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EVALUATING AND EXTENDING CLIGEN PRECIPITATION GENERATION FOR THE LOESS PLATEAU OF CHINA[1]

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ABSTRACT: Climate generator (CLIGEN) is widely used in the United States to generate long-term climate scenarios for use with agricultural systems models. Its applicability needs to be evaluated for use in a new region or climate. The objectives were to: (1) evaluate the reproducibility of the latest version of CLIGEN v5.22564 in generating daily, monthly, and yearly precipitation depths at 12 stations, as well as storm patterns including storm duration (D), relative peak intensity (ip), and peak intensity (rp) at 10 stations dispersed across the Loess Plateau and (2) test whether an exponential distribution for generating D and a distribution-free approach for inducing desired rank correlation between precipitation depth and D can improve storm pattern generations. Mean absolute relative errors (MAREs) for simulating daily, monthly, annual, and annual maximum daily precipitation depth across all 12 stations were 3.5, 1.7, 1.7, and 5.0% for the mean and 5.0, 4.5, 13.0, and 13.6% for the standard deviations (SD), respectively. The model reproduced the distributions of monthly and annual precipitation depths well ($p > 0.3$), but the distribution of daily precipitation depth was less well produced. The first-order, two-state Markov chain algorithm was adequate for generating precipitation occurrence for the Loess Plateau of China; however, it underpredicted the longest dry periods. The CLIGEN-generated storm patterns poorly. It underpredicted mean and SD of D for storms ≥10 mm by −60.4 and −72.6%, respectively. Compared with D, ip, and rp were slightly better reproduced. The MAREs of mean and SD were 21.0 and 52.1% for ip, and 31.2 and 55.2% for rp, respectively. When an exponential distribution was used to generate D, MAREs were reduced to 2.6% for the mean and 7.8% for the SD. However, ip estimation became much worse with MAREs being 128.9% for the mean and 241.1% for the SD. Overall, storm pattern generation needs improvement. For better storm pattern generation for the region, precipitation depth, D, and rp may be generated correlatively using Copula methods.

(KEY TERMS: weather generator; CLIGEN; precipitation generation; storm pattern.)

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INTRODUCTION

Daily weather data are commonly needed by hydrologic and crop models. Stochastic weather generators such as Weather Generator (WGEN) (Richardson and Wright, 1984), USCLIMATE (Hanson *et al.*, 1994), Climate Generator (CLIGEN) (Nicks *et al.*, 1995), and LARS-Weather Generator (LARS-WG) (Semenov and Barrow, 2002) are often used to

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generate daily weather data when measured data are insufficient or unavailable. Among these commonly used weather generators, CLIGEN is the only one that generates internal storm patterns, which are critical for simulating event runoff and soil erosion. Zhang and Garbrecht (2003) evaluated v5.107 and showed that CLIGEN-generated duration was generally too long for small storms and too short for large storms for U.S. Oklahoma. Thus, it is necessary to evaluate its applicability to a new region or climate prior to its adoption. The CLIGEN was developed for the Water Erosion Prediction Project (WEPP) model to predict runoff and soil erosion (Nicks *et al.*, 1995; Laflen *et al.*, 1997). It has been used to synthesize daily weather that statistically resembles the present climate or generate daily weather for ungauged areas through spatial interpolation of model parameters from adjacent gauged sites (Baffault *et al.*, 1996). Recently, CLIGEN has been used to downscale monthly projections of general circulation model (GCM) to daily weather series for assessing crop production and soil erosion under climate change (Zhang, 2003, 2005a; Zhang and Liu, 2005). Because each variable in CLIGEN is generated independently and each variable's mean and standard deviations (SD) are explicitly used in its probability distribution function, incorporation of GCM projected monthly changes in statistical moments into CLIGEN input parameters becomes straightforward (Zhang, 2005a). Comparatively, adaptation of other weather generators such as WGEN for generating climate change scenarios through modifying relevant distribution parameters is more complex, and requires additional constraints and assumptions that would result in additional alternatives for a possible climate change scenario (Wilks, 1992; Mearns *et al.*, 1997). Compared with other weather generators such as WGEN and LARS-WG, CLIGEN is one weather generator that also generates dew point temperature, wind velocity, and direction in addition to precipitation depth, maximum and minimum temperature, and solar radiation. Wind speed and direction are required for better estimation of evapotranspiration.

Several studies were conducted to evaluate the ability of CLIGEN to generate the precipitation parameters. Johnson *et al.* (1996) thoroughly evaluated and compared the ability of CLIGEN and USCLIMATE to generate precipitation at six locations dispersed across the contiguous United States (U.S.) and concluded that annual and monthly precipitation statistics including mean, SD, and extremes were adequately replicated by both models. But daily precipitation depths, particularly extreme values in any given year, were not entirely satisfactorily generated by either model. They further reported that the first-order, two-state Markov chain used in both models adequately replicated sequences of wet and dry days. Wilks (1999) compared several formulations for generating precipitation occurrence using 30 widely dispersed stations across the U.S. and found that first-order Markov model seemed broadly appropriate for the central and eastern U.S. stations but was inadequate for the western stations with respect not only to overall goodness-of-fit but also its capacity to represent the observed variance of the number of wet days per month as well as the durations of extremely long dry spells. Headrick and Wilson (1997) evaluated CLIGEN daily weather parameters at five Minnesota locations, found that CLIGEN replicated daily precipitation depth reasonably well, but storm duration (D) was not satisfactorily generated. Zhang and Garbrecht (2003) evaluated the ability of CLIGEN (v5.107) to generate precipitation parameters in Oklahoma, as well as the potential impacts of generated storm patterns on WEPP runoff and erosion prediction. Their results illustrated that CLIGEN reproduced monthly, annual, and annual maximum daily precipitation reasonably well; however, the daily precipitation distribution was less well simulated. Simulated D was too long for small storms and too short for large storms and was not correlated to precipitation depths. Zhang (2005b) used a distribution-free approach for inducing desired rank correlation between storm depth and D to improve storm pattern generation. The results showed that the distribution-free approach was capable of inducing desired rank correlation between storm depth and duration and consequently between storm depth and relative peak intensity (ip); however, estimation of ip worsened after the induction of correlation. Yu (2003) assessed the impacts of CLIGEN-generated precipitation parameters on WEPP runoff and erosion and revised universal soil loss equation (RUSLE) erosivity prediction, found that CLIGEN could generate the required climate data for WEPP, but generated rainfall erosivity for RUSLE was systematically greater than the measured erosivity. More importantly, all the above studies used earlier CLIGEN versions (prior to v5.107), and several major improvements were made by Mr. Charles Meyer since the release of v5.107 (http://topsoil.nserl.purdue.edu/nserlweb/weppmain/cligen/). The main modifications include capping the precipitation skewness coefficient to keep CLIGEN from generating an inordinate percentage of negative values, introducing quality control to the gamma distribution used to generate storm intensity, replacing a chi-square test with a Kolmogorov-Smirnov (K-S) test for quality control, improving simulation of individual storm characteristics, and increasing the lot size of random numbers (generated for the gamma distribution for rainfall intensity) from 20 at a time to 30 at a time. Overall, a much more stringent form of quality control for random numbers was implemented in CLIGEN (v5.22564). These modifications need to be evaluated for their ability to improve overall model performance in a wide range of climate and geographic conditions.

The Loess Plateau of China is one of the most severely eroded regions in the world due to its fine aeolian deposits, steep slope, sparse vegetation cover, and frequent heavy storms. Great effort has been taken to combat soil erosion in the region in the past several decades. There is a need to generate synthetic climate data for evaluating the effectiveness of soil and water conservation measures in controlling runoff and soil loss in ungauged areas and for assessing the potential impacts of future climate changes on soil erosion in the region using the WEPP model that requires storm pattern data. Therefore, the ability of CLIGEN to generate precipitation in the region needs to be thoroughly and systematically evaluated before it is adopted. However, only a few studies were conducted in China to evaluate the CLIGEN. Miao *et al.* (2004) compared the abilities of CLIGEN and Break Point Climate Data Generator (BPCDG) and reported that BPCDG was better than CLIGEN for using in soil erosion prediction. Zhang (2004) evaluated the applicability of CLIGEN at three stations in the Loess Plateau and found that CLIGEN was successful in reproducing annual and monthly precipitation mean, but SD were less well simulated. Shi *et al.* (2006) evaluated the applicability of CLIGEN (v5.111) at the Ansai Station in the Loess Plateau, and found that it reproduced the annual precipitation, monthly distribution of precipitation very well. Li *et al.* (2006) evaluated the ability of CLIGEN (v5.111) to produce precipitation parameters at the Changwu station in the Loess Plateau. They reported that the mean of daily, monthly, and annual precipitation were adequately preserved by CLIGEN but the SD were all underpredicted and that CLIGEN-generated *rp* was overestimated while *D* was overpredicted for small storms and underpredicted for large storms compared with measured values. All the above evaluations of CLIGEN were focused on evaluating the precipitation depth at just one or a few stations on the Loess Plateau. To date no one has systematically evaluated the performance of the latest version of CLIGEN for generating precipitation parameters, especially for generating storm patterns using stations dispersed across the Loess Plateau.

