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Evaluation and improvement of the CLIGEN model for storm and rainfall erosivity generation in Central Chile

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ABSTRACT

CLIGEN (CLImate GENerator) is a stochastic weather generator that produces daily estimates of precipitation and individual storm parameters, including time to peak, peak intensity and storm duration. These parameters are typically used as inputs for other models, such as the Water Erosion Prediction Project (WEPP) model. Although CLIGEN has been proven to be effective for predicting daily estimates, some discrepancies have been observed when generating storm parameters, such as the storm duration. Therefore, a study was conducted to evaluate and improve CLIGEN for storm generation. Individual rainfall events were identified from 1-h pluviograph records that were collected from 30 sites in Central Chile. In this study, 415 years of data were used; 18,012 storms were analyzed. In addition, rainfall erosivity was computed for all storms using the prescribed method to compare the energy provided by the measured and generated rainfall events. Using measured rainfall data, a procedure was developed to improve the CLIGEN estimates by calibrating the input parameter that controls the storm durations. This procedure in turn improved the rainfall intensities and erosivities. The model was tested before and after calibration with the measured rainfall data from the 30 sites in both the wet and dry seasons. Based on a monthly rainfall analysis, the results demonstrated that the number of storms and rainfall amounts, which are not affected by the calibration process, were accurately estimated with CLIGEN. However, before the calibration, especially in the wet season, the storm durations and maximum intensities were consistently overestimated and underestimated, respectively, at most of the sites and for most months. Therefore, the annual rainfall erosivities were underestimated with CLIGEN at 19 of the 30 sites. After performing the calibration, the R^2 value for the CLIGEN-generated storm durations increased from 0.41 to 0.65. The maximum intensities also exhibited an improvement; the R^2 value increased from 0.31 to 0.60. Consequently, annual rainfall erosivities were generated with an R^2 value of 0.89; these erosivities were accurately estimated at 29 of the 30 sites. Therefore, this calibration procedure proved to be an effective alternative for generating more reliable storm patterns. This paper explains the procedure in detail and analyzes the parameters related to the individual storm generation process.

1. Introduction

CLIGEN is a stochastic weather generator that simulates daily precipitation, maximum, minimum and dew point temperatures, solar radiation and wind velocity and direction (Nicks et al., 1995). Among the commonly used stochastic daily weather generators, CLIGEN is the only model capable of simulating the temporal distribution of storms (Zhang et al., 2008). Because the rainfall intensity affects rill and interrill erosion by controlling the runoff rate and shear stress (Yu, 2000; Pieri et al., 2007), CLIGEN has been incorporated as part of the physically-based Water Erosion Prediction Project (WEPP) model interfaces (Flanagan and Nearing, 1995).

Previous studies have reported that CLIGEN can acceptably simulate daily precipitation occurrence and total rainfall (Johnson et al., 1996; Zhang and Garbrecht, 2003; Kou et al., 2007). However, only a limited number of studies have evaluated the temporal distribution of storms (Yu, 2000; Zhang and Garbrecht, 2003; Zhang, 2005; Zhang et al., 2008). These studies have reported that the weather generator tends to overestimate the duration of brief storms and underestimate the duration of prolonged storms, which results in inadequate intensity estimations (Headrick and Wilson, 1997; Zhang and Garbrecht, 2003). In particular, when the storm durations are underestimated, the intensities are overestimated, increasing the erosive power of the rainfall generated by the model (Zhang and Garbrecht, 2003). This result was reported by Yu (2002) when using CLIGEN to generate the R-factor of the Revised Universal Soil Loss Equation (RUSLE) (Renard et al., 1997) for various sites in the US. By comparing generated and measured erosivity values, Yu's study showed that CLIGEN overestimated the R-

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factor at every site, which indicates that the storm durations and intensities were underestimated and overestimated, respectively.

Yu (2000), Zhang and Garbrecht (2003) and Zhang (2005) suggested that the equations used in CLIGEN for storm patterns should be modified because they do not adequately simulate storms. However, none of these studies proposed a specific change in the equations or a method for obtaining more reliable storm patterns when using CLIGEN. Therefore, the objective of this study was to develop and test a method to improve CLIGEN-generated storm patterns without modifying the model's equations and source code. The method was tested using 30 meteorological stations located in Central Chile and more than 415 years of hourly precipitation data.

1.1. CLIGEN model for storm generation

CLIGEN version 5.3 generates daily precipitation occurrence and amount and internal storm variables, such as peak storm intensity, duration and time to peak (Yu, 2000). Rainfall occurrence is predicted using a first-order two-state Markov chain, which utilizes monthly probabilities of precipitation occurrence for a wet day following a wet day and for a wet day following a dry day from daily historical precipitation data (Yu, 2005). When a precipitation event is predicted, the rainfall amount is calculated using the following skewed normal distribution (Nicks et al., 1995):

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

where x is a standard normal deviate, R is the generated daily precipitation amount (mm) and μ (mm), s (mm) and g are the mean, standard deviation and skewness coefficient of the daily precipitation amounts for the month, respectively. The values of μ, s and g are directly extracted from historical data, while two random numbers are used to generate the normal deviate (x), which is then used to estimate the daily rainfall amount (R) (Zhang and Garbrecht, 2003).

