Using SWAT to simulate crop yields and salinity levels in the North Fork River Basin, USA

Aaron R. Mittelstet[1], Daniel E. Storm[1], Art L. Stoecker[2]

(1. *Department of Biosystems and Agricultural Engineering, Oklahoma State University, Stillwater, Oklahoma 74078, USA*;
2. *Department of Agricultural Economics, Oklahoma State University, Stillwater, Oklahoma 74078, USA*)

Abstract: Crop yields and salinity levels in the North Fork of the Red River (North Fork River) basin, located in southwestern Oklahoma and the Texas Panhandle, were analyzed based on the diverse climate in the region. Saline irrigation water is a major problem in the basin. The Elm Fork Creek flows through salt deposits, making the creek and its receiving stream, the North Fork River, too saline to use for irrigation. This greatly reduces the number of hectares that can be utilized for agricultural crops within the basin. A baseline SWAT model was setup, calibrated and validated to simulate streamflow and wheat and cotton yields. The SWAT model and a regression equation were used to analyze variable weather impacts on crop yields and salinity levels. Using the weather generator WXGEN and 58 years of observed weather data, ten 50-year weather datasets were generated. Output from the weather generator was input into the calibrated SWAT model to simulate wheat and dryland and irrigated cotton yields for the ten weather scenarios. Using an empirical relationship between ionic strength and streamflow, salinity levels were estimated. Though the crop yields varied greatly from year to year, the yields were not significantly different over the 50-year simulation period. The electrical conductivity (EC, expressed in decisiemens per meter or dS/m) at the US Geological Survey gage station just downstream of the salt deposits was significantly different with levels ranging from 40 to 65 dS/m. Though the water in the Elm Fork is much too saline to use for irrigation, the water in the North Fork River may be used as long as the flow rates in the river are greater than 0.60 m^3/s. In order to optimize the available cropland, a salinity control must be installed upstream of the salt deposits on the Elm Fork Creek.

Keywords: salinity, SWAT, crop yield, wheat modeling, cotton modeling, Red River
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1 Introduction

The effects of saline irrigation water on crop yields are major problems worldwide[1]. In the western USA, climatic conditions are generally characterized by low precipitation and high evaporative demand, resulting in crop production systems that are heavily dependent on irrigation[2,3]. Much of the irrigated cropland in the region has been greatly impacted by high salinity levels in local stream systems, groundwater and other sources of irrigation water. As a result, irrigated crop yields have been negatively impacted by saline irrigation water[2,3], resulting in a total estimated reduction in revenue of approximately $2.5 billion for the western USA crop production region[2]. These negative salinity impacts could be further exacerbated if variability in climatic patterns intensifies in the future.

Due to increased water demand, many agricultural producers in various regions across the globe are forced

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Biographies: Daniel E. Storm, PhD, Professor. Department of Biosystems and Agricultural Engineering, Oklahoma State University, 121 Agricultural Hall, Stillwater, Oklahoma 74078, USA. Email: dan.storm@okstate.edu. **Art L. Stoecker,** PhD, Associate Professor. Department of Agricultural Economics, Oklahoma State University, 312 Agricultural Hall, Stillwater, Oklahoma 74078, USA. Email: art.stoecker@okstate.edu.
***Corresponding author: Aaron R. Mittelstet**, Research Engineer, PhD Candidate. Department of Biosystems and Agricultural Engineering, Oklahoma State University, 117 Agricultural Hall, Stillwater, Oklahoma 74078, USA. Email: aaron.mittelstet10@okstate.edu; Phone: +1-405-744-8429 or +1-405-612-9987; Fax: +1-405-744-6059.

to use irrigation water which is often characterized by high salinity levels. In turn, the continued irrigation of saline water and the subsequent water removal by the plants often results in salt accumulations in the soil[4]. The increased salinity levels in the soils not only produces toxic effects on plant growth, but also significantly reduces the potential water uptake by plants and thus inhibits plant growth and reduces yields[5].

Excessive salinity levels have been found to result in significant decreases in lettuce, alfalfa and cotton yields in the western USA[3]. Decreases in crop yields in response to high soil and irrigation water salinity levels have also been reported in other countries[1]. In India for example, wheat and cotton yields decreased by 11% and 30%, respectively, when the electrical conductivity (EC, expressed in decisiemens per meter or dS/m) of the irrigation water increased from 2-4 to 4-6 dS/m[6]. These crop yields further decreased 40% and 45% when the salinity levels were 6-8 dS/m. Some crops are more resistant than others to saline water[7]. At 6 dS/m, cotton yields are not affected, alfalfa yields decrease by half and lettuce yields drop to near zero[3]. In the Ibshwai District in Africa they found that wheat yields were not affected, onion yields decreased by 33%, peppers by 50% and summer tomatoes by over 75% when the EC of the irrigated water increased from 0.5 to 2.8 dS/m[1,8].

Crop growth models are important tools in evaluating the potential growth and yields of crops in different climatic and environmental conditions, including saline affected watershed systems. There have been several studies predicting wheat yields using various models, such as the CERES-wheat model[9,10], the Environmental Policy Integrated Climate (EPIC) field-scale environmental model[10,11], and the Soil and Water Assessment Tool (SWAT) water quality model[12,13]. Vaghefi et al.[14] and Faramarzi et al.[15] used SWAT to simulate wheat yields in Iran. Sun and Ren[16] used SWAT to simulate winter wheat-summer maize double cropping system for various irrigation and nutrient stress scenarios in China, while Nair et al.[17] used SWAT to calibrate wheat, soybean and corn yields and compare the simulated crop yields to observed yields. Other models, such as EPIC[18,19] and GRAMI[20], have been utilized to predict cotton yields. Sarkar et al.[21], Panagopoulos et al.[22] and Gikas et al.[23] used SWAT to estimate cotton yields, though none of these studies separated cotton into dryland and irrigated, and only Sarkar et al.[21] compared the SWAT simulated yields to observed yields. Previous research has also underscored the importance of incorporating calibration of crop yields within overall hydrologic and water quality testing of SWAT applications[21].

The Elm Fork River, a major tributary of the North Fork of the Red River (North Fork River) in southwest Oklahoma, USA, flows through salt deposits upstream of its confluence with the North Fork River, resulting in all water downstream becoming too saline to use for irrigation purposes. However, Bhavsar et al.[24] found that there were over 20 000 hm^2 of soil with irrigation potential along the Elm and North Fork Rivers in the overall North Fork River basin. Thus, it is urgent to determine if the excessive saline content of the North Fork River stream system can be mitigated to overcome current limitations for irrigation use, especially within the context of potential future climatic variability. The application of a model, such as SWAT, could be very useful in such an analysis.

At present, SWAT does not simulate salinity directly in streamflow; however, Gikas et al.[25], Piman et al.[26], and Somura et al.[27] used SWAT to simulate streamflows, and then used the estimated streamflows with other models or regression equations to simulate salinity impacts for studies conducted in Greece, southeast Asia, and Japan. The overall goal of this study is to build on these previous studies to predict in-stream salinity levels for the North Fork River, and then to assess the effects of climatic variability on in-stream salinity levels and the implications of the salinity levels on crop yields based on analyses performed with SWAT. Thus, the specific objectives of this research are to describe: (1) the SWAT baseline streamflow calibration/validation and crop yield calibration procedures and results, (2) the interface between SWAT streamflow estimates and a regression equation in order to predict in-stream salinity levels, and (3) the analysis of potential future salinity levels and corresponding crop yields based on likely weather variability for the North Fork River basin. These results will help watershed planners better understand the potential variability in salinity levels and crop yields in the basin and provide guidance in deciding if a salinity control is necessary and cost efficient.

