Hydrological Modeling Using a Multisite Stochastic Weather Generator

Jie Chen¹; François P. Brissette²; and Xunchang J. Zhang³

Abstract: Weather data are usually required at several locations over a large watershed, especially when using distributed models for hydrological simulations. In many applications, spatially correlated weather data can be provided by a multisite stochastic weather generator, which considers the spatial correlation of weather variables. Prior to using a multisite weather generator for hydrological modeling, its ability to adequately represent the proper hydrological response needs to be assessed. This study assesses the effectiveness of a new multisite weather generator (MulGETS) for hydrological modeling over a Canadian watershed in the Province of Québec. Prior to hydrological modeling, MulGETS is first evaluated with respect to reproducing the spatial correlation and statistical characteristics of precipitation and temperature for the studied watershed. Hydrological simulations obtained from MulGETS-generated precipitation and temperature are then compared with those obtained from a single-site weather generator (WeaGETS) and a WeaGETS-based lumped approach (WeaGETS-lumped) that averages the climate series over all stations in a watershed before running the single-site weather generator. The hydrology is simulated using two hydrological models: the conceptually lumped model HSAMI and the physically based distributed model CEQUEAU. When using the conceptually lumped model, the weather time series is first averaged over all stations in the watershed. The results show that the monthly mean discharge is accurately represented by both MulGETS-generated and WeaGETS-lumped-generated precipitation and temperature, whereas it is considerably underestimated by WeaGETS data for the snowmelt period. The MulGETS and WeaGETS-lumped data also show significant advantages in representing the monthly streamflow variability, which is underestimated by the WeaGETS outputs. Additionally, MulGETS and WeaGETS-lumped consistently perform better than WeaGETS for simulating extreme flows (snowmelt high flows and summer-autumn high and low flows). However, no obvious difference in performance was found between MulGETS and WeaGETSlumped data for hydrological modeling. Moreover, the use of a physically based distributed model with MulGETS did not result in any significant performance gain compared with the much simpler combination of WeaGETS-lumped with a lumped hydrological model for the studied watershed. Overall, this study indicates that a single-site weather generator combined with a lumped hydrological model is sufficient for accurate hydrological simulations, even in the case of a large watershed. DOI: 10.1061/(ASCE)HE.1943-5584.0001288. © 2015 American Society of Civil Engineers.

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Introduction

Stochastic weather generators have been widely used to provide meteorological data for modeling and predicting surface hydrology and crop production (Xia 1996; Caron et al. 2008; Zhang and Garbrecht 2003; Chen et al. 2012a). Compared with station-based observations that usually have a limited length and missing values, a stochastic weather generator can provide climate time series with arbitrary lengths and with no missing values. They can be coupled with ensemble weather forecasts (Chen et al. 2014a) to provide probabilistic time series to ensemble streamflow systems (Chen

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and Brissette 2015). Stochastic weather generators have also been used as downscaling tools to produce future climate change scenarios by perturbing their parameters on the basis of climate change signals (e.g., Semenov and Barrow 1997; Wilks 1992, 1999; Pruski and Nearing 2002; Zhang et al. 2004; Zhang 2005; Zhang and Liu 2005; Qian et al. 2005, 2010; Kilsby et al. 2007; Chen et al. 2012a). Several weather generators, such as the Weather GENerator (WGEN) (Richardson 1981; Richardson and Wright 1984), the Climate Generator (ClimGen) (Stockle et al. 1999), the CLImate GENerator (CLIGEN) (Nicks et al. 1994), the Weather generator of École de technologie supérieure (WeaGETS) (Chen et al. 2012b), and the Long Ashton Research Station-Weather Generator (LARS-WG) (Semenov and Barrow 2002) have been developed and widely used for climate generation and climate change impact studies.

Most weather generators are single-site based and can only generate meteorological data at a single point or independent time series at several points. However, for hydrological studies, weather data are usually required to be known at several locations within a watershed. This is particularly true for precipitation, which often displays a large variability in time and space. Hence, proper representation of spatial correlation in meteorological variables is particularly important for generating multisite climate data within a large watershed. Several approaches have been developed to simultaneously generate multisite precipitation (e.g., Wilks 1998; Kottegoda et al. 2003; Wilby et al. 2003; Clark et al. 2004a, b;

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Fowler et al. 2005; Mehrotra and Sharma 2007; Sharif and Burn 2007; Eum et al. 2010; Li 2014).

Srikanthan and McMahon (2001) grouped multisite weather generation algorithms into three categories: conditional models (Zucchini and Guttorp 1991; Bardossy and Plate 1991; Charles et al. 1999), extension of Markov-chain models (Wilks 1998; Brissette et al. 2007), and random cascade models (Jothityangkoon et al. 2000). Conditional models are usually achieved by linking atmospheric circulation patterns to precipitation occurrence and amounts by using a hidden or semi-Markov chain model. Conditional models rely on single-site weather generators driven with temporally independent and spatially correlated random numbers to induce multisite correlation (Wilks 1998; Brissette et al. 2007; Chen et al. 2014b). Jothityangkoon et al. (2000) proposed a random cascade model to generate synthetic fields of space-time daily rainfall. A first-order, four-state Markov chain model was first used to generate a daily time series of the regionally averaged rainfall, and a nonhomogeneous random cascade process was then used to disaggregate the regionally averaged rainfall to produce daily rainfall spatial patterns. More recently, Baigorria and Jones (2010) alternatively classified multisite weather generators into parametric (e.g., Wilks 1998; Qian et al. 2002; Brissette et al. 2007; Khalili et al. 2007; Leander and Buishand 2009; Srikanthan and Pegram 2009), nonparametric (e.g., Wilby et al. 2003; Beersma and Buishand 2003; Burton et al. 2008), and hybrid (e.g., Palutikof et al. 2002; Fowler et al. 2005; Apipattanavis et al. 2007; Cannon 2008) approaches.

Among existing approaches, Wilks' (1998) conditional method is the most widely cited in the literature. This approach extends the commonly used single-site weather generator (WGEN) (Richardson 1981; Richardson and Wright 1984) by driving it with temporally independent but spatially correlated random numbers. Several other studies have improved on Wilks' approach to reduce its computational burden (e.g., Qian et al. 2002; Brissette et al. 2007; Mehrotra and Sharma 2007). In particular, Brissette et al. (2007) presented a simple algorithm to find the random number time series with desired correlation matrices for generating precipitation occurrence and amounts. Additionally, an occurrence index approach was used to deal with the spatial intermittence problem of precipitation amounts (Wilks 1998). These were taken into account in Chen et al.'s (2014b) multisite weather generator (MulGETS). This multisite weather generator was thoroughly assessed over five different watersheds in its ability to adequately reproduce the observed spatial correlations and statistical characteristics of both precipitation and temperature (Chen et al. 2014b).

