

A SIMPLE TECHNIQUE FOR OBTAINING FUTURE CLIMATE DATA INPUTS FOR NATURAL RESOURCE MODELS



J. Trotochaud, D. C. Flanagan, B. A. Engel

ABSTRACT. *Those conducting impact studies using natural resource models need to be able to quickly and easily obtain downscaled future climate data from multiple General Circulation Models (GCMs), future scenarios, and timescales for multiple locations. This article describes a method of quickly obtaining future climate data over a wide range of scenarios, GCMs, and timescales from the Intergovernmental Panel on Climate Change AR4 and AR5 model families using the MarkSim DSSAT Weather Generator and a Microsoft Excel VBA Macro, the final result being a properly formatted parameter (.par) file which can be used by CLIGEN (CLimate GENerator) within the Water Erosion Prediction Project (WEPP) model. We developed a fast and simple method to create WEPP climate input files by using software which already exists on most computers that does not require climatological or modeling knowledge to operate. Ultimately, the method was modified to create continuous daily data for use with the Soil and Water Assessment Tool (SWAT) as well. The final product is an automated spreadsheet with a simple user interface which imports, analyzes, and generates climate input files for the WEPP and SWAT models. This article describes the methods, development, and testing of the tool for use with CLIGEN and WEPP model simulations.*

Keywords. *Climate change, Downscaling, GCM, Modeling, SWAT, WEPP.*

With the reality of a changing climate comes the need for scientists, policymakers, and engineers to consider the effects of increasing weather extremes when analyzing, regulating, and designing natural resource conservation systems and strategies. Soil research needs to determine if erosion will increase under projected future climates and whether or not current conservation measures will be effective in the future. The lack of the latter, referred to as impact studies, can partially be explained by two factors: the difficulty of retrieving and downscaling future climate data, and the uncertainty associated with predicting future climates as far as 80 years into the future. With persistent advances in General Circulation Models (GCMs) and ever-expanding climate databases comes a decrease in uncertainty, allowing for the gap between the

detailed science of climate change and the use of future climate data in localized impact studies to close.

To obtain precipitation and temperature projections from GCMs for use in localized impact studies, the combined technique of spatial and temporal downscaling is recommended (Wilby et al., 2004). GCMs produce synoptic-scale data which must be scaled down to avoid leaving out local meteorological, topographical, and circulatory phenomena which exist at the meso- or micro-scale. Downscaling is a quantitative method which involves regressing modeled 20th century synoptic-scale atmospheric trends to observed micro-scale localized weather to determine correlations which are then applied to modeled 21st century synoptic-scale data in the same location to create micro-scale, localized weather. The Intergovernmental Panel on Climate Change (IPCC) is the most widely recognized source for GCM output (<http://www.ipcc.ch>).

Downscaling methods can be broken into several simplified categories based on the mathematical or technological methods they use. Delta-change or change-factor methods are the simplest and involve linearly scaling 21st century GCM outputs based on the absolute or relative difference between micro-scale historical observations and synoptic-scale 20th century GCM output for each variable independently (Zhang et al., 2004; Woznicki et al., 2011; Joh et al., 2011). Transfer function methods operate similar to change-factor methods, in that they scale GCM output variables independently, but use non-linear relationships to scale historical data relative to synoptic-scale GCM output (Zhang, 2005; Sheshukov et al., 2011). More sophisticated statistical methods regress one or more input predictors to

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one or more local variables and scale synoptic-scale 21st century GCM output based on those multi-variable regression models to obtain downscaled data on a much finer scale (Mearns et al., 1999; Wilby et al., 2002). Cutting-edge computer modeling methods such as meso-scale Regional Circulatory Model coupling or artificial neural networks generate high-quality downscaled data, but require computational, financial, and human resources which are prohibitive to most institutions (Kendon et al., 2010).

The chaotic nature of the atmosphere and the uncertainty of any one model to produce realistic results necessitate the use of multiple GCMs under multiple greenhouse gas forcings to conduct a comprehensive impact assessment of climate change (Mearns et al., 2003; Wilby et al., 2004; Chiew et al., 2009, 2010). Issues arise when determining which downscaling method to use, since emulating previous impact studies which have traditionally focused on a single downscaling method, GCM, scenario, and time period limit the scope of results. Creating a spread of possible climates using multiple GCMs and emission scenarios involves an often steep learning curve, and can take substantial resources and time to downscale for even a single location. Additionally, locating raw GCM output and predictor variables has only recently become readily available through the IPCC.

Several combinations of GCMs and future time periods have been used in published research involving the Water Erosion Prediction Project (WEPP; Flanagan et al., 2007; Flanagan et al., 2012), with little to no similarity in the techniques employed by each author. Zhang published a number of papers in which he used several different downscaling techniques for use with WEPP (Zhang et al., 2004; Zhang, 2005; Zhang, 2007; Zhang et al., 2011). Taken as a whole, these papers represent a spread of the most common statistical and transfer function downscaling techniques. In the first three papers, Zhang used native GCM output cells from the Hadley Centre Coupled Model version 3 under various IPCC Special Reports on Emission Scenarios (SRES) and Greenhouse Gas (GGa) emission scenarios from the IPCC 3AR and 4AR for a variety of locations. He then spatially and temporally downscaled the GCM outputs to modify the precipitation and temperature parameters within a CLIGEN (CLimate GENerator; Nicks et al., 1995) input file. These three studies analyzed only a single location using climate data from a single model, possibly due to time and resource constraints. However, the most recent study (Zhang et al., 2011) used multiple GCMs and emission scenarios.

The IPCC acknowledges that impact studies have traditionally been restricted to single locations and climate scenarios, likely due to the resource requirements involved with advanced statistical methods and computer software (Wilby et al., 2004). Several barriers exist for those wishing to obtain downscaled future climate data for impact studies. Time requirements for learning and applying downscaling methods, while absent from the literature, can be daunting for those with limited statistical or programming skills. Statistical downscaling methods, for example, represent a balance between spatial resolution and resource

requirements, but have steep learning curves which require extensive time to produce data for a single location. Time requirements can be compounded in regional or national collaboration projects where climate data inputs must be developed for multiple locations. Additionally, with each new iteration of the IPCC assessment report every few years, new or updated GCMs and emission scenarios are released, and regression equations or transfer functions must be updated to downscale the GCM output. For regions outside of the United States, and in developing countries in particular, it may be difficult to obtain observed weather data required for validating the accuracy of the chosen downscaling method to reproduce historical climate, a key requirement for assessing the usefulness of any future climate impact analysis. A rapid method of obtaining downscaled future climate data using models which are already globally validated to observed datasets would therefore greatly expand the availability of such data to scientists and policy planners wishing to conduct future climate impact analyses.