Storm intensities are generated using a double exponential function, which assumes that rainfall rates increase exponentially until the peak storm intensity is attained and subsequently decrease in the same way (Nicks et al., 1995). The peak storm intensity is calculated using the following equation proposed by Arnold and Williams (1989):

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

where r_p is the peak storm intensity (mm h^{-1}), R is the daily precipitation amount (mm) and $\alpha_{0.5}$ is a dimensionless parameter defined as the ratio of the maximum 0.5-h rainfall amount to the daily precipitation amount. The value of $\alpha_{0.5}$ is determined from a two-parameter gamma distribution described by Sharpley and Williams (1990) with a shape parameter set to 6.28 and a scale parameter that is computed using the mean of $\alpha_{0.5}$ ($\alpha_{0.5mean}$) for the month (Zhang and Garbrecht, 2003). The latter is calculated as follows:

$$\alpha_{0.5mean} = \frac{R_{0.5mean}}{R_{mean}} \tag{3}$$

where $R_{0.5mean}$ is the monthly mean of the maximum 0.5-h rainfall amount (mm) and R_{mean} is the monthly mean precipitation amount per storm (mm). Furthermore, $R_{0.5mean}$ is calculated using the following equation (Sharpley and Williams, 1990; Zhang and Garbrecht, 2003):

$$R_{0.5mean} = \begin{cases} -\dfrac{R_{0.5\max}}{\ln\left(\dfrac{2}{2n+1}\right)} & n > 2.18 \\ R_{0.5\max} & n \le 2.18 \end{cases} \tag{4}$$

where $R_{0.5\max}$ is the mean of the annual 0.5-h maximum amount for each month (mm) and n is the average number of rainy days for a given month (Yu, 2005). The user must estimate the values of $R_{0.5\max}$ for each month from historical rainfall data using the procedures described in Yu (2005).

The storm duration is computed for every storm as follows:

$$D = -\frac{0.5\Delta}{\ln(1-\alpha_{0.5})} \tag{5}$$

where D is the storm duration (h) and Δ is a dimensionless parameter set to 3.99 in CLIGEN v5.3 based on the calibration of Yu (2000). Both Eqs. (2) and (5) are subject to modification as more historical precipitation data are analyzed (Nicks et al., 1995).

Once the rainfall amount per storm (R), peak intensity (r_p) and duration (D) are computed for a single storm, the relative peak intensity (i_p) is calculated using the following ratio (Nicks et al., 1995):

$$i_p = \frac{r_p D}{R} \tag{6}$$

Then, the relative storm intensity for the entire event is computed using the following double exponential function (Nicks et al., 1995):

$$i(t) = \begin{cases} i_p e^{b(t-t_p)} & 0 \le t < t_p \\ i_p e^{d(t_p-t)} & t_p \le t < 1 \end{cases} \tag{7}$$

where $i(t)$ is the relative storm intensity at relative time t, t_p is the relative time to peak and b and d are parameters that are determined using the assumptions and procedures described in Nicks et al. (1995). The time to peak is a parameter that must be estimated by the user from historical data using the procedures described in Yu (2005).

2. Materials and methods

2.1. Meteorological stations and climatic data

The data used in this study were obtained from the 30 meteorological stations shown in Table 1, which are located in Central Chile and distributed between latitudes 32° 04′ S and 39° 47′ S (Fig. 1). The stations are part of two national rain gauge networks managed by the Dirección General de Aguas DGA and the Sistema Nacional de Calidad del Aire SINCA. These stations were selected according to the availability of hourly measured rainfall data, which ranged from 3 to 28 years. These stations provided data for 418 years and 18,012 storms. The climate in this region of Chile is primarily semi-arid. Rainfall is typically generated by frontal systems and is highly erosive in some areas (Escobar and Aceituno, 1998; Bonilla and Vidal, 2011). Moreover, precipitation amounts increase with increasing latitude (Table 1). CLIGEN input files were constructed for each station based on hourly and daily rainfall data and other measured data that are required by the model, such as maximum, minimum and dew point temperatures, solar radiation and wind velocity and direction.

2.2. Input file preparation

A first set of input files was constructed for the 30 sites mentioned in Section 2.1 using existing meteorological information. Because 0.5-h rainfall data are not typically recorded in Chile, these values were estimated from hourly data by fitting the following intensity–duration–frequency (IDF) curve proposed by Wenzel (1982):

$$I = \frac{K}{D^n + b} \tag{8}$$

where I is the storm's mean intensity (mm h^{-1}) for duration D (h) and K, n and b are dimensionless parameters that are fitted for every storm. The intensities for durations of 1–6 h were computed and a non-linear

Table 1
Meteorological stations used in this study. The length of the hourly rainfall records may be shorter than the measurement period because of missing data.

Station Name	Latitude	Longitude	Elevation (m.a.s.l.)	Years of hourly rainfall records	Measurement period	Average annual precipitation (mm)
Pedernal	32°05′	70°48′	1100	21	1972–1992	40
Sobrante	32°14′	70°47′	810	21	1972–1992	46
Los Vientos	32°50′	70°60′	130	4	2007–2011	27
Rancagua	32°50′	70°60′	170	10	2004–2013	171
Quillota	32°54′	71°13′	130	10	1982–1991	35
Lliu Lliu	33°06′	71°13′	260	14	1979–1992	139
Pirque	33°40′	70°35′	670	2	1979–1980	183
Melipilla	33°41′	71°12′	170	18	1975–1992	136
Rengo	34°25′	70°52′	310	23	1970–1992	169
Popeta	34°26′	70°47′	400	6	1970–1974	152
C. Las Nieves	34°30′	70°43′	700	22	1971–1992	287
Potrero Grande	35°11′	71°06′	460	21	1972–1992	316
Fundo el Peral	35°24′	71°47′	110	13	1974–1986	353
Colorado	35°38′	71°16′	420	24	1969–1992	532
Melozal	35°46′	71°47′	110	22	1971–1992	227
Ancoa Embalse	35°54′	71°17′	430	22	1971–1992	532
Bullileo	36°17′	71°25′	600	22	1971–1992	1236
Chillán Viejo	36°38′	72°06′	125	9	1984–1992	511
Colhueco	36°39′	71°48′	300	8	1984–1992	709
Caracol	36°39′	71°23′	620	6	1987–1992	972
Diguillin	36°52′	71°39′	670	28	1965–1992	770
Quilaco	37°41′	71°60′	225	28	1965–1992	786
Cerro el Padre	37°47′	71°52′	400	17	1976–1992	1067
El Vergel Angol	37°49′	72°39′	75	5	1976–1981	307
Contulmo	38°01′	73°14′	25	4	1987–1992	236
Traiguen	38°15′	72°40′	170	5	1988–1992	506
Manzanar	38°28′	71°42′	790	17	1972–1988	831
Pueblo Nuevo	38°44′	72°34′	100	4	1989–1992	444
Freire Sendos	38°58′	72°37′	100	3	1985–1987	316
Pucón	39°17′	71°57′	230	9	1984–1992	1042

regression technique was used to fit the data. Then, the 0.5-h maximum precipitation amount was calculated for each storm and the maximum value for every month was averaged for every year, yielding the monthly $R_{0.5max}$ parameters. CLIGEN also requires 0.5-h and 6-h rainfall amounts with a return period of 100 years to control extreme values. These two values were calculated for every station using the IDF curves developed by Pizarro et al. (2010).