However, one of the ultimate goals of using a multisite weather generator is for hydrological modeling or forecasting. Any hydrological study that ignores the spatial correlation of meteorological variables may introduce significant errors in the final results (Wilks and Wilby 1999; Srikanthan and McMahon 2001; Mehrotra et al. 2006; Khalili et al. 2011). Thus, the performance of a multisite weather generator has to be evaluated for hydrological modeling at the watershed scale. Until now, only a few studies (Watson et al. 2005; Khalili et al. 2006, 2011) have been conducted to assess the effectiveness of using multisite weather generators for hydrological modeling. The main reasons for that are likely that robust multisite weather generators are hard to set up, and that using stochastic weather generation brings additional uncertainty to the forcing data, especially when compared with other approaches such as resampling approaches. Watson et al. (2005) compared the ability of single-site and multisite weather generators for hydrological modeling in the Woady Yaloak River catchment (306 km²) located in Victoria, Australia. Little difference was found between those models, likely because of the watershed's small size and flat topography, limiting the precipitation gradients. However, they strongly

suggested evaluating the effectiveness of the multisite weather generator in other watersheds. Khalili et al. (2006) evaluated the performance of a spatial autocorrelation-based multisite weather generator for hydrological modeling using a conceptually lumped hydrological model. As expected, the results indicated that the multisite weather generator performed better than the single-site weather generator at representing the summer-autumn flow. However, hydrological modeling using distributed hydrological models may be more appropriate to evaluate the performance of multisite weather generators because the distributed model specifically takes into account the spatial variation of the hydrological response throughout the watershed. Accordingly, Khalili et al. (2011) further evaluated the efficiency of their multisite weather generator for hydrological modeling over the same watershed using a physically based distributed model. The hydrological simulations derived from the multisite weather generator synthesized time series were also compared with those derived from a single-site weather generator, which are used to produce watershed-averaged time series with a lumped approach. Even though Khalili et al. (2011) recommended the coupling of a distributed hydrological model with a multisite weather generator for hydrological modeling, using a single-site weather generation with a lumped approach nonetheless presents a few advantages over a multisite approach in terms of hydrological modeling. The lumped approach is much simpler, and in this case, it performs better for the simulation of summer streamflows. This is probably because the watershed size (9,700 km²) is not large enough to reveal to the advantage of using a multisite weather generator, especially when taking into account the fact that five out of seven stations are closely concentrated in the southern part of the watershed. Additionally, the performance of a multisite weather generator for hydrological modeling depends on the ability of the weather generator itself and that of the hydrological model.

Accordingly, this study aims at assessing the effectiveness of a new multisite weather generator (MulGETS) for hydrological modeling over a very large watershed in the Province of Québec, Canada. Two very different hydrological models (a conceptually lumped model and a physically based distributed model) are used for hydrological simulations. This makes it possible to investigate whether or not a multisite weather generator should be coupled to distributed hydrological model to reach maximum efficiency. The hydrological simulations obtained from the MulGETS-generated time series are then compared with those obtained from a singlesite weather generator (WeaGETS) using two approaches. Weather data from all stations are first averaged and then watershedaveraged data are simulated with WeaGETS (referred to as the WeaGETS-lumped approach). This is expected to answer the question of whether the use of a multisite weather generator has advantages over the commonly used single-site weather generator on watershed-averaged weather variables for hydrological modeling. The second approach uses the single-site weather generator independently at all station sites (referred to as the WeaGETS approach). This would not be a sound approach in real-life applications and is used in this paper as a baseline against which to compare the other two methods (MulGETS and WeaGETS-lumped). Additionally, the use of the second approach is expected to outline where the multisite weather generator is better than the single-site weather generator for hydrological modeling (e.g., mean flow, flow variability, or extreme flow).

Study Area and Data

This study was conducted over the Lac-Saint-Jean (LSJ) watershed (Fig. 1) located in the Province of Québec, Canada. The LSJ

watershed belongs to the Saguenay-Lac-Saint-Jean (SLSJ) hydrological system in northern Québec. The total area of this hydrological system is about 73,800 km², and it extends between 70.5°–74.3°W and 47.3°–52.2°N (Coulibaly and Dibike 2004). The LSJ watershed has a 45,432-km² surface area and contributes to approximately 60% of the total area of the SLSJ catchment. Water from north and south converges at the Saint-Jean Lake and flows to the Saint-Laurence River through the Saguenay River. Annual precipitation in the LSJ watershed is about 914 mm with about 30% in the form of snow. Mean annual maximum and minimum temperatures ($T_{\rm max}$ and $T_{\rm min}$) are 6.4°C and –5.1°C, respectively, over the last 26 years. The mean annual discharge of the LSJ watershed is about 870 m³/s. Snowmelt peak discharge usually occurs in April with a multiple-year average of about 4,300 m³/s.

Fifteen meteorological stations dispersed across the LSJ watershed (Fig. 1) are used in this study. The meteorological data (precipitation, $T_{\rm max}$, and $T_{\rm min}$) and streamflow time series are from 1985 to 2010 at the daily scale. The hydrometeorological data was provided by Rio Tinto Alcan Company (Montreal, Quebec, Canada). Natural inflow series have been reconstructed by Rio Tinto Alcan using operation data from the upstream reservoir.

Methodology

Stochastic Weather Generators

The single-site and multisite weather generators used in this study are WeaGETS and MulGETS, respectively. Both weather generators have been described in detail in previous studies (Chen et al. 2012b; Brissette et al. 2007; Chen et al. 2014b). They are only briefly presented in the following paragraphs. The *MATLAB* codes to both WeaGETS and MulGETS are freely available on the MathWorks file exchange website.

WeaGETS is a WGEN-based (Richardson 1981; Richardson and Wright 1984) single-site weather generator for daily precipitation, $T_{\rm max}$, and $T_{\rm min}$. The precipitation occurrence is generated using a first-order two-state Markov chain. In other words, the probability of precipitation occurrence on a given day is on the basis of the wet or dry status of the previous day. For a predicted wet day, a two-parameter gamma distribution is used to generate the precipitation amount. $T_{\rm max}$ and $T_{\rm min}$ are conditioned on the wet and dry statuses and generated using a first-order linear autoregressive model (Chen et al. 2011a).