The objective of this study was to develop a rapid and simple method for creating future climate inputs for the WEPP model. WEPP is a continuous simulation, physically-based model which uses process-based equations to predict runoff, soil erosion, water balance, and crop yield with input from four parameter files: slope topography, crop/land management, soil, and climate. Climate input to WEPP is normally simulated using the CLIGEN stochastic weather generator (Nicks et al., 1995), which requires monthly means of daily weather for various temperature and precipitation statistics stored in a parameter file. The goal of this project was to devise a method of creating CLIGEN parameter files which takes less than 15 min and has a minimal learning curve. The purpose of this article is to describe the tool developed and the procedure to use it together with CLIGEN and WEPP model simulations. We also present results of example applications. The MarkSim Decision Support System for Agrotechnology Transfer (DSSAT) Weather Generator was used to downscale climate data from various GCMs under three SRES scenarios for multiple future time periods.

MATERIALS AND METHODS

MarkSim is a weather simulator based on a third-order Markov Chain process which predicts the occurrence of a rain day (Jones and Thornton, 1993; 1997; 1999; 2000) and as a result of its continuous development over the past 20 years, is now a globally valid model. MarkSim has been calibrated to the WorldClim dataset which incorporates historical weather data from a number of databases including the National Oceanic and Atmospheric Administration's (NOAA) National Climate Data Center (NCDC) Global Historical Climatology Network (GHCN), which uses stochastic downscaling and climate typing to downscale future climate projections for the IPCC GCM model families (Hijmans et al., 2005; Jones and Thornton, 2013). The DSSAT weather file generator was developed for use with the DSSAT crop model, but can also be used

to produce rainfall, temperature, and solar radiation information for other model applications. MarkSim has been applied globally (Bharati et al., 2014; De Trincheria et al., 2015; Rao et al., 2015); however, limited information exists in the peer-reviewed literature regarding testing and validation of the tool. Some evaluation articles (Mavromatis and Hansen, 2001; Mzirai et al., 2005; Kahimba et al., 2009) indicate that MarkSim can perform acceptably, but for some locations does not do well at reproducing inter-annual variability and may not always perform as well as other weather generators at specific locations. The noted advantages of MarkSim include minimal input requirements and global database applicability.

In addition to the standalone DSSAT weather generator, an easy-to-use online web application (<http://gisweb.ciat.cgiar.org/MarkSimGCM/>) has also been released to retrieve MarkSim model output (fig. 1) for the 4th IPCC assessment report (IPCC, 2007). The web application downscales future climate data from six GCMs using three SRES scenarios from the IPCC 4AR (IPCC, 2007). An ensemble average of the six GCMs is also available. The data generated are representative of a climate that could be expected within a 10-year time slice. The user can also specify a number of replications to produce, each containing continuous daily series for precipitation, minimum temperature, maximum temperature, and solar radiation.

The MarkSim DSSAT weather file generator web application was used to acquire downscaled future climate data on a daily time step. A Microsoft Excel VBA macro (fig. 2) specifically designed as a user interface was then used to produce and write a CLIGEN parameter file based on the future climate data. CLIGEN is a stochastic weather

generator which generates daily weather variables for a single location using summary statistics for precipitation, temperature, solar radiation, and wind patterns derived from historical observations (Nicks et al., 1995). Initially, 40 replicates representing 40 years of daily future weather were generated, based on the observation that existing CLIGEN .par files were typically generated from around 40 year periods of record. The replicates are downloaded from the web application as 40 individual text files formatted for use in the DSSAT model; aggregation is needed to format the data for use with CLIGEN.

The Microsoft Excel VBA macro automated importing, analyzing, aggregating, calculating the necessary statistics, and writing the CLIGEN .par file, a process which undertaken manually takes several hours. The function of this macro is similar to adding a climate station in the WEPP Windows interface, with the added benefit of being able to visualize the data, compare the new data with other CLIGEN .par files, and make changes to the data before creating a new .par file. Microsoft Excel was chosen for several reasons, the most immediate being its availability on most computers. Additionally, we found no compatibility issues after testing on three computers with different Excel releases and Windows operating systems, which we credit to file reverse-compatibility and VBA persistence over multiple releases of Excel.

CALCULATED VALUES

For non-precipitation variables, the CLIGEN parameter file (.par file) requires mean and standard deviations for minimum temperature, maximum temperature, and solar radiation variables. Monthly standard deviations and means for daily temperature and solar radiation were determined