2 Materials and methods

This study was divided into three steps. The first step was to setup, calibrate and validate streamflow in the basin using the SWAT model. The second step was to use historical weather data and the weather generator WXGEN to generate ten 50-year datasets as input for the calibrated SWAT model. The final step was to estimate and analyze the range of crop yields and salinity levels in the basin resulting from weather variability. Since SWAT does not simulate salinity, a regression equation was developed using streamflow and EC.

2.1 Study area description

The North Fork River basin occupies 5 900 km^2 in southwest Oklahoma and the Texas panhandle (Figure 1). The basin receives an average annual rainfall of 695 mm with average minimum and maximum temperatures of 10°C and 23°C, respectively. There are two major reservoirs, Atlus-Lugert and Tom Steed. The two major tributaries in the basin are the Elm Fork and North Fork Rivers, which are listed on the US Environmental Protection Agency 303(d) list as impaired by chloride[28]. High salinity levels were due to natural salt springs on the Elm Fork just west of the US Geological Survey (USGS) gage station 07303400 (Figure 2). From 1982 to 2005 the average EC at the gage station was 18 dS/m with a range of 4.1 to 65 dS/m[29], which was well above 3.0 dS/m where the degree of restriction on irrigation use is severe[30]. Ayers and Westcot[30] indicated that EC levels less than 0.7 dS/m have no restrictions on irrigation use and those between 0.7 and 3.0 dS/m have slight to moderate restrictions. The EC levels greater than 10 dS/m are classified as highly saline and only very tolerant crops can be successfully grown[1]. Further downstream in the basin at USGS gage station 07305000 (Figure 2), diluted streamflow decreased salinity levels to an average of 6.3 dS/m with a range from 1.6 to 14 dS/m during the years 1982 to 2005[29]. The average flow at the two USGS gage stations was 1.13 and 9.85 m^3/s for 07303400 and 07305000, respectively, for the same period of record.

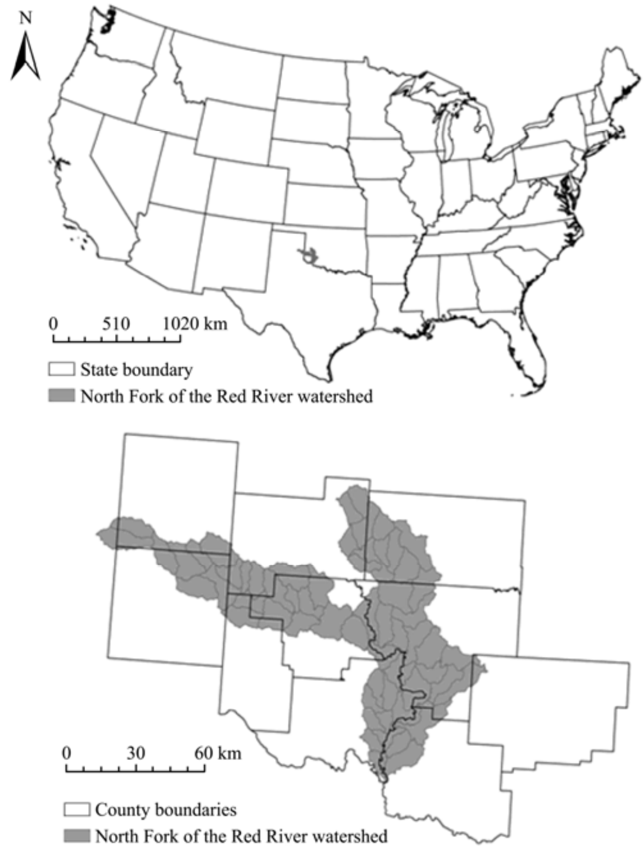

Figure 1 Location of the North Fork of the Red River basin with state and county boundaries in southwest Oklahoma and the Texas Panhandle

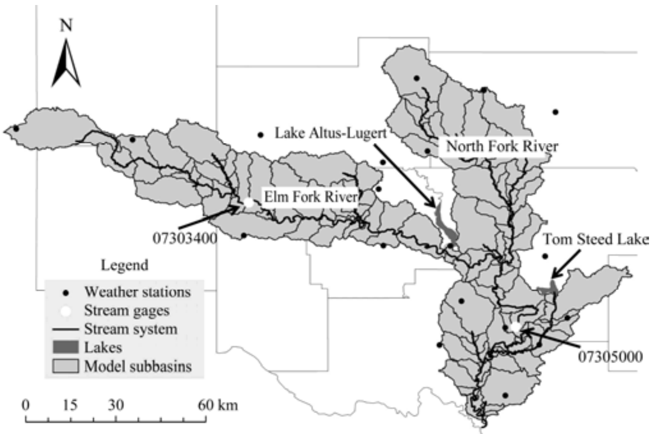

Figure 2 Location of the Elm Fork and North Fork Rivers, Altus-Lugert and Tom Steed reservoirs, 19 National Weather Service stations, and the U.S. Geological Survey gage stations 07303400 and 0730500 in the North Fork of the Red River basin

The two most prevalent crops within the basin are wheat and cotton[31]. Whereas wheat and dryland cotton are found throughout the basin, irrigated cotton was mainly grown in the Texas Panhandle and the southern reaches of the basin within the Lugert-Altus Irrigation

District. Irrigation water from the Altus-Lugert reservoir was transported through canals to the irrigation district.

2.2 SWAT model description

The SWAT model is a basin-scale hydrological/water quality model used to predict streamflow and pollutant losses (phosphorous, nitrogen and sediment) from basins made up of mixed land covers, soils and slopes. The model was developed to assist water resource managers in assessing water quantity and/or quality in large river basins and as a tool to evaluate the implementation of different agricultural conservation practices[12]. The SWAT model, a product of over 30 years of model development by the US Department of Agriculture Agricultural Research Service, has been extensively used worldwide[13]. The model is process based and can simulate the hydrological cycle, crop yield, soil erosion and nutrient transport. The model divides the watershed into subbasins, which are further split into hydrological response units (HRUs). Each HRU is made up of one soil, one land use and one slope. The model uses the Modified Universal Soil Loss Equation (MUSLE) to calculate sediment yield in each HRU. This sediment along with any nutrients are summed up for each subbasin and routed through the reach. The water and sediment along with any other pollutants are routed from reach to reach until it arrives at the watershed outlet. Many field-scale activities, such as planting dates, irrigation, fertilization, grazing, harvesting and tillage, are utilized by SWAT as management options scheduled by date. Further details on the theoretical aspects of hydrology, nutrient cycling, crop growth and their linkages are provided in Neitsch et al.[32]. ArcGIS[33] can be utilized for model input of land cover, soils, elevation, weather, and point sources. For this project SWAT 2005 and a monthly time step were utilized.

2.3 SWAT model setup

2.3.1 Land cover

Land cover data were obtained from two sources, the Cropland Data Layer (CDL)[34] and 2001 National Land Cover Data (NLCD)[35,36]. The CDL contained crop-specific digital data and was combined with the non-agricultural data from NLCD. Each of the 30 land cover categories were delegated to one of seven land cover categories that were used in the SWAT model (Table 1). For example, canola, rye, oats, alfalfa, wheat and other small grains were combined to form the small grain crops category. Row crops, of which the majority was cotton, were then divided into dryland and irrigated cotton based on Landsat 5 satellite imagery taken on August 10, 2006[37].

