Stoch Environ Res Risk Assess (2018) 32:1337–1353
https://doi.org/10.1007/s00477-017-1458-0

ORIGINAL PAPER

Evaluation of multiple stochastic rainfall generators in diverse climatic regions

Tue M. Vu[1] · Ashok K. Mishra[1] · Goutam Konapala[1] · Di Liu[1]

Published online: 6 October 2017

Abstract Long term synthetic precipitation data are useful for water resources planning and management. Commonly stochastic weather generator (SWG) models are useful to produce synthetic time series of unlimited length of weather data based on the statistical characteristics of observed weather at a given location. However, it is difficult to find a single model which works best for all weather (climate) patterns. The objective of this study is to evaluate five different SWG models namely CLIGEN, ClimGen, LARS-WG, RainSim and WeatherMan to generate precipitation at three diverse climatic regions: a Mediterranean climate of western USA, temperate climate of eastern Australia and tropical monsoon region in northern Vietnam. The performance of SWG models to generate precipitation characteristics (i.e., precipitation occurrence; wet and dry spell; and precipitation intensity on wet days) varies between three selected climatic regimes. It was observed that the second order Markov chain (ClimGen and WeatherMan) performed well for all three selected regions in generating precipitation occurrence statistics. All models are able to simulate the ratio of wet/dry spell lengths with respect to observed precipitation. The RainSim performed well in reproducing wet/dry spell lengths in comparison to other models for wetter regions in Australia and Vietnam. ClimGen and WeatherMan are the two best models in simulating precipitation in the western USA, followed by CLIGEN and LARS. Similarly, ClimGen and WMAN are the two best models for synthetic precipitation generation for eastern Australian and northern Vietnam stations, but CLIGEN performs poorly over these regions. All SWG model performed differently with respect to climatic regimes, therefore careful validation is required depending on the weather pattern as well as its application in different water resources sectors. Although our findings are preliminary in nature, however, in order to generalize the performance of SWG's in a given climate type, it is recommended that more number of stations needs to be evaluated in future studies.

Keywords Stochastic weather generator · CLIGEN · ClimGen · LARS-WG · RainSim · WeatherMan

1 Introduction

Stochastic weather generators (SWG) are often used for investigating climate variability, water resources planning, risk assessment and analysis of hydro-climatic extreme events. Observed time series only represent one 'realization' of the climate, whereas a weather generator can simulate many 'realizations', thus providing a wider range of feasible situations (Semenov et al. 1998). SWG have been applied in many disciplines, such as, assessing large-scale atmospheric circulation (Katz and Parlange 1993; Katz et al. 2003), hydrologic applications (Xia 1996; Caron et al. 2008), ecology (Birt et al. 2010) and agriculture sectors (Semenov and Porter 1995; Grondona et al. 2000). In addition, SWG's are also applied to assess the climate change impact via statistical downscaling of Global Climate Models (GCMs) outputs (Semenov and Barrow 1997; Kilsby et al. 2007; Wilks 2010). Compared to other

Electronic supplementary material The online version of this article (doi:10.1007/s00477-017-1458-0) contains supplementary material, which is available to authorized users.

✉ Ashok K. Mishra
ashokm@g.clemson.edu

[1] Glenn Department of Civil Engineering, Clemson University, 202A Lowry Hall, Clemson, SC 29634-0911, USA

statistical downscaling methods such as regression-based approaches and weather typing schemes, the weather generator-based approach has an advantage in terms of producing an ensemble of climate change projections for analyzing risk-based environmental impacts (Chen and Brissette 2014).

The SWG models requires to model two precipitation components: (1) Occurrence (the sequence of wet and dry days), and (2) Intensity (the amount of precipitation on wet days). Commonly, two types of model are used to generate precipitation process, such as Markov chain-based model and alternating renewal process. Markov chain models are widely used in the literature (Katz 1977; Richardson 1981; Wilks 1989). However, first order Markov chain faced criticism as it may produce synthetic series exhibiting longer dry spells too infrequently (Wilks 1999). Higher order (second-, third- and fourth-order) Markov chain dependence models, as well as hybrid Markov chain process (Stern and Coe 1984), were evaluated by Wilks (1999) for simulating precipitation over 30 stations in the US. It was observed that the first-order Markov chain was found adequate for stations located in the central and eastern part of US, but poor performance was observed for stations located in the western US (i.e., drier climate). Jones and Thornton (2000) also recommended higher order Markov chain for sites that are not located in temperate regions. Chen et al. (2012a, b) indicated that higher order Markov models perform better for generating longer dry or wet spells in comparison to first order model. Racsko et al. (1991a, b) applied one-parameter geometric distribution for wet spell lengths and mixed geometric distribution for dry spell lengths. Wilby et al. (1998) used alternating negative binomial recurrence process to simulate wet- and dry-spell lengths. Semenov et al. (1998) applied a semi-empirical distribution to model sequences of wet and dry spells.

Precipitation amounts are usually simulated using parametric, semi-parametric and non-parametric approaches. The commonly used parametric approaches are gamma distribution (Richardson 1981), skewed normal distribution (Nicks and Gander 1994), Weibull distribution (Stöckle et al. 1999), exponential distribution (Roldan and Woolhiser 1982) to name a few. Semi-parametric approaches are used to resample historical data using empirical distribution function (Semenov and Barrow 1997; Mehrotra and Sharma 2007). Non-parametric weather generator approach does not make an assumption for identifying the underlying distribution of the process (Verdi et al. 2015). The commonly used non-parametric approach utilizes K-nearest neighbor (KNN) methodology to generate precipitation amounts based on resampling the weather variables based on the historical data (Rajagopalan and Lall 1999; Lall and Sharma 1996).

A number of stochastic weather generator models are applied in hydro-climatic research, for example, Richardson and Wright (1984) published the Fortran source code for WGEN (Weather GENerator) (Richardson 1981), which was later applied in many other studies (Semenov et al. 1998; Castellvi and Stöckle 2001; Soltani and Hoogenboom 2003). Subsequently, a modified version of WGEN model was developed by Campbell (1990) in Pascal language named ClimGen (Climate Data Generator) which was further improved by Stöckle et al. (1999) as stochastic weather generator standalone model for a crop model known as CropSyst. Semenov and Barrow (1997) developed LARS-WG (Long Aston Research Station—Weather Generator), which has been widely used in generating local climate scenarios for crop modeling and climate change impact assessments (Semenov and Shewry 2011). The WGEN code was further refined as Weather-Man model (Pickering et al. 1994) and it was coupled with DSSAT model (Decision Support System for Agrotechnology Transfer) (Jones et al. 2003) for generating weather events as inputs for crop modeling. Nicks and Gander (1994) developed CLIGEN (CLImate GENerator) weather generator model to generate climate inputs for water resources management. It was subsequently incorporated into WEPP model (Water Erosion Prediction Project) to predict runoff and soil erosion (Nicks et al. (1995). CLIGEN has the capability to synthesize daily weather for the ungauged area through spatial interpolation the model parameters from nearby gauges (Baffault et al. 1996). The Generalized Neyman–Scott Rectangular Pulses (GNSRP) model (Cowpertwait 1994, 1995) was implemented in a modeling package RainSim (Burton et al. 2008). RainSim model has the advantage of generating spatial stochastic weather information as well as they are used for stochastic downscaling of climate models in climate change studies (Burton et al. 2010a, b; Bordoy and Burlando 2014; Camera et al. 2017).

The literature review suggests application of multiple SWG's in different sectors, however, it is also important to know appropriate (best) models for a given climatic region. The objective of this paper is to evaluate five different stochastic weather generator models in three diverse climatic regions over the world: (a) the dry climate region in the western USA, (b) very wet climate region in the tropical monsoon rainfall area at the northern Vietnam, and (c) temperate climatic zone in the southern hemisphere in the eastern Australia. Overall nine rainfall stations are selected representing three rainfall stations from each climate type in our analysis. The rainfall characteristics for selected climate type differs in terms of inter (intra) annual precipitation variability (statistics) and they behave differently with response to the ENSO (El Nino Southern Oscillation). The five SWG models that are evaluated in our analysis includes: CLIGEN, ClimGen, LARS-WG, RainSim and WeatherMan. Table 1 provides an overview of the five SWG models and abbreviations used in this study.

The remainder of this paper is organized as follows. Section 2 provides an overview of the selected study areas and a brief description of the five SWG models used in our analysis. Section 3 explains the methodology, while the analysis of the results is discussed in Sect. 4 based on precipitation occurrence, wet/dry spell lengths and precipitation intensity. Conclusions are provided in Sect. 5.

2 Study region and models

2.1 Study region

Nine rainfall stations are selected to represent three diverse climatic regions. An overview of climate type and rainfall station's is discussed here:

(a) Mediterranean climate: San Francisco International airport (SFO), Los Angeles International airport (LAX) and Santa Barbara Municipal Airport (SBM), and they are categorized as a warm summer Mediterranean climate [Koppen climate classification Csb (Peel et al. 2007)]. The precipitation data were obtained from National Climatic Data Center (NCDC), NOAA, the USA via the website: http://www.ncdc.noaa.gov/. These stations are located along the west coast of the United States with average annual precipitation ranges from 100 to 500 mm and virtually no-rain during summer.

(b) Temperate climate: The Sydney airport (SYD) and the New Castle Nobbys (NEW) signal station in New South Wales, the Amberley in Queensland (near to Brisbane city) (BRB) all situated on the east coast of Australia in the southern hemisphere. They are located in a temperate climate (Koppen climate type Cfa) and precipitation is evenly spread throughout the year. The data was obtained from the Bureau of Meteorology (BOM), Australia (http://www.bom.gov.au). Annual average precipitation recorded at these eastern Australian stations range between 700 and 1700 mm.

(c) Tropical climate: Hanoi (HAN), Hoa Binh (HOA) and Hai Duong (HAI) rainfall stations are selected and the data were collected from the Institute of Meteorology, Hydrology and Climate Change (IMHCC), Hanoi, Vietnam. The Koppen classification type of Hanoi is Cwa with the humid subtropical climate in the northern hemisphere. Located in the tropical monsoon Asia wind system, the rainy season of northern Vietnam stations coincide with the southwest monsoon, which occurs during summer. The total annual precipitation is as high as 1200–2100 mm. For all these nine aforementioned stations, daily precipitation datasets were collected for the 1961–1990 period. The locations of the nine stations are displayed in Fig. 1 and their locational information is given in Table 1.

