### ASSESSING IMPACT OF INTERANNUAL CLIMATE VARIATIONS ON WATER RESOURCES AND CROP PRODUCTIVITY USING **CLIGEN** AND **WEPP** MODELS

X. John Zhang \* USDA-ARS Grazinglands Research Laboratory, El Reno, Oklahoma

## 1. INTRODUCTION

Great efforts have been taken 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 in smaller spatial and temporal scales pertinent to most impact questions (Katz, 1996; Grotch and MacCracken, 1991). Most physically based response models, which are most 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 natural resource responses to seasonal and interannual climate variations is of greater practical use than long term impact assessment. Agricultural production, especially dryland farming, which is planned at a seasonal scale, is largely dependent upon 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. Undoubtedly for dryland farming, seasonal climate forecasts, such as National Oceanic and Atmospheric Administration (NOAA) long range experimental forecasts, provide a unique opportunity for minimizing production risks and maximizing productivity. Physically based response models are the best 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 serve as an effective tool for bridging 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 the two commonly used daily weather generators (Johnson et al., 1996), takes a simple approach and generates each variable independently using monthly derived parameters. CLIGEN was primarily used to generate daily weather that statistically resembles the climates of the past 30 to 100 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) 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. 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 reasonably well for use in impact studies.

Schneider and Garbretch (2002, 2003) have developed approaches 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 achieved by use of the CLIGEN model. The objectives of this study are (i) to evaluate the ability of the CLIGEN model to reproduce *typical* dry, average, and wet year climate scenarios from historical data, and (ii) to assess hydrological and crop productivity responses to the generated climate scenarios using the WEPP model.

### 2. MATERIALS AND METHODS

To test the ability of the CLIGEN model to simulate typical dry, average, or wet year conditions, a site (35.70 °N, 96.88 °W) located at Chandler, OK, which has 99 years of National Weather Service (NWS) daily weather data, was used. 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- and 1016-mm precipitation, were arbitrarily used to divide years into dry, average, and wet year categories, and there were 21, 37, and 20 vears in each corresponding category. 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 parameters for that year category for the Chandler station using a CLIGEN-support parameterization

3.14

<sup>&</sup>lt;sup>\*</sup> Corresponding author address: X. John Zhang, USDA-Agricultural Research Service, Grazinglands Research Laboratory, 7207 West Cheyenne Street, El Reno, OK 73036; e-mail: jzhang@grl.ars.usda.gov.

program. The derived monthly parameters were then used to generate 100 years of daily weather for each category. Hereinafter, the year category will specifically refer to the dry, average, and wet scenarios as described above.

A t-test was used to test the equality of means of the generated and historical daily maximum and minimum temperatures on the site. A nonparametric Wilcoxon rank sum test that is applicable to any distributions was used to test the null hypothesis that the two populations of measured and generated monthly precipitation are identical.

Four Water Resources and Erosion (WRE) watersheds established in 1976 at the Grazinglands Research Laboratory, El Reno, Oklahoma were used to calibrate the WEPP water balance and plant growth sub-models. The each watershed is 80 m wide and 200 m long. The longitudinal slopes of the watersheds are 3 to 4%. Soils are predominantly silt loam. Sand, silt, clay contents in the top 10-cm soil layer are about 23, 56, and 21%, respectively. Clay content increases with depth to about 40% at 1-m depth. The watersheds were cropped into winter wheat under different tillage and cropping systems since 1979. The above ground biomass at harvest and grain yield were measured. Daily precipitation was recorded by four rain gauges on the perimeter of the watersheds. An H-flume was used to measure runoff rates for each watershed. A neutron probe was used to measure soil moisture (up to 1.3 m deep) at three locations in each watershed in approximately 10-day intervals. Measured climate, soil properties, and actual tillage operations and cropping systems were used to build the WEPP climate, slope, and management input files. Measured runoff, soil moisture, and crop data were used to validate or calibrate model parameters. Saturated hydraulic conductivity of the infiltration sub-model, and energy-tobiomass conversion ratio and harvest index of the crop sub-model were the key calibration parameters.

The calibrated WEPP model along 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 the Chandler site. The simulation was conducted as if the WRE watersheds were relocated to the Chandler site. For simplicity, a generic one-year rotation of conventionally tilled winter wheat was used. In the simulation, winter wheat was planted on October 15 and harvested on June 20 each year, and the field was moldboard plowed on July 1 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 September 1 each year. Because each vearoccurrence is a possible outcome of the year category in question, initial soil moisture storage was reset to the The 45-day window period same level each year. 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.

