A WEATHER GENERATOR-BASED STATISTICAL DOWNSCALING TOOL FOR SITE-SPECIFIC ASSESSMENT OF CLIMATE CHANGE IMPACTS

J. Chen, X. J. Zhang, X. Li

ABSTRACT. *Statistical downscaling approaches are usually used to bridge the gap between climate model outputs and data requirements of impact models such as crop and soil erosion models. This study synthesizes, integrates, and standardizes a statistical downscaling method that was initially developed in 2005 and subsequently evaluated and improved during the last decade. A new downscaling software program, Generator for Point Climate Change (GPCC), has been developed to automate and visualize the method to assist end users with detailed technical and user documentation. GPCC readily generates daily time series of climate change scenarios for local and site-specific climate change impact studies using monthly projections from global climate models or regional climate models. The downscaled variables include precipitation and maximum and minimum temperatures. This software provides a simple but effective climate downscaling tool for assessing the impacts of climate change on crop production, soil hydrology, and soil erosion at a field scale. The tool can also provide an alternative downscaling method to facilitate the international collaborative efforts of the Agricultural Model Intercomparison and Improvement Project (AgMIP) for simulation of world food production and food security assessment. The detailed downscaling methods, their scientific bases, and the advantages of GPCC over other commonly used downscaling methods are presented. GPCC is written in the Matlab language, and a standalone version can be run on Windows XP or above without Matlab software. The tool has a graphical user interface that is simple and easy to generate downscaled climates as well as to visualize downscaled outputs. Each interface tab and key button and their functions are described to facilitate its widespread application.*

Keywords. *Agricultural system models, Climate change impacts, Generator for point climate change, Interface, Statistical downscaling, Stochastic weather generator.*

The potential impacts of climate change on world food security have been a concern for several decades (Rosenzweig and Parry, 1994). World leaders and decision-makers need probability-based analysis of future food production to prioritize and identify mitigation and adaptation strategies to cope with potential climate change. To attack this key question, the Agricultural Model Intercomparison and Improvement Project (AgMIP, http://www.agmip.org/) was established as a major international collaborative effort aimed at improving simulation of world food production and security as well as better understanding climate change impacts on the agricultural sector at global and regional scales (Rosenzweig et al., 2013). The assessment of climate change impacts usually relies on global climate models (GCMs), which can provide climate change information for both historical and future periods. However, the resolution of GCMs is too coarse for GCM outputs to be used as direct inputs to impact models, especially for running point-scale crop models (Xu, 1999; Sharma et al., 2007; Maraun et al., 2010; Chen et al., 2015). For example, for assessing climate change impacts on crop yields, soil water dynamics, and soil erosion, site-specific climate change scenarios are needed to drive process-based crop and hydrological models (Zhang, 2005a; Rosenzweig et al., 2013).

Downscaling has been developed to bridge the gap between GCM outputs and the data requirements of impact models. There are two downscaling techniques: dynamical and statistical. Dynamical downscaling nests a regional climate model (RCM) within a GCM output field by using GCM initial and boundary conditions to achieve higher resolution. However, RCMs still cannot be directly used for point-scale climate change impact studies due to the inherent biases of the "drizzle effect" (i.e., more wet days, and too many small events with too few extreme events) and limited spatial and temporal availability (Murphy, 1999; Fowler et al., 2007; Chen et al., 2013a). Compared to GCMs, which usually provide a large ensemble with long time periods, RCMs usually provide limited climate change ensembles with short time periods, especially for less developed regions

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such as Africa. For example, only five RCM simulations are provided by the Coordinated Regional Climate Downscaling Experiment (CORDEX) for East Asia (http://cordex-ea.climate.go.kr/). Among them, four RCMs do not provide future time series after the 2050s. Statistical downscaling is one of the techniques that link the state of some variables representing a large scale (predictors) to the states of other variables representing a much smaller scale (predictands). Compared to dynamical downscaling, statistical downscaling is computationally inexpensive and much easier to apply. The most common statistical downscaling approaches can be classified into three categories: perfect prognosis (PP), model output statistics (MOS), and stochastic weather generator (SWG) (Maraun et al., 2010), as shown in table 1.

The PP method involves estimating the statistical relationship (e.g., linear or nonlinear) between large-scale predictors (e.g., vorticity, mean sea-level pressure, geopotential height, and relative humidity) and local or site-specific predictands (e.g., precipitation and temperature) using observed climate data (Wilby and Wigley, 2000; Wilby et al., 2002; Chen et al., 2012a, 2014a). The regression-based method is one of the typical PP downscaling methods, which is also one of the most widely used methods for climate change impact studies such as the Statistical DownScaling Model (SDSM, Wilby et al., 2002). The reliability of a regression-based method relies on relationships between observed daily climate predictors and predictands. However, these relationships are usually weak, especially for daily precipitation. The climate predictors usually explain less than 30% of daily precipitation variance (Wilby et al., 2002; Chen et al., 2012a, 2014a). In addition, the regression-based method is usually incapable of downscaling precipitation occurrence and generating proper temporal structure of daily precipitation, which is critical for crop simulation (Chen et al., 2012a, 2014a; Mullan et al., 2016a). Moreover, the PP downscaling method establishes a relationship between predictors and predictands for the historical period and then applies it to future periods (Wilby et al., 2002). However, this relationship may not hold for the future in a changed climate (Chen et al., 2012a, 2014a). In particular, the relationship between predictors and predictands is usually established using reanalysis predictors and then applied to GCM predictors based on an assumption that the reanalysis predictors and GCM predictors are both "perfectly" simulated at the grid scale (Wilby et al., 2002; Dibike and Coulibaly, 2005; Chen et al., 2011). This apparently supports the use of large-scale predictors for statistical downscaling, especially taking into account the fact that the large-scale circulation features are more accurately simulated than small surface variables. While reanalysis and GCM data share some similarities, they are completely independent. Reanalysis aims at representing the real world, whereas GCMs operate in their own virtual world. Reanalysis data are based on the assimilation of real-world observed data into a climate model, whereas GCMs operate in their own virtual world at a scale that limits the resemblance between both worlds (Essou et al., 2016, 2017). Previous studies (e.g., Gleckler et al., 2008; Johnson and Sharma, 2009; Johnson et al., 2011) showed that the performance of GCMs in simulating large-scale variables is model-, variable-, and location-dependent. In other words, reanalysis and GCM variables are both biased, while they may be biased differently. This explains in large part why GCMs exhibit relatively large variance for both temperature and precipitation. Given these conditions, it is unlikely that the relationships established for reanalysis predictors will hold with GCM data under both current and future climate conditions.

The MOS approach involves estimating a statistical relationship between a climate model variable (e.g., precipitation) and the same variable of the observations to correct the climate model outputs (Christensen et al., 2008; Mpelasoka and Chiew, 2009; Piani et al., 2010; Themeßl et al., 2012; Johnson and Sharma, 2012; Chen et al., 2011a, 2013a). The commonly used change factor methods (also called the delta change method), which applies the climate change signal estimated using climate model simulation to observed time series, were also grouped as a MOS method in several studies (e.g., Chen et al., 2013b). The MOS approach has the following drawbacks:

Table 1. Characteristics and limitations of three downscaling approaches.

Approach	Characteristics	Limitations
Perfect prognosis (PP)	Estimates a statistical relationship between large-scale predictors and local or site-specific predictands.	(1) There is usually no strong relationship between predictors and predictand, especially for precipitation. (2) It is incapable of downscaling precipitation occurrence and generating a proper temporal structure of daily precipitation. (3) The relationship estimated for the historical period may not hold for the future period. (4) The relationship established for reanalysis predictors in the historical period may not hold for GCM data in the future period.
Model output statistics (MOS)	Estimates a statistical relationship between a climate model variable and the same variable of observations.	(1) They are incapable of correcting the sequence of precipitation occurrence. (2) Bias of climate model outputs may not be stationary between historical and future periods. (3) Bias correction methods may change the climate change signal provided by climate models. (4) The delta change method assumes that precipitation occurrence will not change in the future period. (5) The delta change method assumes that the climate change signal at the GCM grid scale is the same as that at the point scale.
Stochastic weather generator (SWG)	Adjusts stochastic weather generator parameters based on climate change signals projected by climate models.	(1) Most SWG-based methods do not take into account the correction of precipitation occurrence. (2) The adjustment of precipitation occurrence is usually based on a delta change method. (3) Precipitation extremes are usually not specifically downscaled.

(1) Even though some complicated bias correction methods can correct the wet-day frequency, they are incapable of correcting the sequence of precipitation occurrence, which can considerably affect the hydrological modeling and plant growth simulation (Chen et al. 2013a).

(2) All bias correction methods are based on the assumption that the biases of climate change model outputs are constant over time. However, recent studies have shown that this assumption is not valid for some regions, especially for precipitation, because of natural climate variability (Chen et al., 2015). Thus, a bias correction method that is valid for a historical period may not be valid for a future period.

(3) Some studies have shown that the bias correction method can change the climate change signal provided by climate models (Hagemann et al., 2011; Maraun, 2013; Maurer and Pierce, 2014). For example, Maurer and Pierce (2014) found that modifications of GCM-projected trends by a quantile mapping method can be as large as the original GCM-projected changes.

(4) The delta change method assumes that the precipitation occurrence will not change in a future period (Chen et al., 2011; Teutschbein and Seibert 2012). However, this is not the case in the real world.

(5) The delta change method applies the climate change signal at the GCM grid scale to point observations (Chen et al., 2011; Teutschbein and Seibert 2012). However, the climate change signal at a point scale may not be the same as that at a grid scale, especially in mountainous regions.

SWG has been used as a downscaling tool for many climate change impact studies since the seminal article by Wilks (1992). Downscaling using SWG methods involves adjusting SWG parameters based on climate change signals projected by climate models (Wilks, 1992; Zhang, 2005a; Qian et al., 2010; Chen et al., 2012b). Downscaling SWG parameters makes it possible to produce climate scenario ensembles for any desirable length for studying the impacts of risk-based climate events. However, most SWG-based methods do not take into account the correction of precipitation occurrence, such as the Marksim model (Jones and Thornton, 1993, 2000). Even though the occurrence adjustment is considered in a few studies, the adjustment is usually based on a delta change method (e.g., Wilks, 1992; Chen et al., 2012b) and inherits its drawbacks. For example, Wilks (1992) downscaled the precipitation occurrence through adjusting an unconditional probability of precipitation occurrence and a dependence parameter using climate change information projected by climate models. Similarly, Chen et al. (2012b) adjusted two transitional probabilities of precipitation occurrence. In addition, precipitation extremes are usually not specifically downscaled when using SWG-based methods. In other words, all methods assume that extreme precipitation events have the same change as other precipitation events. That is, the possible storm intensification in the future, as reported in the Fifth Assessment Report of IPCC (IPCC, 2013), is not considered. The parameter linking to precipitation extremes is not specifically adjusted.

To overcome the drawbacks of the above downscaling methods, a statistical downscaling method based on a stochastic weather generator (CLIGEN) was developed by Zhang (2005a). During the past decade, this method has been intensively tested using multiple locations in various climates. Specifically, the method has been evaluated and validated for both stationary and non-stationary climate changes and variations using historical climate data for multiple climate stations dispersed in the U.S., the U.K., Canada, Australia, and Brazil (Zhang et al., 2012a; Zhang, 2013a; Mullan et al., 2016a). The method has been successfully used to downscale GCM projections for impact studies of climate changes in the U.S., the U.K., China, and Japan. Zhang (2007) has demonstrated that this sophisticated downscaling method, compared with conventional downscaling approaches, simulates extreme daily precipitation events better due to its separate treatment of spatial and temporal variations. The method has been used to estimate rainfall erosivity changes under climate change for northeastern China (Zhang et al., 2010) and the southern Appalachian region of the U.S. (Hoomehr et al., 2016). Rainfall erosivity is mainly a function of rainfall intensity. The method has been used to simulate the site-specific impacts of climate change on soil erosion, surface hydrology, water resources, and crop production in the Loess Plateau of China (Li et al., 2009, 2010a, 2010b, 2010c; Zhang et al., 2009). Zhang et al. (2012b) modeled the climate change effects on runoff and soil erosion in southeastern Arizona rangelands and implications for mitigation with conservation practices using the downscaling method. Zhang (2012) studied the effects of cropping and tillage systems on wheat production, soil erosion, and surface runoff under climate change in central Oklahoma. Mullan et al. (2016b) studied the effects of climate change on the long-term viability of the world's busiest heavy-haul ice road using the downscaling method. Mullan et al. (2016c) also modeled the effectiveness of grass buffer strips in managing muddy floods under a changing climate in Belgium. In addition, a similar method was used by Gunawardhana and Kazama (2012) to study the impacts of climate change and variability on aquifer levels and groundwater temperatures in Japan. All the above evaluations and applications revealed the advantages of this downscaling method over other methods from various aspects, as presented later in the "Advantages of GPCC" section. With the development and application of this downscaling method over the last decade, it is timely to synthesize and integrate all these achievements and provide open-source software to more interested end users.