The precipitation patterns at the nine stations are influenced differently by ENSO (Evans et al. 1998; Manatsa et al. 2008; Zhang and Zhou 2015). The spatial correlation map between the Sea Surface Temperature Nino 3.4 index (using 6 months average) and the monthly gridded 0.5° spatial resolution precipitation from Climate Research Unit (CRU) is provided in Fig. 1. The western USA has a significant positive correlation, while eastern Australia has a significant but negative correlation, both with a confidence level higher than 90%. Northern Vietnam has relatively no significant correlation with ENSO indices.

2.2 Stochastic weather generator models

Five SWG models are selected for model simulation and analysis (Table 2). The occurrence of precipitation model

Table 1 Location of nine selected stations used in this study including their climate type

Region	Station	Abbr.	Longitude	Latitude	Elevation (m)	Koppen Climate	Source
Western United States	San Francisco Int. airport	SFO	237.6	37.6	2.4	Mediterranean climate (Csb)	NCDC
	Los Angeles Int. Airport	LAX	241.8	34.1	85.0		
	Santa Barbara Mun. Airport	SBM	240.2	34.4	2.7		
Eastern Australia	Sydney Airport	SYD	151.1	−33.7	10.0	Temperate climate (Cfa)	BOM
	Amberley, Brisbane	BRB	153.0	−27.5	10.0		
	New Castle Nobbys	NEW	151.9	−32.9	33.0		
Northern Vietnam	Hanoi	HAN	106.0	21.0	5.0	Tropical climate (Cwa)	IMHCC
	Hai Duong	HAI	106.3	20.9	2.0		
	Hoa Binh	HOA	105.3	20.8	23.0		

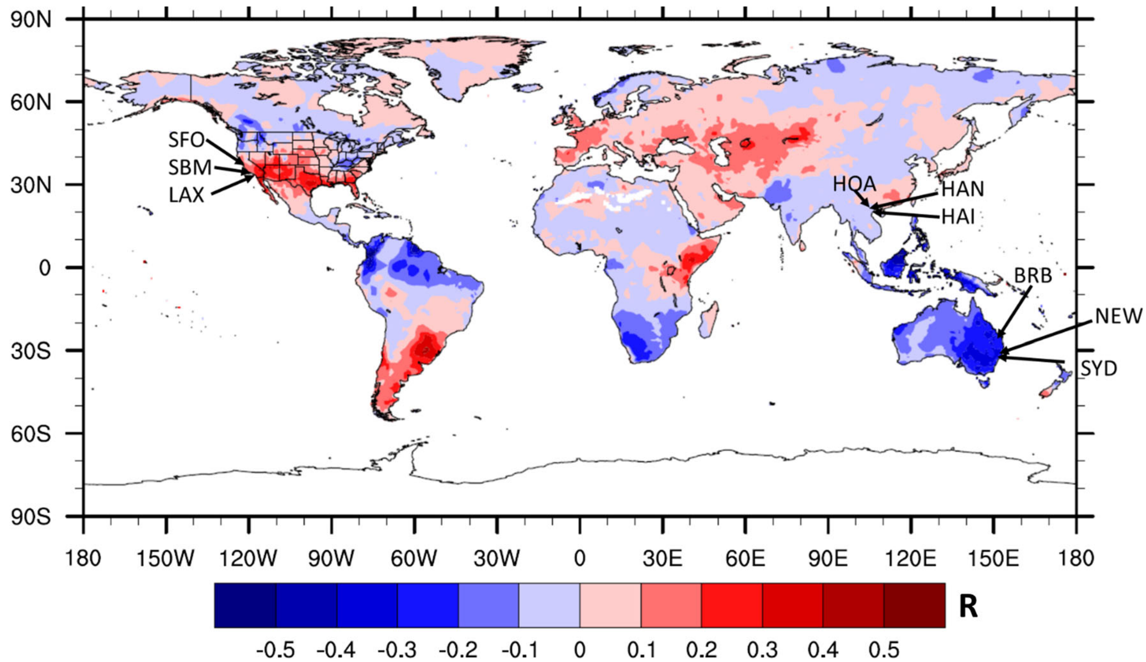


Fig. 1 Location of nine selected rainfall stations. The correlation map between sea surface temperature Nino 3.4 index and monthly gridded precipitation from climate research unit (CRU) (both using 6 months average) for the period 1901–2014

for WMAN, CLIG and CLIM follow the Markov chain process. However, WMAN, CLIG, CLIM are modeled with different distribution functions to generate precipitation on wet days based on three-parameter mixed exponential (also known as a hyper-exponential (Whitt 1981), skewed normal and Weibull distributions respectively. The simulation of precipitation occurrence in LARS is based on more flexible semi-empirical distribution. This approach overcomes the limitation of the Markovian approach for generating the longer dry spell at certain locations (Semenov and Barrow 1997). For a wet day, the precipitation value is generated from the semi-empirical precipitation distribution for the particular month independent of the length of the wet series or the amount of precipitation on previous days (Semenov et al. 1998). Poisson cluster model was first developed by Neyman and Scott (1958) and incorporated into RSIM model. One advantage of the Poisson process is that it can be extended to simulate continuous spatial–temporal precipitation which is increasingly important in support of distributed hydrological modeling (Burton et al. 2008).

3 Methodology

Wet (dry) spells are important precipitation characteristics and they are commonly evaluated in stochastic weather generator models. We selected different thresholds to quantify wet (dry) spells for three selected locations due to their differences in terms of climatic regimes. The threshold of the wet/dry day is fixed for the northern Vietnam and the eastern Australia at 1 mm/day and for the western USA at 0.1 mm/day. These thresholds are selected based on the previous studies by Westra et al. (2013) for the eastern Australia, Rajagopalan and Lall (1999) for the western United States and Ngo et al. (2014) for the northern Vietnam.

Table 2 Five stochastic weather generators used in this study for precipitation simulation

Model name	Abbreviation	Precipitation occurrence	Precipitation intensity
CLIGEN	CLIG	Two-state, first order Markov chain	Skewed normal distribution
ClimGen	CLIM	Two-state, second order Markov chain	Weibull distribution
LARS-WG	LARS	Semi-empirical distribution	Semi-empirical distribution
RainSim	RSIM	Temporal Poisson process	Neyman–Scott rectangular pulses
WMAN	WMAN	Two-state, second order Markov chain	Three parameter mixed exponential (hyper-exponential)

All models were applied to each precipitation data sets (i.e., 9 stations) to synthetically generate 300 years and their precipitation characteristics were computed, which includes (1) Precipitation Occurrence per month, (2) Wet and Dry spell lengths per month, and (3) Precipitation Intensity on wet days. The wet/dry spell lengths were computed based on a number of consecutive wet/dry day(s). For rainfall occurrence and intensity, the statistics (mean, standard deviation) were computed for comparison between SWG models and observation (OBS). In addition, Quantile–Quantile (Q–Q) plots are used to compare the precipitation intensity distribution between various SWG and OBS, especially at the higher tail. This is an important feature to evaluate the ability of SWG in capturing extreme flood condition for the selected area. For a wet/dry spell, the ratio of a total number of wet/dry days per month and a maximum number of consecutive wet/dry spells are also evaluated.

In addition to statistical tests to compare between two samples, a non-parametric Wilcoxon rank sum test [sometimes referred as Mann–Whitney or Mann–Whitney–Wilcoxon test (Krzywinski and Altman 2014)] was used for wet/dry spell (Chen and Brissette 2014) analysis to evaluate if these two datasets (OBS and SWG) are independent samples and having the equal medians. Being non-parametric, the Wilcoxon rank sum test does not assume normality, but as a test of median equality, it demands both samples are having the same distribution shape (Krzywinski and Altman 2014). Another non-parametric Kolmogorov–Smirnov test (KS-test) was applied to precipitation intensity for investigating the nature of probability distribution between observation and simulations (Fischer et al. 2012; Chen and Brissette 2014). The KS-test computes the distance 'D' between empirical CDF of the observed time series and CDF of candidate distribution (Corder and Foreman 2009). All Wilcoxon rank sum test and KS-test are evaluated with a significant level of p value $= 0.05$.

4 Results

4.1 Precipitation occurrence

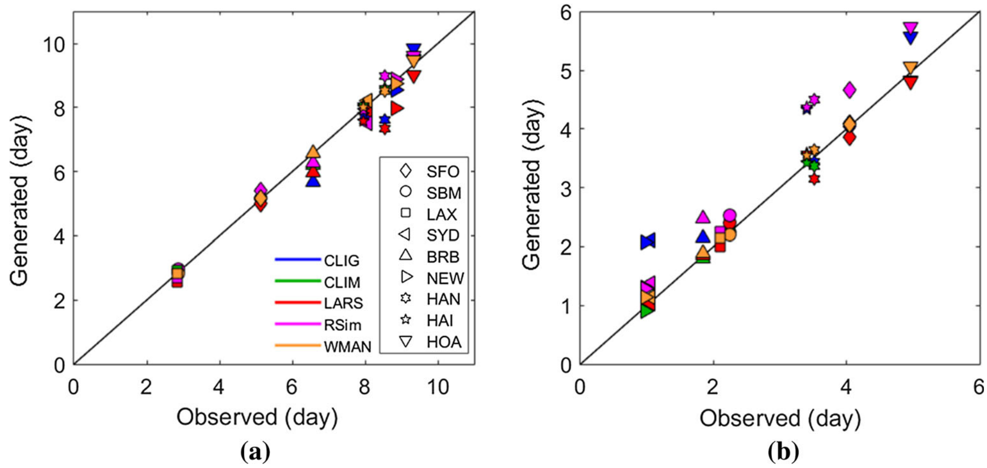
4.1.1 Statistics of precipitation occurrence (wet day)

The statistical characteristics (mean and standard deviation) of the precipitation occurrence in terms of wet day frequency simulated from five stochastic weather generators for nine stations. The scatter plots between SWG models and OBS, computed from daily mean and standard deviation 'SD' respectively are presented in Fig. 2. The values used to develop Fig. 2 are tabulated in Supplementary, Table S1 with bold values are within 10% difference with OBS data. As seen in Fig. 2a, the mean statistics are generally well captured for all stations, especially over three stations in the western United States. There exists some bias for mean values at other two regions. The Markov chain based models are generally good compared to semi-empirical (LARS) and Poisson process (RSIM). The second order Markov chain (CLIM, WMAN) perform slightly better than first order (CLIG) for the eastern Australian stations. The semi-empirical distribution based model LARS underestimates the mean values for all the stations located in the eastern Australia and the northern Vietnam. LARS model consistently performed poorly than the Markov chain based model (Chen and Brissette 2014) in reproducing wet day frequency statistics. The temporal Poisson process in RSIM is capable of simulating well the mean wet day frequency, however, it overestimates the 'SD' values for most of the stations in three study regions (Fig. 2b), especially towards wetter stations in the eastern Australia and the northern Vietnam. The second order Markov chain models are consistently better than first order in term of 'SD' statistics. In a nut shell, CLIM and WMAN (second order Markov chain) are the two best models that capture well OBS mean and 'SD' values over all stations in three different climate regions.