The objectives of this study were to (1) systematically evaluate the reproducibility of the latest version of CLIGEN (v5.22564) in generating daily, monthly, and annual precipitation depths at 12 stations, as well as storm patterns at 10 stations dispersed across the Loess Plateau; and (2) test whether an exponential distribution for generating *D* and a distribution-free approach for inducing desired rank correlation between precipitation depth and *D* can improve storm pattern generations.

CLIGEN (V5.22564) STORM GENERATION

The CLIGEN model generates daily precipitation occurrence, depth, *D*, *ip*, time to peak, and daily values of maximum, minimum air temperatures, dew point temperature, solar radiation, and wind velocity and direction based upon long-term monthly statistical parameters. The precipitation variables are independent of other weather variables. Precipitation and storm pattern generations are only presented here. Mean, SD, and skew coefficient of daily precipitation depth, probabilities of precipitation occurrences (a wet day following a wet day and a wet day following a dry day), mean 0.5-h maximum precipitation intensity of each month and time-to-peak parameter are directly extracted from the station daily precipitation record. A first-order, two-state Markov chain is used to generate precipitation occurrence for a day given the previous day being wet or dry. If a random number that is drawn from a uniform distribution for each day is less than the precipitation probability for the given previous day status, a precipitation event is predicted. For a predicted rain day, a transformed (skewed) normal distribution is used to generate daily precipitation depths for each month (Nicks and Lane, 1989)

$$x = \frac{6}{g}\left\{\left[\frac{g}{2}\left(\frac{R-\mu}{s}\right)+1\right]^{1/3} - 1\right\} + \frac{g}{6}, \tag{1}$$

where x is the standard normal deviate; R is the daily precipitation depth (mm); μ, s, and g are the mean (mm), SD (mm), and skew coefficient of daily depths for the month, respectively. Two random numbers are used to generate x (the second number for today is reused as the first number for tomorrow), which is then used in Equation (1) to compute R.

Assuming rainfall rates during a storm decrease exponentially from the maximum rate, the peak intensity (*rp*) (mm/h) was generated as (Arnold and Williams, 1989)

$$rp = -2R\ln(1-\alpha_{0.5}), \tag{2}$$

where $\alpha_{0.5}$ is the ratio of the maximum 0.5-h rainfall depth to the total depth for the event and is drawn from a two-parameter gamma distribution. The shape parameter of the gamma distribution is set to 6.2832 in CLIGEN (v5.22564), and another parameter is the mean $\alpha_{0.5}$ for the month ($\alpha_{0.5\mathrm{mean}}$) and is estimated in the model by

$$\alpha_{0.5\mathrm{mean}} = R_{0.5\mathrm{mean}}/R_{\mathrm{mean}}, \tag{3}$$

where $R_{0.5\mathrm{mean}}$ and R_{mean} are the means of $R_{0.5}$ (maximum 0.5-h depth) and R for the month, respectively. The $R_{0.5\mathrm{mean}}$ is related to the mean of annual maxima for each month ($R_{0.5\mathrm{max}}$) by

$$R_{0.5\mathrm{mean}} = -R_{0.5\,\mathrm{max}}/\ln F, \tag{4}$$

where $R_{0.5\mathrm{max}}$ is an input parameter and F is the exceedance probability for $R_{0.5\mathrm{max}}$ and is estimated by (Yu, 2000)

$$F = 2/(2n+1), \tag{5}$$

where n is the average number of rain days for the month.

The D (h) is estimated as

$$D = -0.5\Delta/\ln(1-\alpha_{0.5}), \tag{6}$$

where Δ takes a value of 3.99 in v5.22564. Nicks *et al.* (1995) pointed out that Equations (2 and 6) are tentative and subject to modification as more historical precipitation data are analyzed.

The ip is calculated as

$$ip = rpD/R \tag{7}$$

Combining Equations (7 and 2), we get

$$ip = -2D\ln(1-\alpha_{0.5}) \tag{8}$$

Owing to the fact that there are various storm patterns in nature, even during the same season in the same area, it is very difficult to reproduce internal storm patterns. Three assumptions were made in CLIGEN to simplify storm pattern simulation. First, there is only one storm event in a wet day, which implies that multiple rainfall episodes within a day need to be coalesced to calculate D and the maximum D is less than 24 h. Second, each storm process has only one peak. Third, all storm patterns can be described by a double-exponential function.

Arnold *et al.* (1990) indicated that D is exponentially distributed. Therefore, to test this preliminary observation, D was also generated using a standard exponential distribution in this study as:

$$D = -\ln(1-\chi)D_{\mathrm{m}}, \tag{9}$$

where χ is a uniform random number ($0 < \chi < 1$), and D_{m} (h) is the overall mean D for a station (averaged across all months). Equation (7) was then used to calculate the corresponding ip for each storm and newly generated D.

INDUCING RANK CORRELATION BETWEEN STORM DEPTH AND DURATION

Iman and Conover (1982) presented a method (distribution-free approach) for pairing observations of independent input variables to induce the desired rank correlation structure. The theoretical basis of the method is briefly described below. Suppose that [C] is a desired correlation matrix and [X] is a random row vector. The matrix [C] may be written as [C] = [P][P′] because [C] is positive-definite and symmetric. Then the transformed vector [X][P′] has the desired correlation matrix [C]. The detailed procedure in this study is as follows. Suppose that [C] is the desired rank correlation matrix (2×2 matrix in this case) and [C] = [P][P′], where [P] was computed using the Cholesky factorization scheme. It means that the symmetric, positive-definite matrix [C] was factorized into the product of a lower triangular matrix [P] and its transpose [P′] using the Cholesky factorization scheme. Let k be the number of input variables ($k = 2$ in this study) and n be the sample size (n = number of wet days with $R \geq 10$ mm). Let [X] be an $n \times k$ matrix whose columns represent k independent random permutations of an arbitrary set of n scores. The van der Waerden scores were used in this study, which were generated by $\Phi^{-1}\{i/(n+1)\}$, Φ^{-1} is the inverse function of the standard normal distribution and $i = 1\ldots, n$ (SAS, 1990). For example, for $n = 50$ the matrix [X] has a random mix of the van der Waerden scores Φ^{-1} $(i/51)$, $i = 1\ldots, 50$, in each column. For $k = 2$, the 50 van der Waerden scores were independently permutated twice to create two columns of the random mix. As mentioned above, [X][P′] results in an $n \times k$ matrix, denoted as [X*] in this study, which possesses the desired correlation matrix [C] for the k input variables. Further, let [A] be an $n \times k$ matrix whose elements are actual input values. To induce the desired correlation between the input variables, the input values in each column of matrix [A] are rearranged to have the same ordering as the corresponding column of matrix [X*].

In this study, D was also generated using Equation (9) to form a new dataset. The R in the new dataset was maintained, and only the D values were reordered to match up with R to induce proper correlation. The measured Spearman rank correlation coefficient between R and D was calculated for each test station. The calculated rank correlation coefficients were then used to induce the desirable correlation using Microsoft Excel for storms of $R \geq 10$ mm in this dataset. The ip was then recalculated using Equation (7) for each new pair of R and D, and the paring between rp and R remained unchanged. The procedure was repeated for each station. To prevent unrealistic ip values, a range check was imposed on calculated ip. For storms with large R and short D or with small R and long D, the average storm intensity (R/D) was checked against the upper and lower bounds of storm intensity representative of the stations. If the storm intensity is greater than the set upper bound or smaller than the set lower bound, the D was recalculated by dividing R by the set upper or lower bound intensity.

MATERIAL AND METHODS

The daily Rs of 12 stations and the storm patterns of 10 stations dispersed across the Loess Plateau were used in the evaluation (Figure 1). Basic

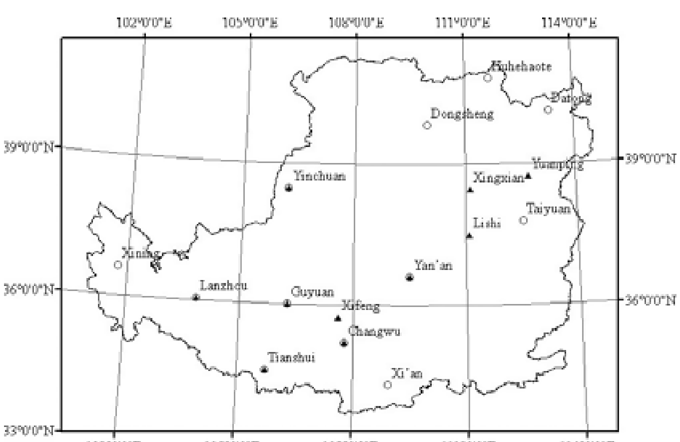

FIGURE 1. Selected Study Stations in the Loess Plateau of China. ○, stations for precipitation evaluation and ▲, stations for storm patterns evaluation.

information including average annual precipitation, longitude, latitude, elevation, and record duration for these stations is given in Tables 1 and 2. Average annual precipitation at these stations varied from 193 mm at Yinchuan to 576 mm at Changwu.

The data collected at these stations included daily precipitation depth, maximum and minimum air temperature, dew point temperature, solar radiation, wind velocity and wind direction, the average of the maximum monthly 0.5-h rainfall intensity and cumulative distribution of 12 "time to peak" classes. These data were used to derive CLIGEN input parameters using the CLIGEN-support parameterization program. The derived parameters were then used to generate daily weather data for 100 years with the default random number seed and no interpolation between months for precipitation generation.

