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A daily stochastic weather generator for preserving low-frequency of climate variability

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SUMMARY

Weather generators are computer models that produce time series of meteorological data that have similar statistical properties as that of observed data. The past decade has seen a sharp and renewed increase in interest in weather generators, linked to their potential use in climate change studies. One appealing property of weather generators is their ability to rapidly produce time series of unlimited length, thus permitting impact studies of rare occurrences of meteorological variables. However, one problem with daily weather generators is that they underestimate monthly and inter-annual variances because they do not take into account the low-frequency component of climate variability. This research aims to present an approach for correcting the low-frequency variability of weather variables for weather generator and to assess its ability to reproduce key statistical parameters at the daily, monthly and yearly scales. The approach is applied to precipitation which is usually the variable displaying the largest inter-annual variability. The daily stochastic precipitation model is a Richardson-based weather generator that uses a first-order two-state Markov chain for precipitation occurrence and a gamma distribution for precipitation amounts. Low-frequency variability was modeled based on observed power spectra of monthly and annual time series. Generation of synthetic monthly and yearly precipitation data was achieved by assigning random phases for each spectral component. This preserved the power spectra, variances and the autocorrelation functions at the monthly and annual scales. The link to daily parameters was established through linear functions. The quality of these corrections was assessed through direct and indirect validation tests, with the direct validation focusing on comparing the means, standard deviations and autocorrelations of different weather series. The results showed that standard deviations of both monthly and annual precipitations were produced almost exactly. The proposed method also preserved the autocorrelation of annual precipitation. The indirect validation involved modelling the discharge of a river basin using a hydrological model driven by different precipitation series. The results showed that the corrected weather series significantly improved the variability of simulated flow discharges at the monthly and annual scales compared to those simulated using the data generated by the standard weather generator.

1. Introduction

A stochastic weather generator is a computer algorithm that uses existing meteorological records to produce a long series of synthetic daily weather data. The statistical properties of the generated data are expected to be similar to those of the actual data for a specified site. Unlike historical weather records, which may have missing data, the weather generator output provides a complete record for any desired period of time, thus enhancing the use of continuous hydrologic models (Kevin et al., 2005). Moreover, it can be used to generate daily weather data for ungauged areas through spatial interpolation of model parameters from adjacent gauged sites (Baffault et al., 1996). An important application of weather generators involves them serving as computationally inexpensive tools to produce multiple-year climate change scenarios at the daily time scale, which are used to assess the impact 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; Minville et al., 2008). Model parameters of the weather generator can be readily manipulated to simulate arbitrary changes in mean and variance quantities for sensitivity analysis, or be deliberately modified to mimic changes in mean and variance as predicted by global climate models (GCMs) for impact assessment. Over the years, several weather generators have been developed, such as the Weather Generator (WGEN) (Richardson, 1981; Richardson and Wright, 1984), USCLIMATE (Hanson et al., 1994), Climate Generator (CLIGEN) (Nicks et al., 1995), Climate

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Generator (ClimGen) (Stockle et al., 1999), Long Ashton Research Station-Weather Generator (LARS-WG) (Semenov and Barrow, 2002), etc. While weather generators are good at preserving the precipitation quantity, they however underestimate low-frequency variations (e.g., 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). This underprediction results from the simplifying assumption that climate, and more specifically, the daily precipitation process, is stationary. These models do not explicitly take into account aspects of low-frequency variability such as decadal oscillations, and thus underestimate monthly and yearly variances.

The low-frequency variability of precipitation depends on the daily precipitation occurrence and intensity processes, especially the variance of the daily precipitation amounts and number of wet days. Several studies have attempted to solve this drawback with weather generators. Wilks (1999) compared the variance of monthly precipitation generated by independent and identical (iid) Gamma distribution, Common-α Gamma distribution and Mixed Exponential distribution. The results showed that the iid Gamma distributions produced substantial overdispersion, and that the Common-a Gamma distribution brings only a slight improvement to this. By contrast, the overdispersion in wet-day variance produced by the Mixed Exponential distribution was substantially smaller, although not zero, meaning that using the Mixed Exponential distribution to represent wet-day precipitation amounts in stochastic weather models should bring about a substantial improvement in the simulation of inter-annual variability. Meanwhile, Wilks (1999) also compared the variance of the number of wet days in each month among different precipitation occurrence models, including first-, second-, third- and hybrid-order Markov models and Negative Binomial and Mixed Geometric distribution, as well as average percentage overdispersion of total monthly precipitation, for all combinations of precipitation occurrence models and precipitation intensity models. The results demonstrated that none of the combinations achieved complete recovery of the observed variance in monthly total precipitation, although increasingly complex component models did succeed in reducing the overdispersion or discrepancy between the synthetic and observed variability. This was unsatisfactory because although the complexity of the models was increased, it still did not take into account the low-frequency component of climate variability. These simple stationary models (whose statistics do not change from month to month and from year to year) cannot fully reproduce the variability of a nonstationary climate, which therefore makes the introduction of some degree of nonstationarity into these models appropriate.

Hansen and Mavromatis (2001) attempted to improve inter-annual variability characteristics by perturbing monthly parameters using a low-frequency stochastic model, and evaluated the effectiveness of the low-frequency component on low-frequency variability of the generated monthly climate at 25 locations in the continental USA. The results indicated that for monthly precipitation, the low-frequency correction reduced total error and eliminated negative bias of inter-annual variability, and reduced the number of station-months with significant differences between observed and generated inter-annual variability, but it over-represented the variability of precipitation frequency.

Dubrovsky et al. (2004) applied the monthly generator (based on a first-order autoregressive model) to fit the low-frequency variability based on the daily WGEN-like weather generator, Met-Roll. The results demonstrated that conditioning the daily generator on a monthly generator has the most positive effect, especially on the output of a hydrological model, and the variability of the monthly streamflow characteristics was better simulated. However, this method still could not reproduce the observed standard deviations and autocorrelations of monthly and annual precipitations exactly, because it did not specifically consider the inter-annual variability, thus indicating that schemes for correcting monthly variability have limited effect on the annual scale.

Wang and Nathan (2007) also provided a method for coupling daily and monthly time scales in the stochastic generation of rainfall series. The key feature of the method involves first generating two similar time series, one preserving key statistical properties at a finer time scale and the other at a coarser time scale. The finer time scale series is then adjusted to make it consistent with the coarser one. This method appears to perform well in that it satisfactorily preserved some key statistical properties at daily, monthly and even yearly scales. However, it was only tested for the coefficient of variation on Australian weather data. Other statistics, such as the autocorrelation of annual precipitation, are important for some applications.

Accordingly, this research aimed to present an approach for correcting the low-frequency variability of precipitation for the weather generator, assess its ability to reproduce key statistical parameters, and to compare it against Wang and Nathan's method.

2. Materials and methods

2.1. Introduction of a stochastic weather generator

Weather Generator École de Technologie Supérieure (WeaGETS), which is a WGEN-like three-variate (precipitation, maximum and minimum air temperature) single-site stochastic weather generator programmed in Matlab, was used as the basic stochastic weather generator in this study. This paper only focuses on precipitation generation.