Accordingly, this study synthesizes and standardizes this statistical downscaling method (methodology and advantages) and presents a new climate downscaling software program that automates and visualizes the downscaling method with detailed technical and user documentation. The software was developed based on our published work to overcome the drawbacks of the above downscaling methods. Because this methodology has been intensively tested in previous studies, no validation is presented. The software program, Generator for Point Climate Change (GPCC), is a statistical downscaling tool based on the SWG CLIGEN. All source codes and a graphical user interface can be downloaded from https://github.com/Jiechenwhu/GPCC/. The detailed downscaling methods, scientific bases, and advantages are reviewed. A detailed user manual on how to use the graphical user interface is documented.

METHODOLOGY OF GPCC

GPCC downscales monthly projections of GCMs or RCMs in a grid box to daily weather series at a point scale or station. The downscaled variables include precipitation, maximum temperature (T_{max}), and minimum temperature (T_{min}). GPCC separates the downscaling process into two stages. The first stage spatially downscales GCM/RCM monthly precipitation and temperature from a grid box scale to a station scale. The second stage disaggregates the spatially downscaled monthly data to daily time series using CLIGEN. These are cascading stages in that the results of spatial downscaling are further used for temporal downscaling. For spatial downscaling using the quantile mapping method, only GCM/RCM monthly precipitation and temperature at grid box scales are required, while observed daily time series are required for temporal downscaling. The observed daily data are used to estimate the baseline parameters of CLIGEN and are also used to establish relationships between probabilities of precipitation occurrence and monthly precipitation for downscaling precipitation occurrence.

SPATIAL DOWNSCALING

Downscaling Precipitation

GCM/RCM-simulated monthly precipitation is downscaled from a grid box scale to a station using a quantile mapping method (or transfer function method) (Zhang, 2005a). When using this quantile mapping method, the observed and simulated monthly precipitation over the historical period is first sorted in an ascending order for each calendar month. First-order and third-order polynomials are then fitted between ranked station-observed and climate model-simulated monthly precipitation for each month. To derive future precipitation scenarios, the fitted polynomials are applied to climate model-simulated monthly data for the future period. Because the third-order polynomial consistently performs better than the first-order polynomial for all months based on the coefficient of determination (r^2) of the regression, the third-order polynomial regression is used to transform the simulated monthly precipitation values that are within the range of the observed (i.e., within which the third-order polynomial regression is fitted), while the first-order polynomial is used for the values outside the range. The use of the first-order polynomial for the out-of-range values is to generate conservative, first-order approximations (Zhang, 2005a; Zhang et al., 2011). The choice of the third-order polynomial is based on a qualitative assessment considering the number of parameters and the danger of overfitting the monthly precipitation. In addition, the quantile mapping method may result in negative values for arid regions and dry months. These values are set to zero in GPCC. At the last step, the mean and variance of monthly precipitation at the target site for the future period are calculated using the spatially downscaled monthly precipitation for further temporal downscaling. The temporal downscaling will then disaggregate the spatially downscaled monthly data to daily time series.

Downscaling Temperature

The climate model-simulated monthly T_{max} and T_{min} are spatially downscaled in the same manner as monthly precipitation (Zhang, 2005a). The mean and variance of monthly T_{max} and T_{min} for the future period are calculated using the spatially downscaled monthly temperatures for further temporal downscaling from monthly to daily scale. Because the future T_{max} and T_{min} values may be out the range in which the transfer function is fitted for most cases due to global warming, especially for a far future period, the implementation of a conservative first-order polynomial for these cases may result in new biases in the spatially downscaled T_{max} and T_{min}. Thus, the more commonly used change factor method is suggested as an alternative option for spatially downscaling T_{max} and T_{min} (Chen et al., 2013b). The change factor involves adjusting the observed monthly mean temperature ($\mu_{obs,m}$) by adding the difference in climate model-simulated monthly mean temperature between the future and reference periods ($\mu_{cm,fut,m} - \mu_{cm,ref,m}$) to obtain the monthly mean temperature for the future period ($\mu_{adj,fut,m}$) (eq. 1). The adjusted variance of monthly temperature for the future period ($\sigma^2_{adj,fut,m}$) is obtained by multiplying the variance of the simulated monthly temperature ratio ($\sigma^2_{cm,fut,m}/\sigma^2_{cm,ref,m}$) by the variance of observed monthly temperature ($\sigma^2_{obs,m}$) (eq. 2):

$$\mu_{adj,fut,m} = \mu_{obs,m} + \left(\mu_{cm,fut,m} - \mu_{cm,ref,m}\right) \tag{1}$$

$$\sigma^2_{adj,fut,m} = \sigma^2_{obs,m} \times \left(\sigma^2_{cm,fut,m} / \sigma^2_{cm,ref,m}\right) \tag{2}$$

The change factor method assumes that the climate change signal at a station is identical to that at the grid box. This may not be true for precipitation, especially in mountainous regions. However, this assumption is likely to hold for temperature because temperature usually displays less spatial variability.

TEMPORAL DOWNSCALING

Temporal downscaling involves adjusting SWG parameters using the spatially downscaled climate change information. The SWG used in GPCC is CLIGEN (Nicks and Lane, 1989; Nicks et al., 1995). CLIGEN was chosen because the mean and standard deviation of each variable are explicitly used in its probability distribution function, so the incorporation of climate model-simulated monthly changes in statistical moments is straightforward (Zhang, 2005a; Chen et al. 2009). Moreover, the skewed normal distribution used in CLIGEN has shown better performance than the other commonly used distributions (e.g., gamma and Weibull distributions) for generating precipitation extremes (Chen and Brissette, 2014a, 2014b). The following section first outlines the main functions of CLIGEN in generating precipitation, T_{max}, and T_{min}, followed by a description of temporal downscaling.

Stochastic Weather Generator

CLIGEN is a stochastic model that can generate a set of climate variables including daily precipitation occurrence, amounts, storm pattern (storm duration, relative peak intensity, and time to peak storm), daily values of maximum and minimum air temperatures, dew point temperature, solar radiation, and wind velocity and direction (Nicks and Lane, 1989; Nicks et al., 1995). The generation of intra-storm patterns is independent of the generation of daily precipitation series. All variables are generated using probability distributions. For example, daily precipitation amounts are simulated using a three-parameter skewed normal distribution, and temperature is simulated using a normal distribution. Because precipitation, T_{max}, and T_{min} are the most commonly used variables for climate change impact studies, GPCC only includes these three variables. Precipitation and temperature in CLIGEN are generated independently, and the mean and standard deviation of both variables are explicitly used in their probability distributions, so incorporating GCM/RCM-projected changes in statistical moments into CLIGEN parameters is straightforward. The inter-variable dependence can also be easily induced as a post-process by using a distribution-free shuffle procedure (e.g., Zhang, 2005b; Li, 2013) or a copula-based joint distribution approach (e.g., Li et al., 2014). Precipitation and temperature generations are presented as follows.

CLIGEN generates precipitation using a two-part model: one for generating precipitation occurrence, and the other for generating precipitation amount. Precipitation occurrence is generated using a first-order, two-state Markov chain. The probability of precipitation on a given day is based on the wet or dry status of the previous day, which can be defined in terms of two transition probabilities: P_{11} and P_{01}:

$$P_{11} = P\{\text{precip. on day } t \mid \text{precip. on day } t{-}1\} \tag{3a}$$

$$P_{01} = P\{\text{precip. on day } t \mid \text{no precip. on day } t{-}1\} \tag{3b}$$

For a predicted wet day, a three-parameter skewed normal distribution is used to generate daily precipitation amounts for each specific month:

$$\chi = \frac{6}{g}\left\{\left[\frac{g}{2}\left(\frac{R-\mu}{s}\right)+1\right]^{1/3} - 1\right\} + \frac{g}{6} \tag{4}$$

where R is the daily precipitation amount for a wet day; μ, s, and g are the mean, standard deviation, and skewness coefficient of daily precipitation amount, respectively; and χ is the standard normal deviate generated using two uniformly distributed random numbers in the interval (0,1). The second number for one day is reused as the first number for the next day to preserve the autocorrelation of daily precipitation.

Daily T_{max} and T_{min} are generated using normal distributions. A long-term observed temperature time series is used to estimate the two parameters (mean and standard deviation) of a normal distribution. For the latest version of CLIGEN (v5.22564), T_{min} and T_{max} are generated conditioned on each other (Chen et al., 2008). Specifically, the temperature with the smaller standard deviation between T_{max} and T_{min} is computed first, followed by the other. If the standard deviation of T_{max} is larger than or equal to the standard deviation of T_{min}, daily temperatures are generated by equations 5 and 6:

$$T_{min} = \mu_{min} + \sigma_{min} \times \chi \tag{5}$$

$$T_{max} = T_{min} + \left(\mu_{max} - \mu_{min}\right) + \sqrt{\sigma_{max}^{2} - \sigma_{min}^{2}} \times \chi \tag{6}$$

If the standard deviation of T_{max} is less than that of T_{min}, daily temperatures are generated by equations 7 and 8:

$$T_{max} = \mu_{max} + \sigma_{max} \times \chi \tag{7}$$

$$T_{min} = T_{max} - \left(\mu_{max} - \mu_{min}\right) - \sqrt{\sigma_{min}^{2} - \sigma_{max}^{2}} \times \chi \tag{8}$$

where μ and σ are the mean and standard deviation of daily temperature for a specific month, respectively, and χ is a standard normal deviate, which is obtained for each day using two uniform random numbers.

For temporally downscaling precipitation, T_{max}, and T_{min}, nine parameters need to be adjusted for each calendar month. They include P_{11} and P_{01} for generating precipitation occurrence; the mean, standard deviation, and skewness coefficient for generating daily precipitation amounts; and the means and standard deviations for generating T_{max} and T_{min}.

Downscaling Precipitation Occurrence

With the first-order, two-state Markov chain, two transition probabilities (P_{11} and P_{01}) are used to generate precipitation occurrence. These two conditional transition probabilities can be equivalently expressed in terms of the unconditional probability of daily precipitation occurrence (π) and a dependence parameter (r) defined as the lag-1 autocorrelation of daily precipitation series (Wilks, 1992; Zhang, 2005a; Chen et al., 2012b):

$$\pi = \frac{P_{01}}{1 + P_{01} - P_{11}} \tag{9}$$

$$r = P_{11} - P_{01} \tag{10}$$

Downscaling of precipitation occurrence involves perturbing the three probabilities of precipitation occurrence (P_{11}, P_{01}, and π). Two options are available for perturbing these probabilities: four points regression and two end points interpolation. The four points regression method adjusts the three probabilities (P_{11}, P_{01}, and π) based on their linear relationships with mean monthly precipitation (R_m) in five steps:

Step 1: For each calendar month (e.g., January), the observed precipitation time series is grouped into wettest and driest groups according to the monthly total precipitation. Specifically, based on the daily precipitation time series, monthly precipitation is calculated and sorted by ascending or descending order for each calendar month. Daily precipitation time series corresponding to the wettest months and to the driest months are pooled together. P_{11}, P_{01}, π, and R_m are calculated for both groups to obtain two data points (one pair for the wet group and the other for the dry group).