Mean, SD, coefficients of skewness and kurtosis, and extreme values of daily, monthly and annual precipitation depths, D, ip, and rp were calculated for both measured and generated daily data, as well as exponentially generated D and the recalculated ip from uncorrelated and correlated, exponentially generated D. In general, an absolute skew coefficient of >1 is considered extremely skewed, between 0.5 to 1 moderately skewed, and <0.5 fairly symmetric (Evans and Olson, 2002). Relative error (RE), computed as the difference between generated and measured values divided by the measured value, was calculated. As the precipitation depth are known not to have normal distributions, instead of a t-test and F-test, nonparametric Mann-Whitney tests and squared ranks tests (Conover, 1999) were conducted to test the equality of the mean and SD of measured and generated data, respectively. In addition, a nonparametric K-S test (Chen, 1989), which is applicable to any type of distributions, was used to test the equality of the two population distributions of measured *vs.* generated data. All the tests are two-tailed and a significance level of $p = 0.01$ was used. Meanwhile, $p = 0.01$ refers to a Type 1 error. The larger the p value, the more likely the two series are similar, and vice versa. Selected percentiles (5th, 15th, 25th, 50th, 75th, 95th, and 99th) of daily, monthly, annual, and annual maximum daily precipitation depths of both generated and measured data as divided by the corresponding measured mean were plotted for trend comparison. Frequencies of both measured and generated wet and dry periods were also compared.

The break point rainfall data were only available for the erosive rainfall events (≥10 mm) from May to September from soil conservation experiment stations in the Loess Plateau of China. The data of erosive storms (May to September) were only used

TABLE 1. Location, Record Period, and Average Annual Precipitation of Station for Evaluating Precipitation Depth.

Station	Longitude (°E)	Latitude (°N)	Elevation (m)	Records of Daily Precipitation	Precipitation (mm)
Yinchuan	106.22	38.48	1,111	1951-2001	193.4
Lanzhou	103.88	36.05	1,517	1951-2001	318.8
Xining	101.77	36.62	2,261	1954-2001	373.4
Datong	113.33	40.10	1,067	1955-2001	378.1
Dongsheng	109.98	39.83	1,460	1957-2001	386.3
Huhehaote	111.68	40.82	1,063	1952-2004	414.6
Taiyuan	112.55	37.78	778	1951-2001	442.5
Guyuan	106.27	36.00	1,753	1957-2001	455.9
Tianshui	105.75	34.58	1,142	1951-2001	516.1
Yan'an	109.50	36.60	958	1951-2001	533.4
Xi'an	108.93	34.30	398	1951-2001	570.4
Changwu	107.80	35.20	1,207	1957-2001	576.4

TABLE 2. Location, Record Period, and Average Annual Precipitation of Station for Evaluating Storm Patterns.

Station	Longitude (°E)	Latitude (°N)	Elevation (m)	Records of Storm Pattern	Precipitation (mm)
Yinchuan	106.22	38.48	1,111	1952-1979	193.4
Lanzhou	103.88	36.05	1,517	1952-1979	318.8
Yuanping	112.72	38.73	828	1956-1980	431.8
Guyuan	106.27	36.00	1,753	1977-1982	455.9
Lishi	111.10	37.50	951	1966-1986	477.6
Xingxian	111.13	38.47	1,013	1966-1986	484.5
Tianshui	105.75	34.58	1,142	1955-1979	516.1
Yan'an	109.50	36.60	958	1959-1967	533.4
Xifeng	107.63	35.73	1,421	1965-1979	544.5
Changwu	107.80	35.20	1,207	1988-2004	576.4

in the evaluation. As 5-min *rp* could be calculated for the Lishi, Xifeng, Xingxian, and Yuanping stations, and 10-min *rp* for the Changwu, Guyuan, Lanzhou, Tianshui, Yan'an, and Yinchuan stations, the direct comparison of the measured *ip* with CLIGEN-generated instantaneous *ip* was inappropriate. Yu (2002) presented a method to calculate the relative maximum rainfall intensity for a given time interval (Δt) from CLIGEN-generated data as:

$$i_{\Delta t} = \frac{ip}{b t_p \Delta t}[1 - \exp(-b t_p \Delta t)], \tag{10}$$

where $i_{\Delta t}$ is the ratio of maximum intensity for Δt over the average intensity, and b is a parameter in the double exponential function describing the storm pattern in CLIGEN, which could be determined for any given value of *ip* and *tp* using Newton-Raphson's method. From $i_{\Delta t}$ CLIGEN-generated *rp* for any given time interval can be estimated. In this study, measured and generated *rp* as well as *ip* were compared for the same time intervals.

RESULTS

Evaluation of Precipitation Depth

Daily Precipitation. The CLIGEN reproduced the mean of daily precipitation ($R \geq 1$ mm) well (Table 3). REs ranged from −11.0% to 2.5% with the mean absolute relative error (MARE) of 3.5%. The Mann-Whitney tests showed significant differences in mean at $p = 0.01$ for 3 out of 12 stations. The squared ranks test showed that SD of daily precipitation were poorly reproduced, with 10 out of 12 stations being different at $p = 0.01$. REs between measured and generated SD ranged from −9.3% to 0.1% across 12 stations with MARE of 5.0%. The distribution of daily precipitation was extremely skewed to the left. CLIGEN replicated this trend with a MARE of 8.5% across 12 stations. The daily precipitation distribution was extremely peaked. The peakedness indicated by the kurtosis coefficient was overpredicted at 7 out of the 12 stations with a MARE of 24.3% across all stations. All-time maximum daily precipitation was reasonably poorly simulated because the transformed

TABLE 3. Statistics of Daily Precipitation Depths (R) and Mean Numbers of Rain Days by Station for Storms >1 mm at 12 Weather Stations.

Station	Mean (mm)	SD (mm)	Skewness Coefficient	Kurtosis Coefficient	All-Time Maximum (mm)	Rain Days Per Year	Mann-Whitney Test p Value	Squared Ranks Test p Value	K-S Test p Value
Tianshui									
M	7.7	8.8	2.8	14.2	88.1	65.1	0.1039	0.0025	0.0199
C	7.6	8.4	3.1	20.0	123.8	66.2			
Changwu									
M	8.5	9.8	2.8	14.8	102.2	66.5	0.8317	0.0015	0.0159
C	8.3	9.2	2.7	13.7	96.0	68.8			
Xi'an									
M	8.7	10.1	2.9	16.7	110.7	63.8	0.1259	<0.0001	<0.0001
C	9.0	9.8	3.2	20.1	114.4	62.8			
Yan'an									
M	9.2	11.3	3.2	19.1	139.9	57.0	0.5421	0.0001	0.0775
C	9.0	11.3	4.1	34.7	191.3	57.6			
Xining									
M	6.2	6.4	2.5	12.2	62.2	57.8	0.0658	<0.0001	0.0041
C	6.2	6.1	3.0	18.6	82.9	58.6			
Lanzhou									
M	6.7	7.5	3.2	21.1	96.8	46.0	0.7361	<0.00013	0.2311
C	6.5	7.1	3.1	18.9	80.3	46.6			
Guyuan									
M	7.7	9.1	3.1	17.3	98.1	57.7	0.0096	0.5778	0.0086
C	7.8	8.7	2.9	16.3	105.1	57.0			
Taiyuan									
M	8.6	11.3	4.1	35.8	183.5	50.1	0.5549	<0.0001	0.0091
C	8.2	10.4	3.8	25.7	133.1	51.1			
Yinchuan									
M	6.6	7.8	3.1	16.6	66.8	28.1	0.0295	0.0007	0.0168
C	6.6	7.1	3.0	16.9	78.0	27.7			
Dongsheng									
M	8.4	11.9	4.4	32.9	147.9	44.5	<0.0001	<0.0001	<0.0001
C	7.5	11.0	4.3	32.5	137.7	48.9			
Huhehaote									
M	8.7	12.5	5.2	49.6	210.1	46.4	<0.0001	<0.0001	<0.0001
C	7.8	11.7	5.5	65.3	246.2	49.9			
Datong									
M	7.4	8.6	2.8	13.4	67.0	50.0	0.1335	0.9644	0.1227
C	7.4	8.4	2.9	14.8	84.5	48.8			

Notes: C, CLIGEN-generated; K-S, Kolmogorov-Smirnov; M, measured; SD, standard deviations.

(skewed) normal distribution is not suited to simulate precipitation extremes, and better results may be achieved if double exponential distributions are used. The mean absolute difference across the 12 stations was 22.2 mm with the largest difference being 50.4 mm (Taiyuan), and RE was 20.2% for average difference and 27.5% for the largest difference. The mean number of rain days ($R \geq 1$ mm) was reproduced well on all stations with a MARE of 2.4% and maximum difference being 4.4 days (Dongsheng). The K-S tests showed that the measured and generated distributions were statistically different for six stations (out of 12) at $p = 0.01$. Daily precipitation was further tested on a monthly basis. Out of 144 month-location combinations, only 21 were rejected by the K-S test at $p = 0.01$.