4.1.2 Annual cycle of precipitation occurrence

Monthly mean climatology of precipitation occurrences for the five stochastic weather models at the nine selected stations are presented in Fig. 3, similar to Vallam and Qin (2016). It is possible to see the distinct pattern of precipitation occurrence (in a number of days per month) for each climate region. For example, all the models are able to capture the "U-shape" pattern of the western United States stations (Fig. 3a) with a very dry spell during summer months and wetter in winter and spring. Similarly, the "A shape" pattern of northern Vietnam is reproduced well in Fig. 3c. In order to examine the match between OBS and SWGs from Fig. 3, we computed the Nash-Sutcliff Efficiency (NSE) (Nash and Sutcliffe 1970) for each of the SWG models for an individual station. The NSE has a range between minus infinity to 1, with a value closer 1 indicates a better match. The NSE values for all SWG models/stations are tabulated in Table S2 in Supplementary. The RSIM model seems to overestimate the OBS in summer months and underestimate the occurrence in spring months for HAN and HAI (Fig. 3c) for northern Vietnam stations. The 'SD' values for RSIM overestimate OBS, although the mean values are generally with in a good range (Fig. 2b). By using annual cycle plots for precipitation occurrence for northern Vietnam, it is able to assess that CLIM is the best model in capturing all monthly mean

Fig. 2 Scatter plots for precipitation occurrence statistics for nine stations located in three climate regions: **a** mean and **b** SD. *Note* For easy reference, the cities are represented using different marker type (e.g., square, circle, and diamond, etc.) and different color for each of SWG model. The markers and color pattern remains same for all the figures



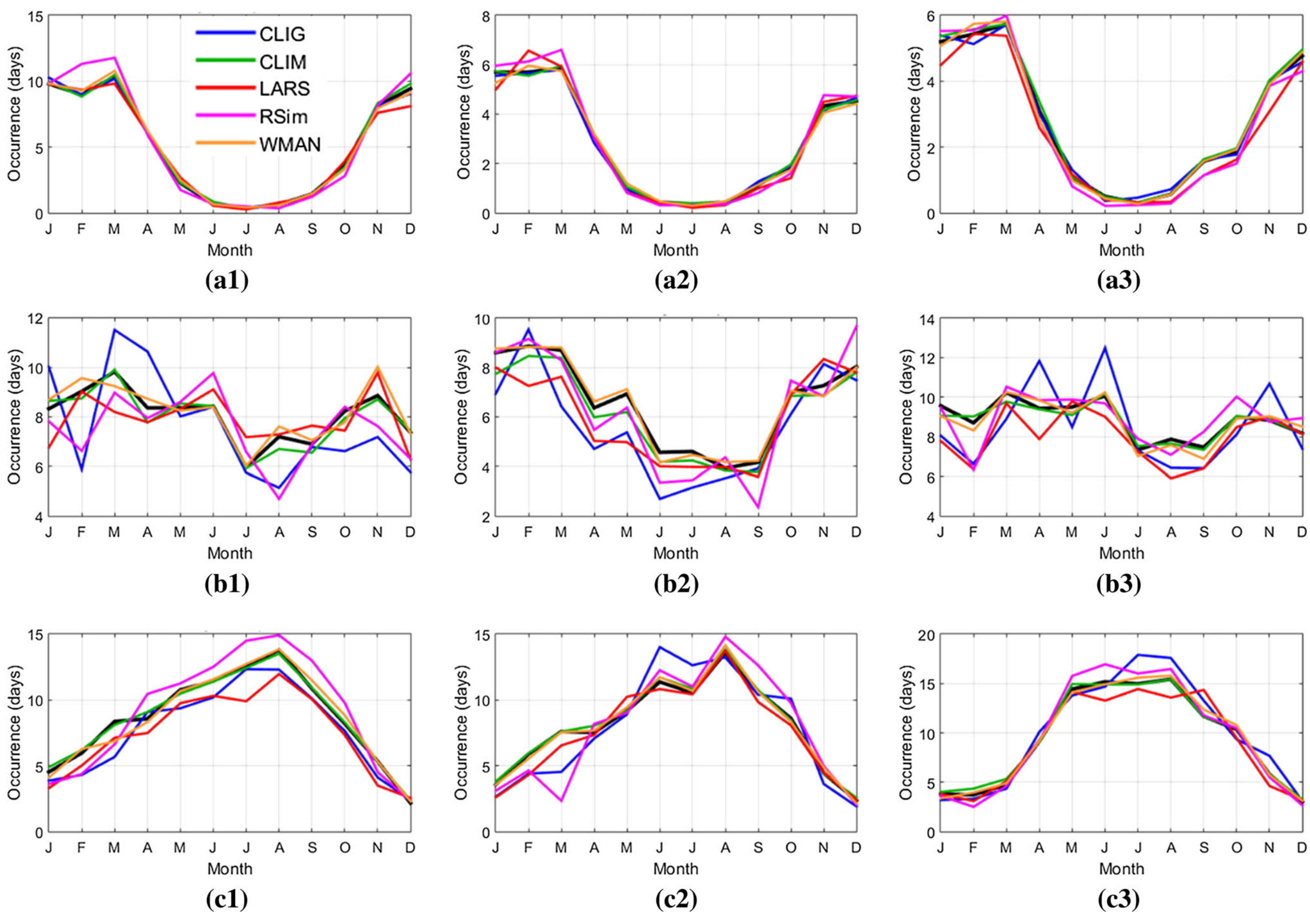


Fig. 3 Annual cycle of precipitation occurrences for nine stations located in three climatic regions: **a1** SFO, **a2** SBM, **a3** LAX; **b1** SYD, **b2** BRB, **b3** NEW; **c1** HAN, **c2** HAI, **c3** HOA

values for all stations, and the substantially good model is WMAN, and both the models used second order Markov chain. The semi-empirical model LARS underestimates precipitation occurrence compared to OBS and other Markov based models for all northern Vietnam stations as seen in Fig. 2.

Among the three climate regimes, the eastern Australian seems to be difficult for the SWG models to accurately generate the precipitation occurrence (Fig. 3b). It is found that CLIM and WMAN are the two best models based on their close mean statistics in Fig. 2. The first order Markov chain CLIG fails to capture the precipitation patterns for several months for all the three selected stations in eastern Australia. The semi-empirical model based on LARS is able to capture the patterns for eastern Australia, but with few fluctuations in magnitudes. The semi-empirical distribution based LARS model is comparable to WMAN, except for the tropical station Hanoi, where it produces the peak rainfall two months earlier than the observed rainfall (Fig. 3c). In general, the second order Markov chain process (CLIM and WMAN) performs well in reproducing the precipitation occurrence statistics for all the stations compared to the first order Markov chain as well as semi-empirical and temporal Poisson process.

4.2 Wet/dry spell lengths

4.2.1 Statistics of wet/dry spell lengths

The wet/dry spell lengths are computed as a number of consecutive wet/dry day(s) per month respectively. Subsequently, statistical measures (mean and standard deviation) for wet/dry spell lengths (unit: day), the ratio of wet (dry) days per month (unit-less) and average maximum spell lengths per month for wet (dry) spell lengths (unit: day) were calculated and displayed in Figs. 4 and 5 (also tabulated in Tables S3, S4 in Supplementary).

For wet spell length (Fig. 4), most of the models are able to simulate within 10% difference (found in Table S3) compared to the OBS for western United States stations with slight overestimation of RSIM model for standard deviation statistics (Fig. 4a). All Markov chain based models and semi-empirical model underestimate mean, 'SD' and max wet spell lengths for eastern Australian and northern Vietnam stations (Fig. 4a, b, d). However, the ratio between wet spell lengths and a total number of days per months are captured well by all SWG models (Fig. 4c). Semi-empirical model (LARS) consistently underestimated OBS and Markov based models for all wet spell statistics. Overall, for wet spell analysis, temporal Poisson based RSIM is the best model for eastern Australian stations while for northern Vietnam, the second order Markov CLIM and RSIM are the two best models (Fig. 4a).

On the other hand, for dry spell length (Fig. 5), all the models able to capture the mean statistics, the ratio of a dry spell and max dry spell, although some bias exist for 'SD'. In contrast to wet spell, Markov chain and semi-empirical models are scattered evenly around the 1:1 line, especially for the mean ratio of a dry spell and max dry spell (Fig. 5c, d). It is seen that semi-empirical and temporal Poisson process are slightly better than Markov chain based models for mean and 'SD' statistics for a dry spell, especially for the wetter regions in eastern Australia and northern Vietnam.

4.2.2 Distributions of wet/dry spell lengths

The Wilcoxon rank sum tests were applied to wet/dry spell length series to check the equality of medians between observed and simulated wet (dry) spell for individual months. Based on the Wilcoxon rank sum tests, the null hypothesis can be used to evaluate if the observed and synthetic precipitation data medians differ at a significant level of p value $= 0.05$. The null hypothesis can be: (a) $\mathrm{H} = 0$: indicates a failure to reject the null hypothesis at the 5% significance level, and (b) $\mathrm{H} = 1$: reject the null hypothesis at 5% significant level.

Number of months per year for wet and dry spell that reject the Wilcoxon rank sum test at significant level of p value $= 0.05$ are tabulated in Tables 3 and 4 respectively. Because the $\mathrm{H} = 1$ indicates the rejection of null hypothesis, therefore, the better model will have lesser H value. Based on the wet spell analysis, the Markov chain models performed better than semi-empirical and temporal Poisson (Table 3) and RSIM performed poorly for the selected stations in western USA. Interestingly, within Markov chain based model, the first order CLIG model is slightly better than second order (CLIM and WMAN) models for LAX station. However, the first order Markov chain based model CLIG performed poor for the wetter stations in eastern Australia and northern Vietnam as seen in Table 3. The semi-empirical distribution based LARS model able to reproduce the wet spell for the western USA but the performance was poor for two regions. In overall, the second order Markov chain based CLIM model is the best for all the stations for wet spell lengths distribution, followed by WMAN. RSIM did not perform well at generating wet spell length for almost stations.