Step 2: For each calendar month, the same observed daily precipitation is divided into two equal length periods. P_{11}, P_{01}, π, and R_m are calculated for both periods to obtain two additional data points (one pair for the first period and the other for the second period).

Step 3: Linear relationships between probability parameters (P_{11}, P_{01}, or π) and R_m are established using the four data points calculated in steps 1 and 2. The inclusion of the wettest and driest groups for estimating the linear relationship is intended to encompass the entire climate range within which P_{01} and P_{11} can be estimated for any climatic conditions, implicitly including non-stationary climate states. The linear relationship can be estimated using the two end states (points) or four points calculated in steps 1 and 2. The linear relationship has been extensively tested over a number of stations all over the world and has proven to be one of the most effective choices (Zhang et al., 2012a; Zhang, 2013a). The regression r^2 is used as a criterion to evaluate the relationship.

Step 4: According to previous studies (Zhang et al., 2012a; Zhang, 2013a; Chen et al., 2014b), π consistently showed stronger correlation with monthly precipitation than the other two conditional probabilities. Thus, for a changing climate, two parameters having the largest r^2 among P_{11}, P_{01}, and π are used to estimate parameters for future climate using the fitted linear equations in step 3 and the spatially downscaled R_m. The remaining parameter is then calculated using equation 9.

Step 5: The dependence parameter r is calculated using P_{11} and P_{01} with equation 10.

The two end points interpolation method only adjusts conditional transition probabilities of precipitation occurrence (P_{11} and P_{01}), and the other two parameters are calculated using equations 9 and 10. Instead of fitting linear relationships using four points, only dry and wet end points (calculated in step 1) are used to establish the linear relationships. The adjusted P_{11} and P_{01} for a changing climate are interpolated using the linear relationships and the spatially downscaled R_m. Previous studies (Zhang et al., 2012a; Zhang, 2013a) showed that the four points regression and two end points interpolation perform similarly in downscaling precipitation occurrence.

Downscaling Precipitation Amounts

Downscaling of precipitation amounts involves adjusting three parameters (mean, standard deviation, and skewness coefficient of wet-day precipitation) of a skewed normal distribution. The adjusted mean daily precipitation amount (μ_d) is calculated using equation 11 (Wilks, 1992):

$$\mu_d = \frac{\mu_m}{N_d \pi} \tag{11}$$

where N_d is the number of days in a month, $N_d\pi$ is the average number of wet days in a month, and μ_m is the mean of spatially downscaled monthly precipitation.

The adjusted daily variance (σ^2_d) is approximated using equation 12, based on the variance of spatially downscaled monthly precipitation (σ^2_m) (Wilks, 1992):

$$\sigma_d^2 = \frac{\sigma_m^2}{N_d \pi} - \frac{(1-\pi)(1+r)}{1-r}\mu_d^2 \tag{12}$$

The other parameter of the skewed normal distribution that needs to be adjusted is the skewness coefficient. The skewness of daily precipitation distribution simulated by climate models (GCM/RCM) does not change gradually but displays large fluctuations (Chen et al., 2012b). Thus, it cannot be directly adjusted using the common change factor method. To simplify the process, previous studies did not specifically consider the adjustment of skewness coefficients. In other words, the skewness of the precipitation distribution was presumed to be unchanged in the future period. Ongoing work shows that the skewness is not linked to monthly precipitation but is largely influenced by extreme precipitation events (Chen et al., 2012b; Zhang, 2013b). Zhang (2013b) showed that the ratio of 99.9th percentile daily precipitation to μ_d is a good predictor for adjusting skewness coefficients. His study tested the relationship between skewness coefficient and the ratio of 99.9th daily precipitation to μ_d for eight stations in Oklahoma and ten stations all over the world. A strong relationship was found between these two variables. In particular, the relationship derived from eight Oklahoma stations is similar to that derived from ten global stations, indicating robustness of the relationship between these two variables. Thus, skewness coefficients can be adjusted based on their relationship with the ratio of 99.9th daily precipitation to μ_d calculated using equation 11. The linear relationship is established using the observed precipitation data. Specifically, the 99.9th percentile daily precipitation in the future period is obtained by multiplying the observed 99.9th daily precipitation by the provided future percent change in 99.9th daily precipitation. The future 99.9th percentile can be estimated using historical trends for near-future climate scenarios. Previous studies showed that there were clear trends in heavy rains in the past century for various regions (e.g., Groisman et al., 2001; Shahid, 2011; Liu et al., 2015). If the trend is assumed to be unchanged in the coming decades, it may be used to estimate the 99.9th percentile for the near future. The future 99.9th percentile can also be estimated using the relative change between reference and future climates projected with RCMs (Zhang, 2013b), as was done in the distribution-based change factor downscaling method (Mpelasoka and Chiew, 2009). The skewness coefficient for a future period is then obtained using the observed linear relationship and using the ratio of future 99.9th daily precipitation to μ_d as a predictor. The adjustment of skewness is optional in GPCC, as the adjustment is only preliminary.

For a simple approach without the adjustment of skewness coefficients, a two-parameter gamma distribution is provided as the other option to generate daily precipitation amounts. The gamma distribution is widely used for simulating daily precipitation amounts. Its probability density function is given by:

$$f(x) = \frac{(x/\beta)^{\alpha-1}\exp[-x/\beta]}{\beta\Gamma(\alpha)} \tag{13}$$

where α and β are shape and scale parameters of the gamma distribution, respectively, and $\Gamma(\alpha)$ indicates the gamma function evaluated at α. The parameters α and β can be expressed in term of μ_d and σ^2 by equations 14 and 15. Thus, the downscaling still involves adjusting μ_d and σ^2, rather than α and β directly:

$$\mu_d = \alpha\beta \tag{14}$$

$$\sigma^2 = \alpha\beta^2 \quad (15)$$

Downscaling Temperature

Downscaling of temperature involves adjusting two parameters of a normal distribution. Means of spatially downscaled monthly T_{max} and T_{min} are directly used as CLIGEN parameters to disaggregate the spatially downscaled monthly data to daily time series. For adjusting temperature variance, variance ratios of T_{max} (and T_{min}) between spatially downscaled monthly temperatures for the future period and observed monthly values are calculated for each calendar month. Adjusted daily T_{max} (and T_{min}) variances are obtained by multiplying the observed daily temperature variances by the calculated variance ratios for each month.

All adjusted parameters, including P_{11}, P_{01}; means, standard deviations, and skewness coefficients (optional) of daily precipitation; and means and standard deviations of T_{max} and T_{min} for each month, are input into CLIGEN to generate future climate projection for any desirable length of time. In order to obtain the true expectancy of a SWG, long time series (i.e., >100 years) are usually generated. Short time series could result in biases due to the random nature of the stochastic process. To correct or offset weather generation errors, the initially adjusted μ_d for each month is scaled by a factor to match the spatially downscaled mean annual precipitation of the future period. This procedure corrects the weather generation error by making sure that the generated precipitation amount equals the spatially downscaled target amount. CLIGEN is run again using the scaled daily means to generate daily series for the future period.

ADVANTAGES OF GPCC

Compared to other commonly used statistical downscaling approaches, GPCC has the following advantages:

(1) GPCC directly downscales monthly precipitation and temperature projections of GCMs or RCMs in a grid box to daily weather series at a point scale or station. Only monthly climate change projections are required as its inputs. Generally, monthly climate simulations are more reliable and skillful than daily simulations (Maurer and Hidalgo, 2008). The downscaled future climate at a particular location is suitable for simulating the site-specific impacts of climate changes on crop production, soil hydrology, and soil erosion on a farm or in a small watershed.

(2) The method is less time-consuming than other statistical downscaling methods. Unlike other regression-based statistical downscaling methods that need a large number of climate variables for screening predictors, GPCC only needs climate model-simulated precipitation and temperature as predictors. Even though climate variables, along with precipitation and temperature, are available in the public domain for most climate models, including a large number of variables significantly increases the computational burden. Moreover, previous studies (e.g., Widmann et al., 2003; Mullan et al., 2016a) found that statistical precipitation downscaling directly using GCM precipitation as a predictor performed mostly better than regression-based methods using other predictors.

(3) GPCC handles spatial and temporal variations individually in two separate stages. The spatial downscaling specifically takes into account the local climate information, such as rainfall sequence and distribution. In other words, the grid climate change information is specifically linked to the target station using this spatial downscaling method, i.e., quantile mapping. The temporal downscaling involves adjusting CLIGEN parameters. The good performance of CLIGEN has been proven in several studies (e.g., Chen et al., 2008, 2009, 2012b; Yu, 2003; Zhang and Garbrecht, 2003; Zhang, 2004). In particular, skewed normal distributions have been shown to perform better in simulating daily precipitation than other commonly used distributions (e.g., gamma and Weibull distributions), especially for simulating precipitation variances and extremes (Chen and Brissette, 2014a, 2014b). In addition, means and standard deviations of each variable in GPCC are explicitly used in its probability distribution function (skewed normal distribution for precipitation and normal distribution for temperature), and thus incorporating climate model-projected changes in statistical moments into GPCC parameters is straightforward.

(4) GPCC spatially downscales monthly precipitation to a target station using a quantile mapping method. The mapping of the two cumulative distributions of monthly precipitation between the point and grid scales is deemed relatively reliable. By considering the transfer function fitted to the historical period as a reference and applying it to the future period, any shift or climate change signal in the future climate distribution relative to the hindcast distribution is well captured and preserved by the method. Because the cumulative distribution is generally smooth, there is no need to further correct the bias and inflate the variance, as is done in SDSM. In addition, values of monthly precipitation for future periods fall mostly within the range of observed data.

(5) GPCC specifically downscales precipitation occurrence based on relationship between precipitation occurrence and monthly precipitation amounts. This relationship is expected to hold for the future period because two extreme cases (the sorted driest and wettest conditions) of precipitation occurrences versus amounts are included when estimating the relationship. In other words, including the two end points for establishing the linear relationship implicitly incorporates non-stationary climate states for estimating transition probabilities of precipitation occurrence for any climatic conditions within the entire range. These relationships have been verified in several studies by dividing long historical time series into contrasting periods representing either the reference or the future climate that have proven valid for nonstationary climates (e.g., Zhang et al., 2012a; Zhang, 2013a).

(6) Empirical relationships with monthly precipitation amounts are used to estimate probability of rainfall occurrence. An analytical relationship among monthly mean precipitation, probability of rainfall occurrence, and daily mean precipitation is used to estimate a new daily mean amount for the changed climate. A semi-analytical relationship among precipitation occurrence and dependency, daily mean precipitation and variance, and monthly precipitation variance is used to calculate a new daily precipitation variance for the changed climate. The combined use of the empirical

and analytical relationships guarantees that the adjustments of precipitation occurrence and amount are internally consistent, so that the target monthly mean precipitation is preserved. If the precipitation occurrence and amount are adjusted independently, as often done in the literature, the preservation of the target monthly mean is not guaranteed.

(7) GPCC takes into account the change in precipitation extremes by adjusting the skewness coefficient of a skewed normal distribution (Zhang, 2013b). Even though the result is preliminary, it is the first attempt of its kind for the SWG-based approach. This is also one of the reasons for using skewed normal distribution to simulate precipitation in GPCC, as the skewness coefficient can be adjusted directly to account for extreme precipitation events.

(8) GPCC is capable of generating climate change scenarios not only for stationary conditions but also for nonstationary conditions. Different from traditional regression methods that fit linear (e.g., SDSM; Wilby et al., 2002) or nonlinear (e.g., smooth support vector machine; Chen et al., 2012c) relationships between predictors and predictands, GPCC downscales precipitation amounts by adjusting parameters of probability distribution functions. This procedure produces a new distribution for nonstationary future climate conditions, while the regression-based method directly applies the regression equations fitted to past climate to future climate, assuming that the fitted parameters are constant over time. Mullan et al. (2016a) validated the performance of GPCC with respect to generating daily precipitation for nonstationary conditions using ten stations all over the world and compared it with the most widely used SDSM. Although the results showed mixed performance for the two downscaling models, GPCC performed better than SDSM with respect to reproducing wet and dry frequency, which is an important advantage for impact studies, especially crop growth and hydrological simulation.