Monthly Precipitation. Monthly mean precipitation depths were well preserved with a MARE of 1.7% across all stations (Table 4). The Mann-Whitney tests showed that the mean of measured data were not different from those of the generated data at $p = 0.01$ for all stations. The SD was slightly underpredicted except for the Yan'an station with a RE of 4.5%, and REs ranged from −9.7% to −1.5% for the other 11 stations. The squared ranks tests showed that there were significant differences at $p = 0.01$ for 4 out of 12 stations for SD. The distribution of monthly precipitation was extremely skewed to the left. The CLIGEN-simulated skewness had a MARE of 13.4% across 12 stations. However, the skewness of monthly precipitation was much smaller than that of daily precipitation. The Kurtosis coefficients of monthly precipitation were poorly simulated with a MARE of 33.8%. All-time maximum monthly precipitation was poorly simulated either with a MARE being 34.8%. Perhaps, the second-order Markov chain would do a better job in

TABLE 4. Statistics of Monthly Precipitation Depths for 12 Weather Stations.

Station	Mean (mm)	SD (mm)	Skewness Coefficient	Kurtosis Coefficient	All-Time Maximum (mm)	Mann-Whitney Test *p* Value	Squared Ranks Test *p* Value	K-S Test *p* Value
Tianshui								
M	43.0	43.1	1.3	4.2	217.8	0.9789	0.9935	0.8853
C	43.1	42.2	1.3	4.8	279.3			
Changwu								
M	48.0	50.2	1.7	6.3	305.9	0.5947	0.7841	0.5465
C	48.4	47.1	1.4	4.9	247.8			
Xi'an								
M	47.5	46.2	1.6	6.9	344.4	0.6086	0.2866	0.727
C	47.8	44.4	1.5	6.0	287.0			
Yan'an								
M	44.4	51.7	1.7	6.0	303.5	0.6009	0.0806	0.6667
C	44.0	53.3	2.4	13.1	524.9			
Xining								
M	31.1	35.0	1.1	3.5	174.9	0.7861	0.2349	0.8036
C	31.1	34.4	1.2	4.1	188.5			
Lanzhou								
M	26.6	32.4	1.8	7.2	236.2	0.6304	0.0017	0.4503
C	26.0	30.7	1.7	5.9	166.1			
Guyuan								
M	38.0	46.5	2.0	8.6	324.4	0.5260	0.9103	0.6999
C	38.0	43.1	1.5	5.4	248.2			
Taiyuan								
M	36.9	48.2	2.2	9.4	360.0	0.8459	0.0090	0.9014
C	35.5	43.5	2.2	12.4	460.6			
Yinchuan								
M	16.1	22.0	2.1	8.7	148.7	0.7858	0.4777	0.7944
C	15.8	21.3	2.4	11.6	193.0			
Dongsheng								
M	32.2	45.2	2.2	7.9	243.3	0.9592	0.0023	0.6121
C	31.3	44.6	2.6	12.4	363.6			
Huhehaote								
M	34.6	49.4	2.5	11.4	360.7	0.9811	<0.0001	0.4601
C	32.8	44.9	2.4	9.9	310.3			
Datong								
M	31.5	39.2	1.8	6.1	231.8	0.9909	0.0591	0.8183
C	31.0	38.6	2.0	7.9	296.2			

Notes: C, CLIGEN-generated; K-S, Kolmogorov-Smirnov; M, measured; SD, standard deviations.

simulating extremely wet months. The K-S tests could not reject the hypothesis that the generated and measured monthly precipitation are from the same distribution at $p = 0.01$ for all stations. The average p value was 0.697 for the K-S tests for all stations. Monthly precipitation was also tested by month on each location (144 combinations), and all the K-S tests for distributions were insignificant at $p = 0.01$. These results illustrated that monthly precipitation was better simulated than daily precipitation.

Annual Precipitation. Mean annual precipitation was satisfactorily simulated with a MARE of 1.7% across all 12 stations (Table 5). The Mann-Whitney tests showed that the mean of measured data were not different from those of the generated data at $p = 0.01$ for all stations. The CLIGEN tended to consistently underpredict SD except for the Yan'an station by a mean of −13.0%. This is because the month-to-month precipitation dependency was not simulated in CLIGEN, and an introduction of a low frequency (seasonal) precipitation variation as in LARS-WG would increase SD of generated annual precipitation. However, the squared ranks tests showed that the SD of the generated data were not different from those of measured data at $p = 0.01$ for all 12 stations. The coefficients of skewness were near zero for most generated and measured values for most stations. The kurtosis coefficients of annual precipitation were smaller than those of daily and monthly precipitation. The MARE of kurtosis coefficient was 33.8%. The MARE of maximum annual precipitation was 10.1%, ranging from −26.6% to 22.1%. The K-S tests for each station showed that cumulative distributions of generated and measured annual precipitation were not different at $p = 0.01$, suggesting that they were likely from the same distribution. The average p value was 0.733 for the K-S tests for

TABLE 5. Statistics of Annual Precipitation Depths for 12 Weather Stations.

Station	Mean (mm)	SD (mm)	Skewness Coefficient	Kurtosis Coefficient	All-Time Maximum (mm)	Mann-Whitney Test p Value	Squared Ranks Test p Value	K-S Test p Value
Tianshui								
M	516.1	112.4	0.2	2.3	772.2	0.8796	0.0108	0.3040
C	517.6	90.1	0.3	3.7	815.8			
Changwu								
M	576.4	127.7	0.2	2.3	822.2	0.7116	0.3552	0.8771
C	580.8	119.7	0.1	2.8	883.2			
Xi'an								
M	570.4	123.6	0.3	3.3	903.2	0.7042	0.4958	0.794
C	573.7	103.3	0.2	2.8	843.6			
Yan'an								
M	533.3	120.4	0.6	3.1	871.2	0.6256	0.8961	0.4014
C	528.5	130.3	1.1	4.5	997.9			
Xining								
M	373.4	73.5	0	3.0	541.2	0.8074	0.2528	0.8264
C	372.8	60.0	0.2	3.1	541.0			
Lanzhou								
M	318.8	76.1	0.8	3.4	546.7	0.7800	0.6837	0.8841
C	311.8	70.4	0.3	3.1	514.2			
Guyuan								
M	455.9	105.6	0.8	3.8	766.4	0.7713	0.3195	0.4181
C	455.7	90.0	0.4	2.8	663.8			
Taiyuan								
M	442.5	118.3	0.5	3.0	749.1	0.4087	0.2362	0.7646
C	425.7	102.9	1.3	6.8	914.5			
Yinchuan								
M	193.4	61.2	0.6	2.7	355.2	0.9170	0.1383	0.9047
C	189.6	52.2	0.2	2.7	328.8			
Dongsheng								
M	386.3	113.9	0.5	3.0	709.7	0.5625	0.3274	0.8249
C	375.2	103.3	0.8	3.0	671.9			
Huhehaote								
M	414.6	133.3	1.2	5.8	929.2	0.4546	0.8245	0.9204
C	394.1	108.9	0.3	2.6	681.8			
Datong								
M	378.1	88.1	0.3	2.5	579.0	0.7163	0.2045	0.8782
C	371.6	80.4	0.3	3.5	611.4			

Notes: C, CLIGEN-generated; K-S, Kolmogorov-Smirnov; M, measured; SD, standard deviations.

all stations, indicating that CLIGEN well reproduced the distributions of annual precipitation.

Annual Maximum Daily Precipitation Depth

Statistics on annual maximum daily precipitation, which is the maximum daily depth of each year, are given in Table 6. The mean of annual maximum daily precipitation tended to be slightly underpredicted with a mean RE of −5.0%; however, none of the Mann-Whitney tests was significantly different at $p = 0.01$ for all stations. The MARE was 13.6% for SD with all stations past the squared ranks tests at $p = 0.01$. The CLIGEN overpredicted the coefficients of skewness and kurtosis except for Lanzhou and Taiyuan with MAREs of 49.5% and 54.6%, respectively. The K-S tests for each station showed that the hypothesis that the measured and generated annual maximum daily precipitation came from the same distribution could not be rejected at $p = 0.01$. Overall, CLIGEN simulated the maximum annual daily precipitation surprisingly well for the study region because the skewed normal distribution was not tailored to simulate daily precipitation extremes. The better than expected results are very important for simulating soil erosion in the Loess Plateau (most severely eroded region in the world), because most soil erosion occurs only in a few extreme storms.

Cumulative Distributions of Precipitation

Percentile plots could visually reflect the cumulative distribution of samples comparing with each test. The selected percentiles of daily ($R \geq 1$ mm), monthly, annual, and annual maximum daily precipitation depths as scaled by the corresponding measured mean

TABLE 6. Statistics of Annual Maximum Daily Precipitation Depths for 12 Weather Stations.

