Final Report – Ochsner et al. USGS 104b Project FY2015

Title: Threats to the Lugert-Altus Irrigation District: Untangling the Effects of Drought, Land Use Change, and Groundwater Development

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Problem and Research Objectives:

Statement of Critical Regional or State Water Problem

As of October 1, 2014, Lake Altus-Lugert, the primary water supply for the Lugert-Altus Irrigation District (LAID) in southwest Oklahoma, was only 10% full, was recovering from a golden algae bloom which killed all fish in the lake, and did not contain enough water to produce an irrigated cotton crop until 2015. Severe drought in 2011 and 2012 played a major role in the demise of the lake, but local residents suspected upstream land use change and groundwater development may have contributed. Furthermore, according to the Southern Climatic Impact Planning Program (SCIPP), the climate of the region is changing in both precipitation and evapotranspiration, and the region may face increased frequency and severity of drought. The relative importance of these various contributing factors was unknown, and the future of the lake, the irrigation district, and the Altus community which depends on both is highly uncertain. There was a pressing need for research to better understand the drivers of change in this regionally-significant watershed.

Nature, Scope, and Objectives of the Project

The long term goal of this research group is to identify strategies by which the community of Altus can successfully adapt to changing water availability. *The objective of this proposal was to evaluate the effects of climate, groundwater development, and land use change on streamflow into Lake Altus-Lugert.* To accomplish our objective, we devised three specific aims:

Specific Aim #1: Quantify changes in streamflow, climate, groundwater use, and land use in the North Fork of the Red River watershed upstream from Lake Altus-Lugert from 1970-2014

Significant changes and trends in precipitation, reference evapotranspiration (ET_0), groundwater use (for irrigation and non-irrigation), land use (i.e. planted acres), streamflow, and baseflow were identified for the 45-yr period from 1970-2014 and also for relevant sub-periods within the study.

Specific Aim #2: Determine the relative contributions of climate and human factors to changes in flow.

The relative contributions of climate and human factors to changes in flow variables were determined using the climate elasticity model.

Specific Aim #3: Develop statistical models describing the relationships of climate and human variables with flow.

Multiple regression was used to model annual streamflow and baseflow using climate and human variables that were significantly correlated with each flow variable. Variables included precipitation, ET_0, ground water use for irrigation and non-irrigation in the Oklahoma and Texas portions of the watershed, and one year lagged values for each of these variables.

Methodology:

<u>Streamflow</u>

Inflow into Lake Altus-Lugert is determined from changes in reservoir storage volume each month by the United States Department of Interior Bureau of Reclamation (USDOI BOR) (USDOI BOR, 2015), and inflow data obtained from 1970-2014 were used to calculate baseflow, the portion of streamflow that comes from groundwater discharge. The period 1970-2014 was chosen because groundwater and land use datasets prior to 1970 were incomplete. Each flow variable was reported on a water year basis (1 October – 30 September) as a depth of water (water volume divided by watershed area). Baseflow was calculated using the recursive digital filter method (Nathan and McMahon, 1990) on monthly data (Smakhtin, 2001). For month *m*, baseflow was calculated as

$$q_m = \beta\, q_{m-1} + 0.5(1+\beta)(Q_m - Q_{m-1}) \qquad [1]$$

$$QB_m = Q_m - q_m \qquad [2]$$

where q is the filtered monthly inflow, Q is total monthly inflow, β is the filter parameter, and QB is the monthly baseflow. A default β value of 0.925 has been suggested (Nathan and McMahon, 1990), but the optimal value varies by stream. Although baseflow is typically calculated on a daily basis (Smakhtin, 2001), it was necessary to calculate it from monthly data because daily inflow data were not available through the USDOI BOR. Monthly baseflow for Lake Altus-Lugert was calculated after determining the optimal β value for this stream using daily streamflow data from nearby USGS gage station 07301500

(USGS WR, 2015). The station is located approximately 25 km upstream of Lake Altus-Lugert (Fig. 1), and 6870 km^2 of the watershed (94%) is upstream of this station.