2.3. Calibration method

To increase the accuracy of CLIGEN-generated storm durations, a second set of 30 input files was constructed for the same meteorological stations; however, this set of input files was formulated using a two-step calibration procedure. The calibration consisted of computing $R_{0.5max}$ parameters that led to storm durations that more closely corresponded to the measured values by manipulating the equations used in CLIGEN. This calibration was performed by combining Eqs. (3) and (4) and solving for $R_{0.5max}$ as follows:

$$R_{0.5\,max} = \begin{cases} -R_{mean}\alpha_{0.5mean} \ln\left(\dfrac{2}{2n+1}\right) & n > 2.18 \\ R_{mean}\alpha_{0.5mean} & n \leq 2.18 \end{cases}. \tag{9}$$

Assuming that when $\alpha_{0.5} \approx \alpha_{0.5mean}$, Eq. (5) yields the mean storm duration of a given month, the following expression is obtained by combining Eq. (5) solved for $\alpha_{0.5}$ and Eq. (9):

$$R_{0.5\,max} = \begin{cases} R_{mean}\left[e^{-0.5\Delta}/_{D}-1\right] \ln\left(\dfrac{2}{2n+1}\right) & n > 2.18 \\ -R_{mean}\left[e^{-0.5\Delta}/_{D}-1\right] & n \leq 2.18 \end{cases}. \tag{10}$$

Then, using Eq. (10) for every month with the generated R_{mean} and n and measured D values, the resulting $R_{0.5max}$ yields generated durations in CLIGEN that are closer to the measured values. The generated R_{mean} and n values must be used in Eq. (10) because in CLIGEN the storm duration is computed using the generated and not the measured values. By using Eq. (10) the input parameter $R_{0.5max}$ becomes redefined and loses its physical meaning.

Eq. (10) was used to compute the monthly values of $R_{0.5max}$ for the calibrated climatic input files. This calculation was performed using CLIGEN for a 100-year simulation with the uncalibrated input files and extracting the average monthly n and R_{mean} values from the generated data. Then, the average monthly D values were extracted from the measured data to be used in Eq. (10). Fig. 2 provides a summary of the procedure used to calibrate the $R_{0.5max}$ parameter for every month. This procedure adjusts the $\alpha_{0.5}$ for every month in Eq. (5), as $\alpha_{0.5}$ depends on $R_{0.5max}$. An alternative option would be to calibrate Δ in Eq. (5) by changing the source code, however, this is not as effective as calibrating $\alpha_{0.5}$ because Δ is not a month-dependent parameter. Calibrating rainfall parameters other than $R_{0.5max}$, such as R or n can also help increase the accuracy of the generated storms, as $\alpha_{0.5}$ depends on R, n and $R_{0.5max}$ (Eqs. (3) and (4)). However, these values were not calibrated because they also affect key parameters that determine rainfall erosivity, which are the rainfall amounts and number of storms. $R_{0.5max}$ is the only parameter that affects exclusively the shape of the storms, making it the best parameter for calibration. More information about the effect of the rainfall parameters can be found in the study of Yu (2005).

2.4. Testing method

CLIGEN was used to generate climatic data for all of the sites using both the uncalibrated and calibrated input files. The generated rainfall was compared with the measured data based on the monthly number of storms, total rainfall amount per storm, mean intensity, 1-h maximum intensity and storm duration. The time to peak was compared on an annual basis because this parameter is not month-dependent. To test the equality of the measured and generated distributions for all parameters, the nonparametric Kolmogorov–Smirnov test (K–S) was applied with a significance level of 0.05. The K–S test was chosen because rainfall parameters do not often exhibit normal distributions