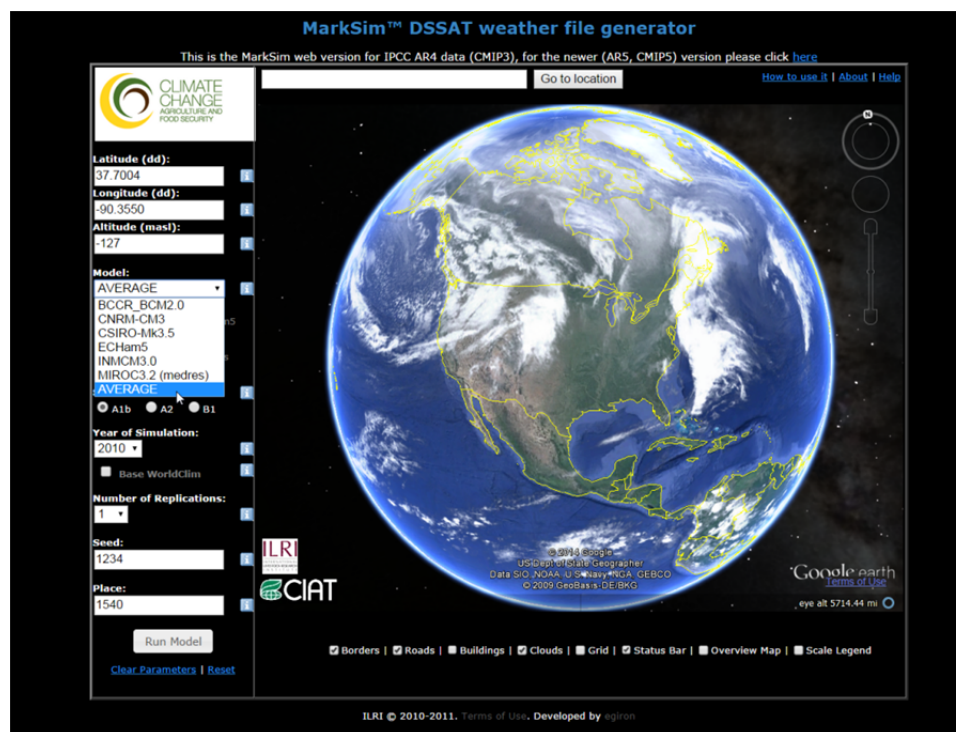


Figure 1. Screen captured image of the MarkSim DSSAT weather generator for the IPCC 4th Assessment Report, available online at <http://gisweb.ciat.cgiar.org/MarkSimGCM/>.

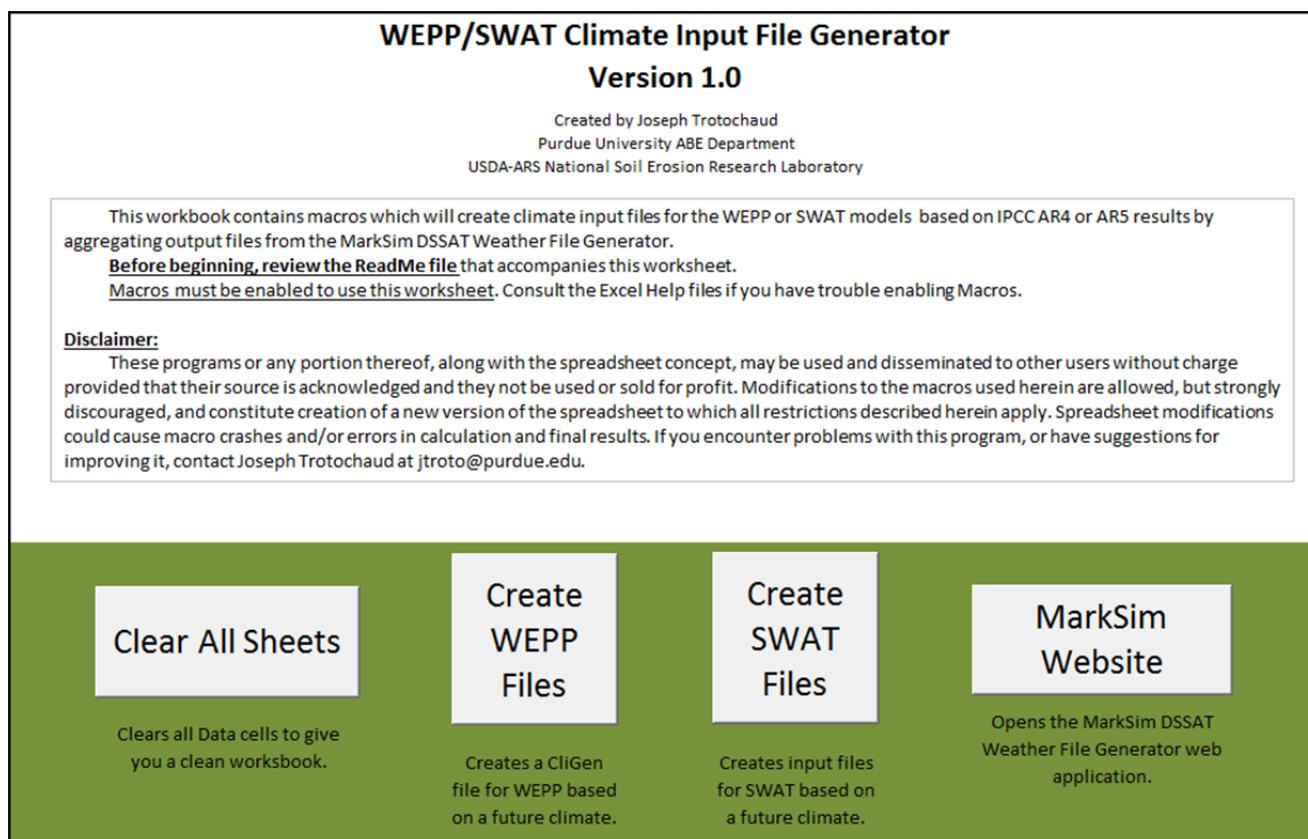


Figure 2. Screen captured image of the main screen of the Excel VBA Macro described in this article.

using conventional methods in which all days of the month were aggregated. Precipitation statistics were calculated based only on those days in which precipitation occurred. Additional probability variables required by CLIGEN include the probability of a wet day following a wet day ($P(W/W)$), probability of a wet day following a dry day ($P(W/D)$), and a skew coefficient for the distribution of the precipitation data.

Mean daily dew point temperature for future climates ($\bar{T}_{DPfuture}$) was determined using the delta change method based on the historical and future mean temperatures, as direct prediction and calculation of this variable are not possible using the MarkSim output. The following equation was used:

$$\bar{T}_{DPfuture} = (\bar{T}_{future} - \bar{T}_{hist}) + \bar{T}_{DPHist}$$

where \bar{T}_{future} is the mean daily projected future temperature, \bar{T}_{hist} is the mean daily historical temperature for the location, and \bar{T}_{DPHist} is the historical mean daily dew point temperature.

ASSUMED VALUES

CLIGEN uses several variables which relate to storm intensity distribution curves that require sub-daily or sub-hourly future climate data to calculate. Most GCMs report climate variables on daily time steps, and most do not forecast precipitation directly but regress precipitation based on other atmospheric variables. This makes it difficult to forecast daily rainfall with any confidence, more

so at the sub-daily level required for peak intensity hyetographs. Nearing et al. (1990) found in a detailed sensitivity analysis of WEPP that the peak rainfall intensities and time to peak rainfall intensities did not play a significant role in soil loss prediction. Therefore, based on the lack of downscaled sub-daily data, historical values for variables related to intensity were assumed for the future climate. The macro extracts these values from a user-specified historical CLIGEN .par file from the WEPP database.