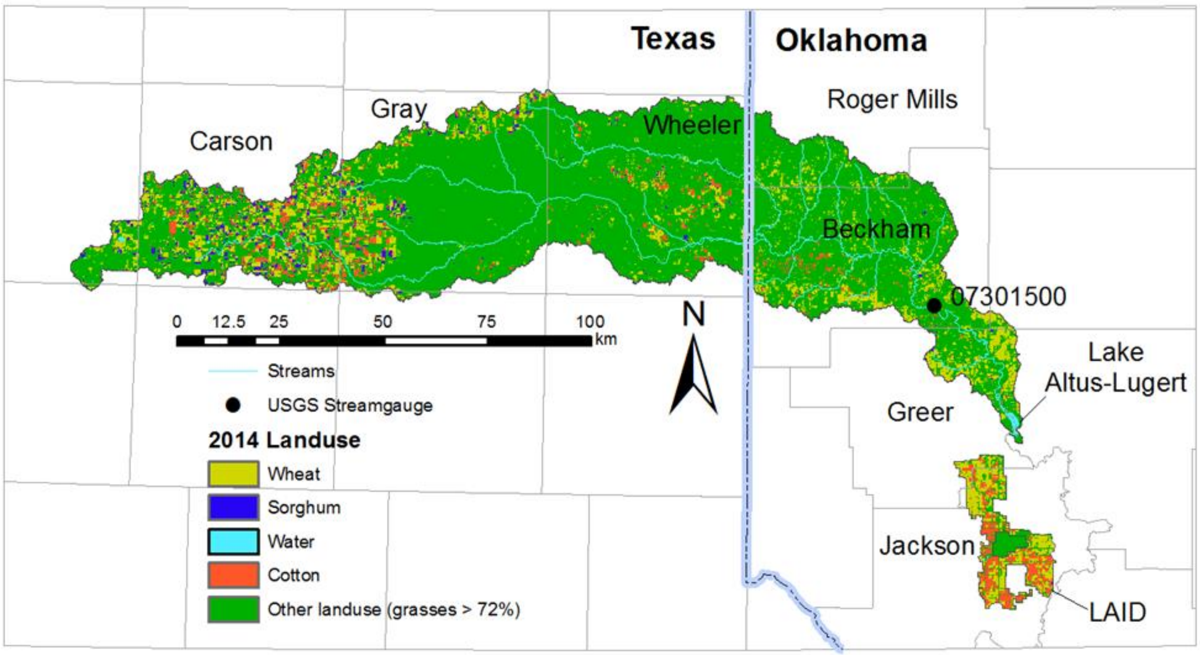

Figure 1. The North Fork of the Red River (North Fork) watershed upstream from Lake Altus-Lugert stretches from the central Texas Panhandle to southwest Oklahoma, covering approximately 7,300 km^2. The Lugert-Altus Irrigation District (LAID) is downstream (south) of Lake Altus-Lugert.

Monthly baseflow for Lake Altus-Lugert was determined by (1) calculating baseflow from daily data from nearby station 07301500 for a range of β values and comparing the results with previously published baseflow data for that station, (2) calculating baseflow from monthly data for station 07301500 and comparing the results with those from step 1, and (3) using the β from step 2 to calculate baseflow from monthly Lake Altus-Lugert inflow. In step one, annual baseflow for station 07301500 was calculated from daily streamflow data (1945-1999), with β adjusted until the resulting calculated baseflow was similar to that reported by Smith and Wahl (2003) for the 1945-1999 period. This step allowed us to determine the optimal β value for calculating baseflow from daily data for station 07301500 (β = 0.985). Baseflow calculated in this way resulted in a median annual baseflow of 4.4 mm, which is comparable to the value of 3.9 mm reported by Smith and Wahl (2003). In step 2, monthly baseflow was calculated after aggregating daily streamflow data for station 07301500 for each month. The value of β was adjusted until baseflow calculated from monthly streamflow data (step 2) most closely matched baseflow calculated from daily streamflow data (step 1) as suggested by Smakhtin (2001). A β value of 0.630 was optimal, resulting in a Pearson correlation coefficient of 0.91 ($P < 0.001$) between monthly baseflow calculated from daily and monthly streamflow data. Finally, in step 3, the β value of 0.630 was applied to monthly inflow data for Lake-Altus Lugert, and monthly baseflow was calculated.