The precipitation component of WeaGETS is a Markov chain for occurrence and a gamma distribution for quantity. A first-order two-state Markov chain is used to generate the occurrence of wet or dry days. 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 the two transition probabilities:

$$\text{P01} = \Pr\{\text{precipitation on day } t | \text{no precipitation on day } t-1\} \quad (1a)$$

and

$$\text{P11} = \Pr\{\text{precipitation on day } t | \text{precipitation on day } t-1\} \quad (1b)$$

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.

For a predicted rain day, a two-parameter Gamma distribution is used to generate daily precipitation depth (Richardson, 1981). The probability density function for this distribution is:

$$f(x) = \frac{(x/\beta)^{\alpha-1}\exp[-x/\beta]}{\beta\Gamma(\alpha)} \quad (2)$$

where the variable x is the daily precipitation depth, α and β are the two distribution parameters, and $\Gamma(\alpha)$ represents the gamma function evaluated at α.

2.2. Correction of low-frequency variability and validations

The aim of the model is to specifically account for low-frequency variability by correcting daily precipitation at the monthly and yearly scales, using power spectra of observed time series at the same scales. The power spectra are computed using Fast Fourier Transforms (FFT). Wang and Nathan's (2007) method, which is arguably the best available for dealing with the low-frequency problem, was also programmed and used as a comparison method.

The key feature of Wang and Nathan's method is that it requires that we first generate two similar time series, one preserving key statistical properties at a finer time scale and the other at a coarser time scale. The resemblance between the two series is achieved by using the finer time scale model as a building block for the coarser time scale model, and then using the same sequence of non-exceedance probabilities for the random elements as inputs to both models. The preservation of the key statistical properties of the two series at their appropriate time scales is achieved by using different sets of estimated parameters for the two models. A coupling transformation technique introduced by Koutsoyiannis (2001, 2003) is then applied to modify the finer time scale series so that this series becomes consistent with the coarser time scale series. This transformation technique is based on a developed generalized mathematical proposition, which ensures preservation of marginal and joint second-order statistics and of linear relationships between lower- and higher-level processes. Wang and Nathan also used a basic weather generator based on WGEN (Richardson and Wright, 1984), but with the exception that its parameters are not smoothed with Fourier harmonics. To allow for a proper comparison, WeaGETS was also used without smoothing. The smoothing process eliminates sharp parameter transitions between computing periods that may occur due to outliers (such as extreme precipitation), especially for shorter time series. In either case, the weather generator should reproduce the exact monthly targeted precipitation mean (either smoothed or raw). WeaGETS parameters are computed every 2 weeks.

The use of FFT is widespread in engineering and signal processing, and it stems from the concept that any discrete signal (such as yearly total precipitation over a basin) 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:

$$C = X + i * Y \quad (i = \sqrt{-1}) \tag{3}$$

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

$$S = |C| = \sqrt{X^2 + Y^2} \tag{4}$$

$$\phi = \tan^{-1}(Y/X) \tag{5}$$

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:

$$C = S * e^{(i*\phi)} \tag{6}$$

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 monthly and inter-annual scales. Throughout this paper, this is referred to as the spectral correction method/approach, and it is comprised of five steps:

(1) A daily precipitation series was generated by WeaGETS using parameters derived from the observed daily precipitation series. In this study, the length of the generated series was 20 times that of the observed one, which allowed a precise evaluation of the statistical parameters of the synthetic time series.

(2) Monthly variability was modeled based on a power spectrum using FFT for each monthly series. The generation of a new power spectrum for monthly precipitation was achieved by assigning random phases to each spectral component and transferring back to the time domain, as discussed above. Random phases were chosen from a uniform distribution over the range $[0, 2\pi]$. Since the length of generated series was 20 times of the observed one, random phases were drawn for each 20-year simulation, and subsequently integrated together. The use of the same random phase for each 20-year simulation would have resulted in identical time series.

(3) The daily precipitation series generated in step (1) was adjusted incrementally. The series of the monthly precipitation derived from the WeaGETS-generated daily series (step (1)) were adjusted to the monthly series generated in step (2), using linear functions. In this adjustment procedure, the value of the increment applied to the daily series was the same for all days within a month. No adjustment was made to the precipitation occurrence.

(4) Following steps (1)–(3), the standard deviation of each monthly precipitation would be corrected exactly, but that of yearly precipitation would still be lower than the observed one, since, as discussed earlier, correcting for monthly variability has limited effect on inter-annual variability. Therefore, in this step, an additional correction for inter-annual variability was made following the procedure outlined in steps (2) and (3). This correction is made on the data that was corrected for monthly variability, not on the original data.

(5) Following step (4), the variance of yearly precipitation was corrected exactly. However, this resulted in an overestimation of the variance at the monthly scale, which was previously perfectly reproduced after step (3). This indicates that the monthly precipitation variances are affected by variability at both the monthly and annual scales. Following the correction of the inter-annual variability, an additional correction was made at the monthly scale. Thus, steps (2)–(4) were repeated in an iterative scheme in order to find the correct initial monthly corrections that would result in the best reproduction of monthly precipitation variance once the yearly correction was applied. The iterative scheme is needed because correcting at either scale influences the other (correcting at the monthly scale affects the yearly scale and vice versa).

The quality of the corrections was assessed through direct and indirect validation tests. The direct validation tries to answer the question as to how the corrected weather series resembles the observed one. It focuses on the reproduction of characteristics representing the distribution of the variables, especially standard deviations of the monthly and yearly precipitations. In this study, the means and standard deviations of WeaGETS-generated, spectral correction and Wang and Nathan's methods corrected monthly, and yearly precipitations relative to observed data were compared. Similarly, autocorrelations of annual precipitations were also compared. Since precipitation amounts are known not to have normal distributions, instead of t- and F-tests, nonparametric Mann–Whitney and squared ranks tests (Conover, 1999) were conducted to test the equality of the means and standard deviations between observed and synthesized monthly and annual precipitation series. In addition, nonparametric Kolmogorov–Smirnov (K–S) tests, which apply to any type of distributions, were used to test the equality of the population distributions of observed versus synthesized data. All the tests were two-tailed, and a significance level of $P = 0.05$ was used. $P = 0.05$ refers to a Type 1 error, and the larger the P value, the more likely it is for the two series to be similar, and vice versa. The indirect validation tries to answer the question as to whether the corrected precipitation series is applicable in a given application. In this study, the indirect validation is done by comparing the statistical properties of output characteristics from a hydrological model driven by different precipitation series generated by WeaGETS, spectral correction and Wang and Nathan's approaches. Like the direct validation, the means and standard deviations of monthly and annual discharges simulated using synthesized precipitation series were

compared to those of the observed series. Nonparametric Mann–Whitney, squared ranks and K–S tests were conducted to test the equality of the mean, standard deviation and distribution for monthly and annual discharges, respectively. The frequency distributions of mean and maximum annual discharges simulated using the observed and synthesized precipitation series were also compared.

