tmax and all time minimum Tmin)

| | Ottawa | | | | Churchill | | | |
| | Tmax | | Tmin | | Tmax | | Tmin | |
Source	OBS	GEN	OBS	GEN	OBS	GEN	OBS	GEN
Mean	11.0	11.0	0.8	0.8	-2.7	-2.7	-10.9	-10.9
Stdev	13.0	12.7	12.0	11.9	15.5	15.3	15	15.2
25th percentile	1.0	-0.7	-7.2	-8.8	-15.2	-14.9	-24.6	-23.6
50th percentile	11.7	12	1.8	2.3	-1.4	-2.2	-8.0	-9.5
75th percentile	22.2	22.4	10.6	11.0	9.3	11.0	1.9	2.8
Max or Min	37.8	38.7	-38.9	-47.4	36.9	36.3	-45.4	-65.4

The means and standard deviation of yearly Tmax and Tmin are reproduced very well by WeaGETS for both stations (Table 6), since a spectral correction scheme is incorporated.

Table 6. Mean and standard deviations of yearly Tmax and Tmin derived from the generated and observed series for Ottawa and Churchill stations.

| | Ottawa | | | | Churchill | | | |
| | Tmax | | Tmin | | Tmax | | Tmin | |
Source	Mean	Std	Mean	Std	Mean	Std	Mean	Std
OBS	10.98	0.84	0.79	1.09	-2.71	1.25	-10.91	1.18
GEN	10.98	0.83	0.79	1.08	-2.71	1.21	-10.91	1.12

Auto and cross-correlations of and between daily Tmax and Tmin are computed for observed and WeaGETS-generated time series (Fig. 2). The autocorrelation is a measure of the persistence of temperature trends, and is an important characteristic to reproduce. The conditional scheme using by WeaGETS reproduces the day-to-day persistence very well. Similar conclusion can also been found when looking at cross-correlation.
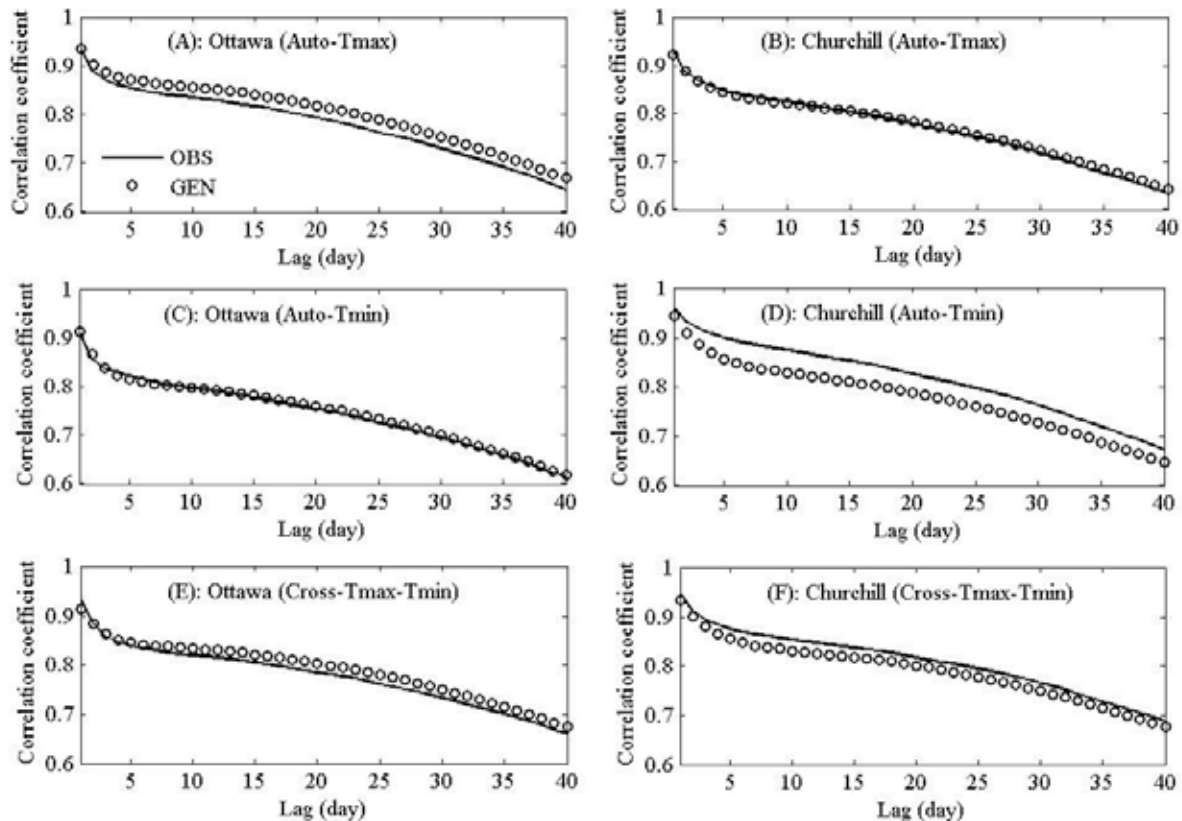

Fig. 2. 40 days of lagged auto and cross-correlation of and between observed (OBS), unconditional and conditional generated data for maximum and minimum temperatures for the Ottawa and Churchill stations.