Precipitation and ET_0

Areal average annual precipitation and reference evapotranspiration (ET_0) were calculated using monthly data retrieved from weather stations within or near the watershed, which included total monthly precipitation and monthly minimum, maximum, and mean temperature (NOAA-NCEI, 2015). Only weather stations with a data record completeness of at least 80% from 1965-2014 were included, resulting in 17 possible stations for precipitation and 15 for temperature. To fill missing data, monthly precipitation or temperature data for each station were correlated against data from all other stations, and data were filled using data from the station with the highest correlation (Peel et al., 2010). If data from the most highly correlated station were also missing, data from the next most highly correlated station were used. Data were generally filled after one attempt, but up to three attempts were necessary in some cases. The correlation coefficients of stations used to fill missing data ranged from 0.70-0.92 for precipitation and were > 0.99 for temperature.

Monthly ET_0 was calculated from filled temperature data using the Hargreaves method, which requires only temperature and extraterrestrial radiation as inputs (Hargreaves and Allen, 2003). The method is commonly used when temperature is the only available weather input (Peel et al., 2010; Sankarasubramanian et al., 2001; Tomer and Schilling, 2009) and has shown reasonable results without local calibration (Allen et al., 1998b). Reference evapotranspiration was calculated as:

$$ET_0 = 0.0023\, R_a\, (T_{mean} + 17.8)(T_{max} - T_{min})^{0.5} \qquad [3]$$

where ET_0 is monthly reference evapotranspiration (mm), R_a is monthly extraterrestrial radiation (mm), and T_{mean}, T_{max}, and T_{min} are monthly mean, maximum, and minimum temperatures (°C), respectively. Extraterrestrial radiation was calculated according to Allen et al. (1998b) using the latitude of each weather station, with monthly sums calculated by multiplying the value at the midpoint of each month by the number of days in the month.

Areal average precipitation and reference evapotranspiration for each water year (1 October – 30 September) were calculated using the Thiessen polygon method (Thiessen, 1911), a commonly used area-weighted average technique (Wang, 2014). Averages were calculated by weighting each station by the proportion of its Thiessen polygon within the watershed, multiplying data values at each station by its weight, and summing values across all stations. For precipitation, data from 11 of a possible 17 stations had Thiessen weights > 0 and were used (i.e., their polygons overlapped the watershed), while data from 9 of a possible 15 stations were used for ET_0, resulting in a spatial measurement density of one station per 668 and 816 km^2 for precipitation and ET_0, respectively. For the stations used, 98% of data were present for precipitation and 95% of data were present for ET_0.

Groundwater and land use

Groundwater use data in the Oklahoma portion of the watershed from 1970-2014 were obtained from the Oklahoma Water Resources Board. Data included estimated annual water use for each permitted well in the North Fork Red River Alluvial Aquifer and were separated by use: irrigated agriculture, public, industrial, commercial, mining, power generation, and recreation. Groundwater use is not measured, but instead data were compiled by the Oklahoma Water Resources Board from estimates of individual waters users. Unlike Texas data that included groundwater use at the county level, Oklahoma data were limited only to those wells in the North Fork Red River Alluvial Aquifer. The aquifer is of major importance along the Oklahoma portion of the river (Ryder, 1996) where it sustains streamflow most of the year (Kent, 1980). A small portion of the alluvial aquifer extends across the state line into southeastern Wheeler County, Texas (Ryder, 1996), but data from this portion of the alluvial aquifer were not available. We did not attempt to assess the impact of surface water diversions upstream of Lake Altus-Lugert on streamflow because permitted diversions are minor, representing < 1% of average annual lake inflow (OWRB, 2016; USDOI BOR, 2015).

Groundwater use data in the Texas portion of the watershed were obtained for Carson, Gray, and Wheeler counties from 1970-1980 and 1985-2013 (TWDB, 2015). Data prior to 1970 were available only for the years 1958, 1964, and 1969. Data included estimated groundwater use for irrigated agriculture (1985-2013 only), municipalities, manufacturing, mining, power generation, and livestock.

Irrigation data for 1974, 1979, 1984, 1989, 1994, and 2000 were obtained from a secondary source (TWDB, 2001). The two datasets contained the same information during the years for which they overlapped (1989, 1994, and 2000), suggesting continuity between them. Groundwater use estimates for municipalities, manufacturing, mining, and steam-electric power sources were derived from annual surveys, whereas annual groundwater use by livestock was estimated from animal populations and typical water use per animal. Groundwater use for irrigated crop production was estimated using annual irrigated cropland data and ET_0, with final estimates reviewed by local authorities (TWDB, 2015). The aquifer from which the groundwater was withdrawn was included for most annual estimates, with 98% of groundwater use by volume in the Texas portion of the watershed coming from the High Plains Aquifer.