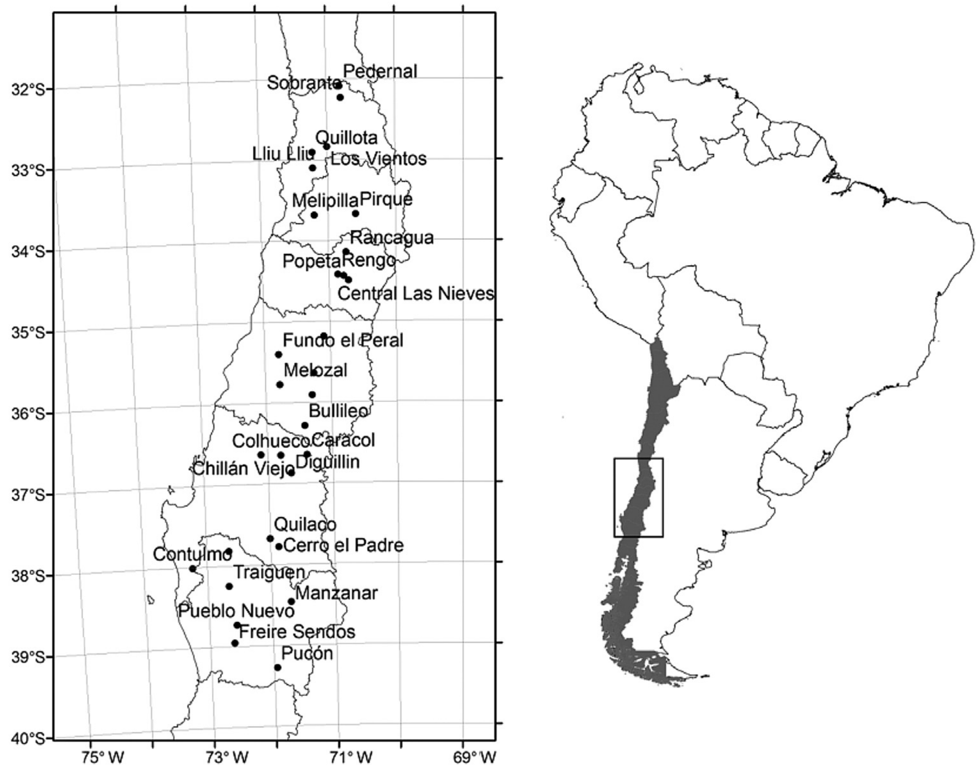

Fig. 1. Spatial distribution of the meteorological stations used in this study.

(Zhang et al., 2008). The mean values and standard deviations for all variables were also compared.

Furthermore, the annual rainfall erosivity was computed for both the measured and generated rainfall data using the equations described by Foster (2008). This calculation was performed to evaluate whether differences in storm durations and intensities between the measured and generated data can affect the erosive power of the rain. As demonstrated by Yu (2002), there is a substantial effect of poorly predicted storm durations and storm intensities on erosivity. Thus, rainfall kinetic energy for each measured and generated storm was calculated as follows (Foster, 2008):

$$E = \sum_{r=1}^{m} 0.29[1-0.72\exp(-0.082 i_r)]\Delta V_r \quad (11)$$

where E is the kinetic energy of the storm (MJ mm ha^{-1} h^{-1}), i_r is the rainfall intensity for the rth period (mm h^{-1}) and ΔV_r is the rainfall amount (mm) for the rth increment of the storm hyetograph, which is divided into m intervals. Each storm's energy is then multiplied by the maximum amount of rain falling within 30 consecutive minutes (I_{30}) expressed in mm h^{-1} to obtain the storm's erosivity. Because the available data were recorded hourly, I_{30} was estimated for every storm using the IDF curve and the procedure described in Section 2.2 to determine the measured erosivity. Finally, the annual erosivity was calculated by adding all the storm's erosivities for a year, and then averaging every year. Moreover, the means and standard deviations of both the measured and generated erosivities were compared; the K–S test was used to evaluate the equality of the measured and generated distributions.

3. Results and discussion

The results presented herein are a comparison of the measured and the generated number of storms, precipitation amount per storm, time to peak, storm duration, storm intensities and rainfall erosivity for both the calibrated and uncalibrated input files. The calibration only affects the durations and the intensities because they are the variables in CLIGEN that depend on the $R_{0.5\max}$ parameter. The erosivity is also

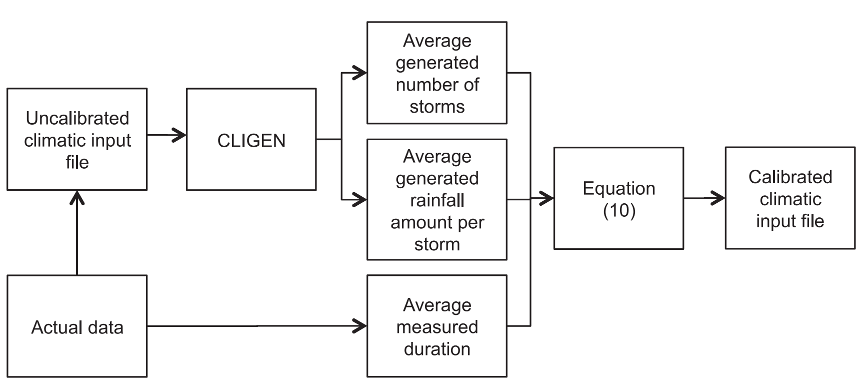

Fig. 2. Procedure used to calibrate the climatic input files. The procedure is applied in every month to yield the monthly $R_{0.5\max}$ parameters.

Table 2
Results of the statistical analysis applied on a monthly basis to the storm parameters of the 30 stations, before and after calibration. For each storm parameter and month, the table shows the number of stations where the generated and measured values were equal according to the K–S test. The calibration process does not affect the number of storms and rainfall amount per storm.

Month	Number of stations out of 30 where the measured and the CLIGEN-generated storm parameters were statistically equal							
	Storm duration		Mean rainfall intensity		1-h maximum intensity		Number of storms	Rainfall amount per storm
	Before	After	Before	After	Before	After		
January	20	18	27	25	29	27	28	28
February	21	24	28	30	27	29	27	28
March	20	24	29	28	29	29	28	29
April	6	20	24	20	24	24	26	24
May	2	7	25	26	15	24	24	23
June	6	11	26	27	13	23	18	20
July	5	13	23	25	12	25	26	23
August	4	11	27	26	15	28	22	28
September	5	14	23	24	18	30	27	27
October	11	18	23	26	19	29	27	26
November	15	20	30	26	28	29	26	27
December	19	20	26	27	24	26	30	26
Average	11.2	16.7	25.9	25.8	21.1	26.9	25.8	25.8

affected by the calibration because it depends on the storm durations and intensities.

Table 2 shows the results of the statistical analysis applied on a monthly basis to the storm parameters of the 30 stations, before and after the calibration. CLIGEN adequately estimated the number of storms for nearly all stations between September and March (the dry season), which corresponds to a period in which there are typically less than five rainfall events per month. However, during the wet season, the accuracy of the model decreased, especially in June where the measured and generated number of storms was statistically equal in 18 of the 30 stations (Table 2). This occurred because CLIGEN overpredicted the number of storms in months with more than five rainfall events (see Fig. 3). Fig. 3 compares the measured and generated monthly average number of storms at the 30 sites. These results are consistent with the findings of Wilks (1992) and Zhang and Garbrecht (2003), who showed that CLIGEN produces reliable results when there are few storms per month and becomes less reliable as the number of storms increases. However, the generated mean number of storms was correlated to the measured values in most months (R^2 value of 0.77). This result demonstrates that the first-order two-state Markov chain that is used to determine the precipitation occurrence in CLIGEN is appropriate, which was also shown by Koutsoyiannis (1994) and Wilks (1999).