It was found that all SWG models performed better in reproducing dry spell length distribution than a wet spell (Table 3 vs. Table 4). Similar to wet spell length, the first order Markov chain model CLIG seems to be good for the western USA but poor performance for other two regions. On the other hand, the second order Markov chain (CLIM and WMAN) models have the least H values indicating its great ability to reproduce good wet/dry spell distribution.

In general, the second order Markov chain based models performed well to reproduce wet/dry spell lengths distribution for all regions, followed by semi-empirical distribution. The first order Markov chain CLIG only performed well for the dry stations in the western USA, whereas RSIM is not a good model to capture this type of distribution.

4.2.3 Annual cycle of mean wet/dry spells lengths

The mean monthly climatology of wet/dry spell lengths for all SWG simulations are plotted in Figs. 6 and 7,

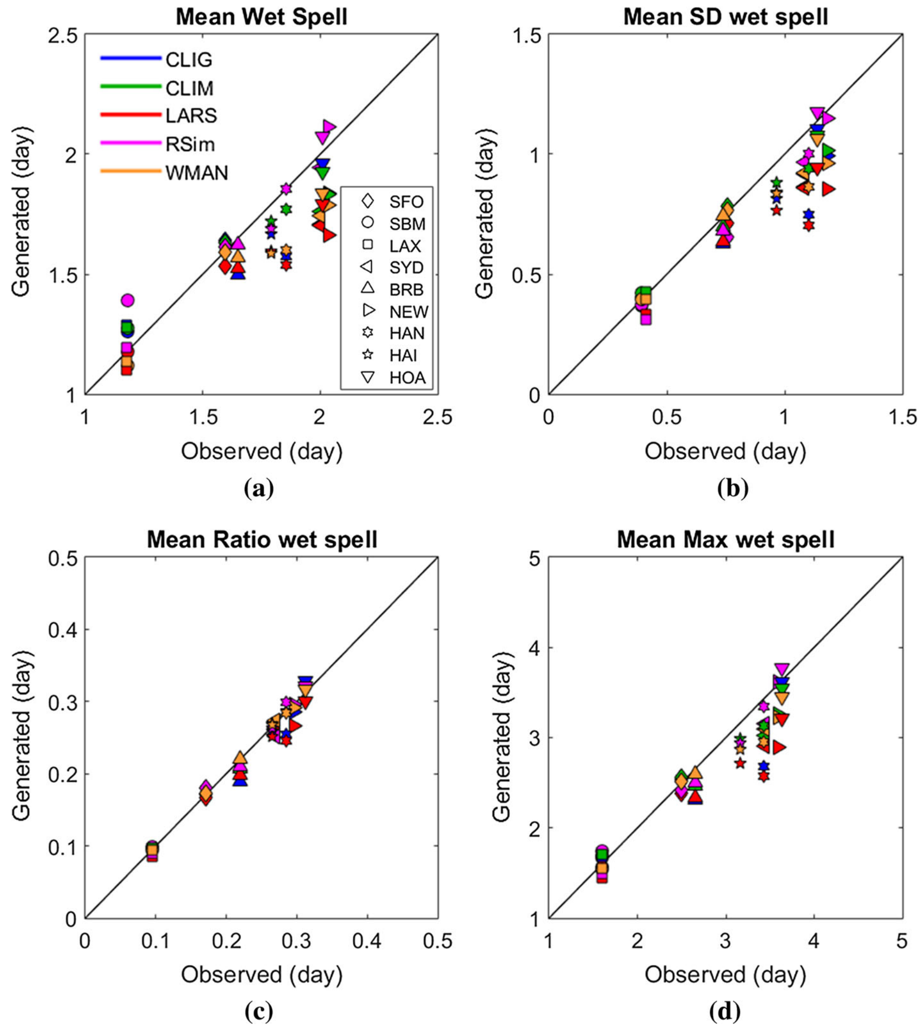


Fig. 4 Scatter plots for wet spell statistics for nine stations located in three climatic regions: **a** mean, **b** SD, **c** ratio of wet spell and **d** max wet spell length

respectively (NSE values can be found in Tables S5 and S6). It was observed that mean climatology of certain locations agrees well with the statistics and Wilcoxon rank sum test results discussed earlier. For example, all models performed well for wet/dry spell statistics and distribution of western United States stations. However, all the models did not perform well for wet spells in other two climate regimes, except second order Markov CLIM and WMAN. However using monthly climatology via annual cycle plot, it is possible to see a clearer pattern of mean values of wet/dry spell at all stations. The overall shapes of wet spell follow closely with precipitation occurrence shape for all stations: "U shape" for western USA stations, "A shape" for tropical monsoon regions in Vietnam (Fig. 6). RSIM model performed poor in reproducing the annual cycle for SBM station (Fig. 6b) with 7 months rejecting the equal median test from Wilcoxon rank sum (Table 3). Overall it is difficult to capture well the annual cycle of wet spell length for eastern Australia and northern Vietnam compared to the western USA. Although CLIM, LARS and WMAN models able to capture the temporal (fluctuating) patterns in eastern Australia (Fig. 6b), however they fails to capture their magnitude completely.

The patterns of a dry spell are opposite to wet spell with "A shape" for the western USA and "flat U shape" for the northern Vietnam (Fig. 7). For the dry spell in northern Vietnam, WMAN overestimates the peak in March for all stations (Fig. 7c) and so does RSIM for Hai Duong station (Fig. 7c2). In a nutshell, the wet/dry spell statistics can provide useful information in addition to precipitation occurrence statistics and distribution. Overall, the Markovian second order CLIM is found to be the best model in precipitation occurrence and wet/dry spell statistic and distribution, followed by WMAN and LARS.

4.3 Precipitation intensity on a wet day

4.3.1 Statistics of precipitation wet day intensity

The wet day rainfall intensity statistics (mean, standard deviation, skew and kurtosis) simulated from the five stochastic weather generators for the nine stations are

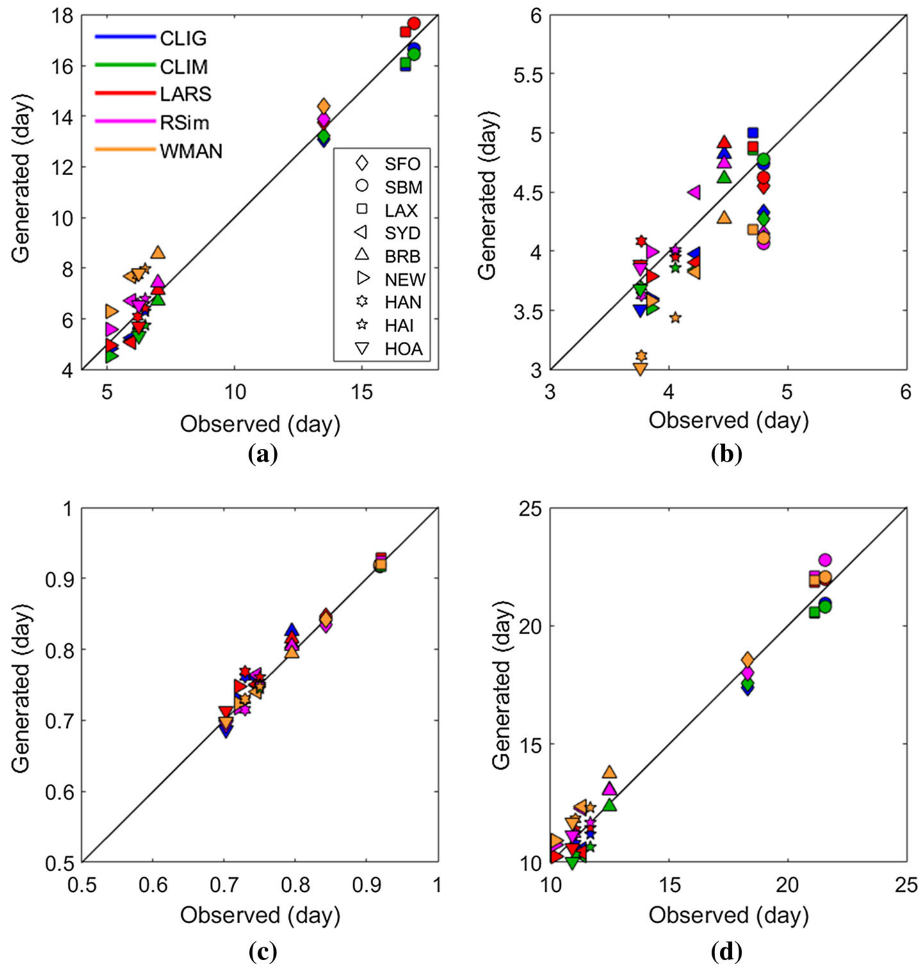


Fig. 5 Scatter plots for dry spell statistics for nine stations located in three climate regions: **a** mean, **b** SD, **c** ratio of dry spell, and **d** max dry spell length

Table 3 Number of months per year that rejects the Wilcoxon rank sum test at significant level of p value = 0.05 for wet spell analysis

Station\model	CLIG	CLIM	LARS	RSIM	WMAN
SFO	0	0	1	3	0
LAX	0	1	1	4	1
SBM	0	0	0	7	0
SYD	8	3	8	2	3
BRB	3	0	3	6	1
NEW	7	3	8	2	4
HAN	7	2	10	3	4
HAI	5	2	4	1	3
HOA	6	1	5	1	4

Table 4 Number of months per year that rejects the Wilcoxon rank sum test at significant level of p value = 0.05 for dry spell analysis

Station\model	CLIG	CLIM	LARS	RSIM	WMAN
SFO	0	0	0	6	0
LAX	0	0	0	3	1
SBM	0	0	0	3	0
SYD	5	0	2	2	0
BRB	3	0	1	4	1
NEW	2	1	1	2	0
HAN	1	0	1	5	1
HAI	2	1	0	4	1
HOA	4	2	3	2	2

shown in Fig. 8 and the values are tabulated in Table S7. Similar to precipitation occurrence, most of the models able to reproduce the mean and standard deviation at all the selected locations within 10% difference compared to observed data. The semi-empirical LARS model slightly overestimated mean, 'SD' but it able to capture well the skewness and kurtosis statistics for all the stations. The hyper-exponential WMAN is better than LARS in capturing mean and 'SD' but underestimated OBS in terms of skewness and kurtosis compared to LARS. The two parameter Weibull distribution CLIM and hyper-exponential WMAN seems to be best in reproducing the mean