Table 1 Seven land use categories and areas utilized in the North Fork of the Red River basin SWAT model

Land use	Basin area	
	Percent/%	km^2
Developed land	4.5	250
Forest	2.1	120
Grassland	24.4	1360
Row crops	3.8	210
Dryland	2.0	110
Irrigated	1.8	100
Shrubland	37.4	2080
Small grain crops	27.1	1510
Water	0.7	390

Thermal band six in Landsat 5 was utilized to identify irrigated fields since surface waters and irrigated areas were cooler than their surroundings (see dark areas in Figure 3). The thermal band data were converted from at-sensor spectral radiance to effective at-sensor brightness temperature using:

$$T = \frac{K_2}{\ln\left(\frac{K_1}{L_\lambda} + 1\right)} \tag{1}$$

where, T was the effective at-sensor brightness temperature (K); K_2 was a calibration constant (K); K_1 was a calibration constant [W/(m^2·sr·μm)]; and L_λ was the spectral radiance at the sensor's aperture [W/(m^2·sr ·μm)][38]. Aided by 2008 National Agricultural Imagery Program images (NAIP)[39] to identify irrigated fields, areas with a temperature below 34°C were identified as water or irrigated row crops. This data layer was then overlaid with the land cover layer and any areas identified as cooler than 34°C and row crops were designated as irrigated row crops. Figure 3 illustrates the identified irrigated fields of the Landsat thermal band six image of the Lugar-Altus Irrigation District in the southern part of the basin.

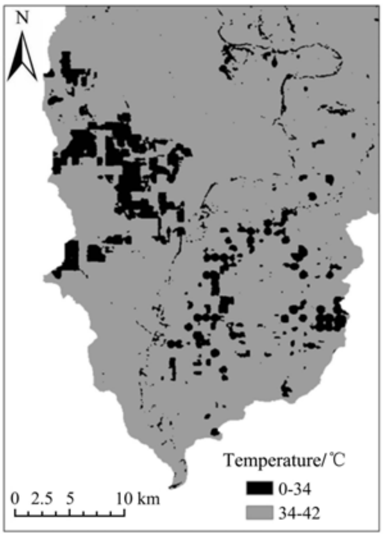

Figure 3 Landsat 5 satellite image taken in 2006 illustrates the areas with cooler temperatures (black) utilized to identify the irrigated row crops and surface water in the North Fork of the Red River basin

2.3.2 Digital elevation model and soils

All data were input into the ArcSWAT 2.1.5a user interface. The first step in setting up the SWAT model was the delineation of the basin using a 1:24 000 scale USGS National Hydrology Dataset and a 10 m USGS DEM to calculate slopes, slope lengths, and to define the stream network. The resulting stream network was used to define a basin consisting of 95 subbasins. For soils, STATSGO[40] 1:25 000 scale soil maps were used. These layers along with the land cover layer were used to define HRUs; 0% slope, 10% land and 10% soil class thresholds were used to create 1 787 HRUs within 95 subbasins for the SWAT simulations.

2.3.3 Weather, point sources, inlets and ponds

Observed daily precipitation and minimum and maximum temperatures were used in the SWAT model. Nineteen National Weather Service Cooperative Weather Network (COOP data) stations were utilized from 1950 to 2007 (Figure 2)[41]. In addition, three major point sources were located within the basin, which were the Elk City Wastewater Treatment Plant (WWTP), Altus SW WWTP, and the Quartz Mountain Regional Authority[42]. The Altus SE WWTP and Quartz Mountain Regional Authority discharged an average flow of 7 600 m^3/d and 600 m^3/d, respectively, from 1996 to 2009. Elk City had a lagoon system and therefore discharged on an irregular schedule.

SWAT inlets were added below the Altus-Lugert and Tom Steed reservoirs. Daily releases were obtained from the USGS gage station 07303000[29] for the Altus-Lugert reservoir and monthly releases from the US Army Corp of Engineers[43] for the Tom Steed reservoir. Since ponds affect the hydrology by impounding water, NAIP from 2008[39] was used to estimate pond and small reservoir areas for each subbasin. Using these NAIP data, the ponds and small reservoirs were vectorized in ArcGIS and their surface areas estimated. The ponds and small reservoirs were assumed to be at their primary spillway elevation, have an average depth of two meters, a drainage area equal to 30 times their surface area[44], and emergency spillways that were active when volume and surface area were 150% of normal.

2.3.4 SWAT management

Each land cover was managed in a different way. Ten surveys, of which eight were returned, were sent to Oklahoma State University Cooperative Extension Service personnel and Agronomy Specialists within the basin. They provided information on typical fertilization types and dates applied, planting and harvesting dates, irrigation practices and tillage operations performed by agricultural producers in the basin. These data were analyzed, composited and entered into the SWAT model as shown in Table 2. The small grain was further split into two land use categories where 75% was grazed with cattle during the winter months and was tilled whereas the other 25% did not have any cattle and was no-till. The irrigated and dry land row crops were also further split into tilled (80%) and no-till (20%).

SWAT overestimated stream flow from 2003 to 2007 after the initial model setup and calibration. The likely cause was the increase in irrigated cotton since 2000 in Wheeler and Collingsworth Counties in Texas[31] (Figure 4). The quantity of irrigated cotton increased from an average of 3 400 hm^2 from 1995 to 2002 to an average of 7 600 hm^2 from 2003 to 2007. A water withdrawal of 1.5 million m^3 per month was added from May through November from 2003 to 2007 to account for this increase in irrigated cotton based on the irrigation needs of the cotton and the precipitation in the area for that time period.

Table 2 Typical fertilization, tillage, grazing, planting and harvesting data obtained from surveys from local Oklahoma State University Cooperative Extension Service personnel and Agronomy Specialists within the basin and utilized in the SWAT model

Land cover	Land cover/%	Operation	Date
Small grain	25	56 kg/hm^2 N	February 1
		Harvest	June 15
		45 kg/hm^2 N 45 kg/hm^2 P	September 1
		Plant	October 1
	75	56 kg/hm^2 N	February 1
		Harvest	June 15
		45 kg/hm^2 N 45 kg/hm^2 P	September 1
		Tillage	September 15
		Plant	October 1
		Graze 2.5 Animal Units/hm^2	November-February
Irrigated row crops	20	56 kg/hm^2 N 34 kg/hm^2 P	May 1
		Plant	May 15
		Harvest	November 1
	80	Tillage	April 15
		56 kg/hm^2 N 34 kg/hm^2 P	May 1
		Plant	May 15
		Harvest	November 1
Dryland crops	20	56 kg/hm^2 N 34 kg/hm^2 P	May 1
		Plant	May 15
		Harvest	November 1
	80	Tillage	April 15
		56 kg/hm^2 N 34 kg/hm^2 P	May 1
		Plant	May 15
		Harvest	November 1

2.4 Weather variability

Weather in the North Fork River basin can vary dramatically from year to year. From 1950 to 2013, the average annual precipitation ranged from 370 mm to 1 100 mm while the maximum and minimum annual temperatures range from 21.3 to 25.8°C and 8.2 to 11.5°C, respectively. From May to October, the cotton growing season, the annual precipitation varied from 150 mm to 875 mm. The temperatures during the cotton growing season can also vary dramatically. For example, the average June maximum temperature was 33°C, ranging from 27°C to 39°C. Figure 5 shows the variability in precipitation and temperature during the cotton growing season. This annual variation in precipitation and temperature can have a dramatic effect on streamflow, salinity levels and crop yields in the basin.