2.3. Hydrological model

Indirect validation was based on modeling the discharge of a river basin using the hydrological model HSAMI, which was developed by Hydro-Québec, and which has been used to forecast natural inflows for over 20 years now. It is used by Hydro-Québec for hourly and daily forecasting of natural inflows on 84 watersheds with surface areas ranging from 160 km^2 to 69,195 km^2, and Hydro-Québec's total installed hydropower capacities on these basins exceed 40 GW. HSAMI is a 23-parameter, lumped, conceptual, rainfall-runoff model. Two parameters account for evapotranspiration, six for snowmelt, 10 for vertical water movement, and five for horizontal water movement. Vertical flows are simulated with four interconnected linear reservoirs (snow on the ground, surface water, unsaturated and saturated zones). Horizontal flows are filtered through 2 hydrograms and one linear reservoir. The model takes into account snow accumulation, snowmelt, soil freezing/thawing and evapotranspiration.

The basin-averaged minimum required daily input data for the model are: minimum and maximum temperatures, and liquid and solid precipitations. Cloud cover fraction and snow water equivalent can also be used as inputs, if available. A natural inflow or discharge time series is also needed for proper calibration/validation. For this study, 10 years of data was used for model calibration (1958–1968), and 34 years for validation (1969–2002). Automatic calibration of the model was performed using the shuffled complex evolution (SCE-UA) algorithm (Duan et al., 1992). The optimal combination of parameters was chosen based on the Nash–Sutcliffe criteria for both calibration and validation runs. The chosen set of parameters yielded values of the Nash–Sutcliffe criteria of 0.67 for calibration and 0.64 for validation. The relatively low values of the Nash–Sutcliffe criteria are linked due to the absence of weather stations in the southern portion of the basin and not to the hydrological model which performs extremely well in several other similar basins in Quebec.

Since the focus of this research was on the development and demonstration of an approach for correcting low-frequency variability for the weather generator, details concerning the calibration and validation of a hydrological model are not discussed here.

2.4. Meteorological and hydrological data

The meteorological data, including daily precipitation, maximum and minimum air temperatures of six stations dispersed across Canada, were used in this study. Basic information, including average annual precipitation, longitude, latitude, elevation, and record duration for these stations is given in Table 1. Average annual precipitation at these stations varied from 268.8 mm in Yellowknife to 1827.3 mm in Langara, which adequately represents the natural climate variability in Canada.

The indirect validation is based on 44 years (1959–2002) of discharge at the Châteauguay River Basin. This unregulated river basin is located in southwest Quebec, Canada, and covers a drainage area of 2543 km^2. The basin overlaps the Canadian and US borders (60% of the basin is in Canada and 40% in the US). The average annual river discharge of the river at the watershed outlet is 40 m^3/s, but may exceed 1000 m^3/s during the spring discharge. Daily area-averaged meteorological data used to estimate parameters for the weather generator and drive the hydrological model was derived from a network of six stations distributed throughout and around the catchment. The discharge was derived from one hydrometric station near the basin outlet.

3. Results

3.1. Direct validation

Fig. 1a and b presents the time series and power spectra of observed annual precipitation at the Victoria station. By assigning random phases to each component of the power spectrum and reverting to the time domain, a new signal (annual precipitation) with an identical power spectrum (and variance) can be created. The annual precipitation time series created (Fig. 1c) and observed data have the same power spectrum as shown in Fig. 1d.

WeaGETS reproduced monthly and annual averaged precipitations very well (Fig. 2), and Mann–Whitney tests showed that there is no significant difference between observed and WeaGETS-generated data at the $P = 0.05$ level (Table 2). It indicates that the Markov chain and gamma distribution are capable of simulating the precipitation occurrence and quantity.

Wang and Nathan's method had little effect on simulating the mean of precipitation at the monthly and yearly scales (Fig. 2). All the Mann–Whitney tests between observed and corrected data were insignificant at $P = 0.05$. Moreover, the spectral correction method also produced the mean of precipitation very well, and it was indeed better than that corrected through Wang and Nathan's method and generated by WeaGETS with precipitations simulated almost exactly for some stations, such as the Langara and Dorval stations. All differences can be attributed to the stochastic nature of precipitation generation.

The weather generator underestimated the variability of monthly precipitation, which is represented by its standard deviation as shown in Fig. 3. The squared ranks tests further showed that standard deviations of monthly precipitations were poorly reproduced, with 22 out of 72 months for six stations being different at the $P = 0.05$ level (Table 2). However, Wang and Nathan's method performed much better at preserving the monthly variability for all months and stations. The squared ranks tests showed that standard deviations were significantly different at $P = 0.05$ for only 1 out of 72 months. Moreover, the spectral correction approach sig-

Table 1
Location, record period, and average annual precipitation for 6 stations.

Region	Station name	Latitude (°N)	Longitude (°W)	Elevation (m)	Records of daily precipitation	Precipitation (mm)
Queen Charlotte Islands	Langara	54.25	133.05	14	1937–2006 (70)	1827.3
Middle St. Lawrence River Basin	Dorval	45.47	73.75	36	1943–1994 (52)	953.4
Vancouver Island	Victoria	48.65	123.32	19	1941–2006 (66)	871.2
Nelson and Churchill River Basin	Churchill	58.73	94.05	29	1947–2006 (60)	439.1
Okanagan River Basin	Vernon Goldstream Ranch	50.23	119.20	482	1907–1996 (90)	413.2
Mackenzie	Yellowknife	62.47	114.43	206	1945–2002 (58)	268.8