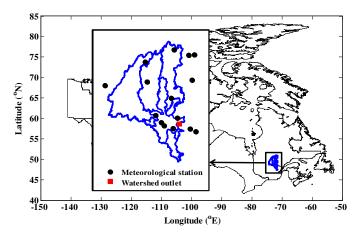


Fig. 1. Location map of the Lac-Saint-Jean (LSJ) watershed

MulGETS is an extended version of WeaGETS using the Wilks' (1998) approach. Instead of generating precipitation occurrence and amounts using temporally and spatially independent random numbers, MulGETS generates precipitation on the basis of temporally independent but spatially correlated random numbers. The spatially correlated random field is preserved using a distribution-free approach (Iman and Conover 1982) with the optimization algorithm proposed by Brissette et al. (2007). Using the spatially corrected random field, precipitation occurrence is first generated using the first-order two-state Markov chain. Daily precipitation amounts are then generated conditioned on precipitation occurrence using a multigamma distribution (Brissette et al. 2007; Chen et al. 2014b). For constructing the multigamma distribution, an occurrence index describing the spatial distribution of precipitation occurrence at a watershed is first calculated for each station and each day if precipitation occurs at that station. The occurrence index, which varies between zero (precipitation occurs at only one station) and one (precipitation occurs at all stations) is then separated into several classes. At the last step, the relationship between the occurrence index and parameters of a gamma distribution is estimated. For convenience, the two parameters of gamma distribution are transformed to the mean and standard deviation of daily precipitation. In other words, the mean and standard deviation are linked to the occurrence index for each station. Practically speaking, this means that larger precipitation amounts will be generated when many stations are wet (large value of occurrence index). The spatially correlated random field for generating T_{max} and T_{min} is also obtained using a distribution-free approach. However, the iterative process used for precipitation occurrence or amounts is not needed because temperature usually has a very high spatial correlation. With the spatially correlated random field, the daily $T_{\rm max}$ and T_{\min} are generated using a first-order linear autoregressive model for each station.

Hydrological Models

Two very different hydrological models were used in this study: HSAMI and CEQUEAU. HSAMI is a conceptually lumped model, whereas CEQUEAU is a physically based distributed model. Both models have been widely used for hydrological simulations and climate change impact studies over the Province of Québec (e.g., Minville et al. 2008; Chen et al. 2011b, c; Poulin et al. 2011; Arsenault et al. 2013).

HSAM

HSAMI is a 23-parameter, lumped, conceptual, rainfall-runoff model developed by Hydro-Québec (Montreal, Quebec, Canada) (Fortin 2000). It has been used by Hydro-Québec and other institutes to forecast natural inflows and assess the climate change impacts on hydrology on nearly 100 watersheds with surface areas ranging from 160 to 69,195 km² for over 20 years (e.g., Minville et al. 2008; Chen et al. 2011b, c; Poulin et al. 2011; Arsenault et al. 2013). Of HSAMI's 23 parameters, 2 parameters account for evapotranspiration, 6 for snowmelt, 10 for vertical water movement, and 5 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 routed through two unit hydrographs and one linear reservoir. The model takes snow accumulation, snowmelt, soil freezing and thawing, and evapotranspiration into account. Model calibration is done automatically using the Covariance Matrix Adaptation Evolution Strategy (CMAES) (Hansen and Ostermeier 1996, 2001).

The watershed-averaged minimum required daily input data for HSAMI are $T_{\rm max}$, $T_{\rm min}$, 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 and validation. For this study, 13 years (1985–1997) of daily discharge data were used for model calibration, and the other 13 years (1998–2010) were used for validation. HSAMI was calibrated with respect to reproducing the observed daily hydrograph. The optimal combination of parameters was chosen on the basis of the Nash-Sutcliffe efficiency criteria (Nash and Sutcliffe 1970). The chosen set of parameters yielded Nash-Sutcliffe criteria values of 0.877 and 0.833 for the calibration and validation periods, respectively. Figs. 2(a and b) present the observed and simulated hydrographs for both calibration and validation periods, respectively. The simulated hydrographs are very close to the observed ones for both periods, a consequence of the good performance of the HSAMI hydrological model.

CEQUEAU

CEQUEAU (Morin et al. 1975; Charbonneau et al. 1977; Singh and Frevert 2001) is a distributed hydrological model taking into account the physical characteristics of watersheds through dividing the watershed into several elements. It has been used over many watersheds in Québec and other parts of the world for hydrological modeling (e.g., Arsenault et al. 2013; Palma et al. 2015; François et al. 2014). Physiographic, meteorological, and hydrometric data sets are required to run this model. The meteorological data used for the model can be obtained from meteorological stations within or near the watershed. For running this model, the watershed is first divided into whole squares (usually $10 \times 10 \text{ km}$) to form smaller hydrological units. This step allows evaluating all the

physiographic characteristics required by the model such as the altitude of the square, average slope, the orientation of the slope, and forest areas. Each square is then assigned to a meteorological station using either the Thiessen polygon method or a weighted average of the three nearest meteorological stations on the basis of various physiographic characteristics such as altitude and geographic distance. The hydrological balance on each surface unit is reconstituted by breaking down the hydrological cycle into distinct elements, including accumulation and snowmelt, infiltration, water redistribution in the soil, evapotranspiration, groundwater reaction, and flow routing in channels.

CEQUEAU was calibrated with the observed daily data using the CMAES method. The model was calibrated with respect to reproducing the observed daily hydrograph. Thirteen years (1985–1997) of data were used for model calibration, and the other 13 years (1998–2010) were used for validation. The chosen set of parameters yielded Nash-Sutcliffe criteria values of 0.842 and 0.826 for calibration and validation periods, respectively. Observed and simulated daily hydrographs are presented in Figs. 2(c and d), both showing the excellent performance of the CEQUEAU model.

Data Analysis

As described earlier, three meteorological data sets were generated using both weather generators. The first data set (Data set 1) was generated using the multisite weather generator MulGETS on the 15 station sites over the watershed. The spatial correlation was preserved for all these time series by using spatially corrected random

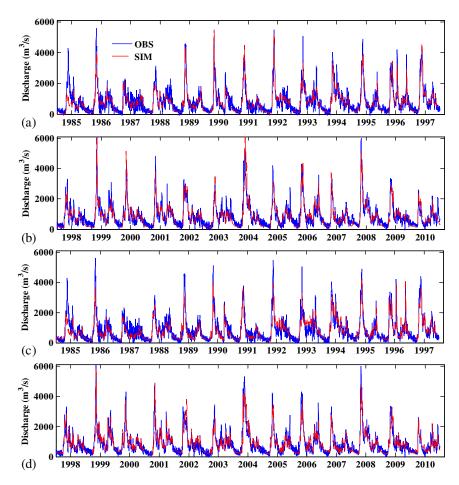


Fig. 2. Observed (OBS) and HSAMI-simulated and CEQUEAU-simulated daily hydrographs for both calibration (1985–1997) and validation (1998–2010) periods: (a) HSAMI calibration; (b) HSAMI validation; (c) CEQUEAU calibration; (d) CEQUEAU validation

numbers. The second data set (Data set 2) was generated with the single-site WeaGETS using a lumped approach (WeaGETSlumped). Prior to running WeaGETS, the observed time series were first averaged over all 15 stations on the basis of weights calculated using the Thiessen polygon method (Rhynsburger 1973). On the basis of this approach, 13 weather stations were retained and average for the lumped approach. The averaged time series was then fed to WeaGETS to generate a new time series. With this approach, only one time series was generated. The lumped approach is a standard way to use weather generators for hydrological modeling and climate change impact studies (Wilby and Harris 2006; Chen et al. 2011a, b). The third data set (Data set 3) was generated by WeaGETS for all 15 stations over the LSJ watershed. Each of the time series was generated independently using uncorrelated random number time series. Daily time series of 500 years were generated for all three data sets. Long time series are used to obtain the true expectancy of the generated data. Shorter time series could result in biases due to the random nature of the stochastic process.

