Assessing Seasonal Climatic Impact on Water Resources and Crop Production Using CLIGEN and WEPP Models

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Abstract. *Physically based response models are useful tools for assessing climatic impact on water resources and crop productivity. Most response models require daily weather, which is often synthesized using stochastic daily weather generators. Synthesis of climate scenarios using weather generators provides an effective means for making impact assessments. The objectives were to evaluate the ability of the CLIGEN model to generate various climate scenarios and to assess further the hydrological and crop productivity responses using the WEPP model. The CLIGEN model was evaluated at four Oklahoma weather stations with mean annual precipitation ranging from 420 to 1150 mm and was then used to generate typical climate scenarios that represent wet, dry, and average conditions for Chandler, Oklahoma. The WEPP model was used to simulate hydrologic and grain yield responses to the generated climate scenarios. Results show that CLIGEN simulated daily and monthly precipitation reasonably well. CLIGEN was capable of preserving statistics of monthly precipitation as well as reproducing seasonal precipitation patterns for the dry, average, and wet year conditions. Simulated surface runoff, deep percolation, and plant transpiration increased as precipitation increased, but the rates of the increase varied with initial soil moisture levels and total precipitation. Predicted percent increase of wheat grain yield per 1% increase of growing–season precipitation, which was a function of initial soil moisture and total precipitation, ranged from 0.5% to 0.75%. Overall results indicate that CLIGEN is capable of translating monthly climate forecasts into daily weather series while preserving statistics of the forecasts. This study demonstrates that CLIGEN, when used in conjunction with response models such as WEPP, provides a useful tool for assessing the impact of seasonal climate variations or forecasts on water resources and crop production.*

Keywords. *CLIGEN, Hydrological model, Impact assessment, Weather generator, WEPP.*

Great efforts have been undertaken to assess potential impacts of long–term climate changes. Large–scale general circulation models (GCMs) are, in principle, appropriate for predicting global climate changes, but they are less reliable in conducting impact studies at smaller spatial and temporal scales pertinent to most impact questions (Katz, 1996; Grotch and MacCracken, 1991). Most physically based response models, which are suitable for impact studies, require inputs of daily weather as well as detailed soil, topography, vegetation, and management information. Several modifications have been made to stochastic climate generators to generate long–term daily weather, which is consistent with assumed future climate changes for use in impact studies (Katz, 1996; Wilks, 1992; Nearing, 2000).

Evaluation of hydrological and crop responses to seasonal climate variations is of great practical use. Agricultural production, especially dryland farming, which is planned on a seasonal scale, is largely influenced by seasonal climate variations. Seasonal climate patterns to a large degree dictate what cropping systems and management practices should be implemented to maximize productivity. With reliable seasonal climate forecasts, agricultural production can be managed to take advantage of favorable climate conditions and to mitigate negative impacts of undesirable variations. Especially for dryland farming, seasonal climate forecasts can provide a significant opportunity for minimizing production risks and maximizing productivity. Physically based response models are the most suitable tools available for this type of study. However, these models cannot be used unless seasonal or monthly climate forecasts are downscaled to daily weather series. Stochastic daily weather generators may be used to bridge the gap.

A number of stochastic daily weather generators have been developed to simulate the present climate for use with physically based hydrological and natural resource management models. The CLIGEN model (Nicks et al., 1995), one of two commonly used daily weather generators (Johnson et al., 1996), takes a simple approach and generates each variable (e.g., precipitation and temperatures) independently using monthly derived parameters. CLIGEN was primarily used to generate daily weather that statistically resembles the climates of the past 30 to 50 years. It has also been used to generate daily weather for ungauged areas through spatial interpolation of model parameters.

Several evaluation and validation studies using various versions of CLIGEN have been reported in the literature. Johnson et al. (1996) and Headrick and Wilson (1997)

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evaluated CLIGEN versions that employed four probabilistic weighting factors to improve cross–correlations between precipitation, temperatures, and solar radiation. Those factors, conditioned on the precipitation states of the current and previous days, were multiplied to the standard deviations of solar radiation and maximum, minimum, and dew point temperatures. Johnson et al. (1996) reported that monthly and annual precipitation statistics were adequately replicated by the model on six dispersed U.S. sites; however, daily precipitation amounts were not entirely satisfactorily simulated. They also reported that means of monthly temperatures were well replicated, but standard deviations were considerably underpredicted. Headrick and Wilson (1997), who evaluated CLIGEN at five Minnesota locations, found that CLIGEN reproduced daily precipitation amounts and temperatures reasonably well. Zhang and Garbrecht (2003) evaluated a later version of CLIGEN (v5.107) on four Oklahoma sites and found that the model simulated daily and monthly precipitation as well as frequencies of wet and dry spells reasonably well for use in impact studies.

The National Oceanic and Atmospheric Administration (NOAA) issues experimental seasonal precipitation and temperature forecasts over large climate divisions for periods of three months up to a year in advance. The forecasts are expressed as probability anomalies relative to average climate conditions experienced in the period from 1971 to 2000. The forecasts are relatively new and represent the best current scientific knowledge on predictable aspects of climate. The seasonal forecasts bring new opportunities for optimizing agricultural production systems using response models. Again, the long–range forecasts must be temporally and spatially downscaled to daily series for specific locations before being used in response models. Schneider and Garbrecht (2002, 2003) have developed simple methods for downscaling precipitation forecasts from three–month total precipitation to monthly values for specific locations. Further downscaling from monthly values to daily series may be realized using the CLIGEN model.