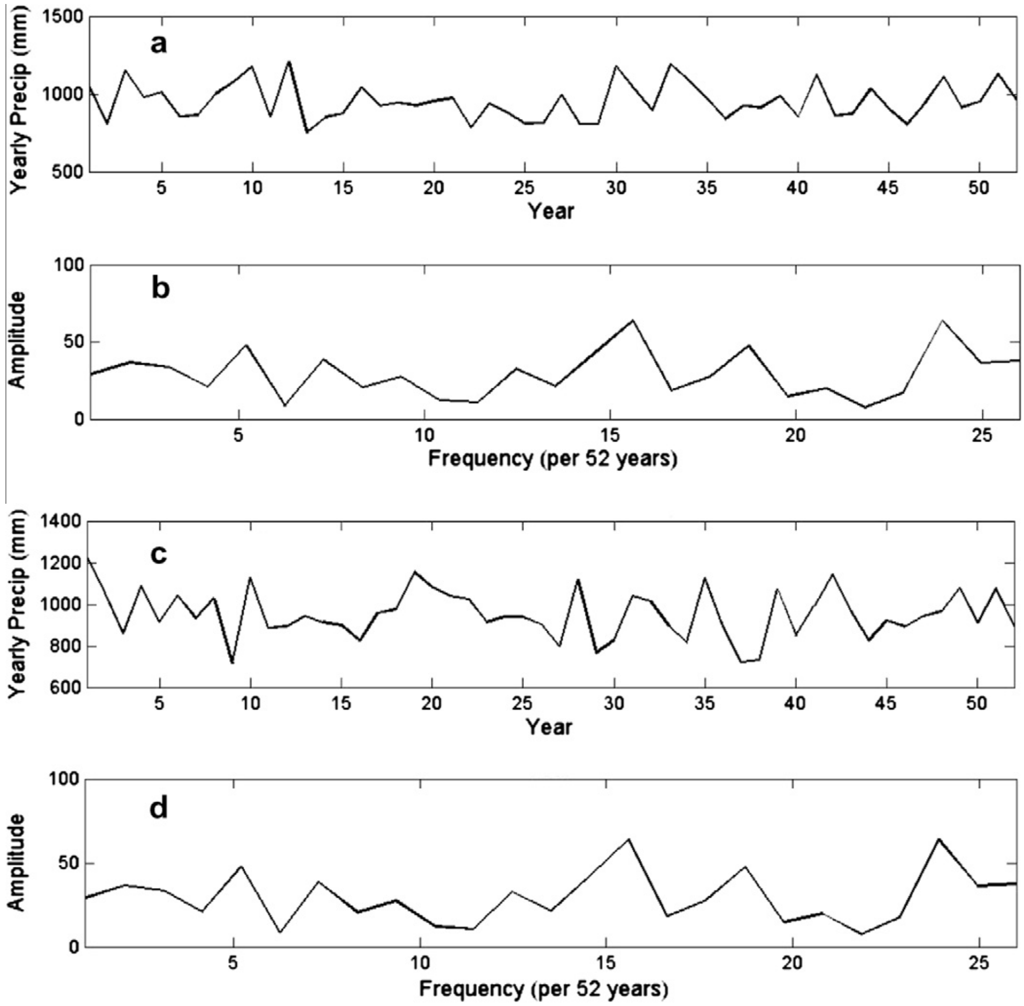

Fig. 1. Time series ((a) and (c)) and their power spectra ((b) and (d)) of averaged annual precipitation at the Victoria station.

nificantly corrected the monthly standard deviations for all months and stations. It reproduced the standard deviation of observed monthly precipitation almost exactly. The squared ranks tests showed that there were no significant differences at $P = 0.05$ for all 72 months on six stations.

As with the underestimation of monthly precipitation, the WeaGETS also under predicted the standard deviation of annual precipitation. The squared ranks test showed significant differences at $P = 0.05$ for five out of six annual precipitation series. Wang and Nathan's method had some effects, but the standard deviation of annual precipitation was overestimated for some cases, such as the Victoria, Langara and Churchill stations. The squared ranks tests showed that there were significant differences at $P = 0.05$ for two out of six stations. The spectral correction method preserved the standard deviations of annual precipitation exactly. All the squared ranks tests were insignificant at the $P = 0.05$ level.

The WeaGETS-generated precipitation had few months which passed the K–S tests (Table 2). Both correction approaches could improve the distribution of the monthly precipitation to some degree. The K–S tests showed that the distributions of monthly observed precipitations were statistically different for only 1 out 72 months from the spectral correction data, and for no month from Wang and Nathan's method corrected data, respectively. The distribution of annual precipitation between WeaGETS-generated and observed data was significantly different for two out of six stations at the $P = 0.05$ level. Both correction methods significantly improved the distributions. The K–S tests showed that there were no significant differences between the distributions of WeaGETS-generated and both corrected yearly precipitations at the $P = 0.05$ level.

The observed annual precipitation autocorrelation functions presented in Fig. 4 display clear trends, which indicate that wetter and dryer years are not random, but rather, come in series, as was shown by the power spectra of annual precipitation series. For several hydrologic applications such as drought studies, it is important to be able to reproduce these successions of dryer/wetter years. The results for autocorrelation of precipitation at the monthly scale were similar and were not shown. WeaGETS could not preserve the autocorrelation function because it does not take into account the low-frequency component of climate variability. Although Wang and Nathan's method reproduced the standard deviations of monthly and annual precipitation well, it did not preserve the observed autocorrelation, while the spectral correction method successfully reproduced the observed autocorrelation for all six stations.

3.2. Indirect validation

The indirect validation was based on modeling of the discharge of the Châteauguay River Basin using the hydrological model, HSAMI, driven by different precipitation series. In order