The average rainfall amount per storm was accurately generated using CLIGEN when less than 15 mm of rain fell per event (Fig. 4), which is typical for rainfall events in the dry season. Fig. 4 compares the measured and the generated monthly average rainfall amount per storm at the 30 sites. These results are consistent with Table 2, which shows that the measured and generated rainfall amounts per storm were statistically equivalent at nearly every station in the dry season. However, in the wet season, when the rainfall amount per storm increases, the number of stations at which the rainfall amount was correctly estimated decreased, especially in June. This same result was reported by both Zhang and Garbrecht (2003) and

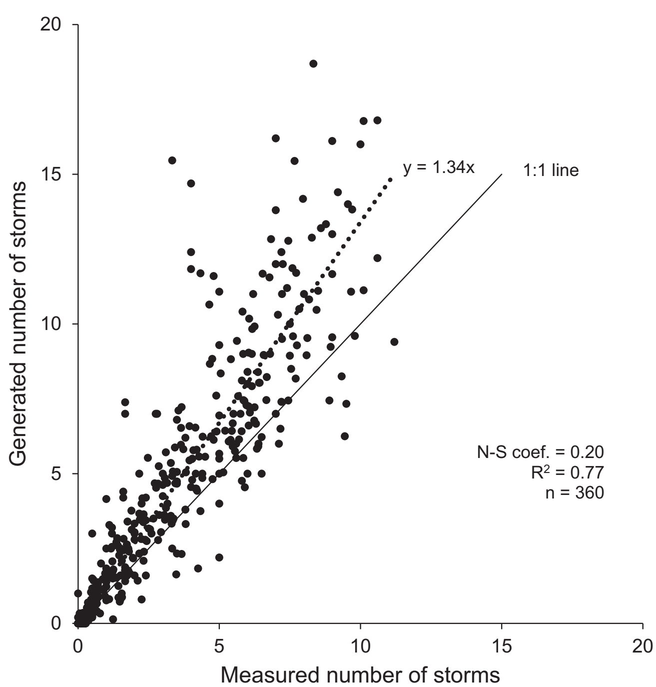

Fig. 3. Comparison between measured and generated monthly average number of storms at the 30 sites.

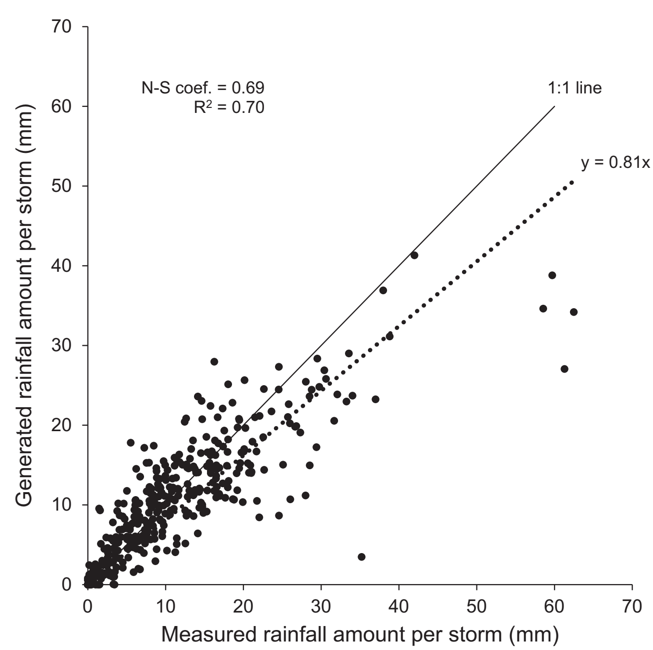

Fig. 4. Comparison between measured and generated monthly average rainfall amounts per storm at the 30 sites.

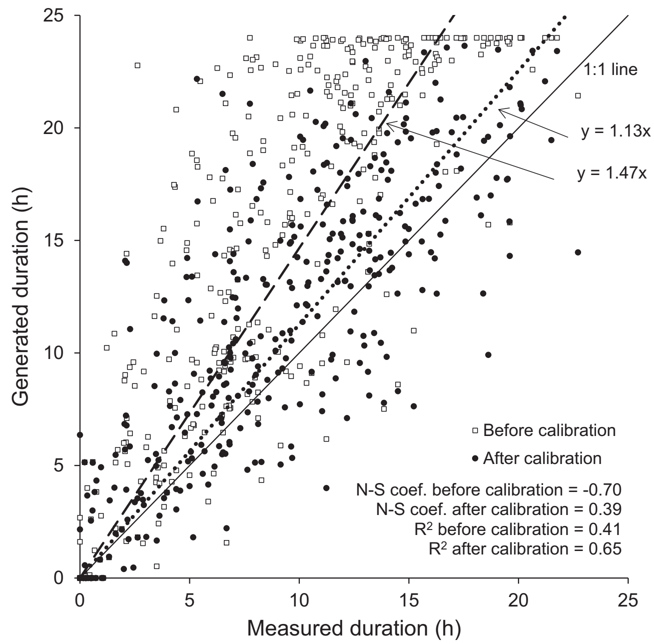

Fig. 5. Comparison between measured and generated monthly average storm durations at the 30 sites. The data are shown before and after the calibration. The dashed and dotted lines show the linear regressions before and after calibrating CLIGEN, respectively.