(9) GPCC is capable of simulating the temporal structure (wet and dry spells distributions) of daily precipitation satisfactorily. The daily precipitation sequence is extremely important for simulating plant growth, soil water dynamics, and surface runoff generation. GPCC uses a first-order Markov chain to simulate daily rainfall sequence, and the conditional transition probabilities are adjusted according to future monthly precipitation amounts for each calendar month (see the model description above). Previous studies using historical non-stationary precipitation data demonstrated that the adjustment method worked well in simulating the precipitation sequence of a changed climate reasonably well (Zhang, 2013a; Zhang et al., 2012a; Mullan et al., 2016a). That is, the distributions of wet and dry spells of a changed climate were well reproduced.

(10) GPCC is scalable and can directly downscale both GCM and RCM outputs. For regions without RCM projections, daily climate change scenarios can be downscaled directly from GCM projections because there are no scale effects for statistically downscaling precipitation with GPCC (Chen et al., 2014b).

(11) GPCC is open-source software, which makes it easy for users to modify the model. In addition, users can circumvent the interface to run programs directly, which is important for meeting users' specific needs, especially for running crop models in batches for multiple locations and scenarios.

Limitations of GPCC

The performance of GPCC in downscaling precipitation and temperature depends on the reliability of the built-in stochastic weather generator and the methods used to adjust its parameters. The weather generator CLIGEN has been used and tested extensively at several locations under various climates in the U.S. (Zhang and Garbrecht, 2003; Zhang, 2004), Australia (Yu, 2003, 2005), China (Kou et al., 2007; Chen et al., 2008, 2009), Korea (Min et al., 2011), and other countries (e.g., Arnold and Elliot, 1996; Caviglione et al., 2013). All these studies found a satisfactory performance of CLIGEN in generating both precipitation and temperature. In particular, CLIGEN performed better than other weather generators, such as WGEN (Richardson, 1981) and CLIMGEN (Stockle et al., 1999), in simulating extreme precipitation events (Chen et al., 2014a, 2014b).

While CLIGEN is good at simulating precipitation and temperature quantity, it slightly underestimates the low-frequency variation (i.e., standard deviation of monthly and annual precipitation). This is a common problem for all stochastic weather generators because they do not consider the low-frequency component of climate variability (Wilks, 1999; Hansen and Mavromatis, 2001; Wang and Nathan, 2007; Chen et al., 2010). Several methods (Hansen and Mavromatis, 2001; Wang and Nathan, 2007; Chen et al., 2010) have been developed to correct the low-frequency variability for precipitation and temperature time series. In these methods, the low-frequency variability of observed data was used as a baseline to correct the generated time series. However, it is not easy to apply these methods for downscaled future time series due to the change of low-frequency variability in changing climates.

Precipitation and temperature are generated independently in CLIGEN. In other words, the inter-variable correlation is not taken into account. This simplification presents advantages in adjusting CLIGEN parameters straightforwardly in downscaling precipitation and temperature, but this is not true in the real world, where precipitation and temperature are correlated to each other. However, these inter-variable correlations can be easily induced using a post-processing approach, such as the distribution-free shuffle proposed by Zhang (2005b) and the copula-based joint distribution approach proposed by Li et al. (2014). This problem will be addressed in the next version of GPCC.

GPCC was developed based on a single-site weather generator. This means that it can only be used to generate climate change scenarios for a single site or for multiple sites with no spatial dependence. For regions or large watersheds, multi-site scenarios are required for studying the spatial variability of climate change impacts. These multi-site climate change scenarios can be generated with two general approaches. First, a multi-site weather generator can be used instead of a single-site method like GPCC. For example, Chen et al. (2017) developed a multi-site precipitation downscaling approach called the Multi-site Weather Generator École de Technologie Supérieure (MulGETS). Second, spatial dependence can be induced using a post-processing method, such as the distribution-free shuffle approach of Li (2013). Because the main goal of this study is to propose a downscaling model for the assessment of crop production and soil erosion at a field scale in a changing climate, only the single-site version is presented.

Design and Implementation of the GPCC Software

GPCC is written in the Matlab language, which has earned a good reputation in the field of engineering for its simplicity of use and the reliability of its built-in functions. The GPCC software reduces the task of spatial-temporal downscaling of precipitation, T_{max}, and T_{min} to five discrete steps: data input, spatial downscaling, temporal downscaling, weather generation, and results analysis (fig. 1). A graphical user interface is provided for all users with or without Matlab programming background, and it can be easily deployed in a computer with or without Matlab software. The interface consists of two pages (welcome page and main page), and the main page consists of five tabs (About, Input, Setting, Run, and Output). Because all methodologies of GPCC have been tested extensively under various climates, only one station (Wuhan station) and one climate model are used to illustrate the implementation of the GPCC software. The Wuhan station includes observed daily precipitation, T_{max}, and T_{min} from 1961 to 2014. Climate model simulations (monthly precipitation, T_{max}, and T_{min}) are derived from a Chinese GCM (BCC-CSM1-1-m) that uses 1971-2000 as the reference period and 2021-2050 as the future period.

The welcome page (fig. 2) presents the software name, author information, and the software version and release date. The user can click Enter to go to the next page or Exit to leave the interface. The user can also leave the interface by clicking the letter E in the top-left corner and can return to this page from any other page or tab by clicking the letter H.

The main page breaks the overall downscaling task down into five parts, which are organized into five tabs. Among these five tabs, the About tab (fig. 3) briefly introduces the main functions of GPCC and its main advantages. The main procedures for running this software and the main references are also listed for users' convenience.

The Input tab (fig. 4) corresponds to the task of data input in figure 1. The basic input data include the observed daily precipitation, T_{max}, and T_{min} for a single site over the historical period, and climate model-simulated monthly precipitation, T_{max}, and T_{min} for both the historical and future periods. If the option of adjusting the skewness coefficient is selected, the multiplicative change factor in the 99.9th percentile of wet-day precipitation is also required as an input. The input files are in free formats and can be prepared in Matlab, Excel, or as ASCII text. All inputs files are loaded on the Input screen. In this example, observed climate, reference hindcasts, and future projections are input for the Wuhan station. The 99.9th percentile is not input. The Input tab also provides functions for viewing and checking the input data. The Check function calculates a set of precipitation, T_{max}, and T_{min} statistics including mean, standard deviation (stdev), range, and maximum (max) and minimum (min) events across the entire time series. For example, the observed maximum daily precipitation was 298.5 mm during the last 54 years (1961-2014) for the Wuhan station, and the temperature ranged between -18.1°C and 32.3°C for T_{min} and between -5.8°C and 39.6°C for T_{max} (fig. 4).

The Setting and Run tabs complete the tasks of spatial downscaling, temporal downscaling, and weather generation in figure 1. Spatial downscaling of precipitation is based on a transfer function method. Transfer functions are fitted for each variable for each calendar month. Two options (skewed normal and gamma distributions) are provided to simulate daily precipitation amounts. GPCC estimates baseline parameters for the selected distribution using statistical moments of observed daily precipitation. T_{max} and T_{min} are downscaled by either a quantile mapping method or a change factor method. Temporal downscaling involves adjusting the CLIGEN baseline parameters. The adjusted parameters include transition probabilities of precipitation occurrence; mean, variance and skewness (optional) of daily precipitation; and T_{max} and T_{min} for each calendar month. Weather generation generates future climate time series by running CLIGEN using the adjusted parameters of daily precipitation and temperature distributions.

The Setting tab (fig. 5) sets a threshold value for precipitation (i.e., determining whether a day is wet or dry; the default value is 0.1 mm) and selects the interpolation and downscaling methods or options. The number of years to be generated for the future period should be entered (the default value is 100 years). In this example, the daily precipitation threshold is set to the default value (0.1 mm). Four points regression and skewed normal distribution are selected to downscale the precipitation occurrence and amounts, respectively. The skewness coefficient is not adjusted, and the change factor method is used to downscale both T_{max} and T_{min}. The number of years to generate is set to the default value (100 years).

The Run tab (fig. 6) calibrates the downscaling model and visualizes the goodness-of-fit of the calibrated downscaling functions. A set of criteria are listed in the left column, and the goodness-of-fit is presented in the right column using graphs and tables. For example, the graph in the right column of figure 6 is a QQ-plot of observed January precipitation versus raw and downscaled BCC-CSM1-1-m simulated January precipitation for the calibration period (1971-2000) at the Wuhan station. The results show that BCC-CSM1-1-m underestimated the January precipitation for the calibration period. However, the probability distribution of observed January precipitation is well reproduced when using the GPCC model, as indicated by the fact that all data points are close to the 1:1 line. This implies that the GPCC model is well calibrated for spatially downscaling January precipitation.

The Output tab (fig. 7) corresponds to the task of results analysis in figure 1. The results analysis involves calculating climate changes in the future period relative to the historical

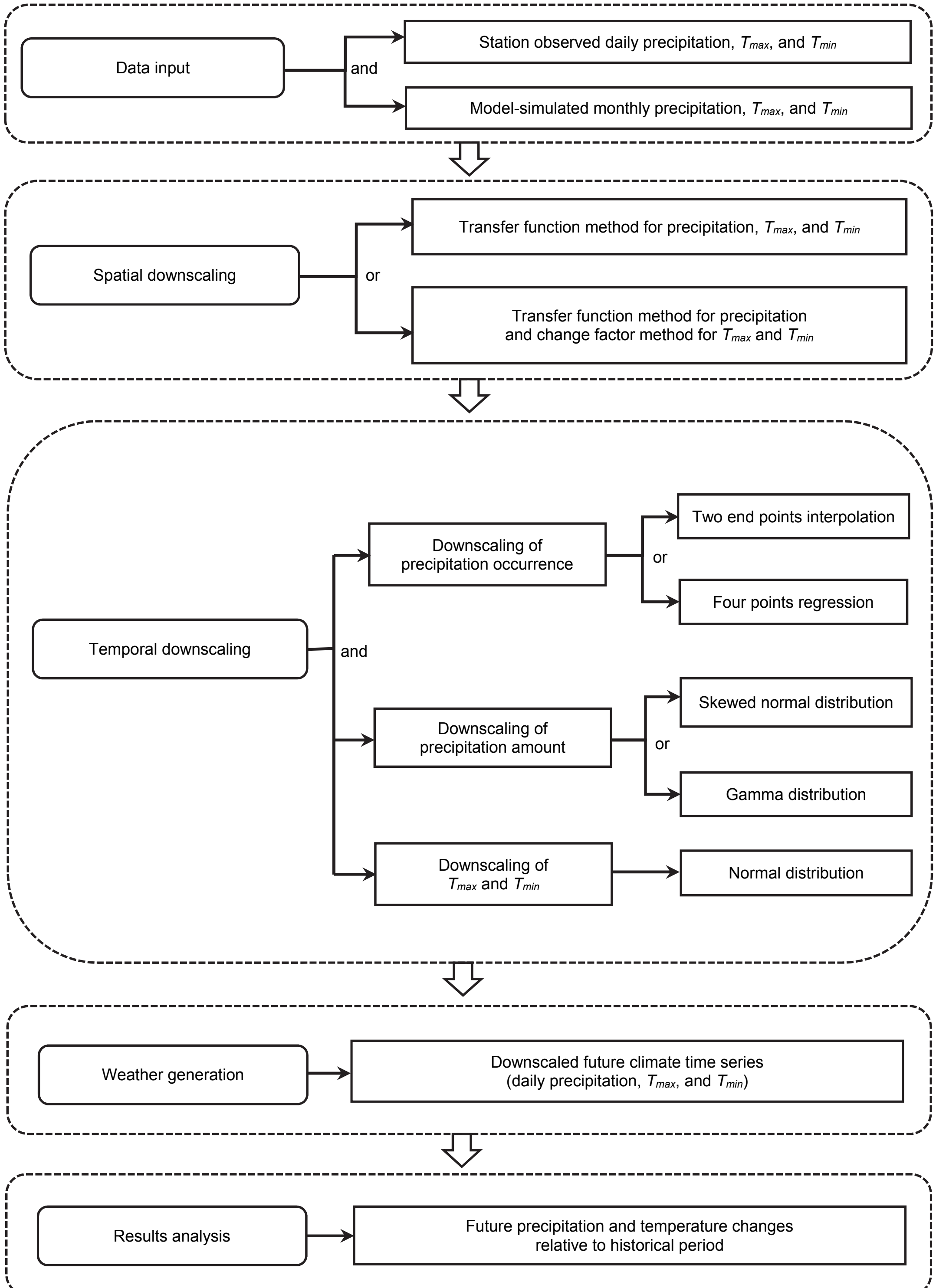


Figure 1. Flowchart and main functions of the Generator for Point Climate Change (GPCC).

period using a set of precipitation and temperature statistics for all parameters at daily, monthly, and annual scales, including changes in wet/dry spell distributions. The output can include two statistics for precipitation occurrence, five statistics for precipitation amounts, and three statistics for temperature. The graphs and corresponding datasets can be saved by clicking the Save Plot & Data button, and the future climate change scenarios can be saved into any specified directory in Excel or text format by clicking the Save Future TS button. For example, by selecting Wet-day frequency, Mean wet-day precipitation, Mean temperature, and Distribution of temperature (as shown in fig. 7), figures 8 and 9 are generated. Figure 8 presents the observed historical

Figure 2. Welcome screen of the GPCC software.