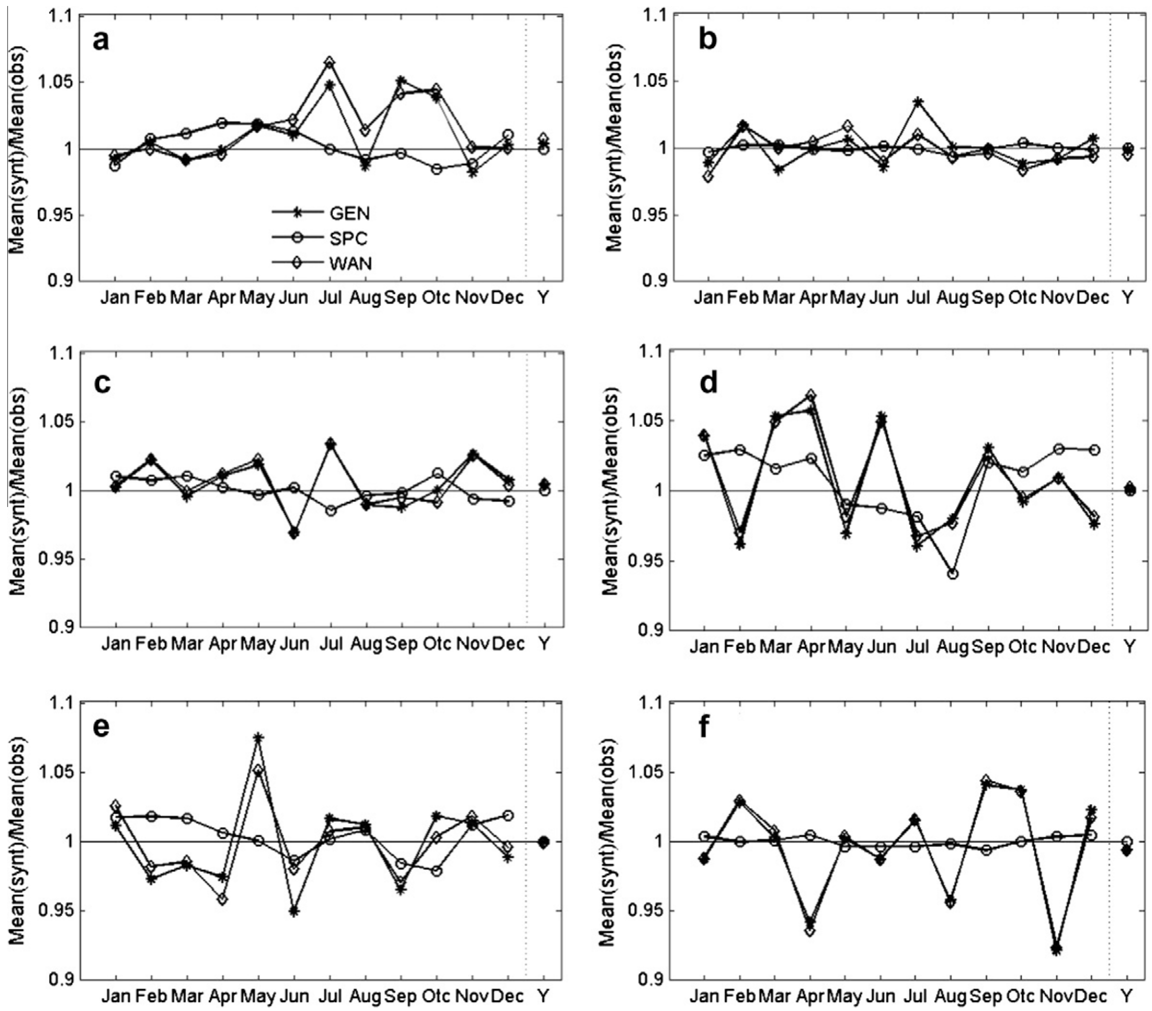

Fig. 2. The ratios of the means of monthly and annual precipitation derived from the synthesized weather series (synt) to the means derived from the observed series (obs) for six stations. The synthesized precipitation series include the data generated by WeaGETS (GEN), corrected using the spectral correction approach (SPC) and Wang and Nathan's method (WAN). The stations include: (a) Victoria, (b) Langara, (c) Vernon Goldstream Ranch, (d) Yellowknife, (e) Churchill, and (f) Dorval.

Table 2
The numbers of monthly and annual precipitation series over 72 months and six stations that rejected the Mann–Whitney, squared ranks and K–S tests; the synthesized data include WeaGETS-generated (GEN), spectral correction (SPC) and Wang and Nathan's methods corrected (WAN).

	Monthly			Yearly		
	Mann–Whitney test	Squared ranks tests	K–S test	Mann–Whitney test	Squared ranks tests	K–S test
GEN	0/72	22/72	4/72	0/6	5/6	2/6
SPC	0/72	0/72	1/72	0/6	0/6	0/6
WAN	0/48	1/72	0/72	0/6	2/6	0/6

to avoid any bias resulting from the hydrological model when comparing different methods, the control period of discharge is represented by modeled data, and not by an actual observed discharge. Further, for the control period, maximum and minimum air temperatures used to simulate the discharge were generated by the weather generator, rather than using observed temperatures. Thus, all differences were solely attributed to the precipitation correction scheme. The hydrological model was then run with four time series: observed, WeaGETS-generated, modified using spectral correction, and using Wang and Nathan's method.

Fig. 5 presents the averaged hydrographs simulated with the four time series for the Châteauguay River Basin. Each synthesized weather data could properly simulate the averaged annual discharge. Moreover, not many differences existed among the discharges simulated using synthesized weather data, but the hydrographs derived from synthesized weather data were smoother because they were produced using longer time series, further indicating that the mean precipitation properties are well reproduced by the weather generator.

Fig. 6a and b presents the ratios of means and standard deviations of monthly and annual precipitations derived from the synthesized weather series to those derived from the observed series. The results again show that WeaGETS significantly underestimated the standard deviations of monthly and annual precipitation, while the two corrected series reproduced the standard deviations very well; indeed both corrected series reproduced the standard deviation of yearly precipitation almost exactly. The observed and synthesized weather series were used to drive the hydrologic model to simulate the discharge.

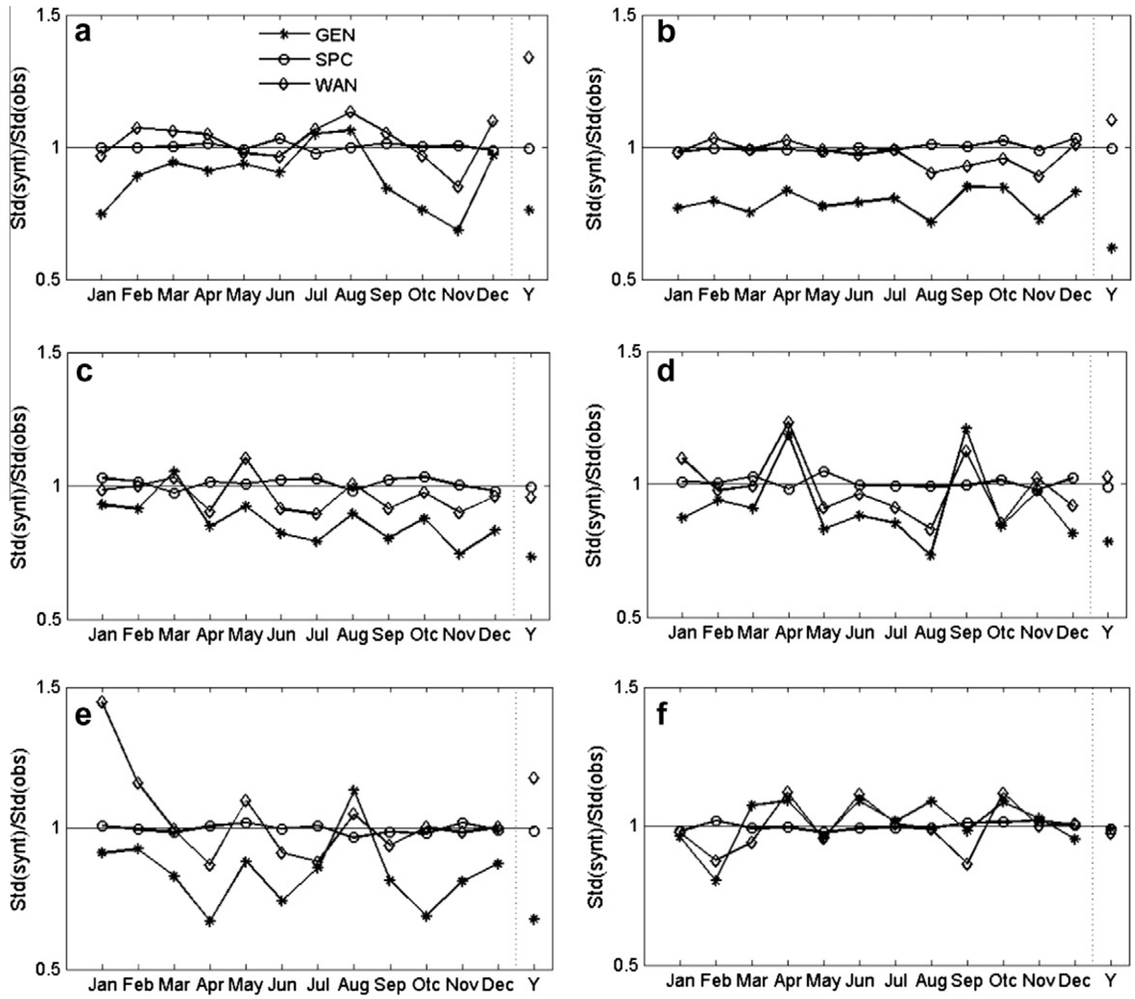

Fig. 3. The ratios of the standard deviations of monthly and annual precipitations derived from the synthesized weather series (synt) to the standard deviations derived from the observed series (obs) for six stations. The synthesized precipitation series include the data generated by WeaGETS (GEN), corrected using the spectral correction (SPC) and Wang and Nathan's (WAN) methods. The stations include: (a) Victoria, (b) Langara, (c) Vernon Goldstream Ranch, (d) Yellowknife, (e) Churchill, and (f) Dorval.