Over half of the text in a CLIGEN .par file provides information on surface wind direction and speed (table 1). Synoptic-scale wind patterns at higher altitudes are modeled within GCMs, but the turbulence associated with near-surface wind patterns is not, forcing historical near-surface wind patterns to be assumed for the future climates, also from the historical CLIGEN.par file.

VALIDATION

MarkSim downscales future data by calibrating 20th century output from the GCMs to match the WorldClim data through Markov Chain regression (Jones and Thornton, 2013). The regression equations developed are then applied to 21st century output from GCMs to create downscaled future climate data. For the United States, the WorldClim dataset primarily utilized NCDC data, so the 20th century calibration data from MarkSim should closely match the historical CLIGEN files which were derived from National Weather Service (NWS) data. The option to download the calibrated MarkSim 20th century climate for

Table 1. Summary of parameter data sources for modified CLIGEN .par file inputs.

Parameter description	CLIGEN Variable	Line in .par File	Source		
			Historical .par File	MarkSim Output	From Macro
Max 6 h and 30 min precip. depth	TP5/6	3	X		
Mean precip. for a wet day	MEAN P	4		X	
Standard deviation of daily precip.	S DEV P	5			X
Skewness coeff. of daily precip.	SKEW P	6			X
Prob. of wet day after a wet day	P(W/W)	7			X
Prob. of wet day after a dry day	P(W/D)	8			X
Mean daily max. air temperature	TMAX AV	9		X	
Mean daily min. air temperature	TMIN AV	10		X	
Standard deviation of TMAX AV	SD TMAX	11			X
Standard deviation of TMIN AV	SD TMIN	12			X
Mean daily solar radiation	SOL.RAD	13		X	
Standard deviation of SOL.RAD	SD SOL	14			X
Mean max. 30 min precip. Intensity	MX.5P	15	X		
Mean daily dew point temperature	DEW PT	16			X
Time to peak rainfall intensity	Time Pk	17	X		
Wind direction and speed values	WIND	18-82	X		

1961-1990 (herein referred to as the MarkSim baseline) exists. To determine if the MarkSim baseline climate matched well with the historical .par file from the WEPP directory created from NWS data (herein referred to as the WEPP baseline), the macro was written to include a graphical and tabular comparison of the .par file created from the MarkSim baseline and the WEPP baseline for all calculated variables.

Climate data were compared for 12 locations in the contiguous United States (table 2). These were chosen based on their spatial separation, different climatic regimes, unique agricultural conditions, and availability of a WEPP baseline for that site. Comparisons were also conducted by conducting WEPP version 2012.8 model simulations under both baseline climates as well as for three future time periods forecast by MarkSim under the IPCC SRES A1b storyline (IPCC, 2007). WEPP runs were conducted for four sites representing one good (WI), two acceptable (CO, IN), and one poor (GA) fits according to correlations between MarkSim baselines with WEPP baselines as described in the previous paragraph. CLIGEN version 5.3 was used with the Fourier interpolation scheme to simulate 100 years of weather. A USLE Unit Slope, 22.1 m long at 9% uniform grade, was used throughout, with soils specific to each region as determined by USDA Natural Resources Conservation Service (NRCS) soil surveys. Tilled fallow field conditions were used throughout. WEPP 100-year model simulations were run for each climate, with annual means analyzed for percent change from the WEPP baseline and MarkSim baseline.

RESULTS AND DISCUSSION

Validation comparisons for each of the 12 sites were conducted using Q-Q plots to indicate how well the MarkSim baseline reproduced a particular variable compared to the WEPP baseline. The MarkSim baseline showed a mix of good and poor fits, with temperature expectedly showing a better fit than precipitation as indicated by both Q-Q plots and R^2 values (fig. 3). Mean precipitation showed mixed results, with stations in the southern and southeastern United States showing the poorest, most scattered Q-Q plots. All other regions' mean

precipitation correlations were better with R^2 greater than 0.47. Mean precipitation correlations were best in Wisconsin (WI) and California (CA) with $R^2 > 0.80$, although the MarkSim baseline under-predicted the precipitation mean and standard deviation for the CA site. Precipitation standard deviations were also mixed, with an average R^2 of 0.43, and only five sites had $R^2 \geq 0.50$. Precipitation skew coefficient fits were poor for all sites and had scattered Q-Q plots, as was also evidenced by low correlation across sites. R^2 values for the 12 sites' precipitation variables are shown in table 2.

Initially, low means and skew coefficients for precipitation were observed from the MarkSim baseline. Upon removal of days in which precipitation was below 1.0 mm, the standard deviations and skew coefficients had much better fits to the observed data. Errors in the historical CLIGEN .par files were ruled out by reanalysis of historical data from the NCDC. The scattered nature of the Q-Q plots for precipitation skew could not be explained. Probability values for P(W/W) were generally poor and showed non-linear correlation for most sites. P(W/D) showed a better fit than P(W/W) as was evidenced by higher R^2 values for all but one site. NCDC reanalysis was also conducted to create historical CLIGEN .par files which had identical periods of record to the MarkSim Baseline (1961-1990), but showed R^2 and Q-Q plots similar to the WEPP Baseline. This ruled out differences in the periods of record as an explanation for the poor correlations.

Q-Q plots for the four representative sites used in WEPP simulations are shown in figure 3. Wisconsin (WI) showed the best overall fit, with R^2 values over 0.80 for all but the skew variable. Tifton, Georgia (GA) was the worst, with 4 out of 5 precipitation variables having $R^2 < 0.04$. These four sites were further analyzed to determine if changes in the number of years replicated by MarkSim had any effect on correlation to historical data. All metrics had lower R^2 values for sample sizes less than 45. For sample size over 50, R^2 increased for precipitation mean and variance, but decreased for the probability and skew values. Therefore, while the macro allows the user to download and generate a future .par file based on 1-99 replications, a sample size of 50 is recommended.