Similarly to precipitation, the autocorrelation functions of observed annual Tmax and Tmin presented in Fig. 3 display clear trends, indicating that warmer and cooler years do not occur in random order. The spectral correction method successfully reproduces the observed autocorrelation of Tmax and Tmin for both stations.
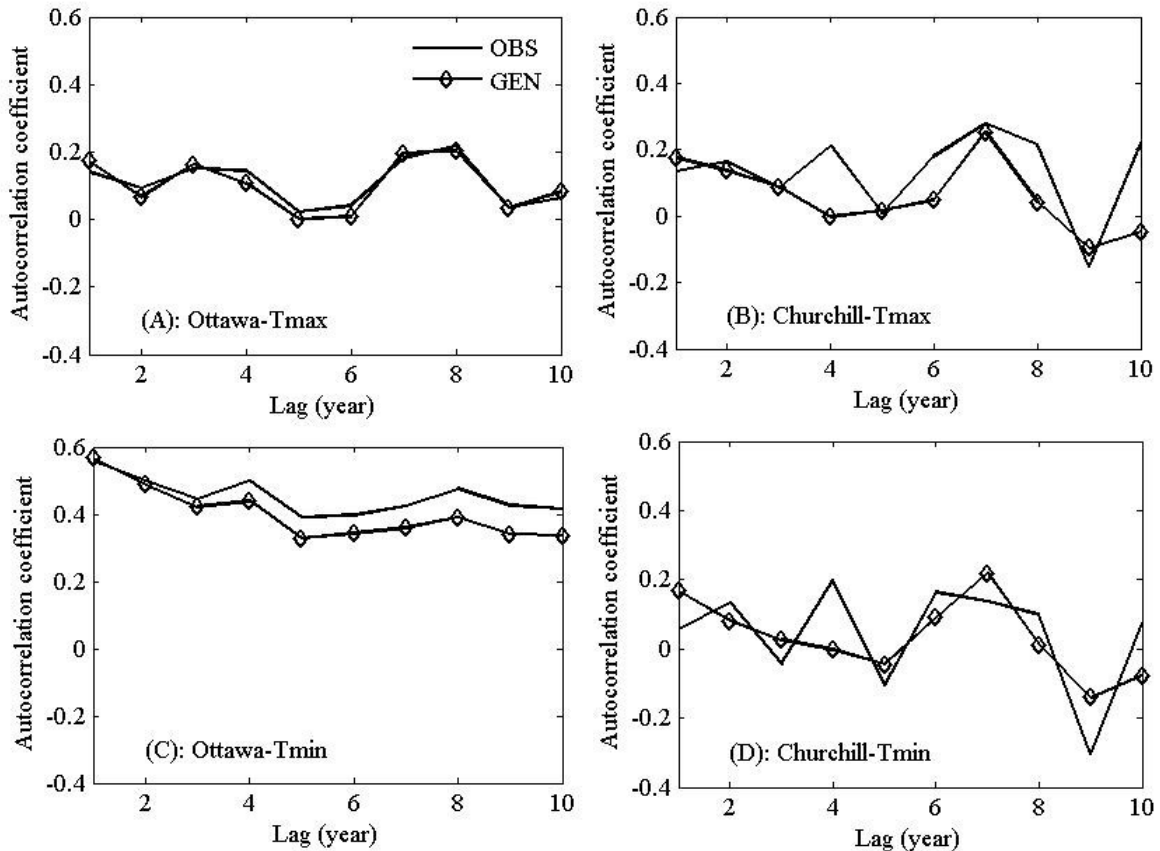
Fig. 3. 10-year lagged autocorrelations of observed (OBS), WeaGETS-generated (GEN) yearly Tmax and Tmin for the Ottawa and Churchill stations.

4. Conclusion

WeaGETS is a Matlab-based daily stochastic weather generator that can generate precipitation, Tmax and Tmin time series of unlimited length, thus permitting impact studies of rare occurrences of meteorological variables. Furthermore, by perturbing its parameters according to changes projected by climate models, it can be used as a downscaling tool for climate change studies. WeaGETS has the 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 inter-annual 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 analyse the data generated by WeaGETS.

Two Canadian stations are selected to illustrate WeaGETS' performance. 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. The gamma distribution is consistently better than the exponential distribution in generating precipitation quantity. However, both distributions are less well in producing precipitation extremes, because they are not heavy-tailed. The extremes of precipitation have been drawn from rather different populations than most daily precipitation observations that the distribution has been fit to [18], because they are associated with unusual meteorological events. Moreover, 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. WeaGETS is also good at simulating temperatures. More importantly, the built in spectral correction approach is very successful in preserving the inter-annual variability.

Acknowledgements

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