In a first step, the MulGETS performance was evaluated with respect to reproducing the spatial correlation because this is one of the most important characteristics of multisite weather generators over single-site weather generators. The performance of MulGETS, WeaGETS-lumped and WeaGETS in reproducing the statistical characteristics of precipitation and temperature for individual stations has been evaluated in other studies (Chen et al. 2012b; Li et al. 2013; Chen et al. 2014b); this study only evaluated their ability with respect to reproducing statistical characteristics of watershed-averaged precipitation and temperature because these are the key values for hydrological modeling. All three data sets were then used as inputs to both hydrological models. Because HSAMI is a lumped model, both Data sets 1 and 3 were first averaged on the basis of weights calculated using the Thiessen polygon method prior to running the hydrological model. However, when using CEQUEAU, all three data sets were fed directly to the model. CEQUEAU has a built-in function for assigning whole squares to metrological stations using Thiessen polygons. The outputs from both hydrological models using three data sets were then compared with the observed streamflow time series in terms of the mean and standard deviation of monthly discharges. Because extreme streamflow values are critical to the management of water resources, it is important that weather generators satisfactorily perform the difficult task of representing extremes. Thus, the three data sets are also compared with respect to their ability at representing the spring (March–May) high flow (the 0.95 quantile) and summerautumn (June–November) high (the 0.95 quantile) and low (the 0.05 quantile) flows.

Results

Precipitation and Temperature Generation

Fig. 3 presents scatter plots of the observed interstation correlations of precipitation occurrence and amounts, $T_{\rm max}$ and $T_{\rm min}$, against MulGETS-generated counterparts for all station pairs over the LSJ watershed. The interstation correlation is well reproduced by MulGETS as indicated by the fact that all correlation coefficients are close to the 1:1 line. This is especially true for the interstation correlation of precipitation occurrence and amounts.

Fig. 4(a) presents the seasonal number of wet days for all 15 stations over the LSJ watershed. The wet day frequency is accurately reproduced by MulGETS for all four seasons and 15 stations. This indicates the solid performance of the Markov chain as shown in several other studies (e.g., Richardson 1981; Chen et al. 2012b; Chen and Brissette 2014). Joint probabilities that station pairs are both dry or both wet are presented in Figs. 4(b and c) to further show the simultaneous precipitation occurrence of MulGETS-generated data. The results indicate that joint probabilities of precipitation occurrence are accurately reproduced for both dry and wet days.

MulGETS, WeaGETS-lumped, and WeaGETS are compared with respect to their ability to reproduce the mean, standard deviation and mean seasonal daily maximum value (mean value

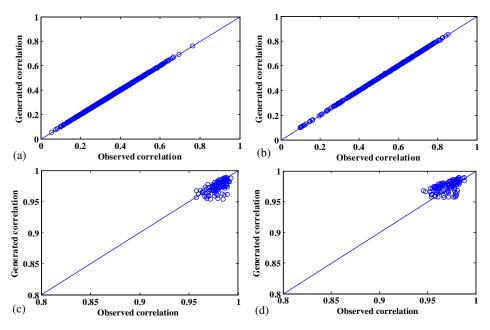


Fig. 3. Scatter plots of observed interstation correlations of precipitation occurrence (a) and amounts (b) and maximum (c) and minimum (d) temperatures versus MulGETS-generated counterparts for all station pairs over the LSJ watershed; the correlation of precipitation occurrence, maximum and minimum is calculated on a monthly basis, whereas the correlation of precipitation amounts is calculated at a seasonal basis

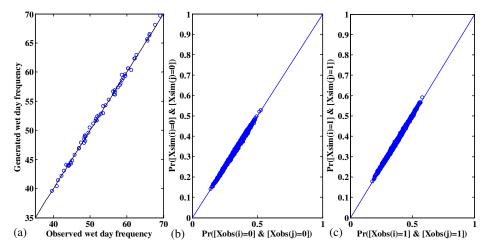


Fig. 4. Observed versus MulGETS-generated wet day frequency (a) and joint probabilities that station pairs (*i* and *j*) are both dry (b) or both wet (c) on a given day for all the combinations of stations pairs over the LSJ watershed

of seasonal daily maximum precipitation) of the watershedaveraged daily precipitation (Fig. 5). Even though it is unfair to compare WeaGETS to the other two methods (MulGETS and WeaGETS-lumped), this is still useful to better understand the different performances of these three approaches in terms of hydrological modeling. Because MulGETS works at the seasonal basis, both mean and standard deviation are calculated at the seasonal scale. Overall, the seasonal mean wet-day precipitation is reasonably reproduced by all three approaches [Fig. 5(a)]. The slight differences can be partly attributed to the stochastic nature of precipitation generation. Averaging all the independently generated weather time series (the WeaGETS approach) obviously does not affect the seasonal mean wet-day precipitation, probably due to the large spatial variability of precipitation for this large watershed. Both the MulGETS and WeaGETS-lumped approaches reasonably reproduce the standard deviation of the watershedaveraged precipitation [Fig. 5(b)]. However, the standard deviation is considerably underestimated by WeaGETS. Similarly, MulGETS and WeaGETS-lumped perform reasonably well for simulating the seasonal daily maximum precipitation, even though the winter daily maximum precipitation is slightly underestimated by WeaGETS-lumped [Fig. 5(c)]. However, WeaGETS severely underestimates the daily maximum precipitation for all seasons. This is expected because heavy precipitation in one station can be offset by light precipitation at neighboring stations.

MulGETS, WeaGETS-lumped, and WeaGETS are further compared with respect to reproducing the mean and standard deviation of the watershed-averaged $T_{\rm max}$ and $T_{\rm min}$ (Fig. 6). All three approaches accurately reproduce the watershed-averaged monthly mean $T_{\rm max}$ and $T_{\rm min}$, and there is no obvious difference among them. This was expected because the same scheme is used by all three methods for modeling the temperature. The observed temperature shows a considerable variability, which is reasonably preserved by the MulGETS and WeaGETS-lumped systems. However, WeaGETS considerably underestimates the temperature variability, especially for winter and spring seasons.