The objectives of this study were (1) to evaluate the ability of the CLIGEN model to reproduce precipitation and temperatures at four Oklahoma sites, (2) to test the ability of CLIGEN to generate "typical" dry, average, and wet year climate scenarios from historical data and to explore further the feasibility of using CLIGEN to downscale seasonal climate forecasts to daily series, and (3) to assess hydrological and crop productivity responses to the generated climate scenarios using the WEPP model.

Materials and Methods

Four Oklahoma sites (Goodwell, Weatherford, Chandler, and Sallisaw in table 1, with mean annual precipitation ranging from 417 to 1153 mm were used to evaluate the ability of CLIGEN to reproduce daily and monthly precipitation and daily maximum and minimum temperatures. The historical daily precipitation and maximum and minimum temperatures (up to year 2000) measured by the National Weather Service (NWS) were used to derive CLIGEN input parameters using a CLIGEN–support parameterization program. The derived parameters were used to generate 100 years of daily weather using the default random number seed and no interpolation. The NWS–historical and CLIGEN–generated daily precipitation were summed to obtain monthly values, and statistics, including mean, standard deviation (STD), and coefficients of skewness and kurtosis, were calculated for the daily and monthly data. Relative error (RE) was computed as the difference between generated and historical values divided by historical value.

Table 1. Site location, record period, and average annual precipitation during the period for five sites in Oklahoma.

Site	Latitude (°N)	Longitude (°W)	Elevation (m)	Period	Precipitation (mm/yr)
Goodwell	36.60	101.62	1005	1948–2000	417
Weatherford	35.53	98.70	499	1948–2000	717
Chandler	35.70	96.88	262	1902–2000	885
Sallisaw	35.47	94.78	161	1948–2000	1153
El Reno	35.54	98.05	427	1977–2000	852

A t–test and an F–test were used to test the equality of means and STDs, respectively, of the generated and historical daily maximum and minimum temperatures for each site. A significance level of P = 0.01 was used in these tests. Principally, t–tests are based on the normality and equal variance assumptions. These requirements may be relaxed when the sample sizes are large (Ott, 1988). Since distributions of temperatures are approximately normal, these tests on daily maximum and minimum temperatures are conducted. In addition, a nonparametric Wilcoxon rank sum test that is applicable to any distribution was used to test the null hypothesis that the two populations are identical.

To test the ability of the CLIGEN model to simulate typical dry, average, or wet year conditions, the longest historical records of 99 years from Chandler were analyzed in more detail. For quality control, 21 years of the station data that had more than 7 consecutive days of missing precipitation were excluded. Annual precipitation amounts of the remaining 78 years were used to generate a cumulative probability distribution curve. The 25 and 75 percentiles in this curve, which corresponded to 742 mm and 1016 mm precipitation, were arbitrarily used to divide years into dry, average, and wet year categories. There were 21, 37, and 20 years in the dry, average, and wet categories, respectively. The daily precipitation amounts and daily maximum and minimum temperatures of those years in each category (dry, average, and wet) were used to derive the CLIGEN input statistics or parameters for that year category for the Chandler site. The derived monthly parameters were then used to generate 100 years of daily weather for each category. Hereinafter, the year category will be specifically used to refer to the aforementioned dry, average, and wet scenarios.

Four Water Resources and Erosion (WRE) watersheds established in 1976 at the USDA–ARS Grazinglands Research Laboratory in El Reno, Oklahoma, were used to test and calibrate the WEPP water balance and plant growth sub–models (Zhang, 2003). The watersheds are 80 m wide and 200 m long with a drainage area of 1.6 ha each. The longitudinal slopes of the watersheds are 3% to 4%. Soils are predominantly silt loams having 23% sand and 56% silt in the tillage layer. The watersheds were cropped into winter wheat under various tillage and cropping systems since 1979. The aboveground biomass at harvest and the grain yields were collected. Daily precipitation, surface runoff, and soil moisture were measured. Measured climate, soil properties, and actual management operations were used to validate or calibrate WEPP model parameters. Saturated hydraulic conductivity of the infiltration sub–model and energy–to–biomass conversion ratio and harvest index of the crop sub–model were the key calibration parameters.

The calibrated WEPP model, with the soil and slope input files compiled for the WRE watersheds, was run for 100 years under the three typical climate scenarios generated for Chandler. The simulation was conducted as if the WRE watersheds were relocated to Chandler. For simplicity, a generic one–year rotation of conventionally tilled winter wheat was used. In the simulation, winter wheat was planted on 15 October and harvested on 20 June each year, and the field was moldboard plowed on 1 July and disked on the first day of August, September, and October. Soil moisture in each soil layer was reset in the model to 40% or 70% of its saturation level on 1 September each year. Because each year–occurrence is a possible outcome of the year category in question, initial soil moisture storage was reset to the same level each year. The 45–day period between the moisture resetting and planting was used to allow soil moisture to adjust for the dry, average, and wet year conditions. Output of crop yield and selected hydrologic variables were compared between the dry, average, and wet year categories.