The results show that WeaGETS-generated data properly simulated the means of monthly and annual discharges although there are some fluctuations (Fig. 6c). All the Mann–Whitney tests between discharges simulated using observed and WeaGEST-generated weather series were insignificant at $P = 0.05$ (Table 3).

The standard deviation of discharge simulated using WeaGETS-generated data was underestimated (Fig. 6d). The squared ranks tests showed that there were significant differences at $P = 0.05$ for 3 out of 12 months between those simulated using observed data and those simulated using WeaGETS-generated weather data. However, the standard deviation of monthly discharge simulated using the data corrected by spectral correction method was more or less improved. The squared ranks tests showed significant differences for only 1 out of 12 months at the $P = 0.05$ level. The monthly discharges simulated using precipitation corrected by Wang and Nathan's method were also significantly improved. None of the squared ranks tests was significantly different at $P = 0.05$ for all 12 months. Fig. 6d shows that both correction methods result in improvement for all months, with the exception of January and February discharges, which are similar to those simulated with WeaGETS-derived data. That is because the Châteauguay River Basin was covered with snow during these months, and the variability of monthly precipitation had little effect on discharges, and furthermore, discharge is also typically very low during these months. There was a significant difference between annual discharges simulated using the observed and WeaGETS-generated weather series, but the spectral correction and Wang and Nathan's methods simulated the standard deviation of yearly discharge very well. The squared ranks tests for standard deviations were insignificant at the $P = 0.05$ level.

The K–S tests showed that distributions of discharges were not different at $P = 0.05$ between those simulated with observed and with each synthesized weather series at the monthly and yearly scales (Table 3).

WeaGETS significantly underestimated the frequency distribution of the mean annual discharge (Fig. 7a). However, those simulated using precipitations corrected through the spectral correction and Wang and Nathan's method were significantly improved, although they were somewhat overestimated. Similarly to the simulation of averaged annual discharge, the maximum annual discharge from spring snowmelt (from February 1st to late May) simulated using WeaGETS-generated data was significantly underestimated (Fig. 7b), but was improved by the corrected weather data. However, they were still lower than the observed ones.

Similarly to the changing trends in yearly precipitation, the flood and drought years are also not random, but rather, come in a series, as shown by the autocorrelation functions of mean yearly discharge (Fig. 8). These provide the decision basis for agricultural management and hydrologic applications. However, the mean yearly discharges simulated using WeaGETS-generated precipitations and

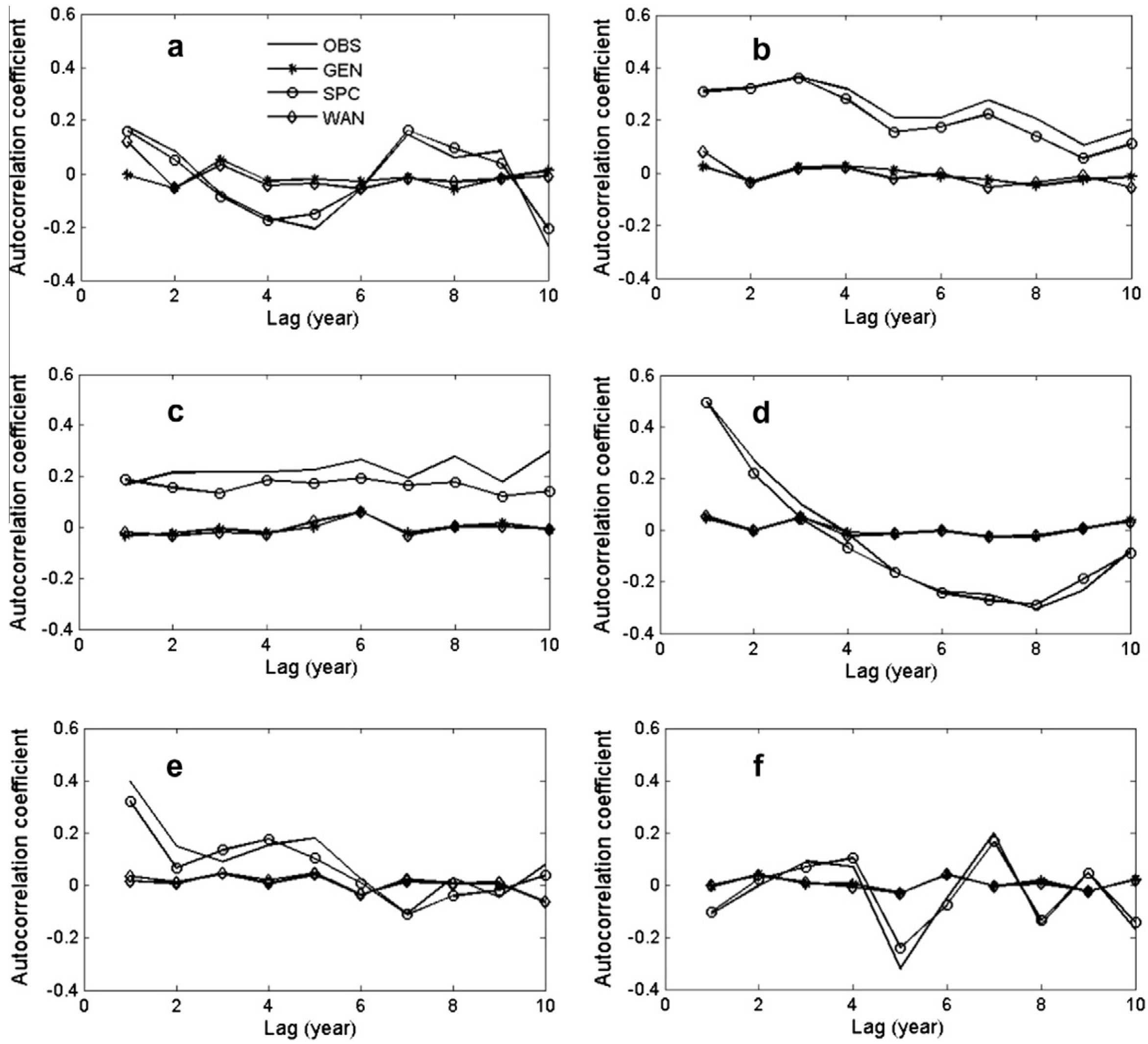

Fig. 4. Ten years lagged autocorrelation of observed (OBS), WeaGETS-generated (GEN), spectral correction (SPC) and Wang and Nathan's methods (WAN) corrected annual precipitations for six stations. The stations include: (a) Victoria, (b) Langara, (c) Vernon Goldstream Ranch, (d) Yellowknife, (e) Churchill, and (f) Dorval.