Kou et al. (2007), in which CLIGEN generated accurate rainfall amounts for small storms and became less accurate as the rainfall amount increased. However, as shown in Table 2, the rainfall amounts per storm were correctly estimated at most stations using CLIGEN regardless of the month. In addition, the mean values were adequately simulated in most months, i.e., an R^2 value of 0.77 and a Nash–Sutcliffe (N–S) efficiency value of 0.69. This finding demonstrates the effectiveness of the skewed normal distribution used in the model, which was previously shown by Elliot and Arnold (2001).

The times to peak generated by CLIGEN were nearly identical to the measured values (data not shown), which is consistent with the findings of Zhang et al. (2008). Out of the 30 meteorological stations, only two stations (Pirque and Freire Sendos) reported different times to peak after the K–S test. Because these two stations had the shortest measurement data sets, the length of the available records may have affected the K–S test more than the quality of the CLIGEN generated data. Nevertheless, at all of the stations, the differences between the means and standard deviations of the measured and generated times to peak were less than 3%.

Based on the K–S test, Table 2 also shows the number of meteorological stations at which the measured and generated storm durations, mean intensities and maximum 1-h intensities were equivalent before and after the calibration. Without the calibration, most of the generated storm durations were significantly different than the measured values, especially in the wet season. Before the calibration, the model consistently overpredicted the storm durations. This result is shown in Fig. 5, which compares the measured and the generated monthly average storm durations at the 30 sites before and after the calibration. In many cases, the CLIGEN-generated storms lasted 24 h, which is the maximum amount of time that a storm can last in the model (Nicks et al., 1995). This phenomenon occurs particularly in Central Chile because of the frontal nature of storms in this region, which makes the storm intensities nearly constant. According to Eq. (5), the storm duration depends only on the parameter $\alpha_{0.5}$; a storm's duration increases as $\alpha_{0.5}$ decreases. The parameter $\alpha_{0.5}$ is defined as the ratio of the maximum 0.5-h rainfall amount to the daily precipitation amount. In a frontal storm, $\alpha_{0.5}$ is typically small because the maximum 0.5-h intensity is nearly identical to the mean intensity. Therefore, CLIGEN tends to generate frontal storms with extended durations, showing that $\alpha_{0.5}$ is not a robust predictor for the durations of this type of storms.

As shown in Table 2, the number of stations at which the CLIGEN-generated durations were equivalent to the measured values increased after the calibration. However, nearly half of the stations still reported differences between the measured and the generated storm durations. The primary effect of the calibration can be observed in Fig. 5, which shows that the means of the generated storm durations are closer to the measured values after calibrating the model. After the calibration, the N–S efficiencies and R^2 values increased from −0.70 to 0.39 and from 0.41 to 0.65, respectively. The new storm durations were compared with the same measured data that were used to calibrate them because the purpose of this process is to generate the same mean duration as the one of the measured data. Because CLIGEN did not precisely reproduce the mean storm durations after the calibration, it is possible to conclude that the assumption used to derive Eq. (10) is not accurate for all cases. In addition, part of the error can also be attributed to the fact that CLIGEN smoothes the monthly $R_{0.5max}$ values for the calculation of D, which is not considered in the calibration.

The standard deviations of the generated storm durations were consistently smaller than the measured values. This result is demonstrated by the variation coefficients of the samples, which ranged from 0.02 to 0.4 and from 0.8 to 1.2 for the generated and measured storm durations respectively. This finding suggests that the storm durations in Central Chile are more variable than those predicted using CLIGEN. Therefore, even though the proposed calibration process produces storm durations that more closely resemble the observed durations, their standard deviations remain different. The model does not incorporate duration variability in its equations. Hence, the only source of variability lies in the gamma distribution that generates the $\alpha_{0.5}$ value described in Eq. (5), which does not accurately represent the variability of the storm durations.

Fig. 6 shows a comparison between the measured and the generated monthly average mean rainfall intensities at the 30 sites before and after the calibration. With the calibration, the R^2 value increased from 0.31 to 0.60, while the N–S efficiency decreased from 0.14 to 0.12. Moreover, Table 2 shows that most of the generated mean storm intensities were statistically equivalent to the measured values regardless of the calibration. This finding shows that the differences between the average mean storm intensities shown in Fig. 6 were not statistically significant.

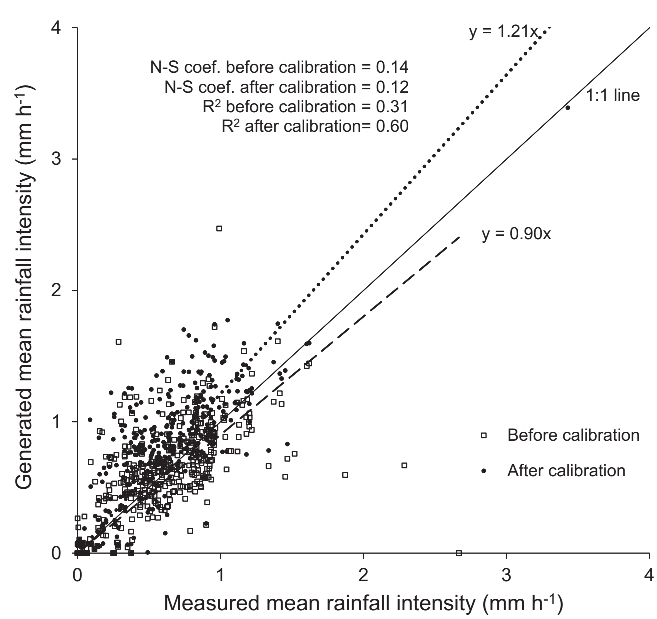

Fig. 6. Comparison between the measured and the generated monthly average mean rainfall intensities at the 30 sites. The data are shown before and after the calibration. The dashed and dotted lines show the linear regressions before and after calibrating CLIGEN, respectively.