For this project a stand-alone version of WXGEN[45] was utilized to generate weather datasets. Statistics (mean and standard deviation) from historical records was input into WXGEN to produce ten 50-year datasets, which included rainfall, minimum and maximum temperatures and solar radiation. The temperature and solar radiation utilized cross- and auto-correlation between the variables[46].

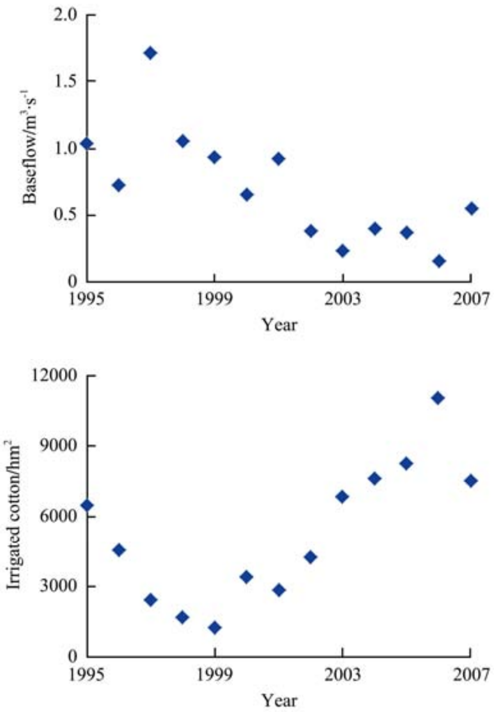

Figure 4 Decrease in baseflow and an increase in irrigated cotton for Wheeler and Collingsworth Counties in Texas from 1995-2007[29,31]

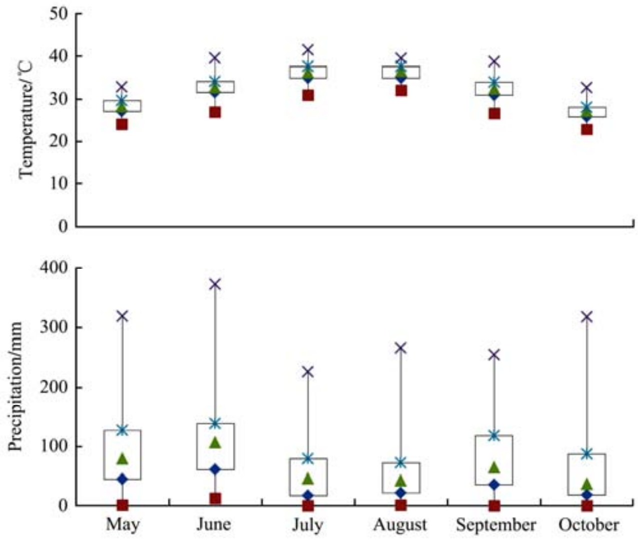

Figure 5 Box plots for average monthly temperature and precipitation for National Weather Service Cooperative Weather Network gage station C340184 from 1950 to 2013 for the cotton growing season of May to October

2.5 Salinity and electrical conductivity

A statistically valid relationship (α=0.05) between EC and streamflow was found at each of the gage stations 07303400 and 07305000 (Figure 6). EC was the preferred method to assess salinity, and was based on the concept that the electrical current carried by a salt solution under standard conditions increased as the salt concentrations of the solution increased. The USGS gage stations 07303400 and 07305000 had EC data from 1982 to 2005 for 37 and 43 days, respectively. The EC (dS/m) was regressed against streamflow to develop a relationship of the form:

$$\log(EC) = Log(a_1) + a_2 \log(Flow) \quad (2)$$

or

$$EC = a_1 Flow^{a2} \quad (3)$$

where, a_1 and a_2 were linear regression coefficients, and *Flow* was stream flow (m^3/s). Muttiah et al.[47] used a monthly relationship between flow and EC as the driver for their in-stream salinity modeling of the Mid-Rio Grande and Wichita watersheds. Somura et al.[27] estimated monthly salinity from a regression curve (R^2=0.53) for Lake Shinji in the Hii River basin. At gage 07303400, all data were used in the analysis except for one outlier when the flow exceeded 1 700 m^3/s, which was over 200 times the second largest flow event for sampling period. All data points were used at the gage station 07305000. The flow and EC regression had a Coefficient of Determination (R^2) of 0.93 and 0.43 at the gage stations 07303400 and 07305000, respectively.

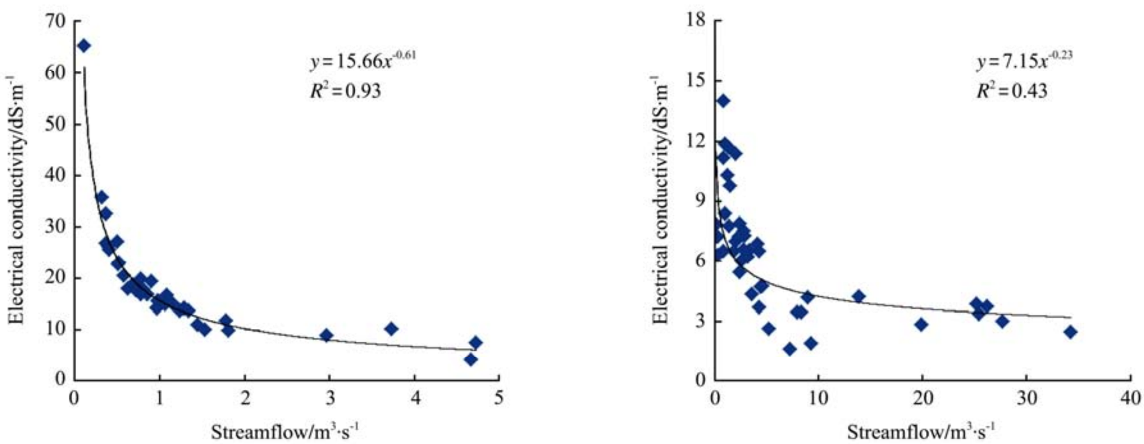

Figure 6 Relationship between streamflow and Electrical conductivity at the US Geological Survey gage stations 07303400 and 07305000 for the period 1982-2005[29]

2.6 Model evaluation

Calibration is the process by which parameters are adjusted to make predictions agree with observations. SWAT was designed for use on large un-gaged basins and can be used without calibration. However, calibration generally improves the reliability and reduces the uncertainty of model predictions. Validation is similar to calibration except model parameters are not modified. Validation tests the calibrated model with observed data that are not used in the calibration process and preferably under conditions outside the calibration period. For both the calibration and validation models, a five-year warm-up was added to insure that the model represented reasonable initial conditions at the beginning of each simulation, i.e., aquifer levels, soil water conditions, vegetative growth, etc.