Hydrological Modeling

The hydrological responses of two hydrological models (HSAMI and CEQUEAU) to MulGETS-, WeaGETS-lumped- and WeaGETS-generated precipitation and temperature time series are first evaluated using mean and standard deviation of monthly streamflow as criteria (Fig. 7). In order to avoid the biases of hydrological model

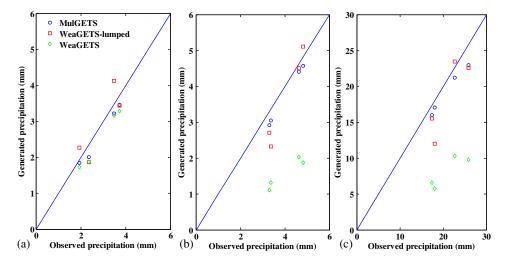


Fig. 5. Scatter plots of the mean (a) standard deviation (b) and mean seasonal maximum daily precipitation (c) of observed versus MulGETS-generated, WeaGETS-lumped, and WeaGETS-generated watershed averaged precipitation for all four seasons

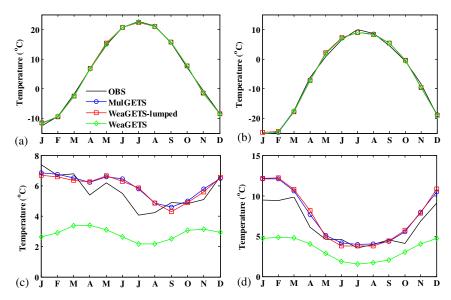


Fig. 6. Mean and standard deviation of watershed averaged monthly maximum and minimum temperatures ($T_{\rm max}$ and $T_{\rm min}$) generated by MulGETS, WeaGETS-lumped, and WeaGETS approaches; mean and standard deviation of watershed-averaged observed monthly $T_{\rm max}$ and $T_{\rm min}$ are also plotted for comparison: (a) $T_{\rm max-mean}$; (b) $T_{\rm min-mean}$; (c) $T_{\rm max-standard\ deviation}$; (d) $T_{\rm min-standard\ deviation}$

outputs, observed streamflows are represented by simulated discharge using observed precipitation and temperature rather than by real observations. This is the reason why the mean and standard deviation of observed monthly streamflow (OBS-SIM in Fig. 7) are slightly different between the two hydrological models. MulGETS data represent the mean streamflows quite accurately, especially during the snowmelt period (March–May). The mean streamflow is also reasonably represented by WeaGETS-lumped data, even though the snowmelt peak discharge is slightly overestimated, especially when using CEQUEAU. However, the spring peak discharge is remarkably overestimated by WeaGETS data with a considerable lag for the time to snowmelt. Additionally, WeaGETS data underestimate the monthly mean flow in November and

December, probably because of the underestimation of temperature variability as shown in Fig. 6. Both MulGETS and WeaGETS-lumped slightly underestimate monthly streamflow variability between March and May, and overestimate it in June and July. Both approaches behave similarly. WeaGETS considerably underestimates the variability of monthly flows because the overall monthly series are smoothed by averaging the uncorrelated climate time series over the watershed.

Fig. 8 presents the extreme flows (spring high flow and summerautumn high and low flows) simulated by HSAMI and CEQUEAU using MulGETS-, WeaGETS-lumped-, and WeaGETS-generated precipitation and temperature. The observed extreme flows and observed meteorological data simulated flows are also presented for

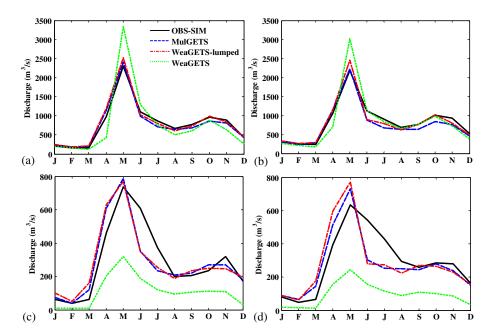


Fig. 7. Mean and standard deviation of monthly streamflow simulated by HSAMI and CEQUEAU using MulGETS-, WeaGETS-lumped-, and WeaGETS-generated precipitation and temperature; the observed precipitation and temperature simulated streamflow (OBS-SIM) is also plotted for comparison: (a) HSAMI mean; (b) CEQUEAU mean; (c) HSAMI standard deviation; (d) CEQUEAU standard deviation

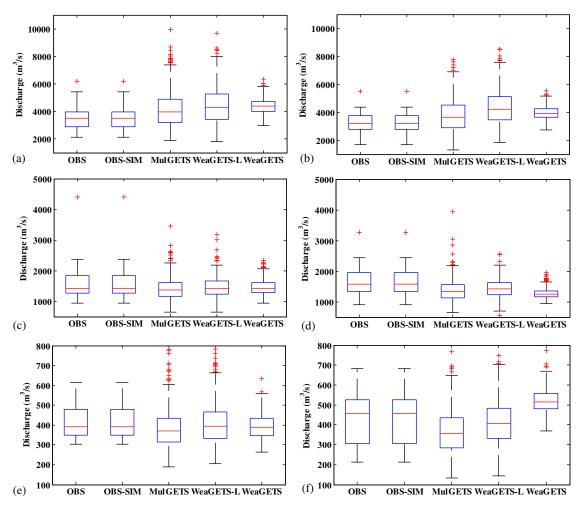


Fig. 8. Boxplots of spring high flow and summer-autumn high and low flows simulated by HSAMI and CEQUEAU using MulGETS-, WeaGETS-lumped- (WeaGETS-L), and WeaGETS-generated precipitation and temperature; observed streamflow and observed precipitation and temperature simulated streamflow are also plotted for comparison: (a) HSAMI spring high flow; (b) CEQUEAU spring high flow; (c) HSAMI summer-autumn low flow; (d) CEQUEAU summer-autumn low flow; (e) HSAMI summer-autumn low flow; (f) CEQUEAU summer-autumn low flow

comparison. Each boxplot is constructed with a number of points equal to the number of years (26 for the observed flow and 500 for the simulated flow). Overall, the spreads of high and low flows are consistently underestimated by WeaGETS. This is expected because high flows in one subbasin can be offset by low flows in neighboring subbasins when using the uncorrelated meteorological time series. MulGETS and WeaGETS-lumped data perform much better at representing the high and low flows, even though the spread of spring and summer-autumn high flows is slightly overestimated. This may be because the generated time series are much longer than the observed ones, thus allowing for additional variability. Biases related to the hydrological modeling processes may be another reason for this overestimation. MulGETS and WeaGETSlumped both behave similarly, with differences smaller than biases resulting from the hydrological modeling process. Moreover, HSAMI and CEQUEAU perform similarly in terms of simulating extreme flows when using stochastically generated data for this watershed. In other words, the combination of a multisite weather generator and a distributed hydrological model did not result in a better performance when compared with the combination of a single-site weather generator and a lumped hydrological model.