Unlike flow data that were presented on a water year basis, groundwater data were necessarily presented on an annual basis. We assume that all irrigation was applied during the growing season of a given year, approximately April through September in Oklahoma (Senay and Elliott, 2000), and therefore within the corresponding water year. Separate analyses for groundwater use for irrigation and non-irrigation purposes were performed for each state. Throughout the manuscript, groundwater use for irrigation in the Oklahoma and Texas portions of the watershed are referred to as Oklahoma irrigation and Texas irrigation, respectively. Likewise, Oklahoma non-irrigation and Texas non-irrigation refer to groundwater use for non-irrigation purposes in the Oklahoma and Texas portions of the watershed, respectively.

Land use trends were assessed using annual county level planted cropland data from 1969-2014 (USDA-NASS, 2015) and conservation reserve program (CRP) data from 1986-2014 (USDA-FSA, 2015). County level planted cropland data for Texas were unavailable prior to 1968. Annual data include crops planted the previous fall for harvest a given year, which is important for fall planted winter wheat. Planted area was used rather than harvested area because it includes land that was not harvested due to crop failure. Data were area weighted by multiplying county level values by the proportion of the county within the watershed and then summing across all counties to get watershed totals for each year (Tomer and Schilling, 2009). The planted area and CRP datasets were 97% and 100% complete, respectively. Missing planted area data were filled using nearest neighbor extrapolation for data at the beginning and end of the time series and linear interpolation for other missing data. These data filling techniques assume area planted is generally consistent from year to year, which was supported by the high autocorrelation of annual county level planted area data in our study. Averaged across counties and major crops (wheat, sorghum, and cotton), the autocorrelation coefficient (r) was 0.85 at a lag of one year and was greater than 0.5 for a lags of up to seven years. Average correlation coefficients were calculated from z-transformed data for each county and major crop and then back transformed (Silver and Dunlap, 1987).

Planted area data may have been missing for a given year because data were not collected, there were no planted acres for that crop and year, or because the number of reporting operations was low. When three or fewer operations report crop data for a given county and year or when one operation controls more than 60% of the reporting area, NASS data are withheld from public view (Allen et al., 1998a). To avoid filling data for years with no or low planted area, missing data was first subjected to a nearest neighbor test. If the value from the year nearest the missing year was low (< 809 ha), it was assumed that the data were not missing (i.e. actual planted area was zero); otherwise the missing value was interpolated or extrapolated as described above.

<u>Detecting Long Term Trends and Change Points</u>

Long term trends in flow, climate, and human factors were assessed using the non-parametric Mann-Kendall test, and Kendall's slope was used to quantify detected changes (Kendall, 1970; Mann, 1945). In small samples, the outcome of the Mann-Kendall test can be influenced by autocorrelation within the time series, with positive autocorrelation potentially increasing trend detection when one does not exist and negative autocorrelation decreasing trend detection when one does (Yue and Wang, 2002). Therefore, data were checked for autocorrelation, and significant positive autocorrelation (P < 0.05) was found for baseflow, Oklahoma and Texas irrigation and non-irrigation, and planted crop area. No variables displayed significant negative autocorrelation. Of the autocorrelated variables, significant trends, and consequently possible influences of autocorrelation, were found for Oklahoma irrigation, Oklahoma non-irrigation, and planted crop area. To protect against the influence of autocorrelation on the Mann-Kendall test, it is often recommended that the autocorrelation component of a trend be removed by prewhitening time series data, but prewhitening is not universally recommended because it can also reduce the power of the test (Bayazit and Önöz, 2007). We applied the approach of Bayazit and Önöz (2007) and found that prewhitening was not necessary because the low coefficients of variation and high absolute values of slope of the autocorrelated variables indicated that the potential impact of autocorrelation was low.

Absence of long term trends is not an indication that variables did not change within the study period, as multiple changes in opposite directions could counteract one another. Therefore, changes in variables without significant long term trends were also assessed using a change point analysis based on the cumulative sum (CUSUM) technique (Taylor, 2000), which is an iterative approach suitable for detecting multiple changes. Change points were identified as the year in which the CUSUM deviation from zero was greatest. The significance of each identified change was determined by performing the CUSUM analysis on 1000 bootstrap samples and assessing the magnitude of the difference (maximum CUSUM – minimum CUSUM) for each bootstrap sample. The significance level was the fraction of bootstraps for which the magnitude of the difference was smaller than the original sample. Next, the time series was divided at the point of the significant change, and the analysis was repeated. In our study, no more than two significant change points were identified.