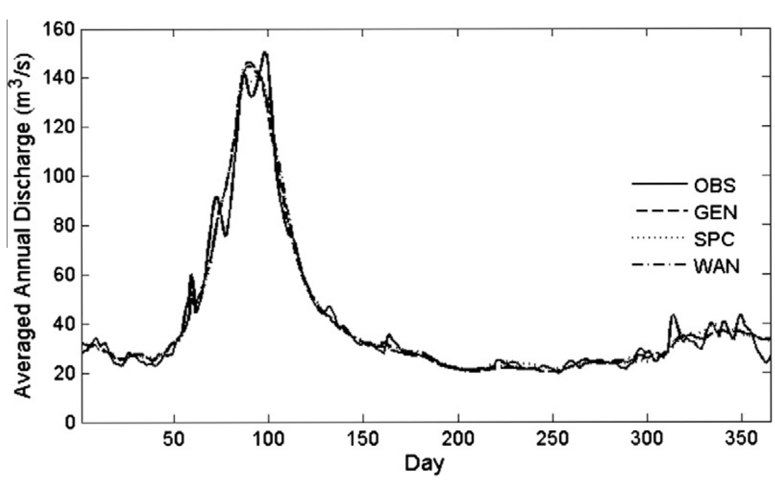

Fig. 5. Averaged hydrographs simulated using the observed (OBS), WeaGETS-generated (GEN), and spectral correction (SPC) and Wang and Nathan's (WAN) methods corrected precipitation series for the Châteauguay river basin.

with precipitations corrected through Wang and Nathan's method could not preserve the observed autocorrelation functions. That was because the WeaGETS and Wang and Nathan's method could not reproduce the observed autocorrelation functions of averaged

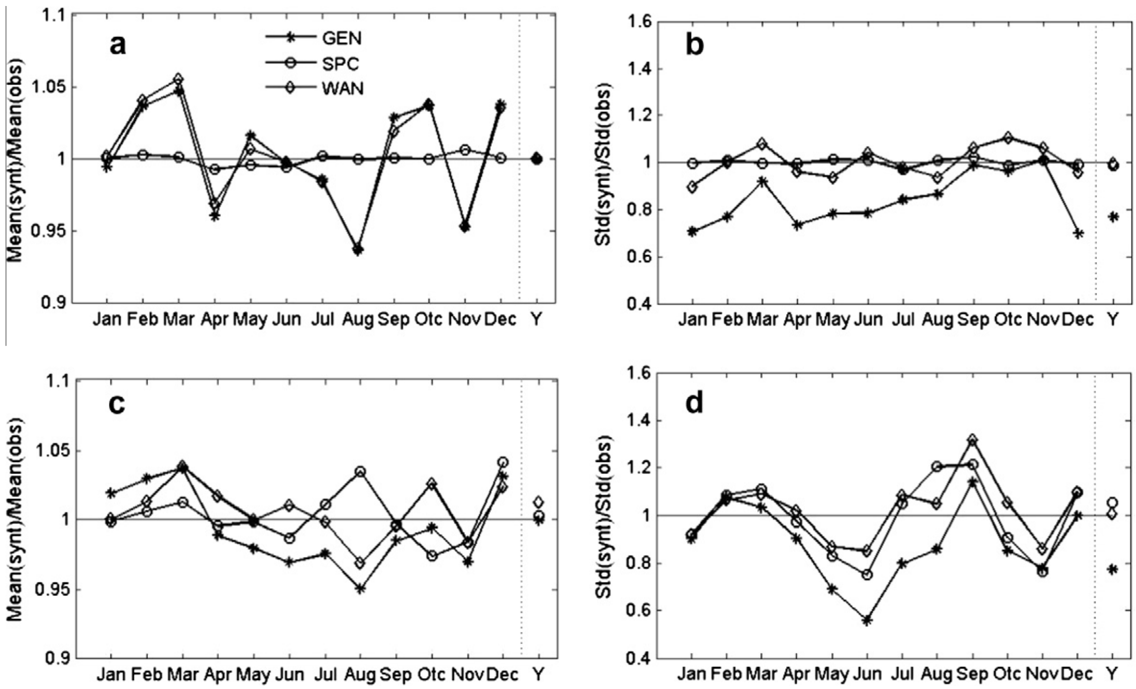

Fig. 6. Ratios of means: (a) and standard deviations (b) of monthly and annual precipitations derived from the synthesized weather series (synt) to the means and standard deviations derived from the observed series (obs); and ratios of the means (c) and standard deviations (d) of discharges simulated with the synthesized precipitation series (synt) to those simulated with the observed precipitation series (obs) at the Châteauguay River Basin; the synthesized precipitation series include WeaGETS-generated (GEN), spectral correction (SPC) and Wang and Nathan's (WAN) methods corrected data.

Table 3
The numbers of monthly and annual discharge series over 12 months and 1 yearly series that rejected the Mann–Whitney, squared ranks and K–S tests; the synthesized data include WeaGETS-generated (GEN), spectral correction (SPC) and Wang and Nathan's (WAN) methods corrected.

	Monthly			Yearly		
	Mann–Whitney test	Squared ranks tests	K–S test	Mann–Whitney test	Squared ranks tests	K–S test
GEN	0/12	3/12	0/12	0/1	1/1	0/1
SPC	0/12	1/12	0/12	0/1	0/1	0/1
WAN	0/12	0/12	0/12	0/1	0/1	0/1

yearly precipitations. The spectral correction method successfully reproduced the observed autocorrelation, although not exactly.

4. Discussions and conclusions

An approach based on a power spectrum for coupling time scales of stochastic time series models is presented in this research. This approach was compared with an existing method (Wang and Nathan's (2007) method) on the basis of how well the low-frequency variability of precipitation is preserved. The ability of each method to simulate the discharge of a river basin using a hydrological model was also evaluated. Low-frequency variability was first modeled using an FFT-derived power spectrum. Generation of monthly and yearly precipitation data was achieved by assigning random phases for each spectral component, which preserved the power spectrum and variances as well as the autocorrelation function. The link to daily parameters was established through linear functions, and direct and indirect validation experiments were conducted to examine the effects of those corrections. In the direct validation experiments, the statistics derived from WeaGETS-generated, spectral correction and Wang and Nathan's methods corrected precipitation series were compared with those derived from the observed series. In the indirect validation experiments, the discharge simulated by a hydrological model driven by observed and synthesized weather data were examined.