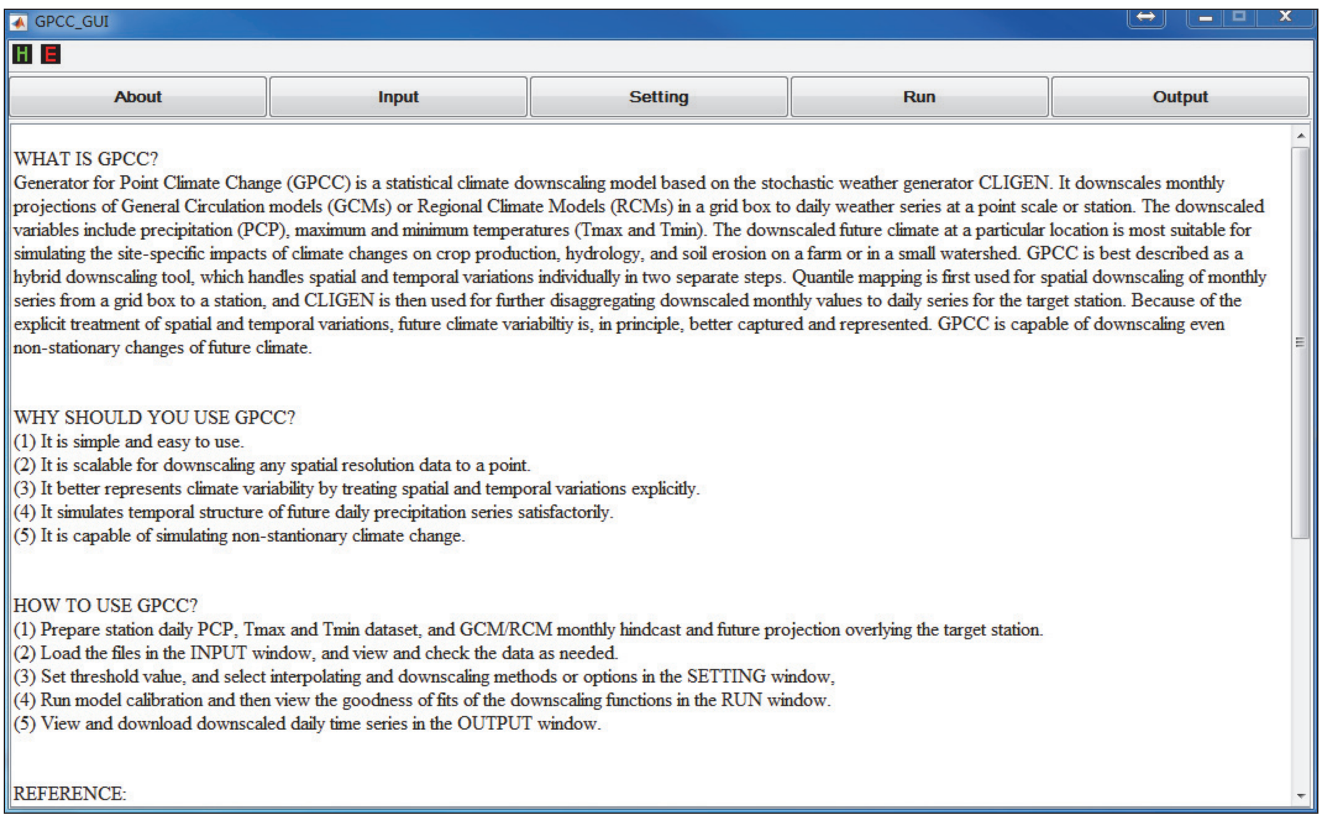


Figure 3. About screen of the GPCC software.

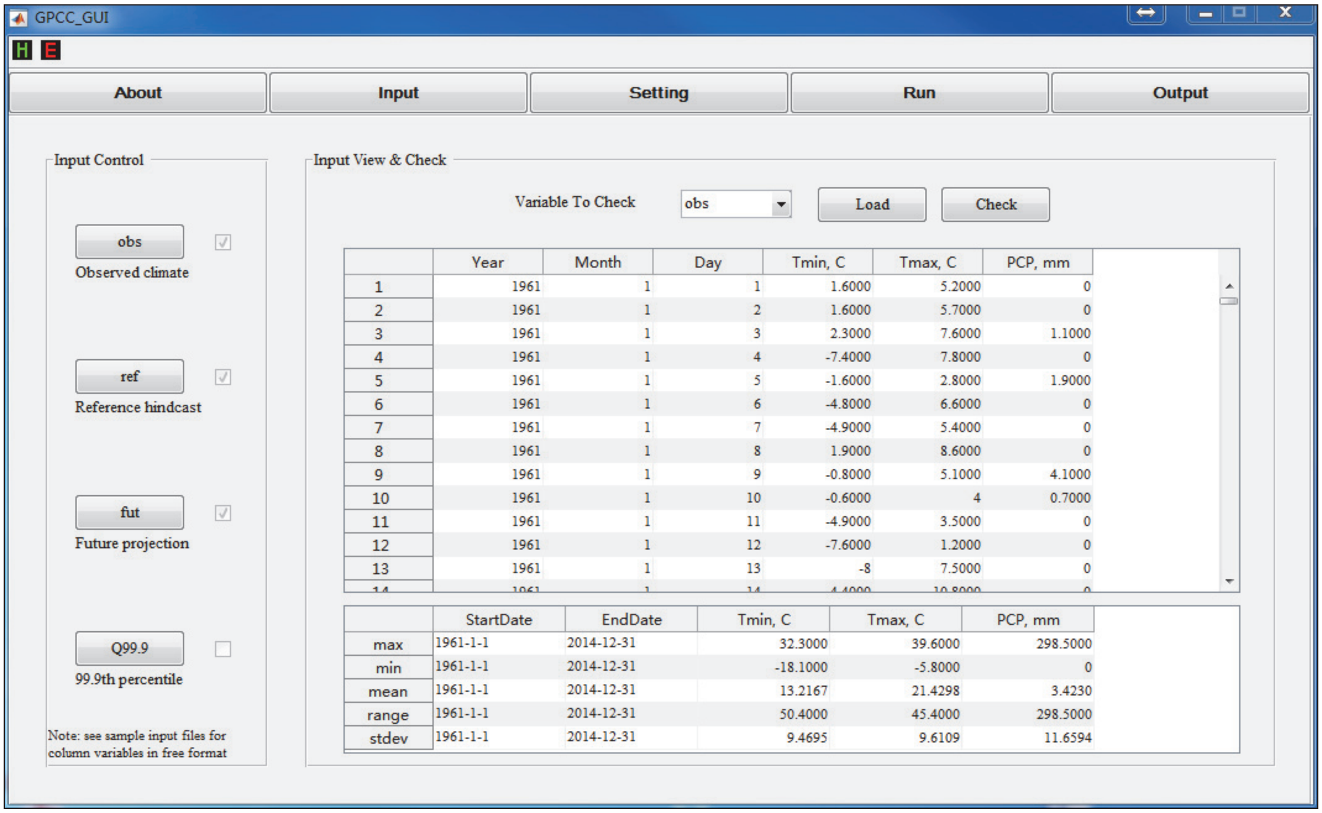


Figure 4. Input screen of the GPCC software.

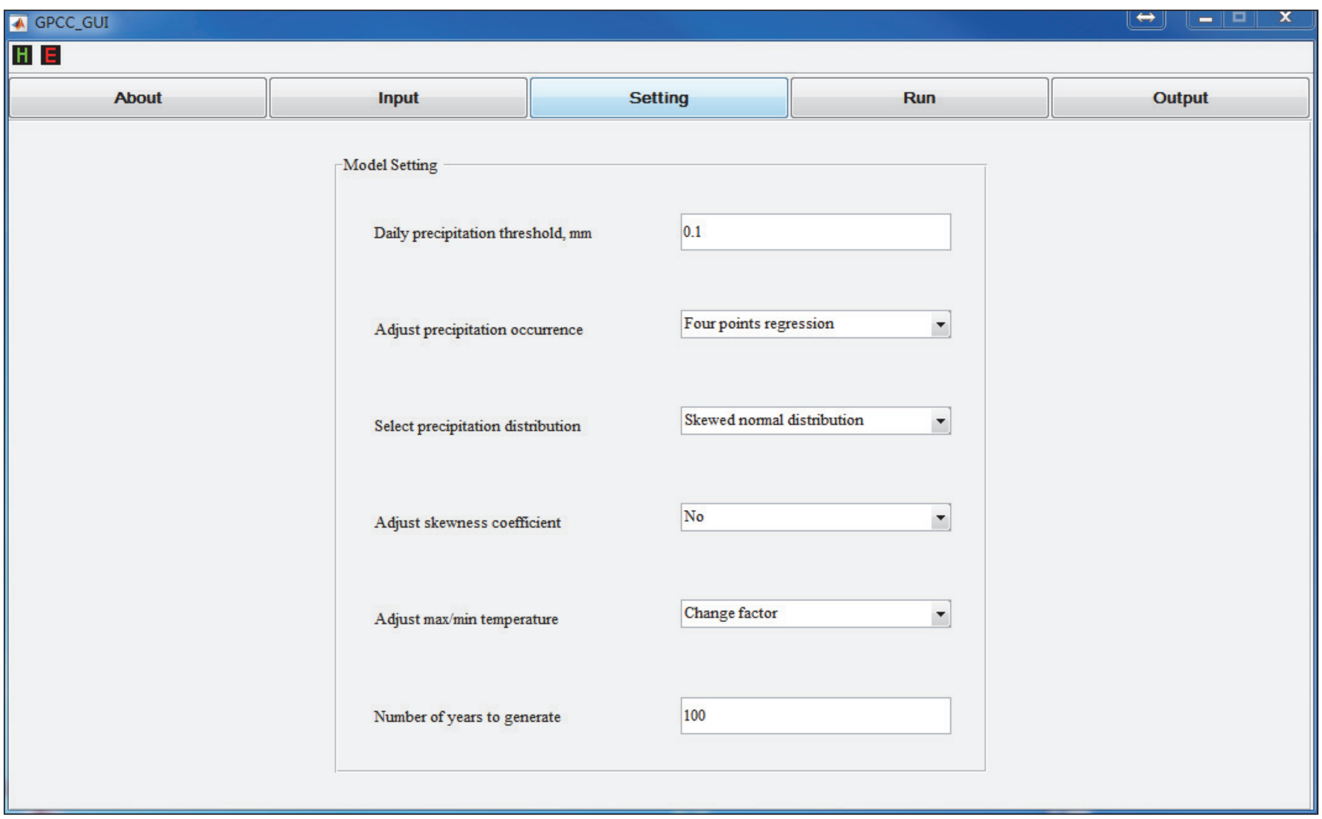


Figure 5. Setting screen of the GPCC software.