Station	Mean (mm)	SD (mm)	Skewness Coefficient	Kurtosis Coefficient	Mann-Whitney Test *p* Value	Squared Ranks Test *p* Value	K-S Test *p* Value
Tianshui							
M	44.4	13.8	1.0	4.2	0.3263	0.4135	0.2322
C	43.2	16.1	1.9	9.4			
Changwu							
M	49.3	16.8	1.0	4.1	0.1623	0.2314	0.2741
C	45.4	14.9	1.2	4.8			
Xi'an							
M	50.3	18.8	1.2	4.5	0.6228	0.3756	0.4014
C	49.9	20.9	1.3	4.1			
Yan'an							
M	57.1	21.0	1.4	6.2	0.1422	0.1584	0.1278
C	55.0	28.0	2.0	8.6			
Xining							
M	30.6	10.1	0.9	4.1	0.9266	0.5955	0.8794
C	31.3	11.6	1.5	6.7			
Lanzhou							
M	34.8	14.8	1.7	8.0	0.6035	0.9824	0.4179
C	33.4	13.8	1.2	4.9			
Guyuan							
M	43.5	17.9	0.9	3.4	0.9370	0.1179	0.4943
C	42.5	15.5	1.2	4.8			
Taiyuan							
M	55.0	25.6	2.6	13.5	0.0492	0.6665	0.0194
C	48.9	22.7	1.3	4.5			
Yinchuan							
M	32.1	14.1	0.8	2.9	0.1679	0.0768	0.4486
C	28.7	12.2	1.4	5.3			
Dongsheng							
M	55.0	31.2	1.1	3.9	0.8963	0.0490	0.5763
C	52.5	26.2	1.6	5.5			
Huhehaote							
M	57.9	34.9	2.0	8.4	0.9069	0.1338	0.9315
C	55.7	32.7	2.9	15.6			
Datong							
M	42.2	12.8	0.3	1.9	0.1957	0.7831	0.5321
C	39.6	14.0	0.7	2.8			

Notes: C, CLIGEN-generated; K-S, Kolmogorov-Smirnov; M, measured; SD, standard deviations.

are plotted in Figure 2 for trend comparisons. As similar results were obtained for all 12 stations, the results of six stations were shown for illustration. Monthly and annual precipitation was well simulated for this period at six stations, as indicated by the fact that monthly and annual precipitation percentiles are close to the 1:1 line. However, the 99th percentiles of daily precipitation and annual maximum daily precipitation were less well simulated. As mentioned above, this is because extreme values generally follow a different distribution and are difficult to simulate.

Frequency of Wet and Dry Periods

Frequencies of measured and generated periods of wet and dry spells at three stations are plotted in Figure 3. The average annual precipitation depths of these three stations are 570.4 mm (Xi'an), 442.5 mm (Taiyuan), and 318.8 mm (Lanzhou), which are representative of the prevailing precipitation conditions in the Loess Plateau. Overall, the frequencies of both wet and dry periods were well replicated by the model, indicating that the first-order, two-state Markov chain model used in daily precipitation generation is adequate for use in the Loess Plateau of China. However, the CLIGEN underpredicted the longest dry periods for all three stations. The underestimation for the drier station is larger than that for the wetter station. For example, the smallest difference occurred at Xi'an (the wettest station) with the longest measured and generated dry periods being 101 and 88 days, respectively; the largest difference occurred at Lanzhou (the driest station) with the measured and generated periods being 164 and 108 days. The difference occurred at Taiyuan with the measured and generated periods being 143 and 108 days. On the other hand, the longest wet periods

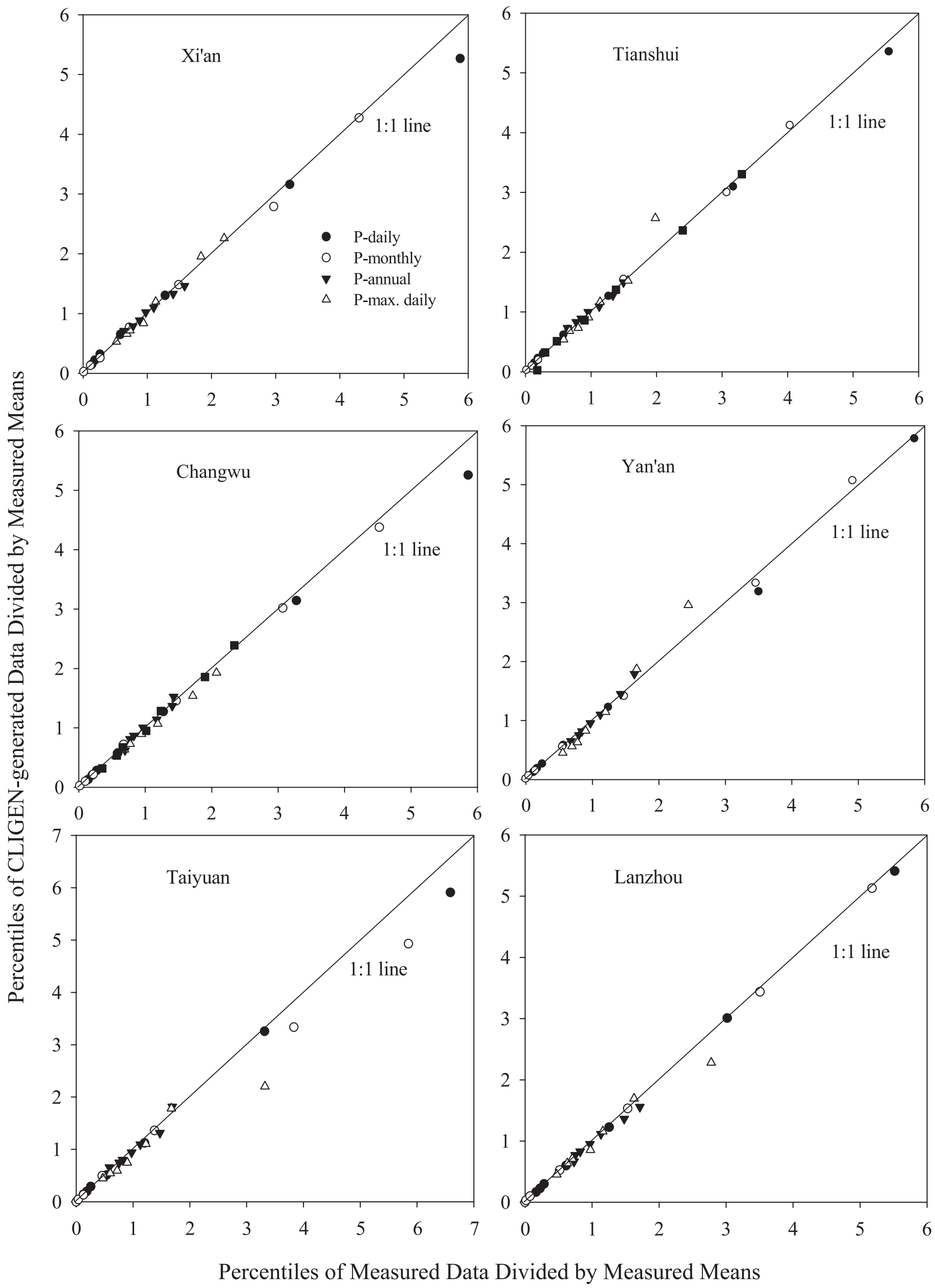

FIGURE 2. Plots of 5, 15, 25, 50, 75, 95, and 99 Percentiles of Measured *vs.* Generated Daily, Monthly, Annual, and Annual Maximum Daily Precipitation at Six Stations. The percentiles of each variable were divided by the corresponding measured mean of the variable.

were much better simulated with the average difference being about 2.3 days.

Evaluation of Storm Pattern

Storm Duration. The CLIGEN underpredicted the mean and SD of D for storms greater than or equal to 10 mm from May to September (Table 7). The REs of mean and SD ranged from −73.9% to −33.7% and from −81.1% to −52.2%, respectively. The Mann-Whitney tests showed significant differences for the mean at $p = 0.01$ for 8 out of 10 stations. The squared ranks tests showed that there were significant differences for SD at $p = 0.01$ for all 10 stations. However, CLIGEN overpredicted the skewness and kurtosis of D except for Lishi with the mean REs of 57.8 and 116.2%, respectively. Similarly, CLIGEN underpredicted all-time maximum D for all 10 stations with the mean RE of −50.4%. The