# 3. RESULTS

# 3.1 Precipitation

The CLIGEN model was used to generate daily weather of three different year categories (dry, average, and wet) on the Chandler site. The generated and historical monthly mean precipitation are plotted in Figure 1, which indicated that CLIGEN was able to adequately reproduce the seasonal sequences of the monthly mean precipitation. Results were also tested by the Wilcoxon rank sum test, and the test results showed that CLIGEN reproduced monthly precipitation distributions reasonably well for each month and year category, with the minimum critical P value greater than 0.3. For some reason, January and August, compared with the other months, were less well reproduced by CLIGEN for all the three year categories.



Figure 1. Seasonal distribution of NWS-historical and CLIGEN-generated monthly mean precipitation for the wet, dry, and average year categories.

# 3.2 Temperature

A t-test was used to test monthly mean temperatures for each year category. 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 Compared with the maximum temperature, 0.79. monthly mean minimum temperature was less well replicated, because the range check that forced daily minimum temperature to be lower than daily maximum temperature on any given day. However, none of the tests was significantly different at the P=0.01 level. CLIGEN tended to reproduce mean minimum temperature better in summer periods (e.g., June, July, and August) when temperature was higher. Neither the monthly mean maximum temperature nor minimum temperature of both NWS-historical and CLIGENgenerated data showed considerable departures between the three year categories (Figure 2). However, discernable departures were exhibited by both NWS-



Figure 2. Seasonal distribution of (A) NWS-historical and (B) CLIGEN-generated monthly mean maximum and minimum temperatures for the wet, dry, and average year categories.

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 indicated that CLIGEN was able to correctly capture small departures of monthly mean temperatures between the year categories.

#### 3.3 Simulated Hydrological And Crop Responses

Predicted growing-season surface runoff (Q), plant transpiration (Ep), soil evaporation (Es), deep

Table 2. Percent increase per 1% increase of							
precipitation (P) during wheat growing season,							
computed from mean values of 100-year simulation							
run under three climate scenarios. (Sat=initial							
saturation level, Q=runoff, Ep=Plant transpiration,							
Es=soil evaporation, Dp=deep percolation)							

	Dry to average		Average to wet					
	%	%	%	%				
Sat	40	70	40	70				
Q	2.96	2.99	3.72	3.87				
Ep	0.52	0.43	0.64	0.63				
Es	1.05	1.05	0.30	0.32				
Dp	11.79	2.04	6.14	1.26				
Yield	0.72	0.53	0.75	0.69				

percolation (Dp), and soil moisture storages at both planting and harvest all increased with total precipitation or year category (Table 1). 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 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 years, indicating increased variability or uncertainty in dry years.

Predicted percent increase of selected parameters 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 2. Percent runoff increase was much greater from average to wet years than from dry to average years. Initial soil moisture storage increased percent runoff, but the increase was greater in wetter years. Predicted percent Ep increase per 1% increase of P was greater in wetter years because of the alleviation of plant water stress. Predicted percent Ep increase was dampened by high initial soil moisture storage, which increased percent

Table 1. Mean  $\pm$  one std of WEPP-simulated growing-season precipitation (P), runoff (Q), plant transpiration (Ep), soil evaporation (Es), deep percolation (Dp) total soil water at harvest (SW<sub>h</sub>) and at planting (SWp), and wheat grain yield for three year categories<sup>\*</sup>.

Year										
group	Р	Q	Ep	Es	Dp	SWh	SWp	Yield		
	mm	mm	mm	mm	mm	mm	mm	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		

\*Lateral soil water discharge was zero for all cases.



Figure 3. Probability distribution of WEPPsimulated winter wheat grain yield at two initial soil moisture levels and for the wet, dry, and average year categories.

runoff and deep percolation. Percent Es increase was little affected by initial soil moisture, and was largely reduced in wetter years due to better canopy cover. Percent Dp increase was greater when initial soil moisture and precipitation were lower. This is simply because the deep percolation in dry years was close to zero under low initial moisture conditions. Similar to Ep. predicted percent yield increase was greater in wetter years under both initial moisture conditions because of However, the greater reduced plant water stress. percent increase in grain yield occurred for the lower initial soil moisture conditions. This is because larger portion of precipitation increase would be taken up by Ep rather than by runoff and deep percolation as was for the higher initial soil moisture conditions. Another reason is that grain yield was generally lower in drier years, especially when initial soil moisture was low. This was clearly demonstrated in Figure 3. The initial soil moisture storage considerably affected predicted grain yield in dry years; however, the effect diminished as total precipitation increased. Figure 3 reflects not only predicted grain yield levels but also their associated probabilities for the year category and initial soil moisture conditions. This information is critical for assessing production risks associated with a particular climate forecast and available soil moisture condition.