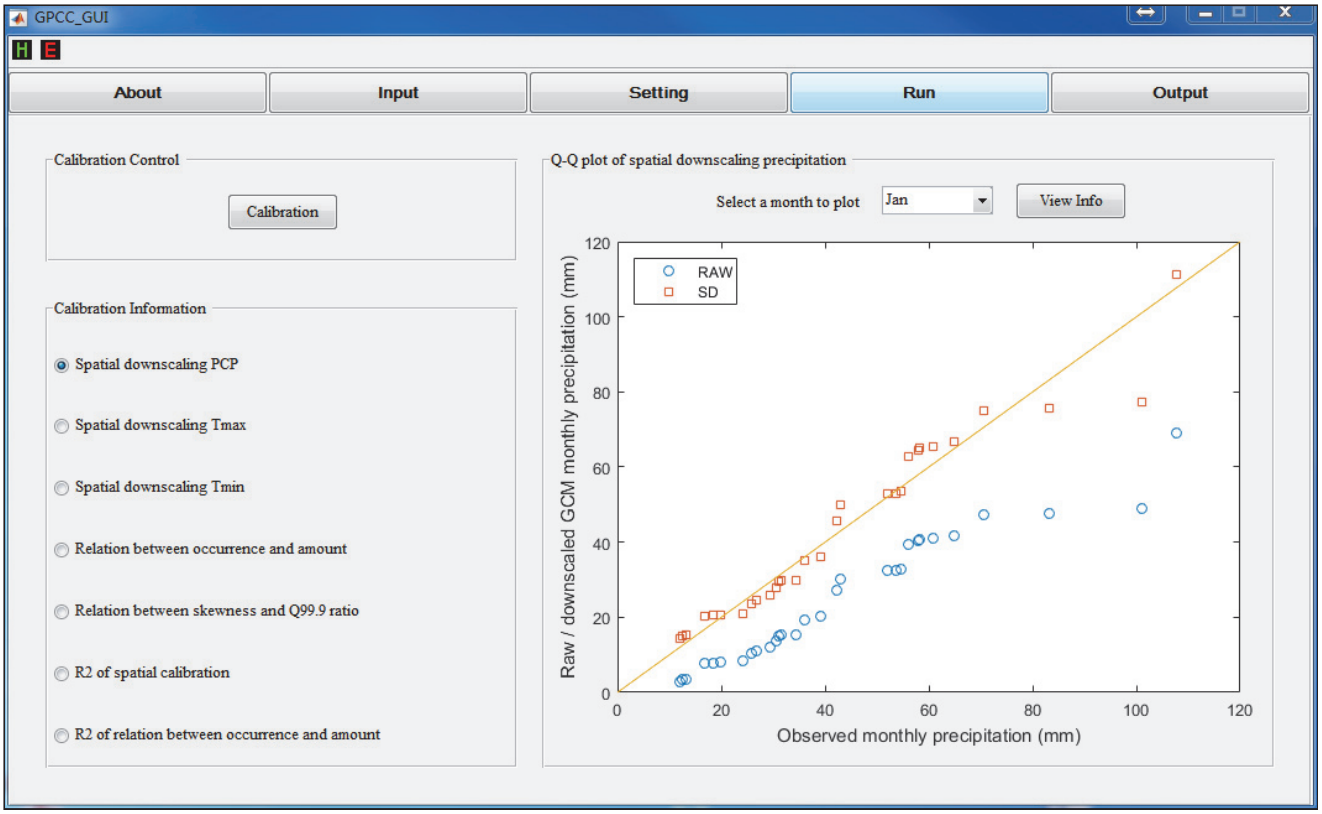


Figure 6. Run screen of the GPCC software.

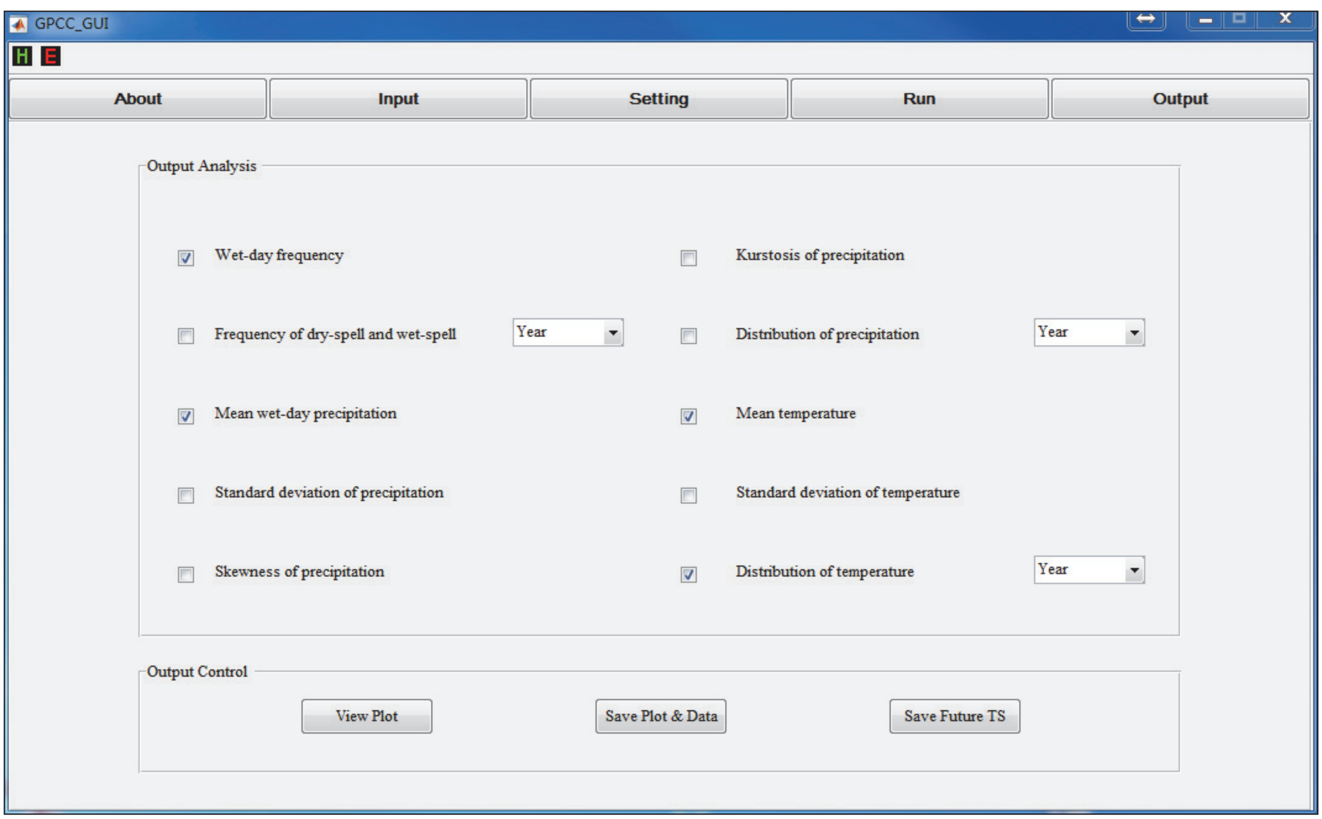
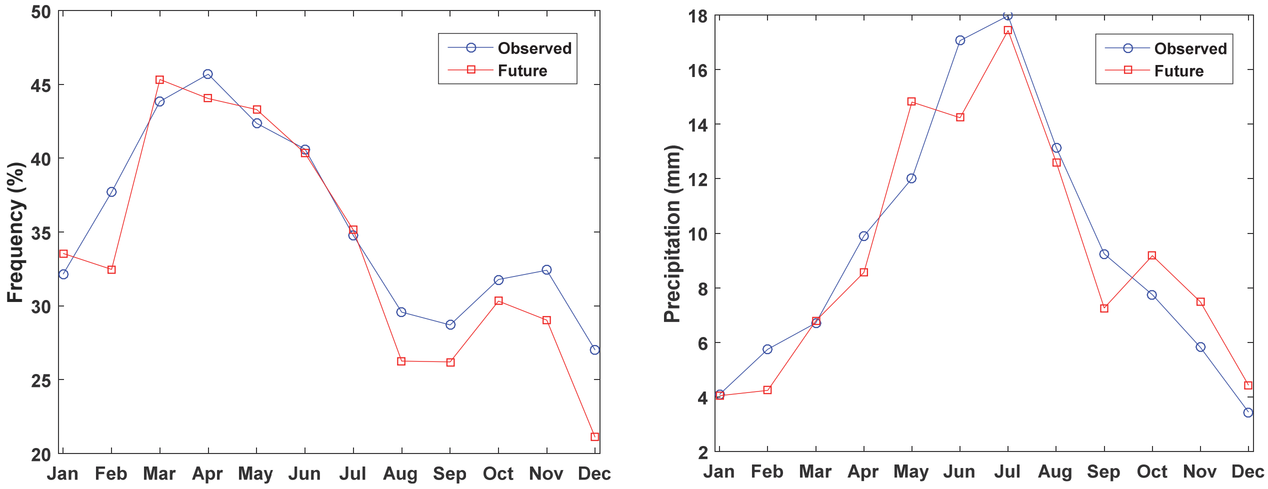
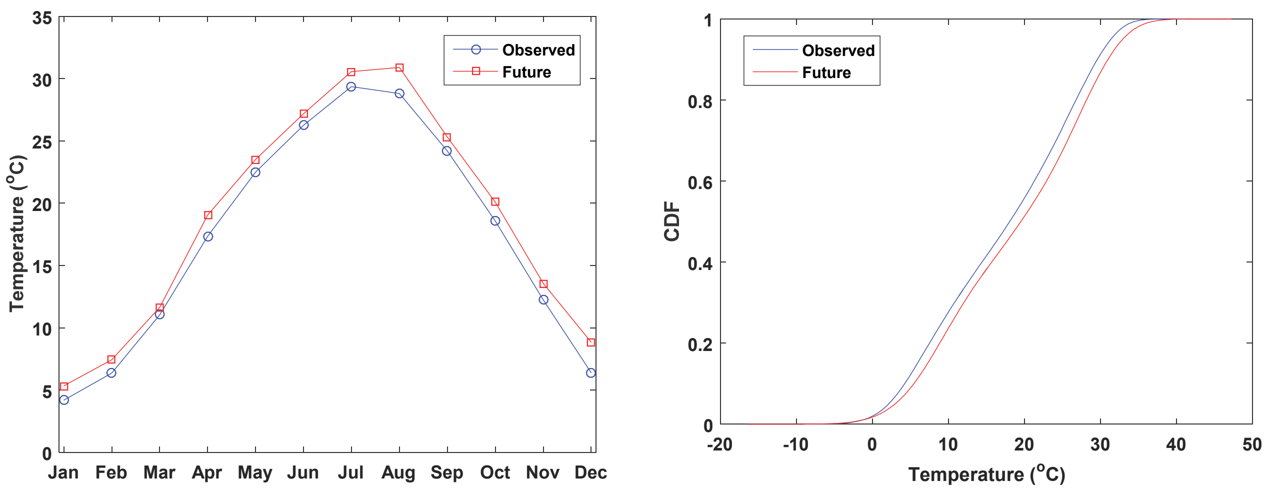


Figure 7. Output screen of the GPCC software.



(a) (b)

Figure 8. Observed historical and projected future (a) wet-day frequency and (b) mean wet-day precipitation for the Wuhan station.



(a) (b)

Figure 9. Observed historical and projected future (a) mean temperature and (b) cumulative distribution function (CDF) of daily temperature for the Wuhan station.

(1971-2000) and projected future (2021-2050) wet-day frequency and mean wet-day precipitation for the Wuhan station. The results show that the wet-day frequency will decrease in the autumn and winter (August to February), with the exception of January for the future period, with only slightly changes for the other months (fig. 8a). The mean wet-day precipitation is projected to increase for four months and to decrease for six months (fig. 8b). For January and March, the mean wet-day precipitation will remain constant in the future period. Figure 9 presents the observed historical and projected future mean temperature and cumulative distribution function of daily temperature for the Wuhan station. The temperature is projected to increase for all months (fig. 9a), and extreme temperature events will be more frequent in the future period (fig. 9b).