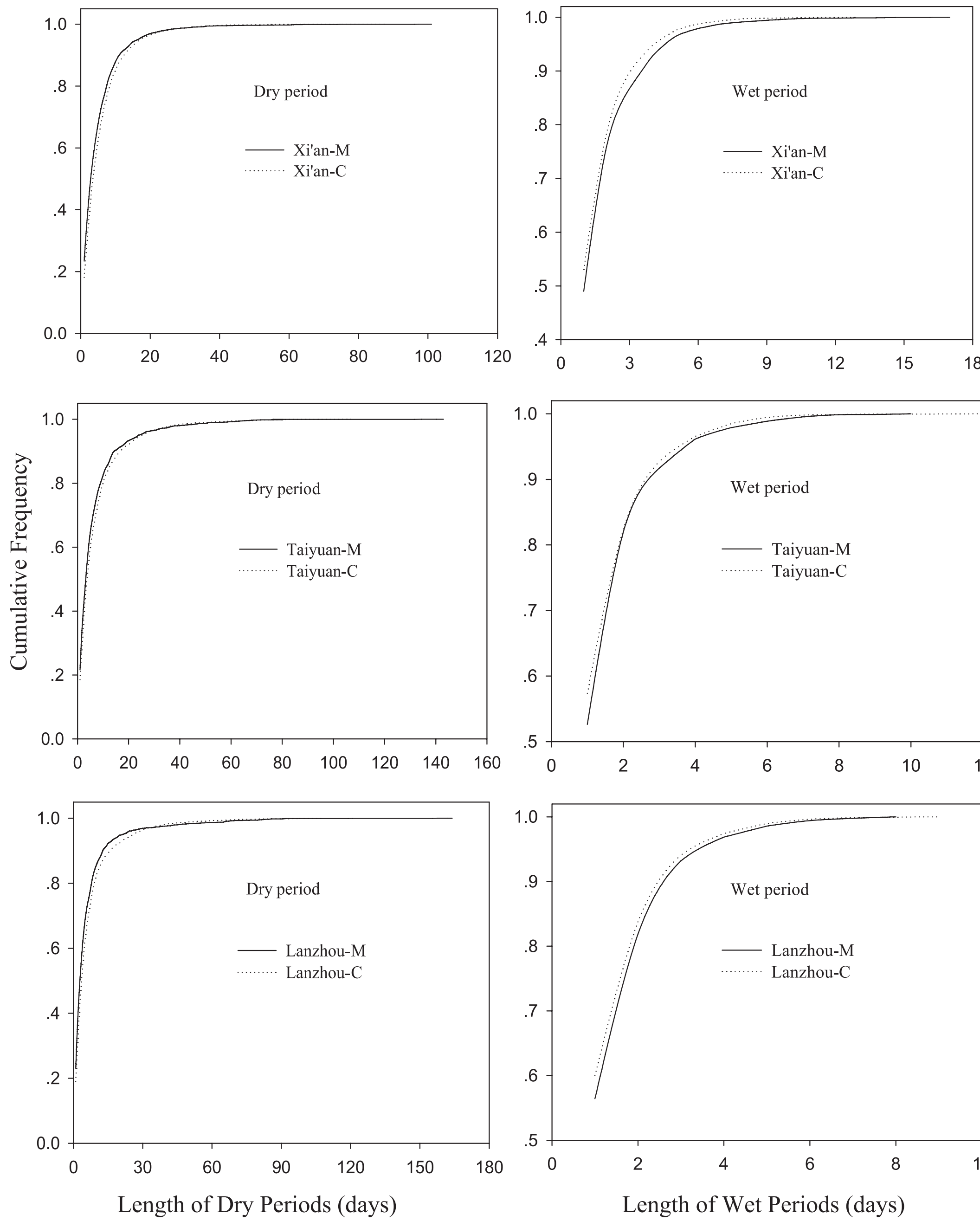

FIGURE 3. Frequency Distributions of Dry and Wet Periods Extracted from Measured Daily Series of Data and CLIGEN-Generated Daily Series at Three Stations (M, Measured and C, CLIGEN-generated).

K-S tests showed significant differences for all 10 stations at $p = 0.01$. The hypothesis that measured and generated D come from the same distribution is rejected for most stations at $p = 0.01$, indicating that Equation (6) is not suitable for use in the Loess Plateau.

Relative Peak Intensity. As mentioned earlier, the instantaneous *ip* cannot be estimated from the break point rainfall charts. The relative 5-min peak intensity (*ip5*) was available for Lishi, Xifeng, Xingxian, and Yuanping; and the relative 10-min peak intensity (*ip10*) available for Changwu, Guyuan, Lanzhou, Tianshui, Yan'an, and Yinchuan. Equation (10) was used to compute CLIGEN-generated *ip5* and *ip10* for corresponding stations for comparisons in Table 8. Although *ip* was derived from D using Equation (7), CLIGEN reproduced the mean and SD of *ip5* and *ip10* better than those of D, even though the REs were still very large. The REs ranged from

TABLE 7. Statistics of Storm Duration (D) for Storm ≥10 mm Using Measured (M) and CLIGEN-Generated (C) Storm Patterns for 10 Weather Stations.

Station	Mean (h)	SD (h)	Skewness Coefficient	Kurtosis Coefficient	All-Time Maximum (h)	Mann-Whitney Test *p* Value	Squared Ranks Test *p* Value	K-S Test *p* Value
Tianshui								
M	5.58	5.03	0.86	2.73	18.00	0.0001	<0.0001	<0.0001
C	2.12	1.34	2.03	9.85	10.89			
Changwu								
M	10.30	7.34	1.16	5.31	40.00	<0.0001	<0.0001	<0.0001
C	4.33	2.43	1.37	5.97	19.25			
Xifeng								
M	8.45	6.98	1.07	3.81	33.00	<0.0001	<0.0001	<0.0001
C	3.06	1.81	1.66	7.41	14.65			
Lanzhou								
M	4.80	5.21	0.89	2.39	16.00	0.1744	<0.0001	0.0008
C	1.57	0.99	1.97	8.57	7.59			
Yan'an								
M	7.97	6.20	0.88	2.80	24.00	<0.0001	<0.0001	<0.0001
C	2.08	1.30	1.96	10.12	12.37			
Lishi								
M	4.69	4.32	1.57	6.28	23.83	0.0031	<0.0001	<0.0001
C	2.67	1.60	1.56	6.53	12.08			
Guyuan								
M	8.82	7.44	1.08	3.64	31.00	<0.0001	<0.0001	<0.0001
C	2.81	1.66	1.45	6.33	13.23			
Xingxian								
M	3.65	3.17	1.35	5.22	17.28	0.0173	<0.0001	<0.0001
C	2.42	1.51	1.81	9.01	13.98			
Yinchuan								
M	3.68	4.05	1.75	5.76	16.67	0.0067	<0.0001	0.0040
C	1.43	0.92	1.85	7.40	6.37			
Yuanping								
M	7.13	6.70	1.21	4.19	31.50	<0.0001	<0.0001	<0.0001
C	1.96	1.27	1.84	8.19	9.88			

Notes: C, CLIGEN-generated; K-S, Kolmogorov-Smirnov; M, measured; SD, standard deviations.

−51.8% to 33.6% for the mean and from −52.2% to 96.9% for the SD with the MAREs of 21.0% and 52.1%, respectively. The Mann-Whitney test and squared ranks test showed significant differences in mean and SD, respectively, for 1 of 10 and 6 of 10 stations. The K-S tests showed significant differences in distributions for 3 of 10 stations at $p = 0.01$. As discussed earlier, the assumption of a single peak for all storms in CLIGEN was an over-simplification. In fact, there are various storm patterns and multiple peaks in the study region. Thus if multiple peak storms can be simulated in CLIGEN, the *ip* simulation might be improved.

Peak Intensity. The mean of *rp* were numerically overgenerated in 9 out of 10 stations with the MARE of 31.2%, and the Mann-Whitney tests showed significant differences in mean for 4 out of 10 stations at $p = 0.01$ (Table 9). The SD of *rp* were numerically overpredicted for all stations but Guyuan with the MARE of 55.2%, and the squared ranks tests showed significant differences in SD for 6 out of 10 stations at $p = 0.01$. The CLIGEN overpredicted skewness and kurtosis for 9 out of 10 stations with a MARE of 162.4% and 122.9%, respectively. All-time maximum *rp* was consistently overpredicted for all stations with a MARE of 124.2%. The K-S tests showed that the measured and generated distributions of *rp* were significantly different at $p = 0.01$ for 5 out of 10 stations, indicating that Equation (2) was inadequate for generating *rp* for the Loess Plateau.

Exponentially Generated Storm Duration

Compared with D generated by Equation (6) in Table 8, exponentially generated D were much better for all stations (Table 10). Both mean and SD were reproduced well with MAREs of 2.6% and 7.8%, respectively. The Mann-Whitney and squared ranks tests showed that the mean and SD of the exponentially generated D were not different from those of measured data at $p = 0.01$ for all stations. The skewness, kurtosis and all-time maximum of D were much better simulated with MAREs of 29.61, 40.05, and 26.51%, respectively. Due to the

TABLE 8. Statistics of Relative Peak Intensive (*ip*) for Storm ≥10 mm Using Measured (M) and CLIGEN-Generated (C) Storm Patterns for 10 Weather Stations.