Discussion and Conclusion

This study investigates the effectiveness of using a multisite weather generator for hydrological modeling over a very large watershed. To achieve this goal, hydrological simulations obtained from a multisite weather generator (MulGETS) are compared with those obtained from a single-site weather generator using either a lumped approach (WeaGETS-lumped) or operating independently at station sites (WeaGETS). It is of course not totally fair to compare a multisite weather generator to independently generated data at multiple stations using a single-site weather generator. This is particularly the case for large watersheds because the latter will lack the spatial coherence to adequately generate variables. Using a single-site weather generator on watershed-averaged weather variables (WeaGETS-lumped) has been by far the most common approach for stochastic streamflow generation. The inclusion of all three approaches allows for a better understanding of the advantages of using the more complex multisite weather generator, especially in conjunction with a distributed hydrological model.

The results indicate that MulGETS accurately preserves the spatial correlation of precipitation and temperature, especially the interstation correlation of precipitation occurrence and amounts. As a

result, MulGETS reproduces reasonably well the mean and standard deviations of watershed-averaged precipitation and temperature, and extreme precipitation. The commonly used WeaGETS-lumped approach also accurately reproduces the mean, standard deviation, and extremes, indicating the reasonable performance of this single-site weather generator in generating watershed-averaged precipitation and temperature. The variability of watershed-averaged precipitation and temperature is consistently underestimated by WeaGETS. This is to be expected because the precipitation is homogenized when averaging all stations. When using the single-site weather generator, there may be a little or no rainfall occurring at one station, even though a neighboring station experiences a heavy rainfall event. This insufficient representation of precipitation and temperature variability would affect the variability of simulated streamflows (e.g., the magnitude and timing of the spring flood).

In terms of hydrological modeling, the use of WeaGETS results in a considerable overestimation of the mean snowmelt peak discharge. This may be because WeaGETS considerably underestimates the variability of watershed-averaged temperature with the consequence of having spring floods occurring in a narrower window than seen with the observed streamflows. In other words, when using WeaGETS data, the spring high flow always occurs at the same short period (usually in April) for each simulated year, whereas the observed spring peak flow occurs between April and June. WeaGETS-lumped data perform much better than WeaGETS data with respect to representing the mean snowmelt peak discharge, even though the mean peak discharge is still slightly overestimated, especially when using the distributed hydrological model. Because spatial correlation is specifically taken into account, MulGETS data accurately represent the mean snowmelt peak discharge, regardless of using the lumped or the distributed hydrological model. WeaGETS data underestimate the summer to winter mean flow simulated by the lumped model HSAMI. However, the summer-autumn mean flow is reasonably represented when using the distributed model CEQUEAU, which is comparable to or even slightly better than that simulated by MulGETS data. Similar performances of the single-site and multisite weather generators in representing the summer-autumn mean flow are expected because both of them accurately reproduce the watershed-averaged precipitation amounts and temperature. However, MulGETS and WeaGETS-lumped represent streamflow variability much better because the variability of watershed-averaged precipitation and temperature is reasonably reproduced. Additionally, MulGETS and WeaGETS-lumped data perform much better than WeaGETS at representing extreme flows (e.g., spring high flow and summerautumn high and low flows).

One of the goals of this study was to compare hydrological simulations issued from a multisite weather generator with those obtained from a lumped single-site weather generator. Results show that both approaches perform quite similarly over the studied watershed. In other words, the multisite weather generator did not result in better hydrological simulations even when coupled with the distributed hydrological model over the large LSJ watershed. This result implied that the simple combination of a single-site weather generator and lumped hydrological model may be sufficient for most watersheds. Over smaller watersheds, the lumped approach should also be just as good as the more complex method and possibly even better due to the absence of the complex numerical scheme dealing with spatial coherence.

This study also shows that the distributed hydrological model was not able to use the generated multisite weather data to its advantage when simulating streamflows at the watershed outlet. Overall, the combination of a single-site weather generator and a conceptually lumped model appears to be sufficient for hydrological

modeling and impact assessments over most watersheds, including very large ones. However, this study was concerned with modeling a single large watershed with hydrographs are strongly snowmelt dominated. During snowmelt, hydrographs are strongly related to temperature which is much less variable than precipitation over most watersheds. For large rainfall-dominated watersheds with complex topography, the use of a multisite weather generator coupled with a distributed hydrological model may be necessary for accurate hydrological simulations.

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References

- Apipattanavis, S., Podesta, G., Rajagopalan, B., and Katz, R. W. (2007). "A semiparametric multivariate and multisite weather generator." Water Resour. Res., 43(11), W11401.
- Arsenault, R., Malo, J. S., Brissette, F., Minville, M., and Leconte, R. (2013). "Structural and non-structural climate change adaptation strategies for the Péribonka water resource system." Water Resour. Manage., 27(7), 2075–2087.
- Baigorria, G. A., and Jones, J. W. (2010). "GiST: A stochastic model for generating spatially and temporally correlated daily rainfall data." *J. Clim.*, 23(22), 5990–6008.
- Bardossy, A., and Plate, E. J. (1991). "Modelling daily rainfall using a semi-Markov representation of circulation pattern occurrence." *J. Hydrol.*, 122(1–4), 33–47.
- Beersma, J. J., and Buishand, T. A. (2003). "Multi-site simulation of daily precipitation and temperature conditional on the atmospheric circulation." *Clim. Res.*, 25(2), 121–133.
- Brissette, F. P., Khalili, M., and Leconte, R. (2007). "Efficient stochastic generation of multi-site synthetic precipitation data." *J. Hydrol.*, 345(3–4), 121–133.
- Burton, A., Kilsby, C. G., Fowler, H. J., Cowpertwait, P. S. P., and O'Connell, P. E. (2008). "RainSim: A spatial–temporal stochastic rainfall modelling system." *Environ. Modell. Software*, 23(12), 1356–1369.
- Cannon, A. (2008). "Probabilistic multisite precipitation downscaling by an expanded Bernoulli-Gamma density network." J. Hydrometeorol., 9(6), 1284–1300.
- Caron, A., Leconte, R., and Brissette, F. (2008). "An improved stochastic weather generator for hydrological impact studies." *Can. Water Resour. J.*, 33(3), 233–256.
- Charbonneau, R., Fortin, J.-P., and Morin, G. (1977). "The CEQUEAU model: Description and examples of its use in problems related to water resource management/Le modèle CEQUEAU: Description et exemples d'utilisation dans le cadre de problèmes reliés à l'aménagement." *Hydrol. Sci. Bull.*, 22(1), 193–202.
- Charles, S. P., Bates, B. C., and Hughes, J. P. (1999). "A spatiotemporal model for downscaling precipitation occurrence and amounts." *J. Geophys. Res.*, 104(D24), 31657–31669.
- Chen, J., Brissette, F., and Leconte, R. (2011a). "Assessment and improvement of stochastic weather generators in simulating maximum and minimum temperatures." *Trans. ASABE*, 54(5), 1627–1637.
- Chen, J., Brissette, F., and Leconte, R. (2011b). "Uncertainty of downscaling method in quantifying the impact of climate change on hydrology." *J. Hydrol.*, 401(3–4), 190–202.
- Chen, J., Brissette, F., Leconte, R., and Caron, A. (2012b). "A versatile weather generator for daily precipitation and temperature." *Trans. ASABE*, 55(3), 895–906.
- Chen, J., Brissette, F., and Li, Z. (2014a). "Post-processing of ensemble weather forecasts using a stochastic weather generator." Mon. Weather Rev., 142(3), 1106–1124.