SUMMARY

This study standardizes a statistical downscaling approach and presents a new statistical downscaling software program (GPCC) that downscales climate model-simulated monthly precipitation and temperature at grid box scales to daily time series at a station scale. The downscaled future climate at a particular location is suitable for driving environmental and agricultural systems models for assessing climate change impacts on crop production, hydrology, and soil erosion on a farm or in a small watershed. The software can be directly used to provide downscaled climate data at any weather station around the world to support the international collaborative efforts of AgMIP to quantify the impacts of climate change on food production. GPCC separates the downscaling method into two stages. The first stage involves spatially downscaling monthly climate model outputs from a climate model scale to the station scale using a quantile mapping method. The second stage disaggregates the downscaled monthly climate projections at the target station to daily time series using a SWG. The detailed methodology was explained, followed by a brief review of the advantages and limitations of GPCC over other commonly used downscaling methods. The main functions of GPCC consist of data input, spatial downscaling, temporal disaggregation, weather generation, and results analysis. Following the above procedures, a user-friendly graphical user interface was developed for all users with different computational skills. The interface is organized by tasks into five screens: About, Input, Setting, Run, and Output. Each screen and its main functions were described. GPCC was developed in the Matlab language. A command-line version is also provided to facilitate users who are familiar with Matlab programming. The program is flexible and can be readily modified to meet any specific computational need, especially for running crop models in batches for multiple locations and scenarios over multiple time periods.

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References

Arnold, C. D., & Elliot, W. J. (1996). CLIGEN weather generator predictions of seasonal wet and dry spells in Uganda. *Trans. ASAE, 39*(3), 969-972. https://doi.org/10.13031/2013.27583

Caviglione, J. H., Fonseca, I. C., & Tavares Filho, J. (2013). Viability of CLIGEN in the climatic conditions of Parana state, Brazil. *Revista Brasileira de Engenharia Agricola e Ambiental, 17*(6), 655-664. https://doi.org/10.1590/S1415-43662013000600012

Chen, J., Zhang, X. C., Liu, W. Z., & Li, Z. (2008). Assessment and improvement of CLIGEN non-precipitation parameters for the Loess Plateau of China. *Trans. ASABE, 51*(3), 901-913. https://doi.org/10.13031/2013.24529

Chen, H., Zhang, X. C., Liu, W. Z., & Li, Z. (2009). Evaluating and extending CLIGEN precipitation generation for the Loess Plateau of China. *JAWRA, 45*(2), 378-396. https://doi.org/10.1111/j.1752-1688.2008.00296.x

Chen, J., Brissette, F. P., & Leconte, R. (2010). A daily stochastic weather generator for preserving low-frequency of climate variability. *J Hydrol., 388*(3-4), 480-490. https://doi.org/10.1016/j.jhydrol.2010.05.032

Chen, J., Brissette, F. P., & Leconte, R. (2011). Uncertainty of downscaling method in quantifying the impact of climate change on hydrology. *J. Hydrol., 401*(3), 190-202. https://doi.org/10.1016/j.jhydrol.2011.02.020

Chen, J., Brissette, F. P., & Leconte, R. (2012a). Coupling statistical and dynamical methods for spatial downscaling of precipitation. *Climatic Change, 114*(3), 509-526. https://doi.org/10.1007/s10584-012-0452-2

Chen, J., Brissette, F. P., & Leconte, R. (2012b). Downscaling of weather generator parameters to quantify hydrological impacts of climate change. *Climate Res., 51*(3), 185-200. https://doi.org/10.3354/cr01062

Chen, H., Xu, C.-Y., & Guo, S. (2012c). Comparison and evaluation of multiple GCMs, statistical downscaling, and hydrological models in the study of climate change impacts on runoff. *J. Hydrol., 434-435*, 36-45. https://doi.org/10.1016/j.jhydrol.2012.02.040

Chen, H., Brissette, F. P., Chaumont, D., & Braun, M. (2013a). Finding appropriate bias correction methods in downscaling precipitation for hydrologic impact studies over North America. *Water Resour. Res., 49*(7), 4187-4205. https://doi.org/10.1002/wrcr.20331

Chen, J., Brissette, F. P., Chaumont, D., & Braun, M. (2013b). Performance and uncertainty evaluation of empirical downscaling methods in quantifying the climate change impacts on hydrology over two North American river basins. *J. Hydrol., 479*, 200-214. https://doi.org/10.1016/j.jhydrol.2012.11.062

Chen, J., & Brissette, F. P. (2014a). Stochastic generation of daily precipitation amounts: Review and evaluation of different models. *Climate Res., 59*(3), 189-206. https://doi.org/10.3354/cr01214

Chen, J., & Brissette, F. P. (2014b). Comparison of five stochastic weather generators in simulating daily precipitation and temperature for the Loess Plateau of China. *Intl. J. Climatol., 34*(10), 3089-3105. https://doi.org/10.1002/joc.3896

Chen, H., Brissette, F. P., & Leconte, R. (2014a). Assessing regression-based statistical approaches for downscaling precipitation over North America. *Hydrol. Proc., 28*(9), 3482-3504. https://doi.org/10.1002/hyp.9889

Chen, H., Zhang, X. J., & Brissette, F. P. (2014b). Assessing scale effects for statistically downscaling precipitation with GPCC model. *Intl. J. Climatol., 34*(3), 708-727. https://doi.org/10.1002/joc.3717

Chen, J., Brissette, F. P., & Lucas-Picher, P. (2015). Assessing the limits of bias-correcting climate model outputs for climate change impact studies. *J. Geophys. Res. Atmos., 120*(3), 1123-1136. https://doi.org/10.1002/2014JD022635

Chen, J., Chen, H., & Guo, S. (2017). Multi-site precipitation downscaling using a stochastic weather generator. *Climate Dyn., 50*(5), 1975-1992. https://doi.org/10.1007/s00382-017-3731-9

Christensen, J. H., Boberg, F., Christensen, J. H., & Lucas-Picher, P. (2008). On the need for bias correction of regional climate change projections of temperature and precipitation. *Geophys. Res. Lett., 35*(20). https://doi.org/10.1029/2008GL035694

Dibike, Y. B., & Coulibaly, P. (2005). Hydrologic impact of climate change in the Saguenay watershed: Comparison of downscaling methods and hydrologic models. *J. Hydrol., 307*(1), 145-163. https://doi.org/10.1016/j.jhydrol.2004.10.012

Essou, G. R. C., Brissette, F. P., & Lucas-Picher, P. (2017). The use of reanalyses and gridded observations as weather input data for a hydrological model: Comparison of performances of simulated river flows based on the density of weather stations. *J. Hydrometeorol., 18*(2), 497-513. https://doi.org/10.1175/jhm-d-16-0088.1

Essou, G. R. C., Sabarly, F., Lucas-Picher, P., Brissette, F. P., & Poulin, A. (2016). Can precipitation and temperature from meteorological reanalyses be used for hydrological modeling? *J. Hydrometeorol., 17*(7), 1929-1950. https://doi.org/10.1175/jhm-d-15-0138.1

Fowler, H. J., Ekstrom, M., Blenkinsop, S., & Smith, A. P. (2007). Estimating change in extreme European precipitation using a multimodel ensemble. *J. Geophys. Res. Atmos., 112*(D18). https://doi.org/10.1029/2007JD008619

Gleckler, P. J., Taylor, K. E., & Doutriaux, C. (2008). Performance metrics for climate models. *J. Geophys. Res. Atmos., 113*(D6). https://doi.org/10.1029/2007JD008972

Groisman, P. Y., Knight, R. W., & Karl, T. R. (2001). Heavy precipitation and high streamflow in the contiguous United States: Trends in the twentieth century. *Bull. American Meteorol.*

Soc., 82(2), 219-246. https://doi.org/10.1175/1520-0477(2001)082<0219:hpahsi>2.3.co;2

Gunawardhana, L. N., & Kazama, S. (2012). Statistical and numerical analyses of the influence of climate variability on aquifer water levels and groundwater temperatures: The impacts of climate change on aquifer thermal regimes. *Global Planet. Change, 86-87*, 66-78. https://doi.org/10.1016/j.gloplacha.2012.02.006

Hagemann, S., Chen, C., Haerter, J. O., Heinke, J., Gerten, D., & Piani, C. (2011). Impact of a statistical bias correction on the projected hydrological changes obtained from three GCMS and two hydrology models. *J. Hydrometeorol., 12*(4), 556-578. https://doi.org/10.1175/2011jhm1336.1

Hansen, J. W., & Mavromatis, T. (2001). Correcting low-frequency variability bias in stochastic weather generators. *Agric. Forest Meteorol., 109*(4), 297-310. https://doi.org/10.1016/S0168-1923(01)00271-4

Hoomehr, S., Schwartz, J. S., & Yoder, D. C. (2016). Potential changes in rainfall erosivity under GCM climate change scenarios for the southern Appalachian region, USA. *Catena, 136*, 141-151. https://doi.org/10.1016/j.catena.2015.01.012

IPCC. (2013). Summary for policymakers. In Stocker, T. F., Qin, D., Plattner, G.-K., Tignor, M., Allen, S. K., Boschung, J., ... Midgley, P. M. (Eds.), *Climate change 2013: The physical science basis*. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge, UK: Cambridge University Press.

Johnson, F., & Sharma, A. (2009). Measurement of GCM skill in predicting variables relevant for hydroclimatological assessments. *J. Climate, 22*(16), 4373-4382. https://doi.org/10.1175/2009jcli2681.1

Johnson, F., & Sharma, A. (2012). A nesting model for bias correction of variability at multiple time scales in general circulation model precipitation simulations. *Water Resour. Res., 48*(1), W01504. https://doi.org/10.1029/2011WR010464

Johnson, F., Westra, S. P., Sharma, A., & Pitman, A. J. (2011). An assessment of GCM skill in simulating persistence across multiple time scales. *J. Climate, 24*(14), 3609-3623. https://doi.org/10.1175/2011jcli3732.1

Jones, P. G., & Thornton, P. K. (1993). A rainfall generator for agricultural applications in the tropics. *Agric. Forest Meteorol., 63*(1-2), 1-19. https://doi.org/10.1016/0168-1923(93)90019-E

Jones, P. G., & Thornton, P. K. (2000). MarkSim: Software to generate daily weather data for Latin America and Africa. *Agron. J., 92*(3), 445-453. https://doi.org/10.2134/agronj2000.923445x

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. https://doi.org/10.1016/j.jhydrol.2007.09.051

Li, C., Sinha, E., Horton, D. E., Diffenbaugh, N. S., & Michalak, A. M. (2014). Joint bias correction of temperature and precipitation in climate model simulations. *J. Geophys. Res. Atmos., 119*(23), 13,153-13,162. https://doi.org/10.1002/2014JD022514

Li, Z. (2013). A new framework for multi-site weather generator: A two-stage model combining a parametric method with a distribution-free shuffle procedure. *Climate Dyn., 43*(3-4), 657-669. https://doi.org/10.1007/s00382-013-1979-2

Li, Z., Liu, W. Z., Zhang, X. C., & Zheng, F. L. (2009). Impacts of land use change and climate variability on hydrology in an agricultural catchment on the Loess Plateau of China. *J. Hydrol., 377*(1), 35-42. https://doi.org/10.1016/j.jhydrol.2009.08.007

Li, Z., Liu, W. Z., Zhang, X. C., & Zheng, F. L. (2010a). Assessing the site-specific impacts of climate change on hydrology, soil erosion, and crop yields in the Loess Plateau of China. *Climatic Change, 105*(1-2), 223-242.

Li, Z., Liu, W. Z., Zhang, X. C., & Zheng, F. L. (2010b). Assessing and regulating the impacts of climate change on water resources in the Heihe watershed on the Loess Plateau of China. *Sci. China Earth Sci., 53*(5), 710-720. https://doi.org/10.1007/s11430-009-0186-9

Li, Z., Liu, W. Z., Zhang, X. C., & Zheng, F. L. (2010c). Downscaling GCMs output to assess the potential changes of field erosion in the Loess tableland [in Chinese with an English abstract]. *Acta Ecol. Sinica, 30*(19), 5306-5315.