Results

Precipitation

Relative errors (RE) of daily precipitation were 7.4%, 0.8%, 3.6%, and 7.1% for the means and –5.4%, –3.6%, 1.2%, and –4.6% for the STDs on the Goodwell, Weatherford, Chandler, and Sallisaw sites, respectively (table 2). CLIGEN tended to overpredict the daily means (positive RE) on all sites. Relative errors of both mean and STD were slightly greater at the driest (Goodwell) and wettest (Sallisaw) sites. Daily precipitation was extremely skewed, but the skewness was adequately replicated on all sites. Kurtosis, which reflects the peakedness of the distribution, was generated satisfactorily on Goodwell and Sallisaw, but not on Weatherford and Chandler. The mean number of raindays that received more than 1 mm/day was underpredicted on all sites, with RE ranging from –4.9% to –1.5%. The Wilcoxon rank sum test shows that the historical and generated distributions of daily precipitation were different at very low probability levels. It should be pointed out that this test may be biased by sample size. The test is more suitable for small sample sizes, and the test becomes extremely stringent when sample size becomes larger. This will be discussed later.

Relative errors between historical and generated monthly precipitation were 3.5%, –0.8%, –1.6%, and –0.7% for the means and –3.9%, –10.1%, –6.9%, and –5.8% for the STDs on Goodwell, Weatherford, Chandler, and Sallisaw, respectively (table 3). The monthly mean precipitation was better preserved than was the mean daily precipitation on all sites. This is because the errors of overpredicting daily precipitation means and the errors of underpredicting the number of raindays tended to cancel each other out. The STD of monthly precipitation, which was underpredicted on all sites, was generally less well reproduced than for daily precipitation. Monthly precipitation was still extremely skewed, but the skewness was adequately replicated. Similar to the daily statistics, kurtosis was considerably overpredicted on the Weatherford and Chandler sites. The Wilcoxon tests cannot reject the hypothesis that the historical and generated distributions of monthly precipitation are identical at P = 0.01 on all four sites. Further tests by month–location combination show that none of the 48 combinations was significantly different at P = 0.01.

Temperature

The mean, STD, skewness, and kurtosis of daily maximum temperature were reproduced well by the CLIGEN model on all sites (table 4). Interestingly, the Wilcoxon test shows that the two distributions were significantly different (P = 0.01) on the Chandler site. Since the distribution of maximum temperature was approximately normal, a t–test and an F–test were conducted. Neither the t–test nor the F–test shows a significant difference on any site at P = 0.01. Further tests by month–location combination show that none of the 48 tests was significantly different for either the t–test or the F–test, and only one out of 48 was different for the Wilcoxon test at P = 0.01. The discrepancy between the test results by location (table 4) and those by month–location combination may indicate a possible aforementioned sample size effect on the Wilcoxon test.

Table 2. Statistics of daily precipitation amounts and mean number of raindays per year by location and source for storms >1 mm/day (NWS = NWS–historical, C = CLIGEN–generated).

	Goodwell		Weatherford		Chandler		Sallisaw	
	NWS	C	NWS	C	NWS	C	NWS	C
Mean (mm)	9.4	10.1	13.0	13.1	14.0	14.5	15.5	16.6
STD (mm)	11.1	10.5	16.3	15.7	16.5	16.7	17.3	16.5
Skewness coefficient	2.6	2.5	3.4	3.8	2.8	3.1	2.2	2.1
Kurtosis coefficient	9.6	9.7	18.7	28.4	11.3	17.1	7.0	6.3
Mean No. of raindays	44.2	42.1	54.8	54.0	61.8	59.7	72.0	68.5
Wilcoxon P value	0.0001		0.0014		0.0006		0.0001	

Table 3. Statistics of monthly precipitation amounts by location and source (NWS = NWS–historical, C = CLIGEN–generated).

	Goodwell		Weatherford		Chandler		Sallisaw	
	NWS	C	NWS	C	NWS	C	NWS	C
Mean (mm)	34.7	35.9	59.8	59.4	73.7	72.5	96.1	95.4
STD (mm)	38.7	37.2	58.1	52.2	64.0	59.6	67.7	63.8
Skewness coefficient	1.6	1.6	1.6	1.6	1.5	1.6	1.1	1.0
Kurtosis coefficient	2.8	3.3	2.5	3.5	2.8	4.2	1.2	1.1
Wilcoxon P value	0.068		0.189		0.727		0.810	

Table 4. Statistics of daily maximum temperature by location and source (NWS = NWS–historical, C = CLIGEN–generated).[a]

	Goodwell		Weatherford		Chandler		Sallisaw	
	NWS	C	NWS	C	NWS	C	NWS	C
Mean (°C)	21.9	21.8	22.6	22.6	23.0	22.8	22.8	22.7
STD (°C)	10.9	10.9	10.8	10.8	10.3	10.4	9.9	9.9
Skewness coefficient	–0.5	–0.4	–0.4	–0.4	–0.5	–0.4	–0.5	–0.4
Kurtosis coefficient	–0.4	–0.6	–0.5	–0.7	–0.4	–0.6	–0.5	–0.6
Maximum daily (°C)	43.9	48.0	45.6	48.0	47.8	47.6	43.9	45.9
Wilcoxon P value	0.043		0.164		0.007		0.104	

[a] None of the CLIGEN–generated means and STDs is significantly different from their historical counterparts at P = 0.01, using a t–test for means and an F–test for STDs.