Flow, climate, and human variables were then compared between three sub-periods defined based on the results of the change point analysis (1970-1986, 1987-2000, and 2001-2014). The second change points for inflow and baseflow were each adjusted by one year so the sub-periods were the same for each flow variable. Data between sub-periods were compared using either analysis of variance for normally distributed data or Kruskal-Wallis analysis for non-normally distributed data. Normality was determined using the Lilliefores test (P = 0.05), with non-normally distributed data including inflow, baseflow, Texas irrigation, and Texas non-irrigation. With the exception of Texas non-irrigation, between period differences were found for all variables, although differences for precipitation, ET_0, and Texas irrigation were significantly different only at P = 0.11, 0.06, and 0.07, respectively. Variables with significant between period differences were then subjected to a multiple comparisons test using Fishers LSD (P = 0.10) to determine which sub-periods differed from others.

Climate elasticity model

We quantified the relative effects of climate (precipitation and ET_0) and human factors on flow variables (inflow and baseflow) by (1) using the climate elasticity of streamflow model to estimate the response of flow variables to changes in climate (Sankarasubramanian et al., 2001; Schaake, 1990), and (2) using estimated elasticities to determine the relative influence of climate and human factors on observed changes between periods (Ma et al., 2010; Xu et al., 2013; Zheng et al., 2009). The climate elasticity model states that a change in a climate variable such as precipitation will produce a corresponding change in streamflow and is described by:

$$\frac{\Delta Q}{\bar{Q}} = \varepsilon \frac{\Delta P}{\bar{P}}, \qquad [4]$$

where $\Delta Q/\bar{Q}$ and $\Delta P/\bar{P}$ are proportional changes in streamflow and precipitation relative to the pre-change period, respectively, and ε is the elasticity of streamflow to changes in precipitation. Climate elasticity can be interpreted as the degree of sensitivity of streamflow to a change in climate. For $\varepsilon = 2$ in equation 4, for example, the proportional change in streamflow is twice the proportional change in precipitation. Zheng et al. (2009) used a two parameter model to assess the impacts of precipitation and ET_0 on streamflow:

$$\frac{\Delta Q}{\bar{Q}} = \varepsilon_P \frac{\Delta P}{\bar{P}} + \varepsilon_{ET_0} \frac{\Delta ET_0}{\overline{ET_0}} \qquad [5]$$

where $\Delta ET_0/\overline{ET_0}$ is the proportional change in reference evapotranspiration relative to the pre-change period, and ε_{ET0} is the reference evapotranspiration elasticity of streamflow. The advantage of using ET_0 rather than temperature is that it better reflects the impacts of climate on streamflow, and it can integrate multiple climate variables (Zheng et al., 2009).

Climate elasticities (ε) are typically estimated using either nonparametric methods or hydrologic models (Sankarasubramanian et al., 2001). Nonparametric methods use directly observed long-term climate and streamflow data to estimate the response of streamflow to climate, and this approach may be preferred to hydrologic modeling because the resulting elasticities are not influenced by the structure and calibration of the model from which they were derived (Sankarasubramanian et al., 2001). Therefore, we chose a nonparametric (i.e., data based) approach similar to Zheng et al. (2009) who proposed calculating elasticities for individual climate variables as linear regression coefficients:

$$\frac{\Delta Q_i}{Q_{mean}} = \varepsilon \frac{\Delta X_i}{X_{mean}}. \qquad [6]$$

Here, the subscript 'mean' signifies the mean calculated across the entire study period. $\Delta Q_i = Q_i - Q_{mean}$, where Q_i is the streamflow for year i and Q_{mean} is the long term mean and $\Delta X_i = X_i - X_{mean}$, where X_i is the climate variable for year i and X_{mean} is the long term mean.