2.6.1 Crop yields

The wheat and irrigated and dryland cotton yields were compared to National Agricultural Statistical Service (NASS) data using default SWAT model parameters. The SWAT simulated crop yields for wheat and irrigated and dry land cotton were evaluated against county level NASS data for the years 2001 to 2007[34]. These crops were chosen since they represented the dominant crops in the basin. Annual crop yields from the counties within the basin were averaged and compared to predictions from the flow-calibrated SWAT model. No calibration was utilized for the simulated crop yields. Three statistics were used to evaluate the model performance: R^2, Nash-Sutcliffe Efficiency (NSE) and Percent Bias (PBIAS)[48,49]. R^2 is the square of Pearson's product-moment correlation coefficient[50] and represents the proportion of total variance in the observed data that can be explained by a linear model. The NSE indicates how well observed flows versus simulated crop yields fit a 1:1 line[51], given as:

$$NSE = \left(1 - \frac{\sum_{i=1}^{n}(Y_i^{obs} - Y_i^{sim})^2}{\sum_{i=1}^{n}(Y_i^{obs} - Y^{mean})^2}\right) \times 100\% \quad (4)$$

where, n is the total number of observations, and the superscripts *obs*, *sim* and *mean* represent the observed, simulated and mean observed values, respeectively. PBIAS was calculated using:

$$PBIAS = \left(\frac{\sum_{i=1}^{n}(Y_i^{obs} - Y_i^{sim}) \times 100}{\sum_{i=1}^{n}(Y_i^{obs})}\right) \quad (5)$$

where, *PBIAS* is the deviation of data being evaluated, expressed as a percentage.

2.6.2 Streamflow

Following the crop yield evaluation, streamflow was calibrated using monthly and annual streamflow at USGS gage stations 07303400 and 07305000. The monthly and annual SWAT simulated streamflows were calibrated from 2001 to 2007 and validated from 1995 to 2000. Next, the calibrated streamflows were coupled with the regression equations to estimate the EC.

A sensitivity analysis was conducted on 15 parameters based on previously used calibration parameters and documentation from the SWAT manuals. Parameters were adjusted within SWAT recommended range and its sensitivity analyzed. The various parameters were adjusted in order to minimize the relative error and obtain the best goodness-of-fit statistics for each gage station. Ultimately seven parameters were modified in the final calibration (Table 3).

Table 3 Parameters used to calibrate the SWAT model for the North Fork of the Red River basin

Original value	Calibrated value	Subbasin	Variable	Description
0.95	0.51	All basins	ESCO	Soil evaporation compensation coefficient
0.05	0.20	All basins	RCHRG_DP	Aquifer percolation coefficient
1.0	100	All basins	REVAPMIN	Threshold water level in shallow aquifer for revap or percolation to deep aquifer
0.025	0.055	All basins	ALPHA_BF	Baseflow Alpha Factor (d)
0.08-0.23	+0.01	07303400	SOL_AWC	Soil available water capacity
49-84	-4	07303400	CN2	SCS curve number adjustment
39-92	+5	07305000	CN2	SCS curve number adjustment
0	13.5	07303400	CH_K2	Effective hydraulic conductivity in main channel alluvium (mm·h^{-1})
0	4.2	07305000	CH_K2	Effective hydraulic conductivity in main channel alluvium (mm·h^{-1})

The NSE and R^2 were used as indicators of goodness-of-fit. Moriasi et al.[49] assumed a monthly NSE greater than 0.75 indicated a very good model, 0.65 to 0.75 as good and 0.50 to 0.65 as satisfactory when calibrating SWAT for streamflow.

3 Results and discussion

SWAT satisfactorily predicted average annual wheat yields, although it over predicted the yield by 0.33 Mg/hm^2 or 17% in 2007 (Figure 7), the second wettest year in the simulation period. The relationship between SWAT simulated wheat yields versus the NASS observed wheat yields had an R^2 of 0.61 (Table 4). The observed yields ranged from 1.40 to 2.19 Mg/hm^2 while simulated yields ranged from 1.39 to 2.44 Mg/hm^2. These results were similar to those reported by Nair et al.[17] for SWAT simulated wheat yields who reported R^2 values of 0.57 and 0.81 for the calibration and validation periods, respectively. They reported, however, higher NSEs of 0.53 and 0.61 for the calibration and validation periods, respectively. No other studies reported observed vs. simulated results except for Vaghefi et al.[14] and Faramarzi et al.[15], who only reported R and P factors, i.e. data percentage bracketed by the 95% prediction uncertainty.

The observed versus simulated annual dryland cotton yields had an R^2 of 0.74, with observed data ranging from 0.32 to 0.75 Mg/hm^2 compared to 0.46 to 0.87 Mg/hm^2 for the simulated predictions. The model consistently over predicted the yields except for the wettest year. The only reported comparisons between observed vs. dryland cotton was by Sarkar et al.[21] with an R^2 of 0.45.

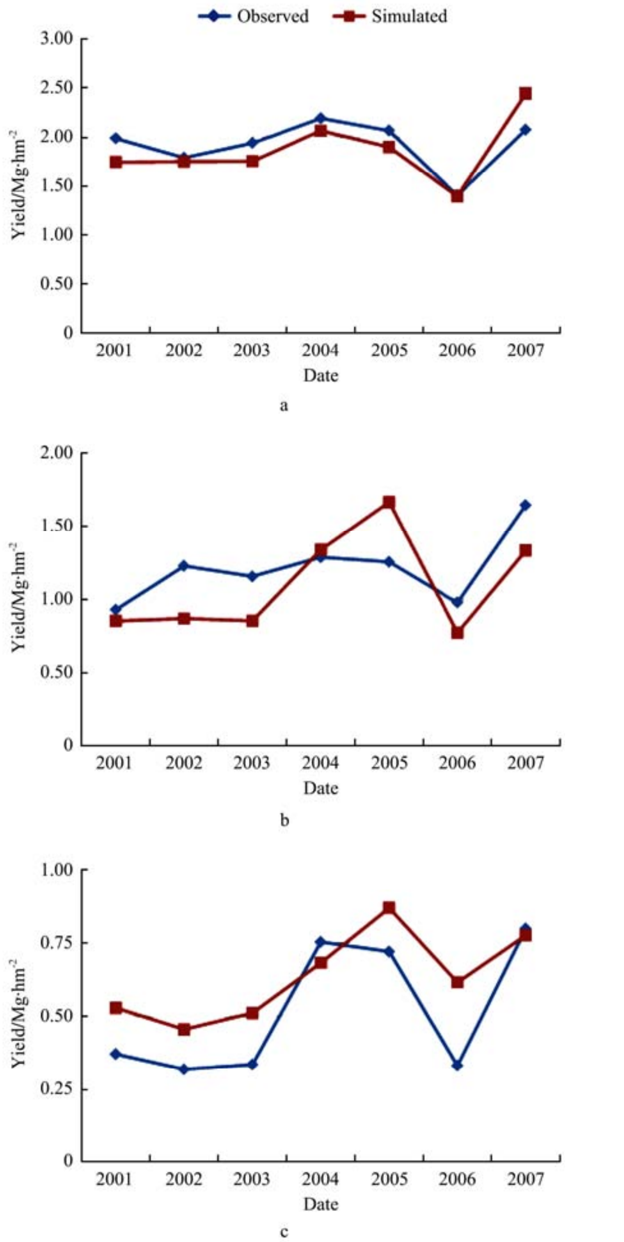

Figure 7 Observed vs. SWAT simulated (a) annual wheat, (b) dryland cotton and (c) irrigated cotton yields from 2001 to 2007

Table 4 Summary statistics for the observed data vs. SWAT simulated wheat, dryland cotton and irrigated cotton yields for the period 2001 to 2007

Crop	R^2	NSE[a]	Percent bias	Yield/Mg·hm^{-2}			
				Observed		Simulated	
				Range	Mean	Range	Mean
Wheat	0.61	0.33	3	1.40-2.19	1.92	1.39-2.44	1.86
Dryland cotton	0.74	0.4	-22.2	0.32-0.75	0.52	0.46-0.87	0.63
Irrigated cotton	0.38	-0.61	9.4	0.93-1.64	1.21	0.85-1.67	1.1

Note: [a]NSE: Nash-Sutcliffe modeling efficiency.