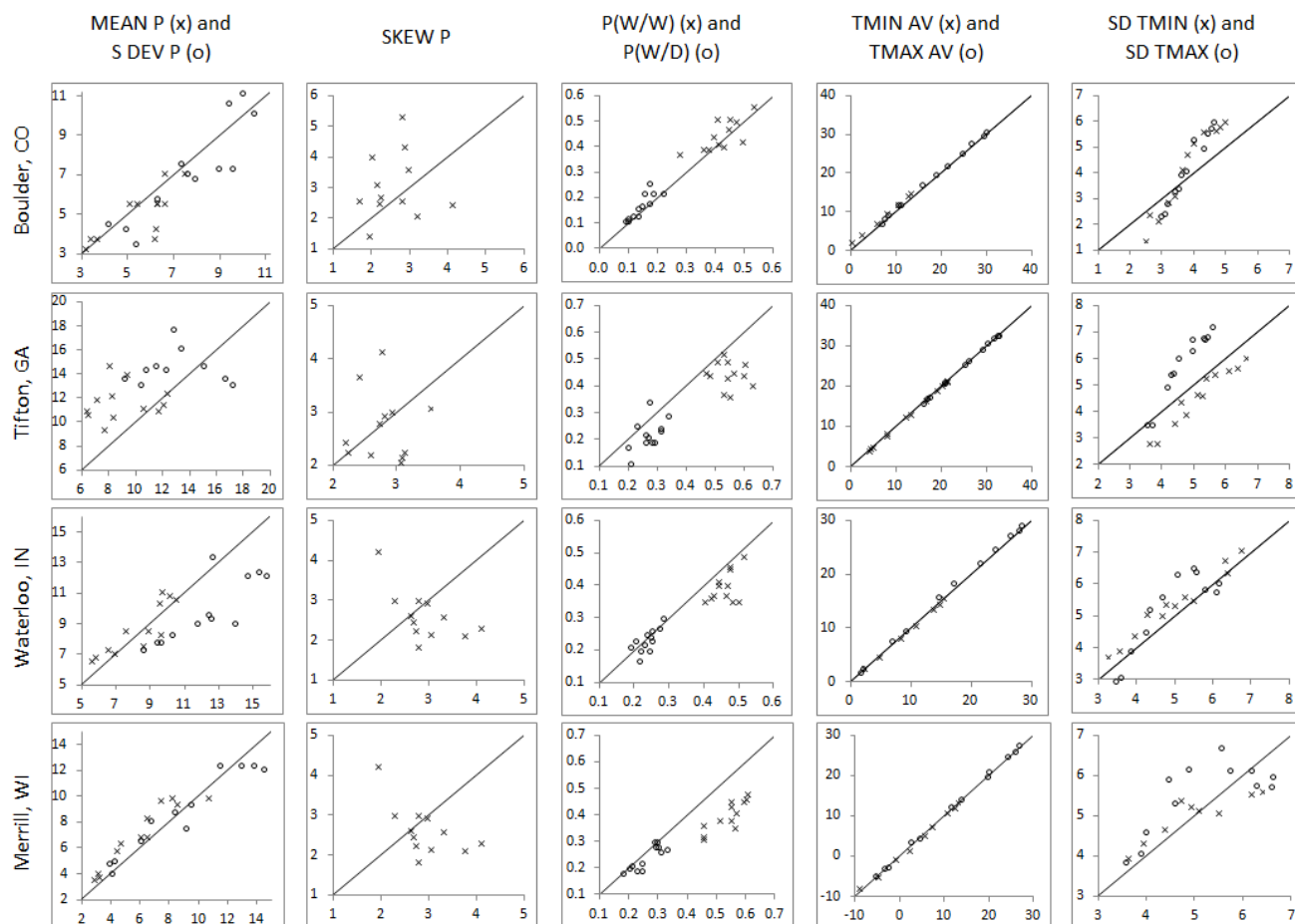


Figure 3. Selected Q-Q plots for MarkSim Baseline (horizontal axis) comparison to WEPP Baseline (vertical axis) 20th century files. Units for precipitation in mm, temperature in Celsius. 1:1 line shown as solid black on each plot. For variable names, refer to table 1.

WEPP erosion model outputs for hydrology and sediment loss were analyzed for each site under five climates: the WEPP Baseline, the MarkSim Baseline, and MarkSim forecasts for three future climates in 2050, 2070, and 2090. Hydrology was analyzed for total precipitation, total number of precipitation events, total number of runoff events, and the proportion of runoff events to precipitation events (table 3). The proportion of runoff events to precipitation events gives an indication of whether the number of storms capable of producing runoff will change compared to the baseline climate. Comparison shows that total precipitation differences between MarkSim baseline

and WEPP baseline were low, while changes in the average annual number of precipitation events, number of runoff events, and proportion of precipitation versus runoff events were much greater. The MarkSim baseline simulations show less precipitation events at the Boulder, CO site due to MarkSim underpredicting the P(W/W) and P(W/D) for some months. Alternately, the MarkSim baseline shows greater precipitation and runoff events for the other three locations due to an overprediction of P(W/W) to a much greater degree. The paradoxical increase in runoff events for the Boulder, CO site can be explained by the overprediction of summer rain-day depths, with most of the

Table 2. Coefficients of determination for regression comparisons of precipitation variables for MarkSim and WEPP baseline climates.

Site	Mean Daily Precipitation R^2	S.D. of Daily Precipitation R^2	Skew of Daily Precipitation R^2	P(W/W) R^2	P(W/D) R^2
San Bernardino, Calif.	0.80	0.49	0.01	0.65	0.87
Boulder, Colo.	0.57	0.80	0.01	0.52	0.76
Clermont, Fla.	0.47	0.23	0.04	0.48	0.55
Tifton, Ga.	0.02	0.01	0.00	0.03	0.30
Waterloo, Ind.	0.77	0.67	0.37	0.25	0.56
Springfield, Mo.	0.48	0.27	0.00	0.00	0.25
Greenville, N.C.	0.23	0.04	0.00	0.00	0.18
Bismarck, N.D.	0.60	0.44	0.00	0.00	0.50
Albany, N.Y.	0.71	0.67	0.00	0.31	0.38
Portland, Ore.	0.64	0.48	0.10	0.87	0.74
El Paso, Tex.	0.48	0.19	0.05	0.22	0.87
Merrill, Wis.	0.89	0.93	0.01	0.71	0.75

rain historically occurring during the summer months for that location. While the results of the hydrology values alone give an idea of the general climatic changes between potential climate scenarios, runoff and sediment results show the implications of these changes.