Table 5. Statistics of daily minimum temperature by location and source (NWS = NWS–historical, C = CLIGEN–generated).

	Goodwell		Weatherford		Chandler		Sallisaw	
	NWS	C	NWS	C	NWS	C	NWS	C
Mean (°C)	5.1	4.9	8.9	8.5[a]	9.7	9.2[a]	9.8	9.3[a]
STD (°C)	10.0	10.0	9.9	10.0	9.9	10.0	9.6	9.7
Skewness coefficient	–1.2	–0.1	–0.3	–0.2	–0.3	–0.2	–0.3	–0.3
Kurtosis coefficient	–0.9	–1.0	–0.9	–1.0	–0.9	–0.9	–0.9	–0.9
Minimum daily (°C)	–30.0	–28.0	–22.2	–24.6	–21.7	–26.0	–19.4	–25.2
Wilcoxon P value	0.056		0.0001		<0.0001		<0.0001	

[a] Significantly different from historical values at P = 0.01, using a t–test for means and an F–test for STDs.

Table 6. Critical probability value of the Wilcoxon rank sum test between CLIGEN–generated and NWS–historical monthly precipitation amounts by month and year category for Chandler, Oklahoma.

Year Group	Jan.	Feb.	March	April	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.
Dry	0.477	0.596	0.697	0.544	0.867	0.878	0.916	0.316	0.382	0.591	0.709	0.774
Average	0.326	0.640	0.994	0.844	0.987	0.755	0.906	0.316	0.829	0.582	0.749	0.642
Wet	0.364	0.680	0.615	0.852	0.354	0.835	0.986	0.358	0.980	0.453	0.686	0.966

Relative errors of the mean daily minimum temperature were –3.9%, –4.5%, –5.2%, and –5.1% on the Goodwell, Weatherford, Chandler, and Sallisaw sites, respectively (table 5). The consistent underprediction resulted from a range check imposed in CLIGEN, which forces the generated minimum temperature to be lower than the maximum temperature on each day. The t–tests showed that the differences were significant at P = 0.01 on three out of four sites. Relative errors for the STDs ranged from 0% to 1%, and none of the differences was significant for the F–test. Skewness and kurtosis coefficients were adequately reproduced on all sites except on the Goodwell site, where daily minimum temperature was extremely skewed. CLIGEN was unable to reproduce this skewed distribution, since it assumes a normal distribution. The Wilcoxon tests showed significant differences on three out of four sites. Further tests by month–location combination showed that 16, 16, and 23 (out of 48) were significantly different for the t–test, F–test, and Wilcoxon test, respectively.

Climate Scenario Generation at Chandler

The CLIGEN model was used to generate daily weather of three different year categories (dry, average, and wet) for the Chandler site. Generated and historical distributions were contrasted using the Wilcoxon rank sum test, and the critical probability values of those tests are given in table 6. The CLIGEN model reproduced monthly precipitation distributions reasonably well for each month and year category, with the minimum P value greater than 0.3. January and August, compared with the other months, were less well reproduced by CLIGEN for all the three year categories. The generated and historical monthly mean precipitation are plotted in figure 1, which indicates that CLIGEN was able to adequately reproduce the seasonal sequences of the monthly mean precipitation.

A t–test was used to test monthly mean temperatures for each year category, and the probability values are given in table 7. The CLIGEN model reproduced monthly mean maximum temperature very well for each month and year category. More than 80% of the P values were greater than 0.9, with the lowest value of 0.79. Compared with the maximum temperature, monthly mean minimum temperature was less well replicated because of the range check; however, none of the tests was significantly different at the P = 0.01 level (table 7). CLIGEN tended to reproduce mean minimum temperature better in summer periods (e.g., June, July, and August) when the temperature was higher. Neither monthly mean maximum temperature nor minimum temperature of the NWS–historical data shows considerable departures between the three year categories (fig. 2). A similar plot of CLIGEN–generated data was omitted because it is almost identical to figure 2. Nevertheless, discernable departures were exhibited by both NWS–historical and CLIGEN–generated data from June to September, where the monthly mean temperatures, especially the maximum, decreased from dry to average to wet years. Results indicate that CLIGEN was able to correctly capture small departures of monthly mean temperatures between the year categories.