The results for the irrigated cotton were not as favorable as indicated by an R^2 of 0.38 and a negative NSE (Table 4). The observed data ranged from 0.93 to 1.64 Mg/hm^2 compared to 0.85 to 1.67 Mg/hm^2 for the simulated predictions. The current literature does not report any other irrigated cotton modeling results obtained with SWAT. These results indicate that further testing is needed on irrigated cotton systems using SWAT.

3.1 Streamflow

Graphical comparisons between the measured and observed aggregated monthly streamflows are shown for the calibration and validation periods for both USGS gauges in Figure 8. The streamflows predicted by SWAT replicated the observed streamflows well for most months although some peak streamflow periods were under predicted by the model, especially in the validation period.

For the average monthly calibration, gage 07303400 had an R^2 of 0.78 and a NSE of 0.68 and gage 07305000 had an R^2 of 0.88 and a NSE of 0.86 (Figures 8a and 8c). Based on the suggested criteria by Moriasi et al.[49], the model performance at the two gage stations could be described as good and very good. The lower NSE for the gage station 07303400 during the calibration period was due to under predicting runoff from several rainfall events at the end of 2002 and 2006. The basin received isolated thunderstorms and being the upstream gage station with a smaller basin, the weather station most likely missed these events. This was not observed in gage station 07305000 since it was further downstream and drained a much larger basin.

Flow validation indicated if the SWAT model predicted reasonable results under conditions outside the calibration period. Even though the validation period was wetter than the calibration period, the model performed 'very good' at both gage stations for average monthly streamflow; gage 07303400 had an R^2 of 0.84 and a NSE of 0.77, and gage 07305000 had an R^2 of 0.89 and a NSE of 0.76 (Figures 8b and 8d).

3.2 Crop yield and salinity variability

3.2.1 Crop yield

The yields for wheat, irrigated cotton and dryland cotton were analyzed for each of the ten 50-year simulations. The range of yields was plotted and statistical significance determined at an α=0.05 level. The average wheat yields for the ten simulations ranged from 1.70 to 1.76 Mg/hm^2 and were not significantly different based on a *t*-test (Figure 9). The annual yields ranged from a minimum of 0.62 Mg/hm^2 to 3.02 Mg/hm^2 (Figure 10). Neither the irrigated nor dryland cotton yields were significantly different for the ten 50-year simulations based on a *t*-test. The irrigated cotton yields averaged 0.85 to 0.95 Mg/hm^2 with an annual minimum of 0.18 Mg/hm^2 and an annual maximum of 2.11 Mg/hm^2. These yields were much higher and more variable than the yields for the dryland cotton, which ranged from 0.48 to 0.52 Mg/hm^2 for the ten 50-year simulations with annual minimum and maximum yields of 0.08 and 1.09 Mg/hm^2, respectively.

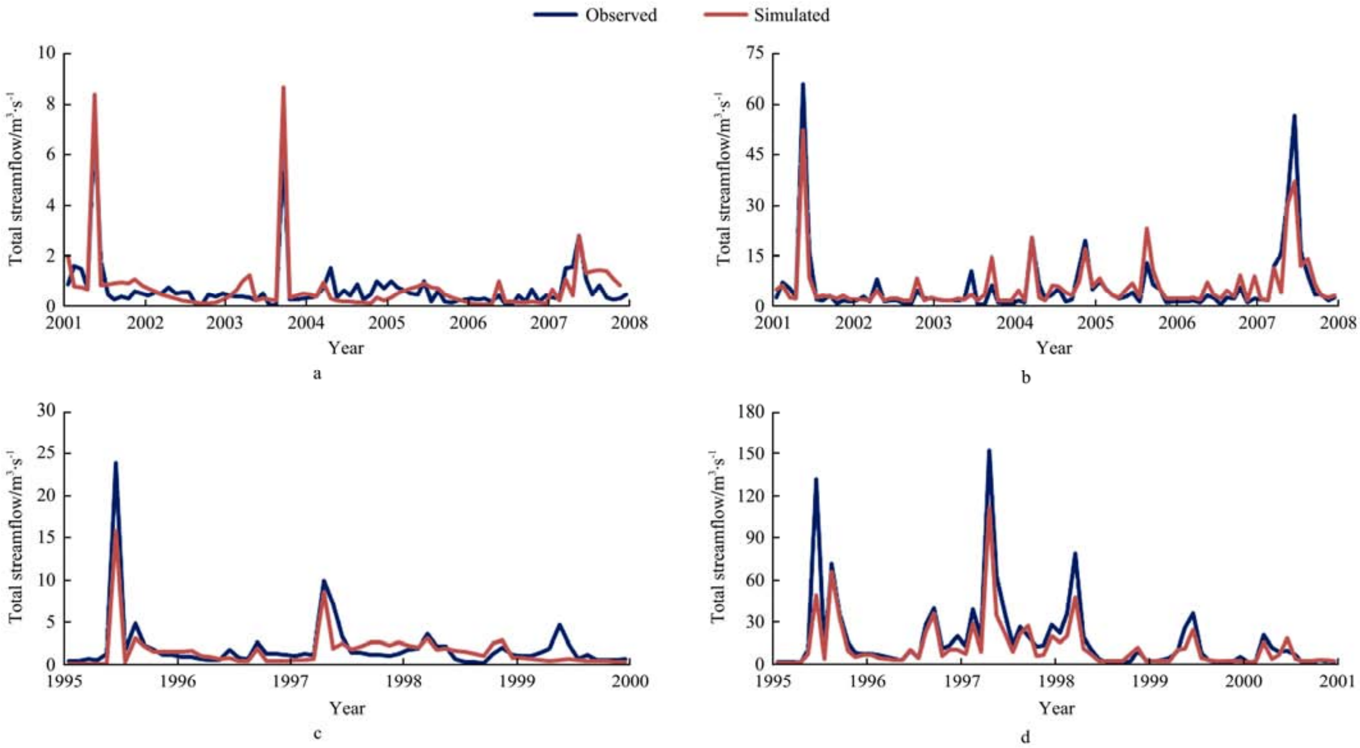

Figure 8 Total streamflow calibration and validation results for monthly SWAT simulations at the US Geological Survey gage stations (a and b, respectively) 07303400 and (c and d, respectively) 07305000

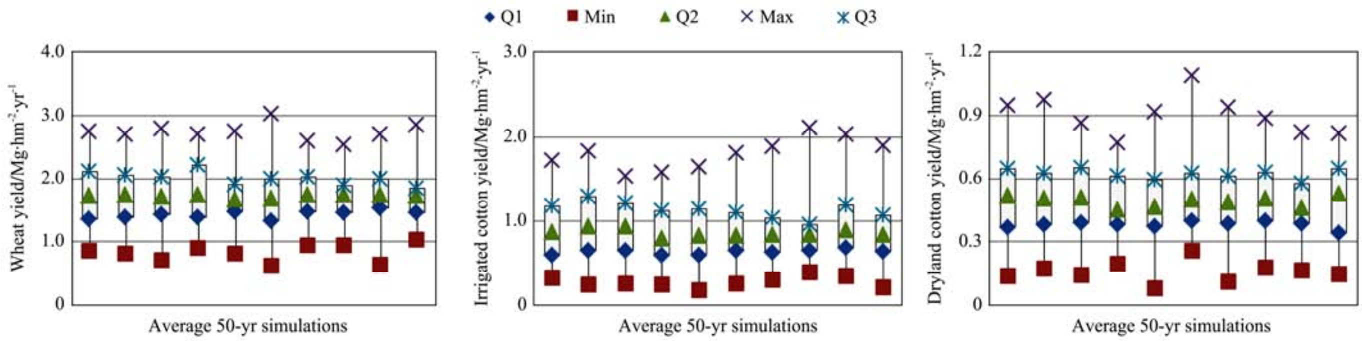

Figure 9 Wheat, irrigated cotton and dryland cotton yields for ten 50-year SWAT simulations based on historical weather variability