In general, each site examined showed substantial variation between the two baseline climates while showing more obvious trends when comparing the MarkSim baseline to the three future periods (table 3). Even at the site with the highest level of correlation between the MarkSim baseline and the WEPP baseline climates (WI), the runoff and sediment loss results were different enough to question absolute evaluation of sediment loss when comparing the WEPP baseline with the three future periods. As such, it is recommended that the future climate inputs created by the macro be used to compare only *relative* changes in runoff, sediment loss, and precipitation due to climate change. In that case, one would compare the MarkSim baseline to the three future periods, and avoid using the WEPP baseline climate when conducting impact studies.

Precipitation and runoff trends simulated by WEPP for the four representative locations (fig. 4) showed variations among sites which indicated that future climate impacts will be regional in nature. In the already arid region around Boulder, CO, precipitation decreases further, while an increase in total precipitation was observed for the Midwestern climates of IN and WI. While WI showed an increase in precipitation and runoff by 2090 (table 2, fig. 4), the sediment yield increased by a much greater percentage (table 4), implying that the frequency of intense, erosion-inducing storms will increase for this region. Unlike WI, GA shows a more direct correlation between

rainfall, runoff, and erosion where all three variables decrease slightly with time. For the Waterloo, IN location, runoff frequency was predicted to increase by 23% to 51%, compared to an 8 to 31% increase in precipitation event frequency, implying that the frequency of runoff-inducing storms will increase. Unlike the other three locations, the Boulder, CO location had a predicted decrease in all precipitation, runoff, and soil loss variables. A common theme at all four sites was a decrease in the number of snowmelt events and runoff depth from snowmelt. This is likely due to the increase in temperature at all four sites of almost 4°C, as shown in figure 5. It is possible that the increase in runoff from rain at the IN site from 2000 to 2050 is due to less snowfall/snowmelt and more rainfall/runoff, although the same trend is not seen in the two later periods. Determining the replacement of one type of runoff with another would require additional analysis which is beyond the scope of this paper, so it may be more beneficial to compare total precipitation and the number of runoff events to simulated erosion to gain a better understanding of the frequency of erosion-inducing events (table 4).

Table 4 highlights the predicted changes in runoff, interrill detachment, and total detachment (soil loss) over the next century. Total runoff (from both rain and snowmelt events) was predicted to decrease between 5% and 19% at the Waterloo, IN location. Interrill and total detachment changes, however, were mixed, ranging from decreases in 2070 of 4.5% to 3.1%, respectively, to increases of up to 10% in 2050. Impacts of predicted climate changes in Merrill, WI were much more pronounced, with average annual runoff increases of up to 35% and average annual soil losses increasing between 33% and 54%. For both of

Table 3. Average annual precipitation and runoff results from WEPP v2012.8, using CLIGEN v5.3 generated weather inputs.

Climate ^[a]	Precipitation		Precipitation Events		Runoff Events		Precip as Runoff ^[b]	
	Depth (mm)	Change from WEPP (%)	No. Storms (Avg/Year)	Change from WEPP (%)	No. Runoff Events (Avg/Year)	Change from WEPP (%)	% as Runoff (%)	Change from WEPP (%)
<u>Boulder, Colo.</u>								
WEPP	438.81	-	85.9	-	1.1	-	1.27	-
MarkSim	420.75	-4.1	71.7	-16.5	1.3	16.5	1.77	39.6
2050	421.61	-3.9	75.7	-11.9	1.0	-7.3	1.33	5.2
2070	407.39	-7.2	80.8	-5.9	1.0	-9.2	1.22	-3.4
2090	391.45	-10.8	86.3	0.4	0.8	-28.4	0.90	-28.7
<u>Tifton, Ga.</u>								
WEPP	1184.82	-	102.1	-	16.2	-	15.84	-
MarkSim	1199.59	1.2	133.7	31.0	18.3	12.9	13.65	-13.8
2050	1152.4	-2.7	134.2	31.4	19.3	19.2	14.36	-9.3
2070	1133.74	-4.3	136.1	33.3	17.1	5.9	12.59	-20.5
2090	1164.62	-1.7	135.9	33.0	18.3	12.9	13.44	-15.1
<u>Waterloo, Ind.</u>								
WEPP	866.77	-	100.8	-	5.3	-	5.30	-
MarkSim	890.26	2.7	109.3	8.4	6.6	22.7	5.99	13.2
2050	936.23	8.0	109.8	8.9	7.2	34.3	6.53	23.3
2070	956.59	10.4	110.6	9.7	7.2	33.9	6.46	22.0
2090	976.99	12.7	132.0	30.9	8.1	51.1	6.12	15.5
<u>Merrill, Wis.</u>								
WEPP	758.71	-	103.8	-	3.4	-	3.24	-
MarkSim	818.59	7.9	128.9	24.1	4.9	44.3	3.76	16.3
2050	824.69	8.7	106.1	2.2	7.3	116.4	6.85	111.7
2070	879.17	15.9	106.1	2.2	7.2	113.7	6.77	109.1
2090	895.99	18.1	107.2	3.2	7.5	123.5	7.01	116.6

^[a] WEPP is WEPP baseline and MarkSim is MarkSim baseline.

^[b] Precip as Runoff category represents the percentage of the number of precipitation events which produce runoff.