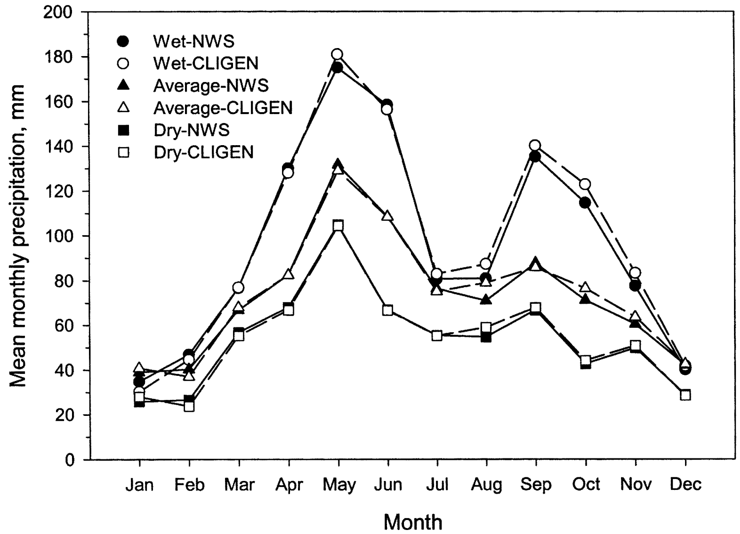

Figure 1. Seasonal distributions of NWS–historical and CLIGEN–generated monthly mean precipitation for the wet, dry, and average year categories for Chandler, Oklahoma.

Table 7. Probability value of a t–test between CLIGEN–generated and NWS–historical mean temperatures by month and year category for Chandler, Oklahoma.

Year Group	Jan.	Feb.	March	April	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.
Monthly Mean Maximum Temperature												
Dry	0.970	0.945	0.931	0.927	0.944	0.952	0.996	0.921	0.915	0.957	0.853	0.899
Average	0.975	0.841	0.893	0.989	0.913	0.984	0.972	0.929	0.934	0.958	0.874	0.912
Wet	0.973	0.791	0.926	0.916	0.988	0.988	0.987	0.950	0.973	0.907	0.942	0.893
Monthly Mean Minimum Temperature												
Dry	0.326	0.371	0.303	0.362	0.619	0.906	0.845	0.886	0.668	0.445	0.412	0.300
Average	0.156	0.041	0.101	0.184	0.573	0.850	0.819	0.828	0.423	0.188	0.185	0.058
Wet	0.302	0.174	0.274	0.188	0.452	0.846	0.878	0.906	0.465	0.407	0.260	0.238

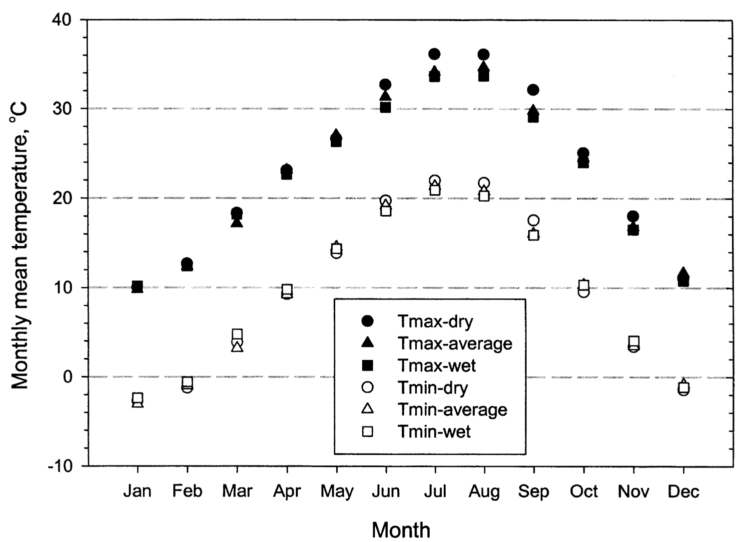

Figure 2. Seasonal distributions of NWS–historical monthly mean maximum and minimum temperatures for the wet, dry, and average year categories for Chandler, Oklahoma.

Simulated Hydrological Responses at Chandler

Predicted growing–season surface runoff, plant transpiration (Ep), soil evaporation (Es), deep percolation (Dp), and soil moisture storages at both planting and harvest all increased with total precipitation or year category (table 8). As precipitation increased, predicted percent runoff and deep percolation relative to total precipitation increased, but percent Ep decreased. The trends of these predicted relative changes were more profound when initial soil moisture was set to 70% as opposed to 40%. The average soil moisture depletion between planting and harvest was about 70 and 135 mm for the 40% and 70% initial moisture levels,

Table 8. Mean ±1 STD of WEPP–simulated growing–season precipitation (P), runoff (Q), plant transpiration (Ep), soil evaporation (Es), deep percolation (Dp), soil water in the 1.8–m profile at harvest (SW_h) and at planting (SWp), and wheat grain yield for three year categories.[a]

Year Group	P (mm)	Q (mm)	Ep (mm)	Es (mm)	Dp (mm)	SW_h (mm)	SW_p (mm)	Yield (kg/ha)
Initial Soil Moisture Saturation = 40%								
Dry	426 ±102	25 ±30	405 ±67	69 ±22	3 ±9	300 ±18	371 ±27	1596 ±422
Average	578 ±135	52 ±46	481 ±84	95 ±27	17 ±21	320 ±23	383 ±27	2007 ±570
Wet	751 ±166	108 ±93	572 ±83	104 ±30	49 ±30	342 ±30	419 ±41	2452 ±614
Initial Soil Moisture Saturation = 70%								
Dry	426 ±102	25 ±30	421 ±64	70 ±22	46 ±24	320 ±15	450 ±25	1722 ±426
Average	578 ±135	52 ±46	486 ±84	96 ±28	79 ±32	331 ±21	461 ±26	2046 ±572
Wet	751 ±166	111 ±96	577 ±83	105 ±32	109 ±35	345 ±28	490 ±35	2466 ±605

[a] Lateral soil water discharge was zero for all cases.