## 4. DISCUSSION AND IMPLICATIONS

Several studies have concluded that the CLIGEN model replicated daily and monthly precipitation and daily temperatures reasonably well (Headrick and Wilson, 1997; Johnson et al., 1996; Zhang and Garbrecht, 2003). This study showed that seasonal sequences of monthly mean precipitation were well simulated for the three year categories by CLIGEN (Figure 1), indicating that CLIGEN may be capable of reproducing sequences of monthly mean precipitation of a particular seasonal climate forecast. As mentioned earlier, 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 impact of seasonal and interannual climate variations derived from seasonal climate forecasts using physically based response models.

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, and the resulting probability distribution of grain yield is then generated in a Monte-Carlo sense. The probabilistic nature of the generated grain yields lays the foundation for developing risk-based management tools. This concept has actually been demonstrated in Figure 3. 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 be 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 the CLIGEN's parameterization 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.

#### 5. CONCLUSIONS

The CLIGEN model reproduced monthly precipitation and daily maximum temperature relatively well. 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 monthly parameterization scheme used in CLIGEN provides the flexibility needed to reproduce seasonal sequences of monthly mean precipitation. This makes the CLIGEN model particular suitable for impact assessments of seasonal climate variations derived from the probabilistic type of forecast using response models. Impact of interannual climate variations can be simulated by a spectrum of year scenarios. Such application circumvents 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. The NOAA seasonal forecasts provide a unique opportunity for simulating impacts using response models. The CLIGEN model has the potential of bridging the gap between monthly forecasts and daily weather requirement 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 wetter years. Predicted crop yield was sensitive to soil moisture storage at planting, especially in dry years. Percent increase in predicted wheat grain yield per 1% increase in precipitation, on average, ranged from 0.5 to 0.75%, varying with initial soil moisture storage and precipitation levels.

## 6. REFERENCES

- Grotch, S.L., and M.C. MacCracken. 1991. The use of general circulation models to predict regional climatic change. Climatic Change 7:267-284.
- Headrick, M.G., and B.N. Wilson. 1997. An evaluation of stochastic weather parameters for Minnesota

and their impact on WEPP. ASAE Paper No. 97-2230. Minneapolis, MN:ASAE.

- Johnson, G.L., C.L. Hanson, S.P. Hardegree, and E.B. Ballard. 1996. Stochastic weather simulation: overview and analysis of two commonly used models. J. of Applied Meteorology 35:1878-1896.
- Katz, R.W. 1996. Use of conditional stochastic models to generate climate change scenarios. Climate Change 32: 237-255.
- Nearing, M.A. 2000. Erosion Forecast: Models predict climate change impacts on erosivity from 2000-2100. Resource Engineering and Technology for a Sustainable World. 7(12):33.
- Nicks, A.D., L.J. Lane, and G.A. Gander. 1995. Weather generator, Ch. 2. In USDA-Water Erosion Prediction Project: Hillslope Profile and Watershed Model Documentation, eds. D.C. Flanagan, and M.A. Nearing. NSERL Report No. 10. West Lafayette, Ind.: USDA-ARS-NSERL.
- Schneider, J.M., and J.D. Garbrecht. 2002. A blueprint for the use of NOAA/CPC precipitation climate forecasts in agricultural applications. p. J71-77. *In Third Symposium on Environmental Applications: Facilitating the Use of Environmental Information.* 13-17 Jan. 2002, Orland, FL:AMS.
- \_\_\_\_\_. 2003. Temporal disaggregation of probabilistic seasonal climate forecast. *In the* 14<sup>th</sup> *Symposium on Global Change and Climate Variations.* 9-13 Feb. 2003, Long Beach, CA:AMS.
- Wilks, D.S. 1992. Adapting stochastic weather generation algorithms for climate change studies. Climatic Change 22:67-84.
- Zhang, X.C., and J.D. Garbrecht. 2003. Evaluation of CLIGEN precipitation parameters and their implication on WEPP runoff and erosion prediction. Trans. of ASAE. (in review).