Direct validation experiments showed that the spectral correction approach reproduced the observed standard deviations of monthly and annual precipitations almost exactly. Although results were not presented, it should be noted that the standard deviation of seasonal precipitation was also significantly improved, although we did not specifically correct for it. Seasonal variance was however not as well reproduced as that of the monthly and yearly scales, which indicates that it may be useful to add the seasonal scale in the correction scheme. More importantly, the spectral correction approach could reproduce the observed autocorrelation of annual precipitation. Wang and Nathan's method also significantly improved the standard deviations of precipitation at monthly and yearly scales, but not as well, especially for annual precipitation. This is because their method only considered the variability and autocorrelation at the monthly scale, whereas the spectral correction approach considered both time scales.

The results of the indirect validation indicate that the modifications of the weather generator improved the reliability of the statistics derived from the output of the hydrological model. The precipitation series corrected through the spectral correction approach improved the statistical properties of the discharge derived from driving the hydrological model. The standard deviations of monthly and yearly discharges were better reproduced, indicating that preserving the observed low-frequency variability is very important in the simulation of discharge when used with synthetic stochastic weather series. The frequencies of mean and maximum annual discharges simulated using the spectral correction approach corrected precipitation series were also obvious improved. Wang and Nathan's method corrected precipitation series also significantly improved the simulation of discharges' variability at monthly and yearly scales compare with those simulated using WeaGETS-generated data. Moreover, the spectral correction

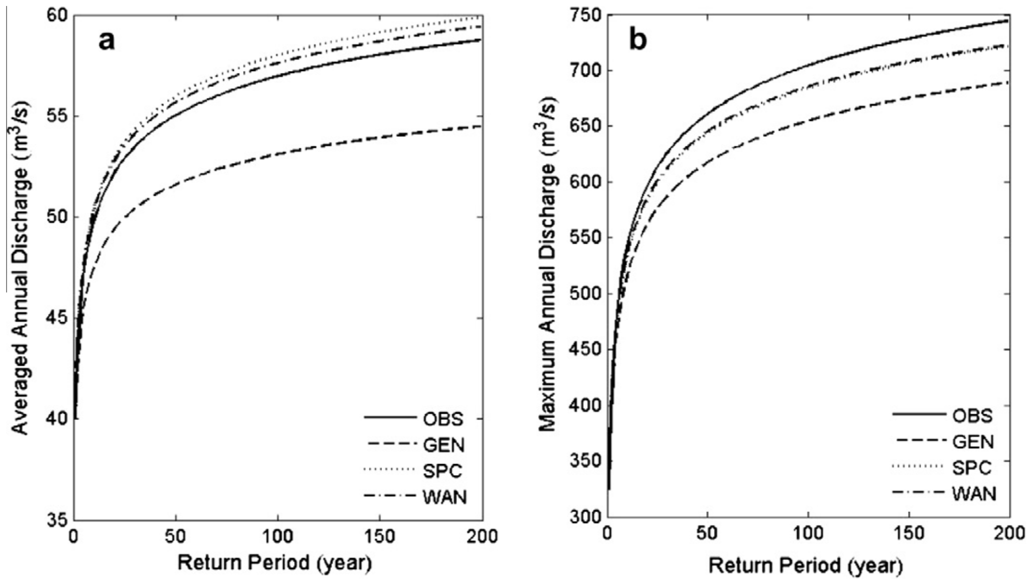

Fig. 7. Frequencies of mean and maximum annual discharges simulated with the observed, WeaGETS-generated (GEN), and spectral correction (SPC) and Wang and Nathan's (WAN) methods corrected precipitation series.

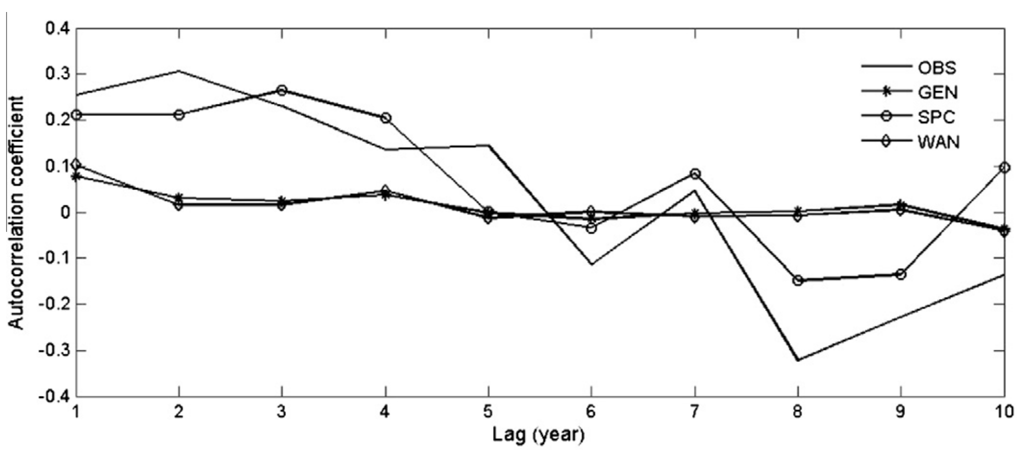

Fig. 8. Ten years lagged autocorrelation of averaged yearly discharges simulated with the observed (OBS), WeaGETS-generated (GEN), spectral correction (SPC) and Wang and Nathan's methods (WAN) corrected precipitations series.

method successfully reproduced the observed autocorrelation of averaged yearly discharge, unlike WeaGETS and Wang and Nathan's method, because the periodicities of the streamflow characteristics, i.e., timing and magnitude of peak flow and specific runoff, are related to the variation in the autocorrelation of the time series of precipitation (Fassnacht, 2006). The spectral correction method preserved the observed autocorrelation functions of mean yearly precipitation, so it could reproduce the autocorrelation of averaged yearly discharge. This is very important in hydrologic applications. It should be noted that although the variability of monthly and yearly precipitations and autocorrelation were reproduced almost exactly by the spectral correction method, the variability of monthly discharge was not as good as that of precipitation. There may be three reasons for this. Firstly, as mentioned above, the corrections of monthly and inter-annual variability has limited effect on other time scales, and so the corrected precipitation series may still not be as good as the observed data. Secondly, the discharge was affected not only by precipitation, but also by temperatures, which control the snow melting. WeaGETS-generated temperatures were used to replace the observed ones, in order to remove any biases due to the temperature generating process. However, by doing so, another bias was introduced in which temperatures and precipitations were no longer correlated in the observed time series. Even though it seemed better to proceed as such, a new bias may however have been introduced. Thirdly, the proposed approach keeps the precipitation occurrence process constant. Ongoing work indicates that transition probabilities also display inter-annual variability, and are partly correlated with annual precipitation. Even though the proposed spectral correction approach significantly improves the simulation of water discharge, further improvements may be required that occurrence variability be specifically taken into account. However, a relatively simple technique for adjusting the daily precipitation occurrence sequence is not immediately obvious (Wang and Nathan, 2007). Furthermore, although indirect validation is generally valid for a given impact model, location and experimental setting, further testing may be needed.

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