Station	Mean	SD	Skewness Coefficient	Kurtosis Coefficient	All-Time Maximum	Mann-Whitney Test *p* Value	Squared Ranks Test *p* Value	K-S Test *p* Value
Tianshui								
M	5.43	4.37	2.17	8.50	23.48	0.1514	0.8827	0.2659
C	4.97	4.55	2.91	16.28	44.36			
Changwu								
M	4.32	2.34	1.05	4.48	13.81	0.0616	0.0123	0.0099
C	4.45	4.06	5.50	58.32	64.13			
Xifeng								
M	4.76	2.26	1.33	4.98	14.00	0.0178	<0.0001	<0.0001
C	5.08	4.45	3.08	21.00	55.70			
Lanzhou								
M	6.87	6.72	1.82	5.73	26.57	0.1170	<0.0001	0.2145
C	4.73	4.24	2.65	12.81	36.88			
Yan'an								
M	6.68	9.11	5.20	36.41	71.63	0.1025	<0.0001	0.0973
C	4.81	4.35	3.17	17.61	38.17			
Lishi								
M	4.36	2.62	1.33	4.51	12.27	0.8147	<0.0001	0.3829
C	5.20	4.96	3.87	31.00	63.94			
Guyuan								
M	5.57	6.45	4.31	23.35	43.21	0.3536	0.0532	0.0715
C	5.09	4.34	2.23	9.49	31.46			
Xingxian								
M	3.87	2.60	1.90	7.13	14.47	0.0206	<0.0001	0.0134
C	5.17	4.73	3.06	18.57	48.72			
Yinchuan								
M	5.56	3.99	1.19	3.33	15.28	0.1275	0.1894	0.3220
C	4.51	3.61	2.18	9.51	26.87			
Yuanping								
M	10.23	7.77	1.28	4.88	38.08	<0.0001	<0.0001	<0.0001
C	4.93	4.35	3.28	20.69	41.99			

Notes: C, CLIGEN-generated; K-S, Kolmogorov-Smirnov; M, measured; SD, standard deviations.

assumption that there is only one storm event in a wet day, the generated maximum D was not longer than 24 h. However, the measured maximum D was longer than 24 h for 4 out of 10 stations. This is the reason that all-time maximum D was poorly simulated. The K-S tests showed that the measured and generated distributions of D were not different at $p = 0.01$ for all stations, indicating that an exponential distribution should be used to generate D in the Loess Plateau.

Relative Peak Intensity Recalculated from Exponentially Generated, Correlated Duration

The distribution free approach was used to induce target rank correlation between R and exponentially generated D by paring R with appropriate D. The CLIGEN-generated rp and its association with R (Equation 2) were unaltered. Equation (7) was then used to recalculate instantaneous ip using pared R and D. To compare with the measured 5-min and 10-min ip, Equation (10) was further used to estimate CLIGEN-generated $ip5$ and $ip10$. The mean of ip from correlated, exponentially generated D were very poorly simulated with a mean RE of 128.9% (Table 11). The Mann-Whitney tests showed that the mean of the simulated data were different from those of measured data at $p = 0.01$ for 7 out of 10 stations. The MAREs of the SD, coefficients of skewness and kurtosis, and all-time maximum values were 241.1, 99.4, 187.9, and 455.6%, respectively. The squared ranks tests showed that the simulated SD were significantly different from measured SD for all 10 stations at $p = 0.01$. The K-S tests showed differences in distributions at $p = 0.01$ for 8 out of 10 stations.

Overall, the ip calculated using exponentially generated, correlated D was much larger than the original CLIGEN ip (Table 8) which was fairly close to the measured ip. The better ip generation of the latter probably resulted from error cancellation. The original CLIGEN tended to undergenerate D (Table 7) but overgenerate rp (Table 9). The underestimation of D and overestimation of rp offset each other when ip was calculated using Equation (7). However, when

TABLE 9. Statistics of Peak Intensity (*rp*) for Storm ≥10 mm Using Measured (M) and CLIGEN-Generated (C) Storm Patterns for 10 Weather Stations.

Station	Mean (mm/h^2)	SD (mm/h^2)	Skewness Coefficient	Kurtosis Coefficient	All-Time Maximum (mm/h^2)	Mann-Whitney Test *p* Value	Squared Ranks Test *p* Value	K-S Test *p* Value
Tianshui								
M	39.16	19.98	0.82	3.75	105.00	0.4981	0.0009	0.2405
C	46.19	32.66	1.73	6.56	205.86			
Changwu								
M	13.71	14.24	2.37	9.89	90.00	<0.0001	<0.0001	<0.0001
C	22.42	18.66	3.08	19.42	198.09			
Xifeng								
M	26.54	23.64	1.24	3.91	106.40	<0.0001	0.5107	<0.0001
C	36.24	29.41	2.37	11.01	224.56			
Lanzhou								
M	46.78	17.23	0.20	1.99	78.00	0.9690	0.0007	0.2464
C	53.94	35.74	1.53	5.75	227.69			
Yan'an								
M	33.57	33.20	1.24	4.24	138.00	<0.0001	0.2980	<0.0001
C	52.22	39.59	1.61	5.52	262.51			
Lishi								
M	34.63	19.30	0.45	2.43	85.20	0.2136	<0.0001	0.0473
C	43.93	36.08	2.22	9.83	285.34			
Guyuan								
M	26.45	35.63	3.61	18.88	225.00	<0.0001	0.8549	<0.0001
C	36.88	30.02	2.54	11.87	249.28			
Xingxian								
M	39.01	28.26	0.97	3.19	118.80	0.0245	0.1273	0.0809
C	47.26	37.05	2.17	10.33	304.82			
Yinchuan								
M	44.05	17.62	1.73	7.21	105.00	0.2317	<0.0001	0.0355
C	58.36	39.12	1.60	6.04	264.68			
Yuanping								
M	57.41	27.34	0.72	3.50	132.00	0.0177	0.0019	0.0001
C	55.81	41.15	1.72	6.20	235.54			

Notes: C, CLIGEN-generated; K-S, Kolmogorov-Smirnov; M, measured; SD, standard deviations.

D was fairly accurately generated by exponential distributions and proper correlation between D and R was introduced, the overestimation of *ip* was very likely caused by the overestimation of *rp*. Thus, for better *ip* generation with exponentially generated D in the Loess Plateau, *rp* generation must be improved.

Correlative Analysis

Spearman rank correlation coefficients between measured and simulated variables are shown in Table 12. Measured D and R were significantly correlated with one another at $p < 0.01$, and these correlation coefficients, ranging from 0.20 to 0.82, were the target correlation values being emulated for inducing correlation between D and R. The CLIGEN-generated D and R were uncorrelated to each other. However, after re-pairing R and D using the distribution-free approach, the desired rank correlation coefficients of the measured data were successfully reproduced. There was little correlation between R and *ip* for the CLIGEN-generated. However, the recalculated *ip* from correlated, exponentially generated D showed similar correlation with R as was found in the measured data. These results demonstrated the validity of and the need for inducing proper correlation between R and D. Generally a proper correlation between R and a better generation of D should result in a better estimation of *ip*. However, this is not the case in this study, simply because of an overestimation error of *rp*. Both CLIGEN-generated data and those from correlated, exponentially D overpredicted the correlative relationship between D and *ip* for most of stations, especially those from correlated, exponentially D. There were positive, negative, and no correlations between R and *rp* in the measured data in the Loess Plateau; however, CLIGEN (Equation 2) generated a strong positive correlation between R and *rp*. The *rp* generation using Equation 2 in CLIGEN needs to be further studied and revised for use in the Loess Plateau.

TABLE 10. Statistics of Storm Duration for Storms ≥10 mm Using Measured (M) and Exponentially Generated Duration for 10 Weather Stations.

Station	Mean (h)	SD (h)	Skewness Coefficient	Kurtosis Coefficient	All-Time Maximum (h)	Mann-Whitney Test *p* Value	Squared Ranks Test *p* Value	K-S Test *p* Value
Tianshui								
M	5.58	5.03	0.86	2.73	18.00	0.5602	0.6491	0.1937
ED	6.10	5.65	1.35	4.40	24.00			
Changwu								
M	10.30	7.34	1.16	5.31	40.00	0.1180	0.0277	0.0140
ED	9.58	7.55	0.68	2.22	24.00			
Xifeng								
M	8.45	6.98	1.07	3.81	33.00	0.7412	0.9164	0.3936
ED	8.23	6.82	0.95	2.92	24.00			
Lanzhou								
M	4.80	5.21	0.89	2.39	16.00	0.4353	0.0110	0.1124
ED	4.83	4.67	1.62	5.69	24.00			
Yan'an								
M	7.97	6.20	0.88	2.80	24.00	0.4770	0.4449	0.7874
ED	7.77	6.63	0.98	2.97	24.00			
Lishi								
M	4.69	4.32	1.57	6.28	23.83	0.9797	0.7146	0.8324
ED	4.75	4.55	1.76	6.59	24.00			
Guyuan								
M	8.82	7.44	1.08	3.64	31.00	0.9382	0.5333	0.9169
ED	8.71	7.15	0.80	2.54	24.00			
Xingxian								
M	3.65	3.17	1.35	5.22	17.28	0.6279	0.7038	0.7077
ED	3.70	3.69	1.98	8.14	24.00			
Yinchuan								
M	3.68	4.05	1.75	5.76	16.67	0.7897	0.5435	0.6319
ED	3.69	3.56	1.65	6.21	21.42			
Yuanping								
M	7.13	6.70	1.21	4.19	31.50	0.6771	0.1495	0.7647
ED	7.15	6.30	1.15	3.58	24.00			

Notes: ED, exponentially generated duration; K-S, Kolmogorov-Smirnov; M, measured; SD, standard deviations.