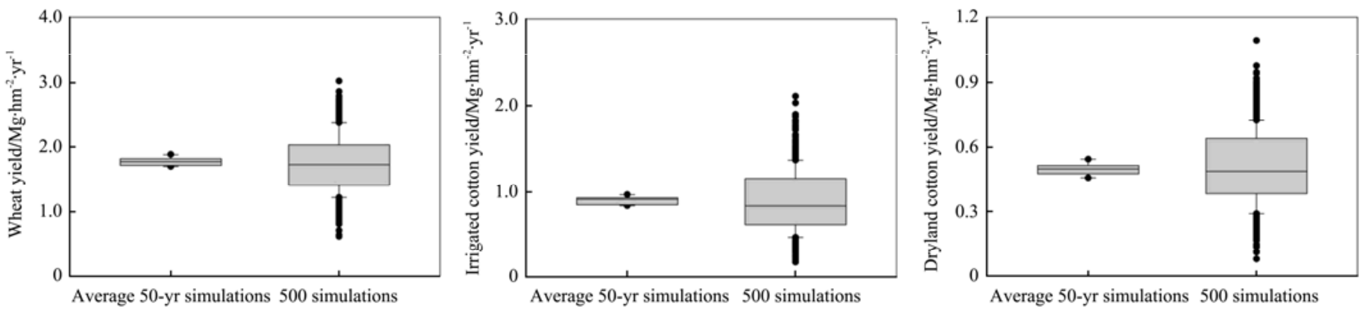

Figure 10 Average annual wheat, irrigated cotton and dryland cotton yields for ten 50-year SWAT simulations and the combined 500 simulations

Based on the results of these simulations, agricultural producers can expect highly variable yields from year to year based on the timing of the precipitation and temperatures; however the long term average yield will likely stabilize (Figure 11). Other factors, such as a late freeze, pests, hail and severe storm, are factors that SWAT currently does not consider that can dramatically affect the crop yields.

3.2.2 Salinity

The average flow at gage station 07303400 for the ten 50-year simulations ranged from 0.35 to 0.84 m^3/s (Figure 11a). The salinity levels between years were statistically significant based on a *t*-test with average EC levels ranging from 40 to 65 dS/m (Figure 11 b). After log transforming these data, a Tukey's multiple comparison test was performed at an α=0.05 showing that two of the ten simulations were significantly different. The annual flows and EC levels ranged from 0.008 to 5.8 m^3/s and 5.4 to 369 dS/m, respectively, for the entire 500 years of simulation (Figures 12a and 12b).

The average annual streamflow and EC levels at gage station 0705000, located near the Lugert-Altus Irrigation District, for the ten 50-year simulations ranged from 4.0 to 6.7 m^3/s and 4.6 to 5.2 dS/m (Figures 11c and 11d), respectively, and were not statistically different. For the combined 500 simulation years the annual flows and EC levels ranged from 0.64 to 31.3 m^3/s and 3.3 to 7.9 dS/m, respectfully (Figures 12c and 12d). Based on Ayers and Westcot[30], when irrigated water is above 5.3 dS/m, full yield potential begins to decrease, and at 19 dS/m the yield potential is zero. Miyamoto et al.[52] reported groundwater with salinity levels averaging 3.5 dS/m and up to 8.0 dS/m being applied in Texas and successfully growing cotton. In Arizona, Dutt et al.[53] successfully grew cotton using irrigated water with salinity levels ranging from 3 to 4 dS/m. Williams[3] states that cotton has a threshold of 5.1 dS/m and shows only a 25% reduction in yield when salinity reaches 8.4 dS/m.

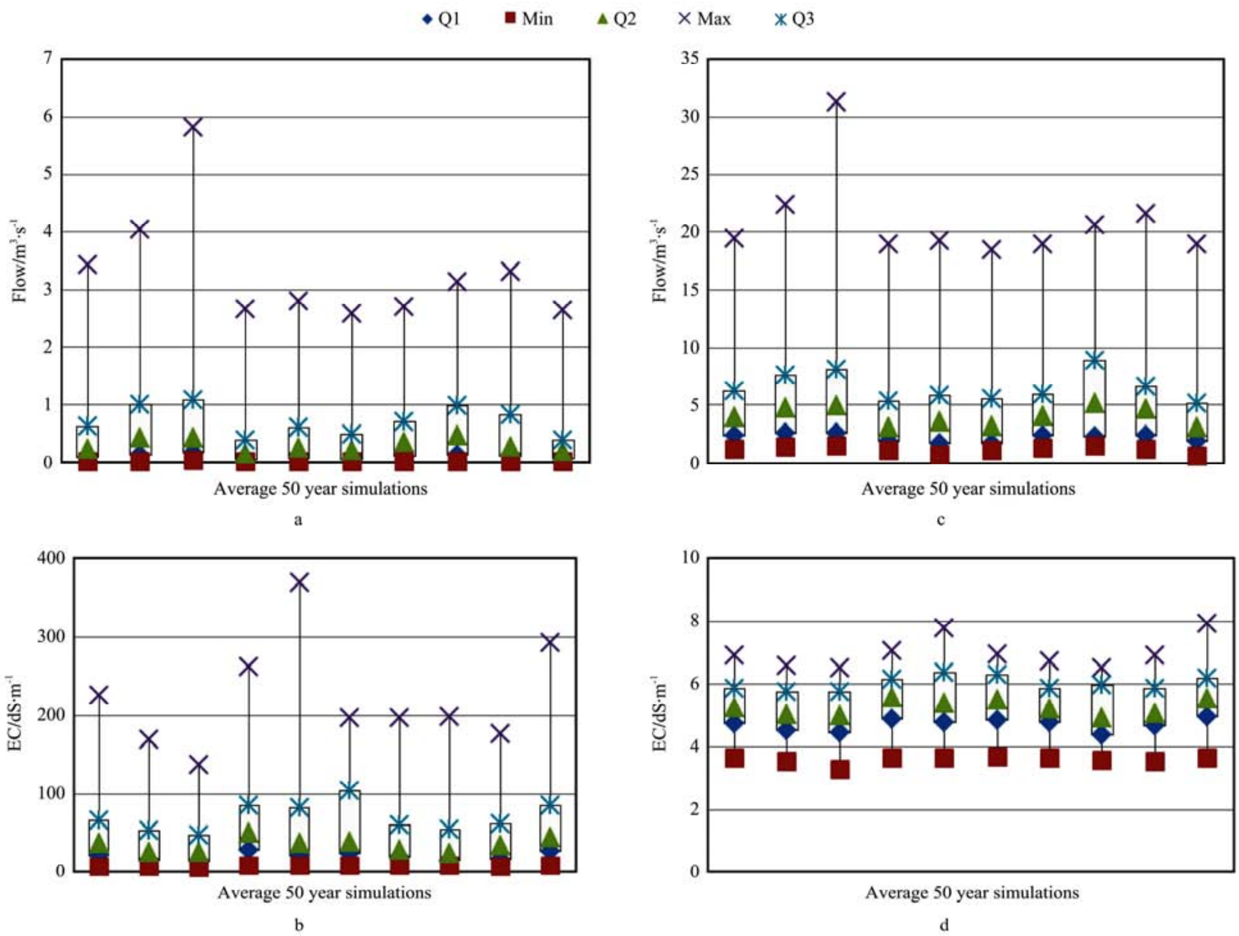

Figure 11 Annual streamflow and Electrical Conductivity (EC) at US Geological Survey gage stations (a and b, respectively) 07303400 and (c and d, respectively) 07305000 for ten 50-year SWAT simulations