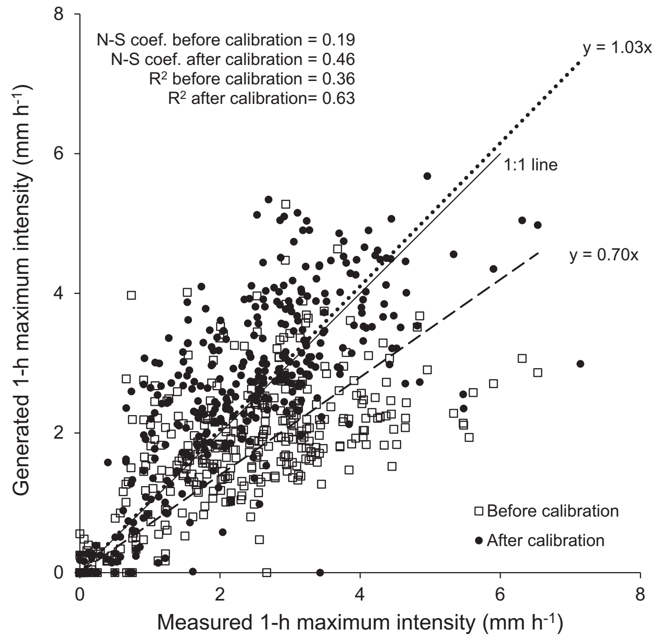

Fig. 7. Comparison between the measured and the generated monthly average 1-h maximum storm intensities at the 30 sites. The data are shown before and after the calibration. The dashed and dotted lines show the linear regressions before and after calibrating CLIGEN, respectively.

Fig. 7 compares the measured and the generated monthly average maximum 1-h storm intensities before and after calibrating the climatic data files. Prior to the calibration, the model consistently underpredicted the 1-h maximum intensities. After the calibration, the results improved. The R^2 value increased from 0.36 to 0.63, while the N–S efficiency increased from 0.19 to 0.46. This finding is supported by the data in Table 2, especially in the rainy months, with a significant increment in the number of stations where the measured and generated 1-h maximum intensities were equivalent after the calibration. Because the model generated more accurate mean storm durations after the calibration and because the total rainfall was correctly estimated, the storm intensities were also correctly estimated.

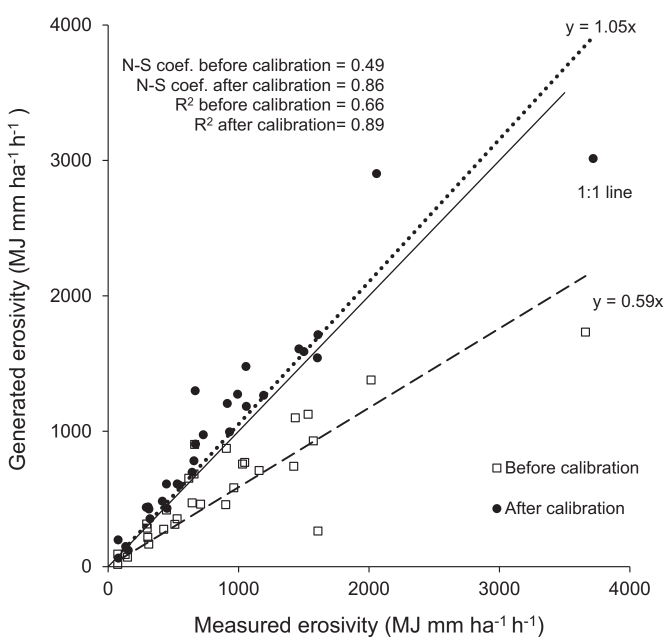

Fig. 8. Comparison between the measured and generated annual rainfall erosivities. The data are shown before and after calibrating CLIGEN for the 30 sites. The dashed and dotted lines show the linear regressions before and after calibrating CLIGEN, respectively.

Fig. 8 shows a comparison between the generated and the measured mean annual erosivities before and after the calibration at the 30 sites. CLIGEN generated better estimations of erosivity when the calibration was used. The R^2 and the N–S efficiency values increased from 0.66 to 0.89 and from 0.49 to 0.86, respectively. Before the calibration, CLIGEN underestimated the maximum storm intensities; therefore, the kinetic energies and the rainfall erosivities were also underestimated. After the calibration, the maximum intensities were more accurately estimated, especially in the rainy months, which is when the erosivity is concentrated in the study area (Bonilla and Vidal, 2011). Because the average number of storms, rainfall amount per storm, storm durations and storm intensities were adequately estimated after the calibration, CLIGEN also provided better erosivity results. Out of the 30 meteorological stations, 11 reported statistically equivalent values of erosivity before the calibration, while 29 stations were statistically equivalent after the calibration. This result demonstrates that CLIGEN generated erosivity values with the same means and standard deviations as the measured data even though the standard deviations of the storm durations were not accurately estimated. Therefore, the storm duration variability does not significantly affect the erosivity variability. Hence, the variable portions of the storms that are not represented in CLIGEN must have low intensities and a minimal effect on erosivity, which is typical during the formation and weakening of storms.

Because erosivity was accurately estimated using CLIGEN after the calibration and erosivity is directly proportional to erosion, soil loss estimates using WEPP will be more accurate when using the calibrated climatic data files. Moreover, because rainfall occurrence and amount increase as the latitude increases in Chile (Table 1), it is possible to conclude that the effectiveness of the calibration is independent of these variables. However, because this calibration was tested on only frontal storms, there is no evidence that this procedure will work as well for other climate types. The method will, however, be effective in areas where frontal storms are predominant.

4. Conclusions

The calibration method developed in this study is simple to implement and improves CLIGEN-generated storms without modifying the source code and the model's equations. By calibrating the input parameter that controls storm durations, the correlation between measured and generated durations increased. The calibration in turn improved the rainfall intensities and erosivities.