Table 9. Percent increase per 1% increase of growing–season precipitation, computed using mean values of 100–year simulations for three year categories under 40% and 70% initial moisture conditions.

	Dry–to–Average Scenario, Initial Moisture		Average–to–Wet Scenario, Initial Moisture	
Selected Variable	40%	70%	40%	70%
Runoff (Q)	2.96	2.99	3.72	3.87
Plant transpiration (Ep)	0.52	0.43	0.64	0.63
Soil evaporation (Es)	1.05	1.05	0.30	0.32
Deep percolation (Dp)	11.79	2.04	6.14	1.26
Grain yield	0.72	0.53	0.75	0.69

respectively. The year–to–year variation of WEPP–simulated results, as indicated by the coefficient of variation (CV), was approximately 23% for precipitation, 16% for Ep, 30% for Es, 7% for soil moisture storages at both planting and harvest, and 26% for grain yield. These CVs were largely independent of the year categories and initial soil moisture status. However, the CVs of predicted surface runoff and deep percolation increased dramatically from wet to average to dry categories, indicating increased variability or uncertainty in dry conditions.

Predicted percent increases of selected variables per 1% increase of precipitation (P), computed from mean values of 100–year WEPP simulation run under the three year categories, are given in table 9. Percent runoff increase was much greater in average–to–wet scenarios than in dry–to–average scenarios. Initial soil moisture storage increased percent runoff, but the increase was greater in average–to–wet scenarios. Predicted percent Ep increase per 1% increase of P was greater in average–to–wet scenarios because of the alleviation of plant water stress. Predicted percent Ep increase was dampened by high initial soil moisture storage, which increased percent runoff and deep percolation. Percent Es increase was little affected by initial soil moisture and was largely reduced in average–to–wet scenarios due to better canopy cover. Percent Dp increase was greater when initial soil moisture and precipitation were lower, partially because deep percolation was near zero in dry conditions.

Simulated Wheat Yield Responses at Chandler

To compare the overall impact of using generated climate vs. measured climate on simulated wheat response, three climate input files were constructed for Chandler: one using historical daily precipitation (P), maximum temperature (Tmax), and minimum temperature (Tmin); one using CLIGEN–generated P, Tmax, and Tmin; and one using historical P and generated Tmax and Tmin. The remaining climate variables in these files were identically generated. The WEPP–simulated distributions of grain yields tended to shift to higher values when generated precipitation and/or temperatures were used (fig. 3). However, standard deviations and CVs of the predicted grain yields under the three

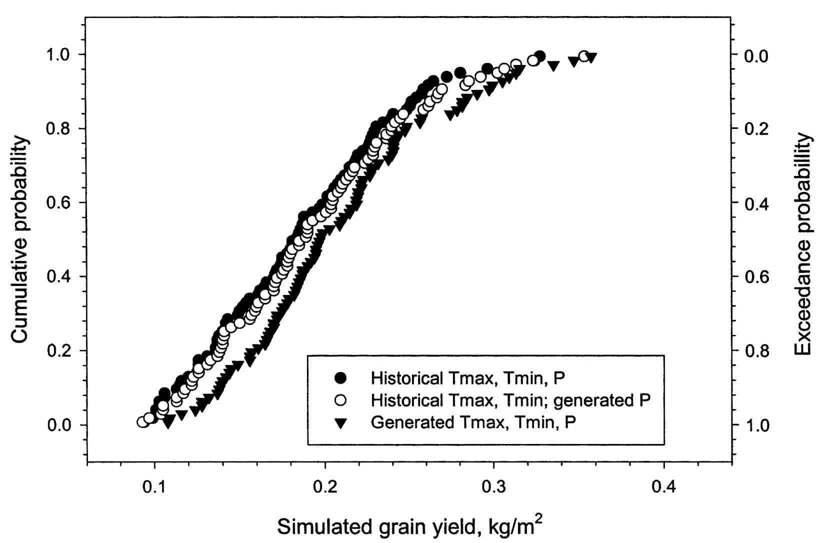

Figure 3. Probability distributions of WEPP–simulated wheat yields for three constructed climates using either measured or generated daily precipitation (P), maximum temperature (Tmax), and minimum temperature (Tmin).