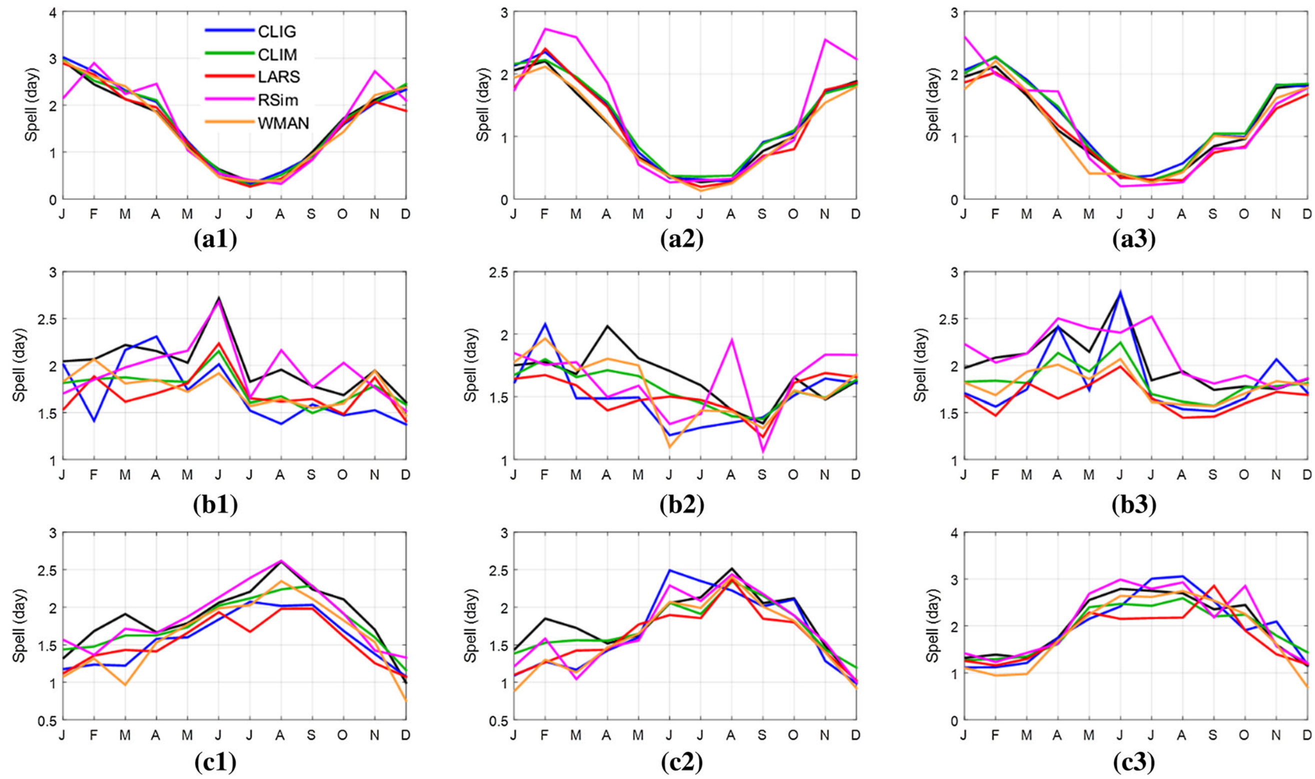


Fig. 6 Annual cycle of wet spells for nine selected stations located in three climate regions: **a1** SFO, **a2** SBM, **a3** LAX; **b1** SYD, **b2** BRB, **b3** NEW; **c1** HAN, **c2** HAI, **c3** HOA

statistics (Fig. 8a) but are not as good as the skewed normal distribution CLIG for 'SD', skewness and kurtosis. The GNSRP model, RSIM, on the other hand performed well at reproducing mean value for all stations, but it slightly underestimates the 'SD' and poses bias in skewness and kurtosis statistics for all the stations. Over eastern Australia, the semi-empirical distribution LARS is able to preserve the wet day intensity statistics at all locations followed by the skewed normal distribution CLIG. The pattern is slightly different for northern Vietnam, given that the hyper-exponential distribution used in WMAN seems to be the best for Hanoi but it performed poorly for other two stations Hai Duong and Hoa Binh.

In summary, the semi-empirical LARS performed consistently for all the stations in terms of precipitation amount on wet days, even though it slightly fails to reproduce the mean values. WMAN and CLIM are good at simulating mean statistics but performed poorly for skewness and kurtosis, especially for the wet stations. Whereas, CLIG model simulated mean, 'SD' and skewness for all stations with a reasonable accuracy.

4.3.2 Monthly mean wet day intensity

The annual cycle of monthly mean wet day intensity is an important analysis as it evaluates the ability of SWG's to capture the rainfall intensity on wet days as well as the inter-annual variability in reproducing peak to peak monthly rainfall. For example, there are two peaks (Jun and Sep months) of rainfall for stations Hanoi and Hoa Binh located in northern Vietnam; whereas three peaks (Mar, Jun, Aug) observed for Sydney. All the models were able to mimic the patterns of monthly rainfall intensity for USA and Vietnam stations. However, there is some mismatch for eastern Australia as the rainfall patterns are chaotic. The wet day precipitation intensity for all SWG models is analyzed and displayed in Fig. 9 and the NSE values are provided in Table S8. Overall, CLIM and WMAN are the best models in generating annual cycle pattern of rainfall intensity for all nine stations at different climate regions. It is to be noted that even for eastern Australia, CLIM and WMAN able to reproduce the dynamics of wet day intensity patterns. LARS and RSIM overestimated the mean wet day intensity at most of the rainfall stations; while CLIG did not perform well for eastern Australian and northern Vietnam stations.

4.3.3 Distributions of precipitation wet day intensity

This section c wet day intensity based on OBS and SWG models for all the 12 months in a year. For each month, the Kolmogorov–Smirnov test (KS-test) was applied between

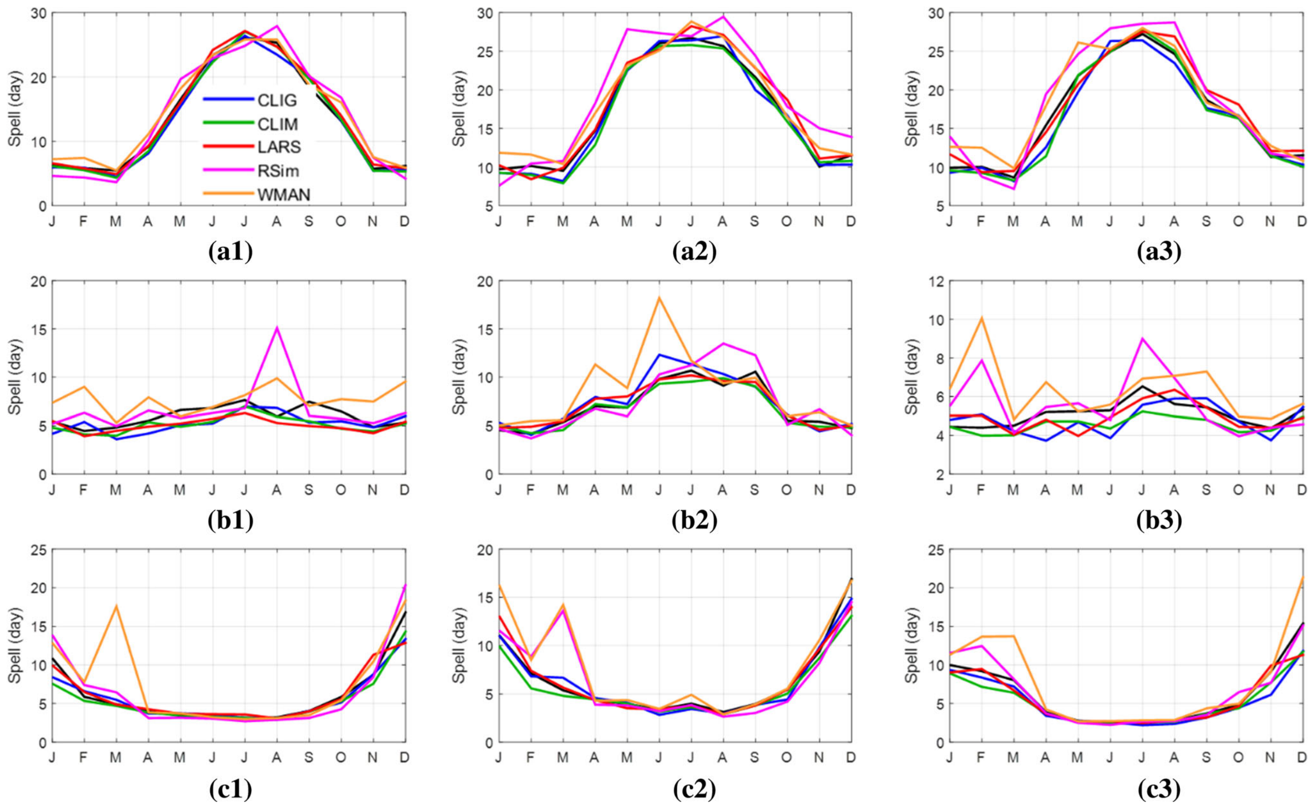


Fig. 7 Annual cycle of dry spell for nine selected stations located in three climate regions: **a1** SFO, **a2** SBM, **a3** LAX; **b1** SYD, **b2** BRB, **b3** NEW; **c1** HAN, **c2** HAI, **c3** HOA

OBS and SWG models for the wet day precipitation amount. In this study, we use the threshold of 0.1 mm for the western USA region and 1 mm for the eastern Australian and the northern Vietnam stations.