- Chen, J., Brissette, F., Poulin, A., and Leconte, R. (2011c). "Overall uncertainty study of the hydrological impacts of climate change for a Canadian watershed." Water Resour. Res., 47(2), W12509.
- Chen, J., Brissette, F., and Zhang, X. C. (2014b). "A multi-site stochastic weather generator for daily precipitation and temperature." *Trans.* ASABE, 57(5), 1375–1391.
- Chen, J., and Brissette, F. P. (2014). "Comparison of five stochastic weather generators in simulating daily precipitation and temperature for the Loess Plateau of China." *Int. J. Climatol.*, 34(10), 3089–3105.
- Chen, J., and Brissette, F. P. (2015). "Combining stochastic weather generation and ensemble weather forecast for short term streamflow prediction." Water Resour. Manage., 29(9), 3329–3342.
- Chen, J., Brissette, F. P., and Leconte, R. (2012a). "Downscaling of weather generator parameters to quantify the hydrological impacts of climate change." Clim. Res., 51(3), 185–200.
- Clark, M. P., et al. (2004b). "A resampling procedure for generating conditioned daily weather sequences." Water Resour. Res., 40(4), W04304.
- Clark, M. P., Gangopadhyay, S., Hay, L., Rajagopalan, B., and Wilby, R. L. (2004a). "The Schaake shuffle: A method for reconstructing space-time variability in forecasted precipitation and temperature fields." *J. Hydro-meteorol.*, 5(1), 243–262.
- Coulibaly, P., and Dibike, Y. B. (2004). "Downscaling of global climate model outputs for flood frequency analysis in the Saguenay River system." *Project No. S02-15-01*, Science Sub-Component of Climate Change Action Fund, Environment Canada, Hamilton, ON, Canada.
- Eum, H., Simonovic, S., and Kim, Y. (2010). "Climate change impact assessment using K-nearest neighbor weather generator: Case study of the Nakdong River basin in Korea." J. Hydrol. Eng., 10.1061/ (ASCE)HE.1943-5584.0000251, 772–785.
- Fortin, V. (2000). "Le modèle météo-apport HSAMI: Historique, théorie et application." Institut de Recherche d'Hydro, Varennes, QC, Canada, 68 (in French).
- Fowler, H. J., Kilsby, C. G., O'Connell, P. E., and Burton, A. (2005). "A weather-type conditioned multi-site stochastic rainfall model for the generation of scenarios of climatic variability and change." *J. Hydrol.*, 308(1–4), 50–66.
- François, B., Hingray, B., Hendrickx, F., and Creutin, J. D. (2014). "Seasonal patterns of water storage as signatures of the climatological equilibrium between resource and demand." *Hydrol. Earth Syst. Sci.*, 18(9), 3787–3800.
- Hansen, N., and Ostermeier, A. (1996). "Adapting arbitrary normal mutation distributions in evolution strategies: The covariance matrix adaptation." Proc., 1996 IEEE Int. Conf. on Evolutionary Computation, IEEE Neural Network council (NNC), NJ, 312–317.
- Hansen, N., and Ostermeier, A. (2001). "Completely derandomized self-adaptation in evolution strategies." Evol. Comput., 9(2), 159–195.
- Iman, R. L., and Conover, W. J. (1982). "A distribution-free approach to inducing rank correlation among input variables." *Commun. Stat.*, B11(3), 311–334.
- Jothityangkoon, C., Sivapalan, M., and Viney, N. R. (2000). "Tests of a space-time model of daily rainfall in southwestern Australia based on nonhomogeneous random cascades." Water Resour. Res., 36(1), 267–284.
- Khalili, M., Brissette, F., and Leconte, R. (2011). "Effectiveness of multisite weather generator for hydrological modeling." *JAWRA*, 47(2), 303–314.
- Khalili, M., Leconte, R., and Brissette, F. (2006). "On the use of multi site generated meteorological input data for realistic hydrological modeling in the context of climate change impact studies." Engineering Institute of Canada (EIC) Climate Change Technology, IEEE, NJ, 1–7.
- Khalili, M., Leconte, R., and Brissette, F. (2007). "Stochastic multisite generation of daily precipitation data using spatial autocorrelation." *J. Hydrometeorol.*, 8(3), 396–412.
- Kilsby, C. G., et al. (2007). "A daily weather generator for use in climate change studies." *Environ. Modell. Software*, 22(12), 1705–1719.
- Kottegoda, N. T., Natale, L., and Raiteri, E. (2003). "A parsimonious approach to stochastic multisite modelling and disaggregation of daily rainfall." J. Hydrol., 274(1-4), 47-61.
- Leander, R., and Buishand, T. A. (2009). "A daily weather generator based on a two-stage resampling algorithm." *J. Hydrol.*, 374(3–4), 185–195.