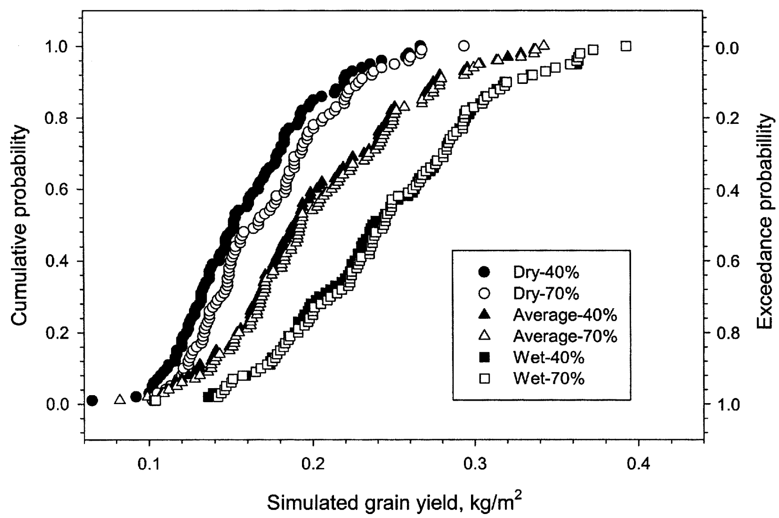

Figure 4. Probability distributions of wheat yields simulated for the wet, dry, and average year categories and at two initial soil moisture levels for Chandler, Oklahoma.

climates were more or less the same. As far as yield distribution is concerned, generated daily P seemed adequate, at least at this location. But generated temperatures, which caused a considerable bias in yield distribution, were less satisfactory. Such bias must be characterized and corrected before meaningful crop forecasts can be derived. Nevertheless, when relative shifts between generated climate scenarios are compared, as below, this type bias may be ignored.

WEPP–simulated yield distributions for the generated wet, dry, and average scenarios and at the two initial moisture levels are shown in figure 4. Predicted yield distributions shifted from dry to average to wet scenarios, and initial soil moisture storage showed a significant impact on grain yields only in the dry scenario. The average yield increase per 1% increase of growing–season precipitation, computed using distribution means, ranged from 0.5% to 0.75% (table 9). Predicted percent yield increase was slightly greater in average–to–wet scenarios than in dry–to–average scenarios under both initial moisture conditions because of reduced plant water stress. However, the greater percent increase in grain yield occurred under the lower initial soil moisture conditions. This is because a larger portion of precipitation increase would be taken up by Ep rather than by runoff and deep percolation, as was the case for the higher initial soil moisture conditions. Another reason is that grain yield was generally lower in dry conditions, especially when initial soil moisture was low.

Discussion

Several studies have concluded that the CLIGEN model replicated daily and monthly precipitation as well as frequencies of wet and dry spells reasonably well (Headrick and Wilson, 1997; Johnson et al., 1996; Zhang and Garbrecht, 2003). In this study, the mean absolute RE of daily precipitation across the four sites was 4.7% for the means and 3.7% for the STDs, and that of monthly precipitation was 1.7% and 6.7%, respectively. The better prediction for the monthly mean precipitation was because the errors of overpredicting daily mean precipitation tended to offset the errors of underpredicting number of raindays. Those errors can be reduced if random numbers are rigorously screened (Garbrecht and Zhang, 2003) or the model is run for more years. Any improvement in daily precipitation simulation by random number screening definitely favors its applications in the scenario–oriented impact studies. Considering that large relative changes in monthly mean precipitation often exist between different year categories, the model performance would be satisfactory for use in evaluating the crop responses to different year scenarios.

Application of CLIGEN to individual year categories reduced RE of STD of monthly precipitation, compared to the case when all year categories were combined. At Chandler, the RE of STD was –4.2%, –5.8%, and –1.8% for the dry, average, and wet year categories, respectively, while it was –6.9% for the lumped case. Johnson et al. (1996) and Zhang and Garbrecht (2003) reported that CLIGEN replicated mean annual precipitation well but consistently underpredicted the year–to–year variations. The underprediction of interannual variability resulted in part from the simplifying assumption that climate is stationary (i.e., lower frequency climate variation is not modeled). The application of CLIGEN to a particular climate scenario seems more consistent with the stationarity assumption.

Precipitation, temperature, and solar radiation are the three important factors affecting plant growth and crop productivity. The WEPP model simulates water stress as well as high and low temperature stress for each crop. The CLIGEN model replicated the statistics of daily maximum temperature well (table 4). The underprediction of STD as reported by Johnson et al. (1996) could be because four probabilistic weighting factors, as discussed earlier, were used in their version. CLIGEN did not satisfactorily reproduce overall daily minimum temperature due to the range check imposed in the model (table 5). Nevertheless, the t–test results in table 7 indicate that CLIGEN replicated monthly mean maximum and minimum temperatures better for each month and year category than for the lumped cases (tables 4 and 5). The tests by month and year category are more consistent with the model applications proposed in this study. Solar radiation is the most predictable variable among the three, being largely determined by latitude and time of the year. A preliminary evaluation shows that CLIGEN simulated solar radiation reasonably well at the four Oklahoma locations (data not presented).