The KS test was applied to SWG models for each month, and the total H value for each SWG for 12 months are tabulated in Table 5. Because the H = 1 indicates the rejection of null hypothesis (i.e., two datasets do not represent the same population), therefore the cumulative lower H value will represent better model. It can be seen that WMAN is the best SWG model for western USA followed by CLIM, with the least number of months that does not have the same population. On the other hand, CLIG and RSIM performed poorly with the maximum number of months that do not have a similar distribution as OBS. These high numbers of months rejecting the null hypothesis of KS test (Table 5) are quite similar to Chen and Brissette (2014) when using the low threshold to define the wet days. In their study, Chen and Brissette (2014) rejected the null hypothesis for all 54 stations in Loess Plateau based on KS-test and they suggested it may be due to the large sample size (with lower threshold).

We further examined the KS-test by increasing the threshold for the western United States to 2 mm/day and the eastern Australia (northern Vietnam) to 5 mm/day. The numbers of months that reject null hypothesis reduce significantly as tabulated in Table 6. LARS is the best model with zero months rejecting the null hypothesis for all the stations. WMAN is the next best model with better performance over the western USA and eastern Australia. CLIM is a good model for the western USA and eastern Australia but a large number of months rejecting the KS-test for northern Vietnam stations.

4.3.4 *Quantile plots of precipitation wet day intensity to assess high tail distribution*

Quantile–Quantile plots (Q–Q plots) for wet day rainfall intensity for all the nine stations (Fig. 10) based on the threshold of 80th, 95th and 99th percentiles of the OBS. The thresholds are set at the minimum of the 80th percentile to assess the high tail distribution (extreme high rainfall induced flooding). As displayed in Fig. 10, all models are able to reproduce the high tail distribution of rainfall for all the stations up to the 95th percentile. The Mean Absolute Error (MAE) between SWG models and OBS are computed for the 95th percentile values and tabulated in Table S9. However, bias exists in the distribution

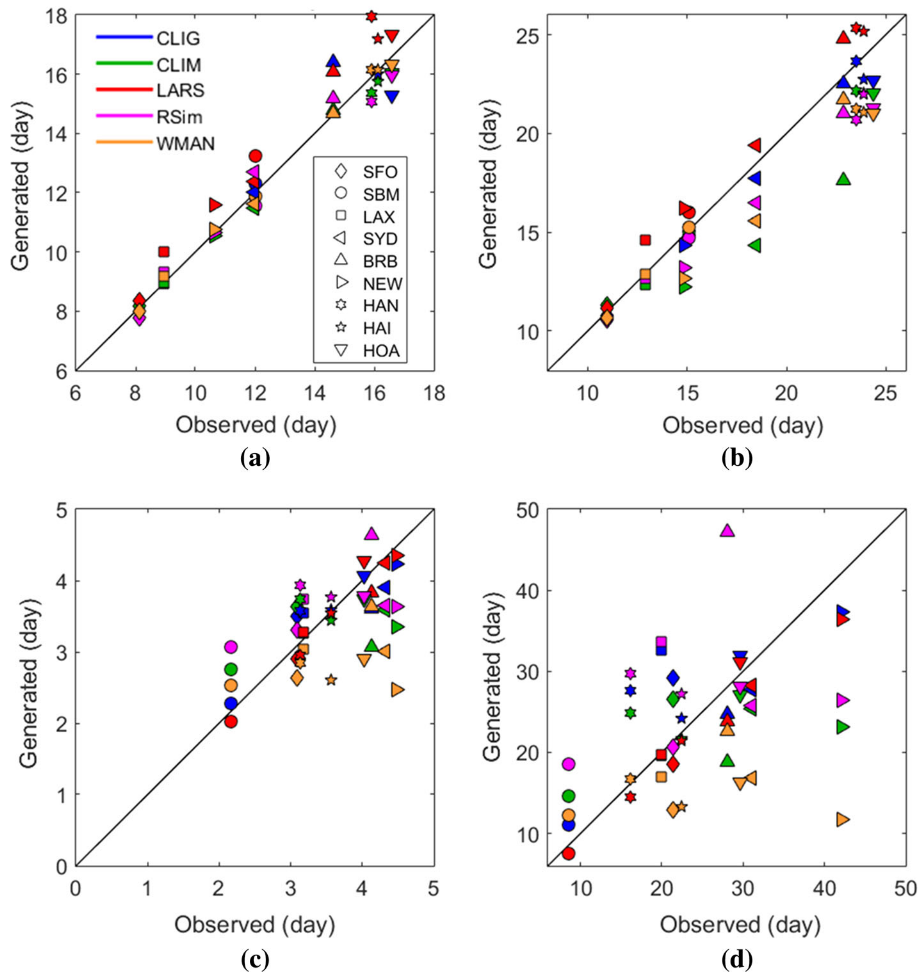


Fig. 8 Scatter plots for wet day intensity statistics for nine stations located in three climatic regions: **a** mean, **b** SD, **c** skewness and **d** kurtosis

at and above the 99th percentile. One important observation is that for western USA stations (Fig. 10a1, b1, c1), all the models overestimated the high tail at 99th percentile compared to OBS. Among all the models, CLIG (skew normal distribution) is the best model to reproduce the high tail distribution above the 99th percentile. LARS, with the semi-empirical distribution process, is consistently overestimating the OBS for all the stations while WMAN and CLIM underestimate OBS. WMAN with hyper-exponential distribution for precipitation amount is not as good as CLIG model. CLIM (modeled by Weibull distribution) model is good for northern Vietnam stations but is not good for eastern Australia.

4.4 Discussion: performances of SWG models in three climate type

Based on our analyses using statistics and distribution of precipitation occurrence, wet/dry spell and precipitation on wet day intensity, we summarized our findings in Table 7 based on different SWG models at all three climatic regions. In Table 7, each SWG model is ranked from one to five with the value one is the highest rank (best performance) based on the statistical test. It is possible that more than one SWG model may have the same rank. The "Overall performance" is computed by summation of all the ranks for each region. Thus, the SWG model that has smallest total points is the best model to be used for that area. Based on overall performance points, it was observed that CLIMGEN is the best model that is recommended to be used for all climatic regions, followed by WMAN. LARS model ranks third and the last rank is shared between CLIG and RSIM. The two states second order Markov chain model coupled in CLIM and WMAN proves to be the best approach to generate precipitation occurrence. In comparison between three climatic regions, western USA has the best rank, since this is a rather dry area with less variability of precipitation. The SWG models are therefore able to better preserve the synthetic precipitation statistics for dry compared to the wet region.

Although our findings are preliminary in nature, however, in order to generalize the performance of SWG's in a

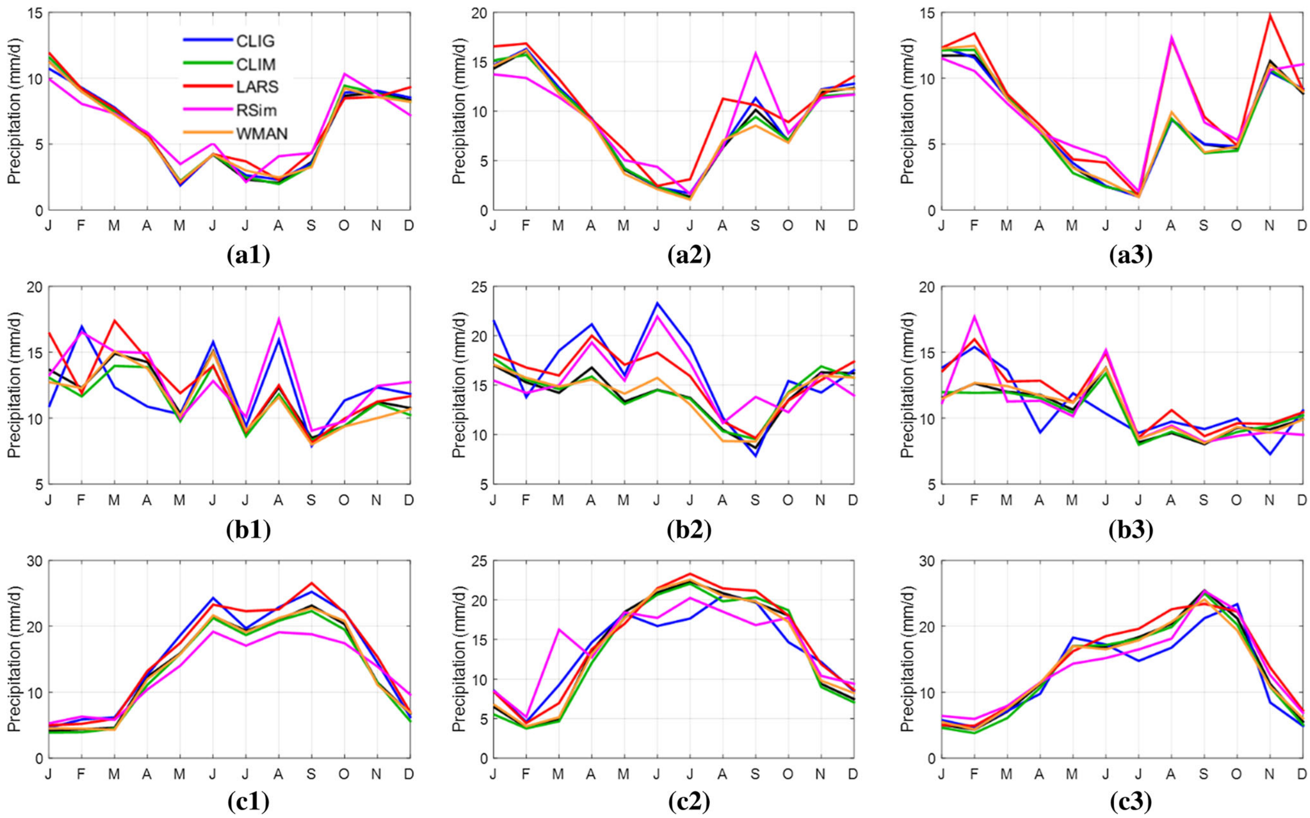


Fig. 9 Annual cycle of wet day intensity for nine stations over the three climatic regions: **a1** SFO, **a2** SBM, **a3** LAX; **b1** SYD, **b2** BRB, **b3** NEW; **c1** HAN, **c2** HAI, **c3** HOA

Table 5 Number of months per year that rejects the Kolmogorov–Smirnov at significant level of p value = 0.05 for precipitation wet day intensity analysis

Station\model	CLIG	CLIM	LARS	RSIM	WMAN
SFO	7	2	7	5	0
LAX	8	1	2	5	0
SBM	5	0	2	3	0
SYD	7	8	0	7	2
BRB	10	9	2	7	0
NEW	9	7	2	4	3
HAN	10	6	3	6	2
HAI	8	5	3	7	2
HOA	9	4	2	6	1

Table 6 Number of months per year that rejects the Kolmogorov–Smirnov at significant level of p value = 0.05 for precipitation wet day intensity analysis

Station\model	CLIG	CLIM	LARS	RSIM	WMAN
SFO	2	2	0	2	0
LAX	3	1	0	0	0
SBM	2	0	0	0	0
SYD	1	1	0	2	0
BRB	4	1	0	3	0
NEW	1	1	0	2	1
HAN	1	6	0	3	2
HAI	2	5	0	5	1
HOA	2	1	0	5	2

The wet day intensity threshold is increased to 2 mm/day (western USA) and 5 mm/day (eastern Australia and northern Vietnam)

given climate type, it is recommended that more number of stations needs to be evaluated in future studies.