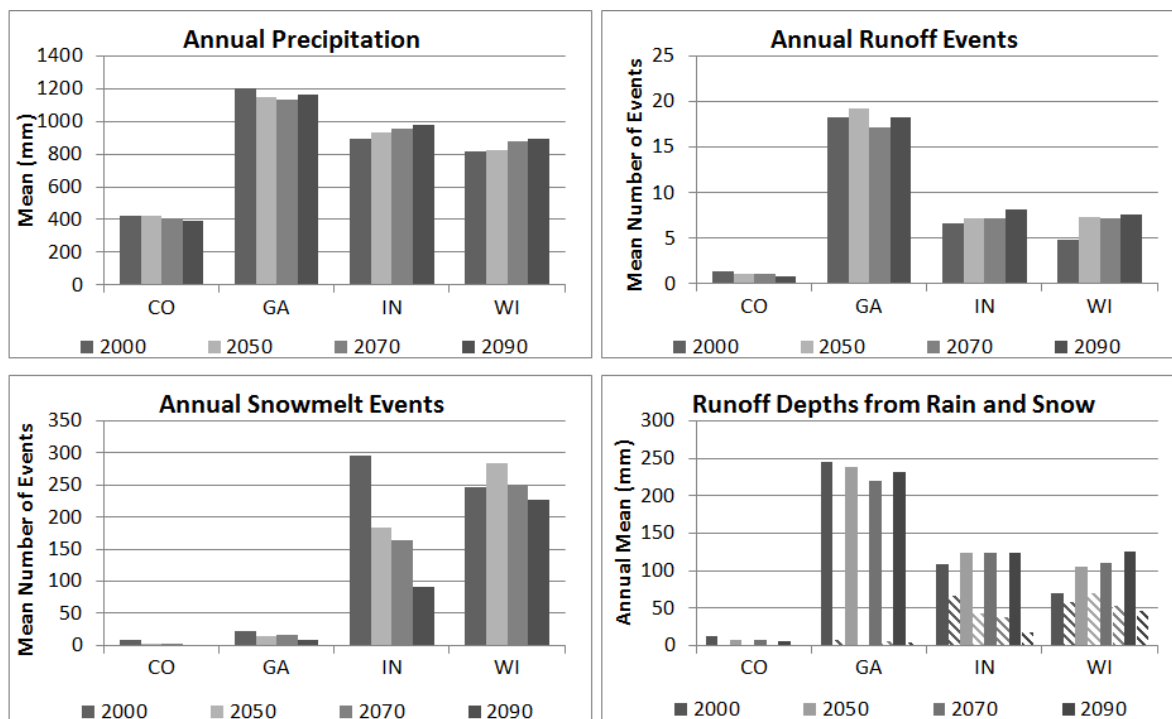


Figure 4. Precipitation and runoff outputs from WEPP. Runoff depth from snowmelt appears as diagonal-filled bars to right of runoff depth from rain as solid-filled bars.

these locations, decreasing snow cover and melt, and increasing runoff from rainfall were the main factors. At the Boulder, CO site, average annual runoff was predicted to decrease by 50% to 60%, and an associated soil loss decrease of 41% to 56%, indicating that at this semi-arid location future climate will become drier (and warmer, fig. 5), with lower risks of soil erosion by water. For the Tifton, GA location, predicted average annual runoff decreased by 5% to 10% compared to 2000, while total soil loss was predicted to decrease by 3% to 9%. The slightly decreased average annual precipitation, combined with the increased temperatures at the GA site modified the water balance towards more evaporation and somewhat less runoff and soil loss.

There are several advantages to the method outlined in this article for obtaining future climate data for the WEPP model. A .par file ready for use with CLIGEN in WEPP takes less than 15 min to create on a modestly equipped computer, and the learning curve to use this method is virtually non-existent, since the MarkSim application uses the familiar Google Earth interface and completes the downscaling, while the macro formats the file properly using automated scripts. The Microsoft Excel VBA Macro described in this article is available free-of-charge from the internet (<http://www.ars.usda.gov/Research/docs.htm?docid=24824>) and includes a detailed step-by-step instruction manual for downloading the data from MarkSim and creating CLIGEN/WEPP or SWAT input files.

As with all climate model downscaling, each GCM and/or downscaling technique may not be appropriate for some regions. A model developed in Europe may not adequately represent North America, while more heterogeneous landscapes may require more advanced

downscaling methods to adequately fit GCM output to a specific location. A verification tool is included in the Excel workbook to determine if the method demonstrated in this article is suitable to a site. The verification tool consists of scatter plots showing the monthly CLIGEN parameters generated by the VBA macro using the MarkSim baseline climate alongside the default WEPP .par file for the same location. In this way, users can obtain a rough idea of how well MarkSim recreates historical climate at the site in question by comparing the scatter plots for both baseline climates. As has been shown here, more advanced downscaling methods may be required in regions where MarkSim poorly replicated historical climates. The primary assumption with using this method lies in the accuracy of the MarkSim downscaling model, however the verification tool can validate the MarkSim baseline for specific locations. Another concern is raised with regards to the iterative aggregation and disaggregation of data inherent in MarkSim; the MarkSim weather generator aggregates GCM data, and then statistically reproduces daily time series. These replications of a statistical nature are then summarized by the macro and used as the input for another weather generator. This creates the possibility for compounding errors which originate in either the CLIGEN or MarkSim weather generator. The differences in period of record for each site and the MarkSim baseline climate cannot be ignored either, as the period of record for the MarkSim historical climate is fixed from 1960-1990, while .par files which come with WEPP may have periods of record extending many years earlier and/or later than that 30-year window. However, recreating historical .par files based on observed NCDC weather station data did not substantially improve R^2 values at the four selected sites.

Table 4. WEPP predicted average annual runoff, interrill detachment, and total detachment (soil loss) from the hillslope profile simulations at the four locations.

Climate (Year)	Total Runoff		Interrill Detachment		Total Detachment	
	Amount/Year mm (in.)	Change from 2000 %	Amount/Year kg m ⁻² (T acre ⁻¹)	Change from 2000 %	Amount/Year kg m ⁻² (T acre ⁻¹)	Change from 2000 %
<u>Boulder, Colo.</u>						
2000	3.70 (0.146)	-	0.329 (1.46)	-	1.01 (4.51)	-
2050	1.86 (0.073)	-49.8	0.195 (0.868)	-40.7	0.534 (2.38)	-47.1
2070	1.97 (0.078)	-46.8	0.209 (0.930)	-36.5	0.595 (2.65)	-41.1
2090	1.47 (0.058)	-60.2	0.169 (0.752)	-48.6	0.443 (1.97)	-56.1
<u>Tifton, Ga.</u>						
2000	63.7 (2.51)	-	5.08 (22.6)	-	10.2 (45.6)	-
2050	60.8 (2.39)	-4.58	4.63 (20.6)	-8.9	9.85 (43.8)	-3.4
2070	57.0 (2.24)	-10.6	4.56 (20.3)	-10.2	9.32 (41.5)	-8.6
2090	59.6 (2.35)	-6.48	4.81 (21.4)	-5.3	9.86 (43.9)	-3.8
<u>Waterloo, Ind.</u>						
2000	44.2 (1.74)	-	1.56 (6.93)	-	7.49 (33.3)	-
2050	42.1 (1.66)	-4.80	1.65 (7.36)	5.8	8.24 (36.7)	10.0
2070	40.6 (1.60)	-8.10	1.49 (6.61)	-4.5	7.26 (32.3)	-3.1
2090	36.0 (1.42)	-18.5	1.61 (7.18)	3.2	7.62 (33.9)	1.7
<u>Merrill, Wis.</u>						
2000	32.6 (1.28)	-	1.20 (5.33)	-	4.88 (21.7)	-
2050	43.9 (1.73)	34.9	1.51 (6.70)	25.8	6.56 (29.2)	34.4
2070	41.4 (1.63)	27.1	1.41 (6.30)	17.5	6.50 (28.9)	33.2
2090	43.6 (1.72)	34.0	1.73 (7.70)	44.4	7.51 (33.4)	53.9