Responses of simulated runoff, plant transpiration, soil evaporation, deep percolation, and grain yield to precipitation or year category were reasonable (tables 8 and 9) and agreed well with the known trends reported in the literature. The predicted runoff coefficient agreed well with field measurements under similar conditions (Zhang and Garbrecht, 2002). Predicted grain yield was sensitive to soil moisture storage at planting, especially under dry conditions. Musick et al. (1994) reported that grain yield of winter wheat was positively related to soil moisture storage at planting in the southern High Plains, where annual precipitation is often less than 550 mm. For 1% increase in precipitation, predicted surface runoff increased 3% to 4%, depending on total precipitation amounts and soil moisture levels. Garbrecht and Van Liew (2001) studied streamflow responses to decade–scale precipitation variations under similar climate conditions on the 610–km^2 Little Washita River watershed near Chickasha, Oklahoma. They found that percent increase in runoff was 3.5 to 6 times the percent increase in precipitation using 11–year moving averages. These sensitivity ratios were comparable with the results obtained here using 100–year averages of the dry, wet, and average year categories.

Implications

Seasonal sequences of monthly mean precipitation were well simulated for the three year categories by CLIGEN (fig. 1), indicating that CLIGEN may be capable of reproducing sequences of monthly mean precipitation of a particular seasonal climate forecast. This is not surprising, since CLIGEN is a monthly parameterization model and generates daily weather independently for each month. This simplifying approach works to its advantage and provides the flexibility needed to reproduce any seasonal sequence of monthly mean precipitation, and therefore is particularly suitable for assessing the impact of seasonal and interannual climate variations derived from seasonal climate forecasts using physically based response models. More importantly, not only the monthly mean precipitation (fig. 1) but also the monthly probability distributions (table 6) were adequately reproduced by the CLIGEN model.

The impact of interannual or seasonal climate variations can be simulated by a spectrum of scenarios of anticipated climate forecasts. Precipitation distribution generated for a climate forecast is propagated through the deterministic WEPP model in a Monte Carlo sense, resulting in a probability distribution of grain yield. The generated yield distributions (e.g., fig. 4) reflect not only yield levels but also their associated probabilities for a given climate scenario and initial soil moisture condition. The probabilistic nature of the generated grain yields lays the foundation for developing risk–based management tools, provided that prediction errors associated with imprecise climate generation and imperfect crop simulation are properly considered. This concept has actually been demonstrated in figure 4. In this example, at the 70% initial saturation level, there is a 50% chance that wheat grain yield would be between 1.37 and 1.97 Mg/ha for any year under a given dry year scenario and between 2 and 2.88 Mg/ha for any year under a wet year scenario.

The NOAA seasonal forecasts are probabilistic in nature and are made in the form of probability anomalies for the upcoming month and for three–month periods out to a year in advance for both precipitation and air temperature. Schneider and Garbrecht (2002, 2003) have developed procedures to downscale the aggregated precipitation of three–month forecasts to monthly probability distributions for a particular location of interest. The downscaled monthly distribution, say for January, can be reconstructed with the historical monthly precipitation data of the location. The daily precipitation records of the months used in the reconstruction will be used to derive daily precipitation statistics using a CLIGEN–support program. This can be done independently for each month. The derived parameters for each month will then be used to generate daily time series. This approach not only provides an innovative means of downscaling monthly forecasts to daily time series but also preserves the monthly probability distribution of the forecasts. More over, the proposed approach is also applicable to downscale the NOAA air temperature forecasts. However, because the monthly mean maximum and minimum temperatures were not much different between the wet, dry, and average year categories, as is shown in figure 2, the downscaling of air temperature appears to have minimal impact on crop productivity forecasts, at least for central Oklahoma.

Conclusions

The CLIGEN model reproduced monthly precipitation relatively well, and the reproducibility was improved when it was applied to different year categories. This could be because the application to different year scenarios is more consistent with the stationarity assumption of the model. Daily mean precipitation was less well simulated than monthly mean precipitation. Daily maximum temperature was satisfactorily simulated, but daily minimum temperature was noticeably altered by the range check imposed in the model.

The CLIGEN model was capable of reproducing not only monthly precipitation distribution of individual months but also seasonal sequences of monthly mean precipitation. The simplifying approach of the monthly parameterization scheme used in CLIGEN, compared with other weather generators, provides the flexibility needed to reproduce seasonal sequences of monthly mean precipitation. This makes the CLIGEN model particularly suitable for impact assessments of seasonal climate variations derived from probabilistic–type forecasts using response models. The impact of interannual climate variations can be simulated by a spectrum of year scenarios. Such application tends to circumvent the stationarity assumption, which is, otherwise, undesirable for long–term climate change simulation.

Physically based response models are the best available tools for impact assessments of seasonal and interannual climate variations. NOAA's seasonal forecasts provide a significant opportunity for simulating impacts using response models. The CLIGEN model has the potential of downscaling monthly climate forecasts to daily weather data required by many response models.

Hydrologic and crop responses predicted by WEPP agreed reasonably well with the known trends. Predicted runoff, plant transpiration, and deep percolation increased with total precipitation. However, the rates of the increase were higher for runoff and plant transpiration but lower for deep percolation in average–to–wet scenarios. Predicted crop yield was sensitive to soil moisture storage at planting, especially in dry conditions. Percent increase in predicted wheat yield per 1% increase of precipitation, on average, ranged from 0.5% to 0.75%, depending upon initial soil moisture storage and precipitation levels.

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