Before the calibration, the mean storm durations were poorly predicted using CLIGEN at almost every site and month. After the calibration, the results improved significantly. However, the model failed to replicate the variability in the storm durations regardless of the calibration, which is because the gamma distribution used in CLIGEN to generate the storm durations produces results that are less variable than the actual durations. Furthermore, after the calibration, the generated 1-h maximum storm intensities were correctly estimated, especially during the wet season, which is the season with the largest effect on water erosion in the study area. After the calibration, the model failed to replicate rainfall erosivity at one of the 30 sites, while before the calibration, the model failed at 19 sites. This finding demonstrates that improving the storm duration estimates was sufficient to yield accurate rainfall intensity erosivity estimates.

Even though the calibration method proposed was used and validated in Central Chile, the method should be effective in other places where frontal storms are predominant because the calibration procedure does not depend on the number of storms or the rainfall amount. The only requirement for using the method is the availability of rainfall data measured at small time intervals, such as every hour. Therefore, the calibration method is a tool that can be used with the current version of CLIGEN because no source code modification is required. Because the equations for estimating the storm durations and maximum intensities are still subject to modification, the calibration can be used to simulate these parameters with improved accuracy until new equations are implemented and validated.

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References

Arnold, J.G., Williams, J.R., 1989. Stochastic generation of internal storm structure at a point. Trans. ASAE 32 (1), 161–167.
Bonilla, C.A., Vidal, K.L., 2011. Rainfall erosivity in Central Chile. J. Hydrol. 410 (1–2), 126–133.
Elliot, W.J., Arnold, C.D., 2001. Validation of the weather generator CLIGEN with precipitation data from Uganda. Trans. ASAE 44, 53–58.
Escobar, F., Aceituno, P., 1998. Influencia del fenómeno ENSO sobre la precipitación nival en el sector andino de Chile central durante el invierno. Bull. Inst. Fr. Détudes Andines 27 (3), 753–759 (In spanish).
Flanagan, D.C., Nearing, M.A. (Eds.), 1995. USDA-Water Erosion Prediction Project: Hillslope Profile and Watershed Model Documentation. NSERL Report No. 10. USDA-ARS National Soil Erosion Research Laboratory, West Lafayette, Ind.
Foster, G.R., 2008. Revised Universal Soil Loss Equation Version 2 (RUSLE2). USDA-ARS, Washington, D.C.
Headrick, M.G., Wilson, B.N., 1997. An Evaluation of Stochastic Weather Parameters for Minnesota and Their Impact on WEPP. ASAE Paper No. 972230. ASAE, St. Joseph, Mich.
Johnson, G.L., Hanson, C.L., Hardegree, S.P., Ballard, E.B., 1996. Stochastic weather simulation: overview and analysis of two commonly used models. J. Appl. Meteorol. 35 (10), 1878–1896.
Kou, X., Ge, J., Wang, Y., Zhang, C., 2007. Validation of the weather generator CLIGEN with daily precipitation data from the Loess Plateau, China. J. Hydrol. 347 (3–4), 347–357.
Koutsoyiannis, D., 1994. A stochastic disaggregation method for design storm and flood synthesis. J. Hydrol. 156 (1), 193–225.
Nicks, A.D., Lane, L.J., Gander, G.A., 1995. Weather generator. Chapter 2. In: Flanagan, D.C., Nearing, M.A. (Eds.), USDA-Water Erosion Prediction Project: Hillslope Profile and Watershed Model Documentation. NSERL Report No. 10. USDA-ARS National Soil Erosion Research Laboratory, West Lafayette, Ind.
Pieri, L., Bittelli, M., Wu, J.Q., Dun, S., Flanagan, D.C., Pisa, P.R., Ventura, F., Salvatorelli, F., 2007. Using the Water Erosion Prediction Project (WEPP) model to simulate field-observed runoff and erosion in the Apennines mountain range, Italy. J. Hydrol. 336 (1–2), 84–97.
Pizarro, R., Aravena, D., Macaya, K., Abarza, A., Cornejo, M., Labra, M., Pavez, M., Roman, L., 2010. Curvas intensidad - duración - frecuencia para la zona centro sur de Chile. Editorial Universidad de Talca, Chile (In spanish).
Renard, K.G., Foster, G.R., Weesies, G.A., McCool, D.K., Yoder, D.C., 1997. Predicting soil erosion by water: A guide to conservation planning with the Revised Universal Soil Loss Equation (RUSLE). USDA Agricultural Handbook No 703. Washington DC, USDA.
Sharpley, A.N., Williams, J.R., 1990. Erosion productivity impact calculator: 1. In: Sharpley, A.N., Williams, J.R. (Eds.), Model Documentation (EPIC), 1st ed. Agricultural Research Service, Baltimore.
Wenzel, H.G., 1982. Rainfall for urban stormwater design. In: Kibler, D.F. (Ed.), Urban Storm Water Hydrology. American Geophysical Union, Water Resources Monograph 7. AGU, Washington D.C.
Wilks, D.S., 1992. Adapting stochastic weather generation algorithms for climate change studies. Clim. Chang. 22 (1), 67–84.
Wilks, D.S., 1999. Interannual variability and extreme-value characteristics of several stochastic daily precipitation models. Agric. For. Meteorol. 93, 153–169.
Yu, B., 2000. Improvement and evaluation of CLIGEN for storm generation. Trans. ASAE 43 (2), 301–307.
Yu, B., 2002. Using CLIGEN to generate RUSLE climate inputs. Trans. ASAE 45 (4), 993–1001.
Yu, B., 2005. Adjustment of CLIGEN parameters to generate precipitation change scenarios in southeastern Australia. Catena 61, 196–209.
Zhang, X.C., 2005. Generating correlative storm variables for CLIGEN using a distribution-free approach. Trans. ASAE 48 (2), 567–575.
Zhang, X.C., Garbrecht, J.D., 2003. Evaluation of CLIGEN precipitation parameters and their implications on WEPP runoff and erosion prediction. Trans. ASAE 46 (2), 311–320.
Zhang, Y., Liu, B., Wang, Z., Zhu, Q., 2008. Evaluation of CLIGEN for storm generation on the semiarid Loess Plateau in China. Catena 73 (1), 1–9.