Liu, R., Liu, S. C., Cicerone, R. J., Shiu, C.-J., Li, J., Wang, J., & Zhang, Y. (2015). Trends of extreme precipitation in eastern China and their possible causes. *Adv. Atmos. Sci., 32*(8), 1027-1037. https://doi.org/10.1007/s00376-015-5002-1

Maraun, D. (2013). Bias correction, quantile mapping, and downscaling: Revisiting the inflation issue. *J. Climate, 26*(6), 2137-2143. https://doi.org/10.1175/jcli-d-12-00821.1

Maraun, D., Wetterhall, F., Ireson, A. M., Chandler, R. E., Kendon, E. J., Widmann, M., ... Vrac, M. (2010). Precipitation downscaling under climate change: Recent developments to bridge the gap between dynamical models and the end user. *Rev. Geophys., 48*(3), RG3003. https://doi.org/10.1029/2009RG000314

Maurer, E. P., & Hidalgo, H. G. (2008). Utility of daily vs. monthly large-scale climate data: An intercomparison of two statistical downscaling methods. *Hydrol. Earth Syst. Sci., 12*(2), 551-563. https://doi.org/10.5194/hess-12-551-2008

Maurer, E. P., & Pierce, D. W. (2014). Bias correction can modify climate model-simulated precipitation changes without adverse effect on the ensemble mean. *Hydrol. Earth Syst. Sci., 18*(3), 915-925. https://doi.org/10.5194/hess-18-915-2014

Min, Y.-M., Kryjov, V. N., An, K.-H., Hameed, S. N., Sohn, S.-J., Lee, W.-J., & Oh, J.-H. (2011). Evaluation of the weather generator CLIGEN with daily precipitation characteristics in Korea. *Asia-Pacific J. Atmos. Sci., 47*(3), 255-263. https://doi.org/10.1007/s13143-011-0014-y

Mpelasoka, F. S., & Chiew, F. H. S. (2009). Influence of rainfall scenario construction methods on runoff projections. *J. Hydrometeorol., 10*(5), 1168-1183. https://doi.org/10.1175/2009jhm1045.1

Mullan, D., Chen, J., & Zhang, X. J. (2016a). Validation of non-stationary precipitation series for site-specific impact assessment: Comparison of two statistical downscaling techniques. *Climate Dyn., 46*(3), 967-986. https://doi.org/10.1007/s00382-015-2626-x

Mullan, D., Swindles, G., Patterson, T., Galloway, J., Macumber, A., Falck, H., ... Pisaric, M. (2016b). Climate change and the long-term viability of the world's busiest heavy-haul ice road. *Theor. Appl. Climatol., 129*(3), 1089-1108. https://doi.org/10.1007/s00704-016-1830-x

Mullan, D., Vandaele, K., Boardman, J., Meneely, J., & Crossley, L. H. (2016c). Modelling the effectiveness of grass buffer strips in managing muddy floods under a changing climate. *Geomorphol., 270*, 102-120. https://doi.org/10.1016/j.geomorph.2016.07.012

Murphy, J. (1999). An evaluation of statistical and dynamical techniques for downscaling local climate. *J. Climate, 12*(8), 2256-2284. https://doi.org/10.1175/1520-0442(1999)012<2256:aeosad>2.0.co;2

Nicks, A. D., & Lane, L. J. (1989). Weather generator. In L. J. Lane & M. A. Nearing (Eds.), *USDA Water Erosion Prediction Project: Hillslope profile version* (pp. 2.1-2.22). NSERL Report No. 2. West Lafayette, IN: USDA-ARS National Soil Erosion Research Laboratory.

Nicks, A. D., Lane, L. J., & Gander, G. A. (1995). Weather generator. In D. C. Flanagan & M. A. Nearing (Eds.), *USDA Water Erosion Prediction Project: Hillslope profile and watershed model documentation* (pp. 2.1-2.22). NSERL Report No. 10. West Lafayette, IN: USDA-ARS National Soil Erosion Research Laboratory.

Piani, C., Haerter, J. O., & Coppola, E. (2010). Statistical bias correction for daily precipitation in regional climate models over Europe. *Theor. Appl. Climatol., 99*(1-2), 187-192. https://doi.org/10.1007/s00704-009-0134-9

Qian, B., Gameda, S., de Jong, R., Falloon, P., & Gornall, J. (2010). Comparing scenarios of Canadian daily climate extremes derived using a weather generator. *Climate Res., 41*(2), 131-149. https://doi.org/10.3354/cr00845

Richardson, C. W. (1981). Stochastic simulation of daily precipitation, temperature, and solar radiation. *Water Resour. Res., 17*(1), 182-190. https://doi.org/10.1029/WR017i001p00182

Rosenzweig, C., & Parry, M. L. (1994). Potential impact of climate change on world food supply. *Nature, 367*, 133-138. https://doi.org/10.1038/367133a0

Rosenzweig, C., Jones, J. W., Hatfield, J. L., Ruane, A. C., Boote, K. J., Thorburn, P., ... Winter, J. M. (2013). The Agricultural Model Intercomparison and Improvement Project (AgMIP): Protocols and pilot studies. *Agric. Forest Meteorol., 170*, 166-182. https://doi.org/10.1016/j.agrformet.2012.09.011

Shahid, S. (2011). Trends in extreme rainfall events of Bangladesh. *Theor. Appl. Climatol., 104*(3), 489-499. https://doi.org/10.1007/s00704-010-0363-y

Sharma, D., Gupta, A. D., & Babel, M. S. (2007). Spatial disaggregation of bias-corrected GCM precipitation for improved hydrologic simulation: Ping River basin, Thailand. *Hydrol. Earth Syst. Sci. Disc., 11*(4), 1373-1390. https://doi.org/10.5194/hess-11-1373-2007

Stockle, C. O., Campbell, G. S., & Nelson, R. (1999). ClimGen manual. Pullman, WA: Washington State University, Department of Biological Systems Engineering.

Teutschbein, C., & Seibert, J. (2012). Bias correction of regional climate model simulations for hydrological climate-change impact studies: Review and evaluation of different methods. *J. Hydrol., 456-457*, 12-29. https://doi.org/10.1016/j.jhydrol.2012.05.052

Themeßl, M. J., Gobiet, A., & Heinrich, G. (2012). Empirical-statistical downscaling and error correction of regional climate models and its impact on the climate change signal. *Climatic Change, 112*(2), 449-468. https://doi.org/10.1007/s10584-011-0224-4

Wang, Q. J., & Nathan, R. J. (2007). A method for coupling daily and monthly time scales in stochastic generation of rainfall series. *J. Hydrol., 346*(3-4), 122-130. https://doi.org/10.1016/j.jhydrol.2007.09.003

Widmann, M., Bretherton, C. S., & Salathe Jr., E. P. (2003). Statistical precipitation downscaling over the northwestern United States using numerically simulated precipitation as a predictor. *J. Climate, 16*(5), 799-816. https://doi.org/10.1175/1520-0442(2003)016<0799:spdotn>2.0.co;2

Wilby, R. L., & Wigley, T. M. L. (2000). Precipitation predictors for downscaling: Observed and general circulation model relationships. *Intl. J. Climatol., 20*(6), 641-661. https://doi.org/10.1002/(SICI)1097-0088(200005)20:6<641::AID-JOC501>3.0.CO;2-1

Wilby, R. L., Dawson, C. W., & Barrow, E. M. (2002). SDSM: A decision support tool for the assessment of regional climate change impacts. *Environ. Model. Softw., 17*(2), 145-157. https://doi.org/10.1016/S1364-8152(01)00060-3

Wilks, D. S. (1992). Adapting stochastic weather generation algorithms for climate change studies. *Climatic Change, 22*(1), 67-84. https://doi.org/10.1007/bf00143344

Wilks, D. S. (1999). Interannual variability and extreme-value characteristics of several stochastic daily precipitation models. *Agric. Forest Meteorol., 93*(3), 153-169. https://doi.org/10.1016/S0168-1923(98)00125-7

Xu, C. Y. (1999). From GCMs to river flow: A review of downscaling methods and hydrologic modelling approaches. *Prog. Phys. Geog., 23*(2), 229-249. https://doi.org/10.1177/030913339902300204

Yu, B. (2003). An assessment of uncalibrated CLIGEN in Australia. *Agric. Forest Meteorol., 119*(3), 131-148. https://doi.org/10.1016/S0168-1923(03)00141-2

Yu, B. (2005). Adjustment of CLIGEN parameters to generate precipitation change scenarios in southeastern Australia. *Catena, 61*(2), 196-209. https://doi.org/10.1016/j.catena.2005.03.004

Zhang, X. C. (2004). CLIGEN non-precipitation parameters and their impact on WEPP crop simulation. *Appl. Eng. Agric., 20*(4), 447-454. https://doi.org/10.13031/2013.16491

Zhang, X. C. (2005a). Spatial downscaling of global climate model output for site-specific assessment of crop production and soil erosion. *Agric. Forest Meteorol., 135*(1), 215-229. https://doi.org/10.1016/j.agrformet.2005.11.016

Zhang, X. C. (2005b). Generating correlative storm variables for CLIGEN using a distribution-free approach. *Trans. ASAE, 48*(2), 567-575. https://doi.org/10.13031/2013.18331

Zhang, X. C. (2007). A comparison of explicit and implicit spatial downscaling of GCM output for soil erosion and crop production assessments. *Climatic Change, 84*(3), 337-363. https://doi.org/10.1007/s10584-007-9256-1

Zhang, X. C. (2012). Cropping and tillage systems effects on soil erosion under climate change in Oklahoma. *SSSA J., 76*(5), 1789-1797. https://doi.org/10.2136/sssaj2012.0085

Zhang, X. C. (2013a). Verifying a temporal disaggregation method for generating daily precipitation of potentially non-stationary climate change for site-specific impact assessment. *Intl. J. Climatol., 33*(2), 326-342. https://doi.org/10.1002/joc.3425

Zhang, X. C. (2013b). Adjusting skewness and maximum 0.5 hour intensity in CLIGEN to improve extreme event and sub-daily intensity generation for assessing climate change impacts. *Trans. ASABE, 56*(5), 1703-1713. https://doi.org/10.13031/trans.56.10004

Zhang, X. C., & Garbrecht, J. D. (2003). Evaluation of CLIGEN precipitation parameters and their implication on WEPP runoff and erosion prediction. *Trans. ASAE, 46*(2), 311-320. https://doi.org/10.13031/2013.12982

Zhang, X. C., Liu, W. Z., Li, Z., & Zheng, F. L. (2009). Simulating site-specific impacts of climate change on soil erosion and surface hydrology in southern Loess Plateau of China. *Catena, 79*(3), 237-242. https://doi.org/10.1016/j.catena.2009.01.006

Zhang, X. C., Liu, W. Z., Li, Z., & Chen, J. (2011). Trend and uncertainty analysis of simulated climate change impacts with multiple GCMs and emission scenarios. *Agric. Forest Meteorol., 151*(10), 1297-1304. https://doi.org/10.1016/j.agrformet.2011.05.010

Zhang, X. C., Chen, J., Garbrecht, J. D., & Brissette, F. P. (2012a). Evaluation of a weather generator-based method for statistically downscaling non-stationary climate scenarios for impact assessment at a point scale. *Trans. ASABE, 55*(5), 1745-1756. https://doi.org/10.13031/2013.42366

Zhang, Y., Hernandez, M., Anson, E., Nearing, M. A., Wei, H., Stone, J. J., & Heilman, P. (2012b). Modeling climate change effects on runoff and soil erosion in southeastern Arizona rangelands and implications for mitigation with conservation practices. *J. Soil Water Cons., 67*(5), 390-405. https://doi.org/10.2489/jswc.67.5.390

Zhang, Y. G., Nearing, M. A., Zhang, X. C., Xie, Y., & Wei, H. (2010). Projected rainfall erosivity changes under climate change from multimodel and multiscenario projections in northeast China. *J. Hydrol., 384*(1), 97-106. https://doi.org/10.1016/j.jhydrol.2010.01.013