DISCUSSION AND IMPLICATIONS

CLIGEN reproduced mean of daily, monthly, and annual precipitation reasonably well with MAREs of 3.5, 1.7, and 1.7%, respectively. The mean of monthly and annual precipitation were slightly better preserved than the mean of daily precipitation. This could be due to error cancellation when daily precipitation depths were summed up to obtain monthly and annual precipitation. Compared with the mean, SD of daily, monthly, and annual precipitation were somewhat less well reproduced with MAREs of 5.0, 4.5, and 13.0%, respectively. The underprediction of interannual variability resulted from the simplifying assumptions that climate, or more specifically the daily precipitation process as referred to here, is stationary, and that there is no month-to-month dependency in precipitation process. The nonstationary climate gives rise to additional low-frequency variability. The implication for stochastic modeling of daily weather data is that simple stationary models cannot fully reproduce the variability of a nonstationary climate and that introduction of some degree of nonstationarity into these models consistent with the underlying climatic variations is appropriate. Wang and Nathan (2007) provided a method for coupling daily and monthly time scales in stochastic generation of rainfall series. A straightforward and practical approach is to generate variations in the stochastic model parameters, by allowing specific parameter choices to be conditioned on a covariate (Hughes and Guttorp, 1994; Katz and Parlange, 1993; Wallis and Griffiths, 1997). And a study of Wilks (1999) showed that using the mixed exponential distribution to represent wet-day precipitation amounts in stochastic weather models should be an appreciable improvement in the simulation of interannual variability. The model predicted the all-time maximum daily, monthly, and annual precipitation less well than it did for their mean with MAREs of 20.2, 34.8, and 10.1%, respectively, across all 12 stations. This is understandable because extreme values than mean values are more difficult to predict, and CLIGEN is not tailored to generate extreme precipitation events. Many of these largest extreme

TABLE 11. Statistics of Relative Peak Intensity (*ip*) for Storm ≥10 mm Using Measured and Recalculated from Exponentially Generated, Correlated Storm Duration for 10 Weather Stations.

Station	Mean	SD	Skewness Coefficient	Kurtosis Coefficient	All-Time Maximum	Mann-Whitney Test *p* Value	Squared Ranks Test *p* Value	K-S Test *p* Value
Tianshui								
M	5.43	4.37	2.17	8.50	23.48	<0.0001	<0.0001	<0.0001
EDC	13.63	15.23	2.27	9.81	123.88			
Changwu								
M	4.32	2.34	1.05	4.48	13.81	0.0308	<0.0001	<0.0001
EDC	7.75	8.97	2.83	15.15	84.33			
Xifeng								
M	4.76	2.26	1.33	4.98	14.00	<0.0001	<0.0001	<0.0001
EDC	13.64	14.71	2.29	10.34	118.31			
Lanzhou								
M	6.87	6.72	1.82	5.73	26.57	0.0198	<0.0001	0.0228
EDC	14.03	16.66	2.74	13.07	123.75			
Yan'an								
M	6.68	9.11	5.20	36.41	71.63	<0.0001	<0.0001	<0.0001
EDC	18.34	21.11	2.36	10.30	170.73			
Lishi								
M	4.36	2.62	1.33	4.51	12.27	0.0007	<0.0001	<0.0001
EDC	9.32	12.20	3.65	21.78	118.13			
Guyuan								
M	5.57	6.45	4.31	23.35	43.21	<0.0001	<0.0001	<0.0001
EDC	15.64	17.01	2.12	8.52	107.23			
Xingxian								
M	3.87	2.60	1.90	7.13	14.47	0.0004	<0.0001	<0.0001
EDC	7.81	9.78	4.34	37.92	134.34			
Yinchuan								
M	5.56	3.99	1.19	3.33	15.28	0.0650	<0.0001	0.0360
EDC	11.10	11.69	1.93	7.26	65.26			
Yuanping								
M	10.23	7.77	1.28	4.88	38.08	0.0058	<0.0001	0.0014
EDC	17.67	19.89	3.15	20.65	227.22			

Notes: EDC, exponentially generated correlated storm duration; K-S, Kolmogorov-Smirnov; M, measured; SD, standard deviations.

TABLE 12. Spearman Rank Correlation Coefficients Among Daily Precipitation (*R*), Peak Intensity (*rp*), Storm Duration (*D*), and Relative Peak Intensity (*ip*) for Storms ≥10 mm.

	R* vs. *D			***R* vs. *ip***			***D* vs. *ip***			***R* vs. *rp***	
Station	**M**	**C**	**EDC**	**M**	**C**	**EDC**	**M**	**C**	**EDC**	**M**	**C**
Tianshui	0.82	0.04	0.81	0.34	−0.07	0.67	0.66	0.66	0.88	−0.44	0.51
Changwu	0.26	0.00	0.25	0.14	−0.03	0.11	0.48	0.62	0.50	0.33	0.62
Xifeng	0.46	0.03	0.49	0.26	−0.03	0.38	0.27	0.63	0.86	0.14	0.59
Lanzhou	0.65	0.09	0.62	0.54	0.00	0.51	0.95	0.66	0.88	0.03	0.52
Yan'an	0.20	0.07	0.16	0.37	0.01	0.15	0.57	0.65	0.88	0.48	0.63
Lishi	0.61	0.04	0.58	0.23	−0.02	0.47	0.58	0.63	0.85	−0.02	0.60
Guyuan	0.65	0.13	0.65	0.32	0.04	0.52	0.33	0.66	0.86	−0.01	0.53
Xingxian	0.62	0.15	0.59	0.29	0.03	0.45	0.36	0.63	0.85	−0.01	0.57
Yinchuan	0.64	0.04	0.66	0.33	−0.02	0.57	0.80	0.66	0.88	−0.03	0.53
Yuanping	0.66	0.13	0.66	0.24	−0.01	0.52	0.50	0.61	0.85	−0.25	0.55
Mean	0.56	0.07	0.55	0.31	0.03	0.44	0.50	0.64	0.83	0.17	0.56

Notes: C, CLIGEN-generated; EDC, exponential duration with correlation; M, measured.

values are associated with unusual meteorological events, suggesting that these have been drawn from rather different populations than most of the daily precipitation observations to which the distributions have been fit (Wilks, 1999). Thus, mixed exponential distribution would do a better job in generating extreme precipitation events. However, the model predicted mean of annual maximum daily precipitation reasonably well across all 12 stations with a mean RE of −5.0%, ranging from −11.0% to −0.8%. Annual precipitation extremes are important for accurate runoff and soil loss prediction using hydrologic and soil erosion models. It has been reported that more than 90% of annual soil loss was from the top few percent of storms (Edwards and Owens, 1991). A similar conclusion was drawn by Zhang and Garbrecht (2003) in their evaluation studies at four Oklahoma stations.

The CLIGEN preserved the distributions of monthly and annual precipitation well. The K-S tests for each station showed that measured and generated cumulative distributions for both monthly and annual precipitation were not different from one another at $p = 0.01$, suggesting that the measured and generated monthly precipitation (annual precipitation as well) were very likely from the same distribution. However, the distributions of daily precipitation were less well reproduced. The model simulated the frequency of wet and dry periods well, indicating that the first-order, two-state Markov chain was adequate for simulating precipitation occurrence in the Loess Plateau. Several studies have reported that first-order, two-state Markov chain was adequate for generating precipitation occurrence in a variety of climate conditions (Johnson *et al.*, 1996; and Zhang and Garbrecht, 2003). However, CLIGEN underestimated the longest dry periods for the Loess Plateau of China. Wilks (1999) reported a similar result at the western stations in the United States and indicated that first-order does better in most climates but not in very wet and dry climates. The second-order may do better in very wet and dry climates. To improve the simulation of extremely long dry-spell lengths, other methods such as high-order Markov model, negative binomial spell lengths, or mixed geometric spell lengths may be adopted for the Loess Plateau of China. Semenov *et al.* (1998) compared the WGEN and LARS-WG for simulating wet and dry series, and showed that every single series from the observed data was represented in the semi-empirical distributions of LARS-WG.

CLIGEN underpredicted the mean and SD of D for storms of ≥10 mm from May to September with a mean RE of −60.4 and −72.6%, respectively. The distributions of D were very poorly reproduced. D generated using Equation 6 in CLIGEN was no good for use in the Loess Plateau. This study showed that distribution of D fit the standard exponential distribution well in the region. When a standard exponential distribution was used to generate D, mean and SD were much better reproduced with MAREs of 2.6 and 7.8% across all 10 stations, respectively.

The mean of CLIGEN-generated rp tended to be greater than those of measured rp at 9 of 10 stations, and rp generated using Equation 2 in CLIGEN was positively correlated to R but there was no consistent correlation pattern in measured data between R and rp. Thus, the applicability of Equation 2 to the Loess Plateau needs to be further studied. The satisfactory generation of ip in the original CLIGEN was probably a result of error cancellation. The ip was calculated using Equation 7, and an overestimation of rp and an underestimation of D would cancel out each other and result in a better estimation of ip. Unexpectedly, ip estimation became much worse, when exponentially generated D even after introduction of proper correlation with R was used to compute ip. Generally a better generation of D and proper correlation between D and R should result in a better estimation of ip. But this is not the case in this study, simply because of an overestimation of rp (provided D and its correlation with R were well generated). For better ip generation for the Loess Plateau, a new rp generation equation needs to be developed; and a correlative approach such as Copula, along with the exponentially generated D, should be used to generate mutually correlated data between R, rp, and D. Copulas are joint distribution functions of standard uniforms, which make it possible to extract the dependence structure from the joint probability distribution function of a set of random variables such as R, rp and D, and simultaneously to isolate such dependence structure from the univariate marginal behavior of these variables. As a result, correlated datasets for R, rp, and D can be generated from independent marginal distributions of these individual variables.

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