5 Conclusions

The performances of the five stochastic weather generator models are evaluated and compared at three diverse climatic stations. The comparisons between these models were evaluated based on the precipitation occurrence, wet/dry spell lengths and rainfall intensity on wet days. Following conclusions can be drawn from this study:

1. In terms of precipitation occurrence, the majority of models (especially two states second order Markov chain: CLIM, WMAN and semi-empirical LARS) are

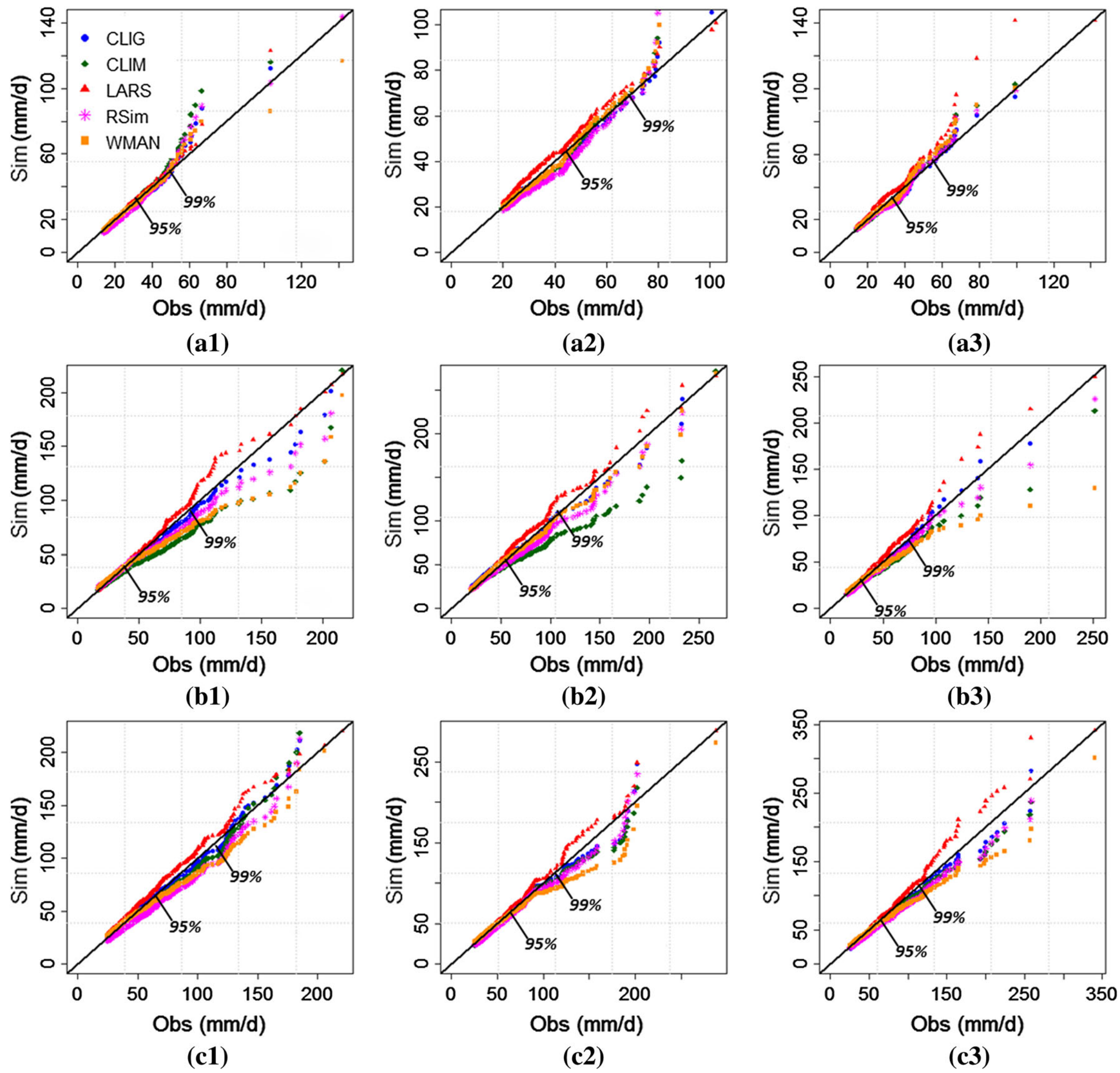


Fig. 10 Quantile–quantile plots for wet day intensity at 80, 95 and 99% percentile. **a1** SFO, **a2** SBM, **a3** LAX; **b1** SYD, **b2** BRB, **b3** NEW; **c1** HAN, **c2** HAI, **c3** HOA

able to capture the mean number of wet/dry days at all the nine stations located over three climatic regions. By analyzing monthly climatology, all the models can capture the temporal pattern of monthly rainfall occurrence with 'U-shape' for San Diego, 'A shape' for Hanoi and 'oscillating pattern' for Sydney. The second order Markov chain is comparatively better than the first order and others in generating precipitation occurrence at all three climatic regions. The semi-empirical based LARS is the next best model in generating wet day frequency.

2. Temporal Poisson based RSIM model performed well in reproducing wet/dry spell lengths in comparison to other models for eastern Australia and northern Vietnam stations. Considering LARS as a semi-empirical distribution, it is flexible in fitting the distribution over wet and dry spells; but it has some drawbacks in reproducing statistics of wet spells. However, for the stations located in a dry climate (i.e., western USA), Markov chains and semi-empirical model are the best models. It might be inferred that RSIM is not a good model for dry climate stations. In general, all models are able to generate good precipitation occurrence as well as a wet/dry spell for the western USA.
3. All the models performed well in terms of wet day intensity statistics for the eastern Australia and the northern Vietnam. LARS model seems to be the best for generating precipitation intensity distribution for the eastern Australia and the northern Vietnam while WMAN is the best one for the western USA. From quantile–quantile plots, RSIM model performs well in

Table 7 Ranking of SWG models based on their performance at nine rainfall stations located in three different climatic regions

Regions	Rainfall characteristics	CLIG	CLIM	LARS	RSIM	WMAN
Western USA	Statistics (mean, SD) wet day frequency	1	1	1	2	2
	Monthly mean climatology wet day frequency	1	1	2	2	1
	Statistics (mean, SD, ratio, max) wet spell	1	1	2	3	1
	Statistics (mean, SD, ratio, max) dry spell	1	2	1	4	3
	Distribution of wet spell (Wilcoxon)	1	2	3	4	2
	Distribution of dry spell (Wilcoxon)	1	1	1	3	2
	Monthly mean climatology wet spell	1	1	1	2	1
	Monthly mean climatology dry spell	1	1	1	3	2
	Statistics (mean, SD, skew, kurtosis) wet day intensity	2	1	1	2	2
	Monthly mean climatology wet day intensity	1	1	2	3	1
	Distribution of wet day intensity, threshold = 0.1 mm/d	5	2	4	3	1
	Distribution of wet day intensity, threshold = 2 mm/d	4	2	1	3	1
	95% percentile of precipitation magnitude	3	1	4	5	2
	Overall performance	23	17	24	39	21
Eastern Australia	Statistics (mean, SD) wet day frequency	4	1	2	3	1
	Monthly mean climatology wet day frequency	2	1	2	2	1
	Statistics (mean, SD, ratio, max) wet spell	3	2	4	1	3
	Statistics (mean, SD, ratio, max) dry spell	1	2	1	1	2
	Distribution of wet spell (Wilcoxon)	4	1	5	3	2
	Distribution of dry spell (Wilcoxon)	4	1	2	3	1
	Monthly mean climatology wet spell	3	1	3	2	2
	Monthly mean climatology dry spell	2	1	1	3	4
	Statistics (mean, SD, skew, kurtosis) wet day intensity	2	4	1	3	3
	Monthly mean climatology wet day intensity	4	1	2	3	1
	Distribution of wet day intensity, threshold = 1 mm/d	5	4	1	3	2
	Distribution of wet day intensity, threshold = 5 mm/d	4	3	1	5	2
	95% percentile of precipitation magnitude	1	2	3	2	1
	Overall performance	39	24	28	34	25
Northern Vietnam	Statistics (mean, SD) wet day frequency	3	1	2	3	1
	Monthly mean climatology wet day frequency	3	1	2	3	1
	Statistics (mean, SD, ratio, max) wet spell	2	1	4	1	3
	Statistics (mean, SD, ratio, max) dry spell	2	3	1	1	4
	Distribution of wet spell (Wilcoxon)	3	1	4	1	2
	Distribution of dry spell (Wilcoxon)	3	1	2	4	2
	Monthly mean climatology wet spell	4	1	4	2	3
	Monthly mean climatology dry spell	1	1	1	2	3
	Statistics (mean, SD, skew, kurtosis) wet day intensity	1	1	1	2	2
	Monthly mean climatology wet day intensity	3	1	2	4	1
	Distribution of wet day intensity, threshold = 1 mm/day	5	3	2	4	1
	Distribution of wet day intensity, threshold = 5 mm/day	3	4	1	4	2
	95% percentile of precipitation magnitude	1	2	4	5	3
	Overall performance	34	21	30	36	28

capturing extreme values and it is in agreement with Burton et al. (2008) that RSIM model matches well with annual extreme.

4. All the stochastic weather generators model performed differently with respect to different climatic regimes. Depending on flood, drought or crop modeling purposes, each type of stochastic model might have a

better fit to a certain type of impact. Based on the statistical tests using the distribution of precipitation occurrence, the wet/dry spell and wet day intensity, it was observed that CLIM is the best model in preserving the observation statistics and it is followed by WMAN and LARS.