The method described here for climate inputs to WEPP was also modified to create continuous daily data for use with the Soil and Water Assessment Tool from the same spreadsheet (SWAT, Arnold et al., 1998), after a request from another researcher. This was accomplished by using portions of the macro used to create the WEPP .par file to string together multiple replicates of MarkSim daily output, end-to-end, to create the four relatively simple climate input text files used by SWAT (daily precipitation, daily

minimum air temperature, daily maximum air temperature, daily solar radiation). More information and an example application with SWAT are described in Flanagan et al. (2014). Additionally, the VBA macro source code is unlocked and can be edited by the user for adaptation to other climate data which is reported in a similar format to MarkSim.

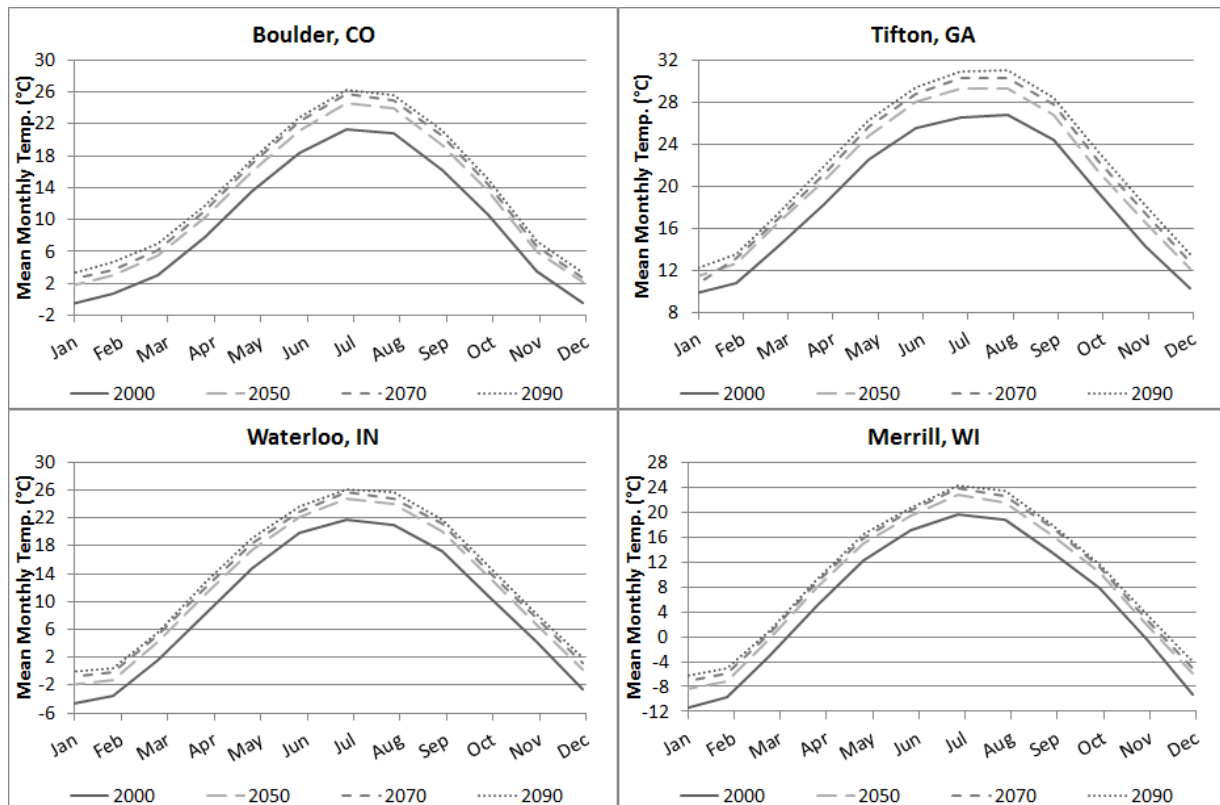


Figure 5. Monthly temperature at the four representative sites for the four simulated periods.

SUMMARY AND CONCLUSIONS

The MarkSim DSSAT weather generator was used to generate downscaled future climate datasets for precipitation, minimum temperature, maximum temperature, and solar radiation values on a daily timescale. The data was then aggregated and formatted into parameter files for use with the CLIGEN weather generator via a user-friendly tool created using a macro-enabled Microsoft Excel Workbook. The macro makes obtaining future climate inputs for the WEPP model fast and simple. Additionally, the ability to create SWAT model climate input files was also added as an option with the tool.

Twelve locations throughout the contiguous United States were analyzed using Q-Q plots and R^2 values to determine that the WEPP baseline parameter files and those created by the MarkSim baseline climate differed enough that only relative changes in erosion should be calculated using this downscaling method. WEPP outputs generated for four representative locations were compared for the two baseline climates as well as three future time periods and showed that regional variations in precipitation and temperature due to future climate change will have different impacts on water balance, runoff, and soil erosion depending on geographic location.

During the writing of this article, a new version of the MarkSim web application was released which generates future climate data based on the IPCC Fifth Assessment Report (AR5) data (<http://gisweb.ciat.cgiar.org/MarkSimGCM/>). The baseline MarkSim climate generated using the IPCC AR5 data showed slightly better R^2 values at the four selected sites, but the improvement was not substantial enough to be considered different from the baseline climate comparisons made in this article. The format of the files from this updated application are identical to those referenced in the methods portion of this article, and can be used in the same manner with the same macro.

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