- Li, Z. (2014). "A new framework for multi-site weather generator: A two-stage model combining a parametric method with a distribution-free shuffle procedure." Clim. Dyn., 43(3–4), 657–669.
- Li, Z., Brissette, F., and Chen, J. (2013). "Finding the most appropriate precipitation probability distribution for stochastic weather generation and hydrological modelling in Nordic watersheds." *Hydrol. Processes*, 27(25), 3718–3729.
- MATLAB [Computer software]. Natick, MA, MathWorks.
- Mehrotra, R., and Sharma, A. (2007). "A semi-parametric model for stochastic generation of multi-site daily rainfall exhibiting low-frequency variability." J. Hydrol., 335(1–2), 180–193.
- Mehrotra, R., Srikanthan, R., and Sharma, A. (2006). "A comparison of three stochastic multi-site precipitation occurrence generators." J. Hydrol., 331(1–2), 280–292.
- Minville, M., Brissette, F., and Leconte, R. (2008). "Uncertainty of the impact of climate change on the hydrology of a Nordic watershed." *J. Hydrol.*, 358(1–2), 70–83.
- Morin, G., Fortin, J. P., and Charbonneau, R. (1975). "Utilisation du modèle hydrophysiographique CEQUEAU pour l'exploitation des réservoirs artificiels." *IAHS Publication No. 115*, IAHS Press, Wallingford, U.K., 176–184 (in French).
- Nash, J. E., and Sutcliffe, W. H. (1970). "River flow forecasting through conceptual models: Part 1. A discussion of principles." *J. Hydrol.*, 10(3), 282–290.
- Nicks, A. D., and Gander, G. A. (1994). "CLIGEN: A weather generator for climate inputs to water resource and other model." *Proc.*, 5th Int. Conf. on Computers in Agriculture, American Society of Agricultural Engineers, St. Joseph, MI, 3–94.
- Palma, A., González, F., and Cruickshank, C. (2015). "Managed aquifer recharge as a key element in Sonora River basin management, Mexico." *J. Hydrol. Eng.*, 10.1061/(ASCE)HE.1943-5584.0001114, B4014004.
- Palutikof, J. P., Goodess, C. M., Watkins, S. J., and Holt, T. (2002). "Generating rainfall and temperature scenarios at multiple sites: Examples from the Mediterranean." J. Climate, 15(24), 3529–3548.
- Poulin, A., Brissette, F., Leconte, R., Arsenault, R., and Malo, J. S. (2011). "Uncertainty of hydrological modelling in climate change impact studies in a Canadian, snow-dominated river basin." *J. Hydrol.*, 409(3–4), 626–636.
- Pruski, F. F., and Nearing, M. A. (2002). "Climate-induced changes in erosion during the 21st century for eight U.S. locations." *Water Resour. Res.*, 38(12), 341–3411.
- Qian, B., Corte-Real, J., and Xu, H. (2002). "Multisite stochastic weather models for impact studies." *Int. J. Climatol.*, 22(11), 1377–1397.
- Qian, B. D., Gameda, S., Jong, R., Fallon, P., and Gornall, J. (2010). "Comparing scenarios of Canadian daily climate extremes derived using a weather generator." *Clim. Res.*, 41(2), 131–149.
- Qian, B. D., Hayhoe, H., and Gameda, S. (2005). "Evaluation of the stochastic weather generators LARS-WG and AAFC-WG for climate change impact studies." *Clim. Res.*, 29, 3–21.
- Rhynsburger, D. (1973). "Analytic delineation of Thiessen polygons." *Geogr. Anal.*, 5(2), 133–144.
- Richardson, C. W. (1981). "Stochastic simulation of daily precipitation, temperature, and solar radiation." Water Resour. Res., 17(1), 182–190.
- Richardson, C. W., and Wright, D. A. (1984). "WGEN: A model for generating daily weather variables." *ARS-8*, U.S. Dept. of Agriculture, Agricultural Research Service, Washington, DC, 83.
- Semenov, M. A., and Barrow, E. M. (1997). "Use of a stochastic weather generator in the development of climate change scenarios." *Clim. Change*, 35(4), 397–414.
- Semenov, M. A., and Barrow, E. M. (2002). "LARS-WG, a stochastic weather generator for use in climate impact studies." *User manual*, Rothamsted Research, Harpenden, Hertfordshire, U.K.
- Sharif, M., and Burn, D. (2007). "Improved K-nearest neighbor weather generating model." *J. Hydrol. Eng.*, 10.1061/(ASCE)1084-0699 (2007)12:1(42), 42–51.
- Singh, V. P., and Frevert, D. K. (2001). *Mathematical models of large watershed hydrology*, Water Resources Publications, MI.
- Srikanthan, R., and McMahon, T. A. (2001). "Stochastic generation of annual, monthly and daily climate data: A review." *Hydrol. Earth Syst. Sci.*, 5(4), 653–670.

- Srikanthan, R., and Pegram, G. G. S. (2009). "A nested multisite daily rainfall stochastic generation model." J. Hydrol., 371(1-4), 142-153.
- Stöckle, C. O., Campbell, G. S., and Nelson, R. (1999). "ClimGen manual." Dept. of Biological Systems Engineering, Washington State Univ., Pullman, WA.
- Watson, B. M., Srikanthan, R., Selvalingam, S., and Ghafouri, M. (2005).
 "Hydrologic response of SWAT to single site and multi-site daily rainfall generation models." *Proc.*, MODSIM05 Int. Congress on Modelling and Simulation, Univ. of Melbourne, Melbourne, Australia, 2981–2987.
- Wilby, R. L., and Harris, I. (2006). "A framework for assessing uncertainties in climate change impacts: Low-flow scenarios for the River Thames, UK." Water Resour. Res., 42(2), W02419.
- Wilby, R. W., Tomlinson, O. J., and Dawson, C. W. (2003). "Multi-site simulation of precipitation by conditional resampling." *Clim. Res.*, 23, 183–194.
- Wilks, D. S. (1992). "Adapting stochastic weather generation algorithms for climate change studies." Clim. Change, 22(1), 67–84.
- Wilks, D. S. (1998). "Multisite generalization of a daily stochastic precipitation generation model." *J. Hydrol.*, 210(1–4), 178–191.
- Wilks, D. S. (1999). "Multisite downscaling of daily precipitation with a stochastic weather generator." Clim. Res., 11, 125–136.

- Wilks, D. S., and Wilby, R. L. (1999). "The weather generation game: A review of stochastic weather generator models." *Prog. Phys. Geogr.*, 23(3), 329–357.
- Xia, J. (1996). "A stochastic weather generator applied to hydrological model in climate Impact analysis." Theor. Appl. Climatol., 55(1–4), 177–183.
- Zhang, X. C. (2005). "Spatial downscaling of global climate model output for site-specific assessment of crop production and soil erosion." *Agric. For. Meteorol.*, 135(1–4), 215–229.
- Zhang, X. C., and Garbrecht, J. D. (2003). "Evaluation of CLIGEN precipitation parameters and their implication on WEPP runoff and erosion prediction." *Trans. ASAE*, 46(2), 311–320.
- Zhang, X. C., and Liu, W. Z. (2005). "Simulating potential response of hydrology, soil erosion, and crop productivity to climate change in Changwu tableland region on the Loess Plateau of China." Agric. For. Meteorol., 131(3-4), 127-142.
- Zhang, X. C., Nearing, M. A., Garbrecht, J. D., and Steiner, J. L. (2004). "Downscaling monthly forecasts to simulate impacts of climate change on soil erosion and wheat production." *Soil Sci. Soc. Am. J.*, 68(4), 1376–1385.
- Zucchini, W., and Guttorp, P. (1991). "A hidden Markov model for space-time precipitation." *Water Resour. Res.*, 27(8), 1917–1923.