Acknowledgements We appreciate the suggestions provided by associate editor and reviewers that helped us to improve quality of our manuscript. Authors would also like to thank Risk Engineering and Systems Analytics Center, Clemson University and American International Group for providing financial support.

Compliance with ethical standards

Conflict of interest All authors declare that they have no conflict of interest.

References

Baffault C, Nearing MA, Nicks AD (1996) Impact of CLIGEN parameters on WEPP-predicted average annual soil loss. Trans ASAE 39(2):447–457

Birt AG, Valdez-Vivas MR, Feldman RM, Lafon CW, Cairns D, Coulson RN, Tchakerian M, Xi W, Guldin Jim (2010) A simple stochastic weather generator for ecological modeling. Environ Model Softw 25(10):1252–1255

Bordoy R, Burlando P (2014) Stochastic downscaling of climate model precipitation outputs in orographically complex regions: 2. Downscaling methodology. Water Resour Res 50(1):562–579

Burton A, Kilsby CG, Fowler HJ, Cowpertwait PSP, O'Connell PE (2008) RainSim: a spatial temporal stochastic rainfall modelling system. Environ Model Softw 23(12):1356–1369. doi:10.1016/j.envsoft.2008.04.003

Burton A, Fowler HJ, Blenkinsop S, Kilsby CG (2010a) Downscaling transient climate change using a Neyman–Scott rectangular pulses stochastic rainfall model. J Hydrol 381(1–2):18–32. doi:10.1016/j.jhydrol.2009.10.031

Burton A, Fowler HJ, Kilsby CG, O'Connell PE (2010b) A stochastic model for the spatial-temporal simulation of non-homogeneous rainfall occurrence and amounts. Water Resour Res 46:W11501. doi:10.1029/2009WR008884

Camera C, Bruggerman A, Hadjinicolaou P, Michaelides S, Lange MA (2017) Evaluation of a spatial rainfall generator for generating high resolution precipitation projections over orographically complex terrain. Stoch Env Res Risk Assess 31(3):757–773

Campbell GS (1990) CLIMGEN, a program that generates weather data (precipitation, maximum and minimum temperatures). Biological systems engineering department, Washington State University, Pullman, Washington, USA

Caron A, Leconte R, Brissette F (2008) A stochastic weather generator applied to hydrological models in climate impact analysis. Can Water Res J 33(3):233–256

Castellvi F, Stöckle CO (2001) Comparing the performance of WGEN and ClimGen in the generation of temperature and solar radiation. Trans ASAE 44(6):1683–1687

Chen J, Brissette FP (2014) Comparison of five stochastic weather generators in simulating daily precipitation and temperature for the Loess Plateau of China. Int J Climatol 34:3089–3105

Chen J, Brissette FP, Leconte R (2012a) Downscaling of weather generator parameters to quantify the hydrological impacts of climate change. Clim Res 51(3):185–200. doi:10.3354/cr01062

Chen J, Brissette FP, Leconte R (2012b) Downscaling of weather generator parameters to quantify the hydrological impacts of climate change. Clim Res 51(3):185–200. doi:10.3354/cr01062

Corder GW, Foreman DI (2009) Nonparametric statistics for non-statisticians: a step-by-step approach. Wiley, London

Cowpertwait PSP (1994) A generalized point process model for rainfall. Proc Royal Soc London 447:23–37

Cowpertwait PSP (1995) A generalized spatial—temporal model of rainfall based on a clustered point process. Proc Royal Soc London 450:163–175

Evans MN, Fairbanks RG, Rubenstone JL (1998) A proxy index of ENSO teleconnections. Nature 394:732–733

Fischer T, Su B, Luo Y, Scholten T (2012) Probability distribution of precipitation extremes for weather index-based insurance in the Zhujiang River Basin, South China. J Hydrometeorol 13:1023–1037

Grondona MO, Podestá GP, Bidegain M, Marino M, Hordij H (2000) A stochastic precipitation generator conditioned on ENSO phase: a case study in southeastern South America. J Clim 13:2973–2986

Jones PG, Thornton PK (2000) MarkSim: software to generate daily weather data for Latin America and Africa. Agron J 92:445–453

Jones JW, Hoogenboom G, Porter CH, Boote KJ, Batchelor WD, Hunt LA, Wilkens PW, Singh U, Gijsman AJ, Ritchie JT (2003) The DSSAT cropping system model. Eur J Agron 18:235–265

Katz RW (1977) Precipitation as a chain-dependent process. J Appl Meteorol 16(7):671–676

Katz RW, Parlange MB (1993) Effects of an index of atmospheric circulation on stochastic properties of precipitation. Water Resour Res 29:2335–2344

Katz RW, Parlange MB, Tebaldi C (2003) Stochastic modeling of the effects of large-scale circulation on daily weather in the Southeastern US. Clim Change 60:189–216

Kilsby CG, Jones PD, Burton A, Ford AC, Flower HJ, Harpham C, James P, Smith A, Wilby RL (2007) A daily weather generator for use in climate change studies. Environ Model Softw 22:1705–1719

Krzywinski M, Altman N (2014) Points of significance: nonparametric tests. Nat Methods 11:467–468. doi:10.1038/nmeth.2937

Lall U, Sharma A (1996) A nearest neighbor bootstrap for resampling hydrological time series. Water Resour Res 32:679–693

Manatsa D, Chingombea W, Matarirab CH (2008) The impact of the positive Indian Ocean dipole on Zimbabwe droughts. Int J Climatol 28:2011–2029

Mehrotra R, Sharma A (2007) A semi-parametric model for stochastic generation of multi-site daily rainfall exhibiting low-frequency variability. J Hydrol 335:180–193

Nash JE, Sutcliffe JV (1970) River flow forecasting through conceptual models part I—a discussion of principles. J Hydrol 10(3):282–290. doi:10.1016/0022-1694(70)90255-6

Neyman J, Scott EL (1958) Statistical approach to problems of cosmology. J R Stat Soc B 20(1):1–43

Ngo DT, Kieu C, Thatcher M, Nguyen LD, Phan VT (2014) Climate projections for Vietnam based on regional climate models. Clim Res 60:199–213

Nicks AD, Gander GA (1994) CLIGEN: a weather generator for climate inputs to water resources and other models. In: Watson DG, Zazueta FS, Harrison TV (eds) Proceedings of fifth international conference on computer in agriculture. ASAE, St. Joseph, MI, pp 903–909

Nicks AD, Lane LJ, Gander GA (1995) Weather generator. In: Flanagan DC, Nearing MA (eds) USDA-water erosion prediction project: hillslope profile and watershed model documentation.

NSERL report no. 10. USDA-ARS Nat. Soil Erosion Research Lab, West Lafayette, in (Chapter 2)
Peel MC, Finlayson BL, McMahon TA (2007) Updated world map of the Koppen–Geiger climate classification. Hydrol Earth Syst Sci 11:1633–1644
Pickering NB, Hansen JW, Jones JW, Wells CM, Chan VK, Godwin DC (1994) WeatherMan: a utility for managing and generating daily weather data. Agron J 86:332–337
Racsko P, Szeidl L, Semenov M (1991a) A serial approach to local stochastic weather models. Ecol Model 57:27–41
Racsko P, Szeidl L, Semenov M (1991b) A serial approach to local stochastic weather models. Ecol Model 57(27):41
Rajagopalan B, Lall U (1999) A k-nearest-neighbor simulator for daily precipitation and other weather variables. Water Resourc Res 35(10):3089–3101
Richardson CW (1981) Stochastic simulation of daily precipitation, temperature, and solar radiation. Water Resour Res 17:182–190
Richardson CW, Wright DA (1984) WGEN: a model for generating daily weather variables. US Department of Agriculture, Agricultural Research Service, ARS-8, 83
Roldan J, Woolhiser D (1982) Stochastic daily precipitation models 1. A comparison of occurrence processes. Water Resour Res 18(5):1451–1459
Semenov MA, Barrow EM (1997) Use of a stochastic weather generator in the development of climate change scenarios. Clim Change 35:397–414
Semenov MA, Porter JR (1995) Climatic variability and the modelling of crop yields. Agr Forest Meteorol 73:265–283
Semenov MA, Shewry PR (2011) Modelling predicts that heat stress, not drought, will increase vulnerability of wheat in Europe. Sci Rep 1(66):1–5
Semenov MA, Brooks RJ, Barrow EM, Richardson CW (1998) Comparison of the WGEN and LARS-WG stochastic weather generators in diverse climates. Clim Res 10:95–107
Soltani A, Hoogenboom G (2003) A statistical comparison of the stochastic weather generators WGEN and SIMMETEO. Clim Res 24:215–230
Stern RD, Coe R (1984) A model fitting analysis of daily rainfall data. J R Stat Soc A147:1–34
Stöckle CO, Campbell GS, Nelson R (1999) ClimGen manual. Biological systems engineering department, Washington State University, Pullman, WA
Vallam P, Qin X (2016) Multi-site rainfall simulation at tropical regions: a comparison of three types of generators. Met Appl 23:425–437
Verdi A, Rajagopalan B, Kleiber W, Katz RW (2015) Coupled stochastic weather generation usingspatial and generalized linear models. Stoch Env Res Risk Assess 29(2):347–356
Westra S, Evans JP, Mehrotra R, Sharma A (2013) A conditional disaggregation algorithm for generating fine time-scale rainfall data in a warmer climate. J Hydrol 479:86–99
Whitt W (1981) Approximating a point process by a renewal process, I: two basic methods. Oper Res30:125–147
Wilby RL, Wigley TML, Conway D, Jones PD, Hewitson BC, Main J, Wilks DS (1998) Statistical downscaling of general circulation model output: a comparison of methods. Water Resour Res 34(2995):3008
Wilks DS (1989) Conditioning stochastic daily precipitation models on total monthly precipitation. Water Resour Res 25:1429–1439
Wilks DS (1999) Interannual variability and extreme-value characteristics of several stochastic daily precipitation models. Agric For Meteorol 93:153–169
Wilks DS (2010) Use of stochastic weather generators for precipitation downscaling. WIRE Clim Change 1:898–907. doi:10.1002/wcc.85
Xia J (1996) A stochastic weather generator applied to hydrological models in climate impact analysis. Theor Appl Climatol 55(1):177–183
Zhang L, Zhou T (2015) Drought over Asia: a review. J Clim 28:3375–3399