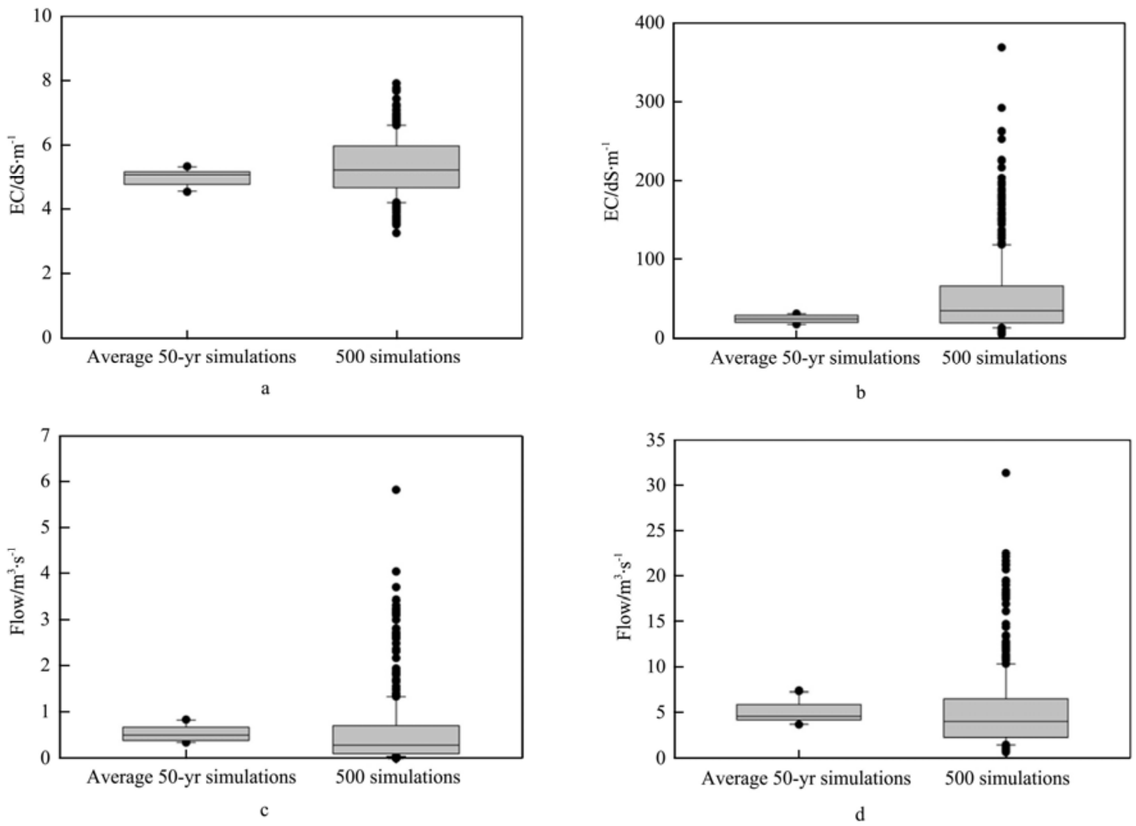

Figure 12 Average streamflow and Electrical Conductivity (EC) for ten 50-year SWAT simulations and the combined 500 simulations at US Geological Survey gage stations (a and b, respectively) 07303400 and (c and d, respectively) 07305000

Based on these results, the likely condition of the stream water on the Elm Fork River will be too saline for irrigation purposes; however, the salinity in the North Fork River should be acceptable to irrigate cotton. One option to utilize the Elm Fork River for irrigation and to further decrease the salinity in the North Fork River is to install a salinity control upstream of the salt deposits on the Elm Fork. Future work could include EC and flow monitoring upstream of the salt deposits on the Elm Fork and upstream of the Elm Fork/North Fork River confluence to determine the EC levels if a salinity control were to be installed. These new data coupled with the SWAT model flow simulations will provide a reasonable indication of the salinity levels if a control point were installed.

Based on a maximum simulated annual EC on the North Fork of 7.9 dS/m, this water can be utilized to irrigate cotton; however, there are two issues that must be considered. Though the maximum annual EC may be 7.9 dS/m, daily levels may be much higher. Based on the empirical relationship between flow and EC, if the flow rate is less than 0.60 m^3/s, then the EC will be greater than 8.0 dS/m. This occurred 22% of the time from 1950 to 2013 and 26% of the time from May to October[29], the cotton growing season. The second issue to consider is the buildup of salt in the soil over time. Studies such as Miyamoto et al.[52] and Dutt[53] should be analyzed to determine the long-term effect of irrigating with saline water has on the soil and crop yields over time.

Recommended future work also includes climate change simulations, which may affect crop yields as well as salinity and flows. The recently released report on climate change by the National Oceanic and Atmospheric Administration[54] reports precipitation and temperature projections for the Great Plains based on the median of the 15 general circulation models (GCMs); high (A2) and 14 GCMs low (B1) emissions scenarios. The projection for temperature is an increase of 4.4°C and 2.5°C for the years 2070 and 2099, respectively. The two scenarios produced mixed results for precipitation with the A2 scenario projecting a 3% decrease and the B1 scenario projecting a 3% increase for the same time period. Precipitation is more challenging to model in the Great Plains area due to the dominance of convective storms; therefore, the precipitation projections may be inaccurate (personal communication, Ray Arritt, March 2014). Additional research is required to better understand how these convective storms affect climate change.

4 Conclusions

Basin-scale models, such as SWAT, are important tools for decision makers and watershed managers to aid in determining the potential effect of weather variability on crop yields, streamflow, salinity levels, etc. While the SWAT model has been used extensively to model streamflow and nutrients, there are few publications that have utilized the model to predict wheat yields. There are even fewer publications using SWAT to model cotton and salinity using a regression equation. The results demonstrated that for the basin studied, SWAT simulated acceptable annual wheat and dryland cotton yields and can be utilized to predict the change in salinity based on an ionic strength/streamflow regression equation.

The effect of weather variability on crop yields and salinity levels were analyzed for the North Fork River basin in southwestern Oklahoma. The crop yields varied greatly from year to year based on the variations in temperature, precipitation, and solar radiation; however, the yields were not significantly different over the 50-year simulation and the long term predicted average yields will likely stabilize. The EC at the USGS gage station just downstream of the salt deposits was significantly different with levels ranging from 40 to 65 dS/m while the diluted EC values downstream at gage station 0705000 averaged 3.3 to 7.9 dS/m. Though the water in the Elm Fork is much too saline to use for irrigation, the water in the North Fork River may be used as long as the flow rates in the river are above 0.60 m^3/s. Further research is required to determine the effect that a salinity control point may have on the two rivers and how cost effective it will be to implement. Additional research should also determine the long-term effect of irrigating with saline water and how future climate change may affect the flow, salinity levels and crop yields in the basin.

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