Elasticities can be estimated separately in this way for each climate variable, but separate estimates can be inaccurate because precipitation and temperature (or temperature derived ET_0) are often correlated, and the residual effect of temperature on streamflow is difficult to determine compared with the direct effect of precipitation (Chiew et al., 2014). In our study, we found that precipitation and ET_0 had a Pearson correlation coefficient of -0.75 ($P < 0.001$). To overcome complications presented by collinearity between climate variables, Ma et al. (2010) proposed estimating elasticities simultaneously as multiple linear regression coefficients rather than using separate simple linear regressions. Multiple regression is preferable because any correlation between independent variables is incorporated into the coefficient (i.e., elasticity) estimation procedure (Potter et al., 2011). Following Ma et al. (2010), we calculated precipitation and ET_0 elasticities as multiple linear regression coefficients (partial slopes) using:

$$\frac{\Delta Q_i}{\bar{Q}} = \varepsilon_P \frac{\Delta P_i}{P_{mean}} + \varepsilon_{ET_0} \frac{\Delta ET_{0_i}}{ET_{0_{mean}}}, \qquad [7]$$

where Q represents individual flow variables (inflow and baseflow) and other variables were previously defined.

After estimating elasticities, we calculated the relative effects of climate and human factors on flow variables between periods, which were determined using the Taylor change point analysis above. The predicted change in each hydrologic variable due to climate factors was calculated by rearranging equation 5 as

$$\Delta Q_C = \left(\varepsilon_P \frac{\Delta P}{\bar{P}} + \varepsilon_{ET_0} \frac{\Delta ET_0}{\overline{ET_0}}\right) \bar{Q}\ , \qquad [8]$$

where ΔQ_c, ΔP, and ΔET_0 are changes in flow variable (inflow or baseflow), precipitation, and ET_0 between periods, respectively (Zheng et al., 2009). $\bar{Q}$, $\bar{P}$, and $\overline{ET_0}$ were calculated as averages across pre and post-change periods for each change (rather than the average for the pre-change period) (Zheng et al., 2009) to avoid the complication of asymmetry associated with standard relative change calculations (Törnqvist et al., 1985). The overbar notation was used to distinguish these means from long term means in equations 6 and 7. Assuming that changes in streamflow are the result of independent climate and human factors (Zheng et al., 2009), the contribution of human factors to the total change in hydrologic variables was then calculated as

$$\Delta Q_H = \Delta Q - \Delta Q_C \, , \qquad [9]$$

where ΔQ_c was calcualted using equation 8 and ΔQ is the total observed change in each hydrologic variable between periods.

Correlation and Multiple Regression

Relationships between flow (inflow and baseflow), climate (precipitation and ET_0) and human activities (groundwater use for irrigation, non-irrigation, and land area planted to crops) were also examined using Pearson's linear correlation. As is often the case with annual streamflow data (Vogel and Wilson, 1996), annual inflow and baseflow were log normally distributed and were therefore subjected to natural log transformation prior to the correlation analysis (Burt et al., 2002; Vogel et al., 1999). Climate and human activities were assessed for concurrent and one-year lagged values. Assessment of longer lags was not possible because Texas groundwater use data before 1969 were available for only two years (1958 and 1964), and no Texas cropland data were available before 1968.

Multiple linear regression models were constructed to explain inflow and baseflow patterns using climate and human variables. Candidate variables were those that were significantly ($P < 0.05$) related to inflow or baseflow in the correlation analysis above. We used a stepwise regression procedure with forward selection and backward elimination of variables, and the best model was identified by the minimization of the Schwarz Bayesian Information Criterion (BIC). An advantage of using BIC for variable selection instead of the commonly used Akaike Information Criteria (AIC) is that BIC often results in a model with a simpler explanatory equation because it is more restrictive than AIC (Hyndman and Athanasopoulos, 2013). Collinearity among included variables was assessed using the variance inflation factor (VIF), with VIF values of < 1.1 for both the inflow and baseflow final models indicating little or no collinearity (Menard, 2001). Our statistical approach is an alternative to comprehensive physical modeling, with such results often offering a meaningful comparison to those derived from modeling (Burt et al., 2002). All statistical analyses were conducted with Matlab R2012a (The MathWorks, Inc., Natick, MA).

Principal Findings and Significance:

Summary of Principle Findings and their Significance

Specific Aim #1:

We found no long-term trends in inflow or baseflow, but found counteracting increases (after 1986) and decreases (after 2000) in each flow variable. Likewise, we did not find a long term trend in precipitation and reference evapotranspiration (ET_0), but found a significant step increase in precipitation around 1984. ET_0 decreased around 1981 and increased around 2006. Groundwater withdrawal for irrigation and non-irrigation uses in the Oklahoma portion of the watershed increased at rates of 0.16 million m^3 yr^{-1} and 0.10 million m^3 yr^{-1}, respectively. No trends in groundwater use in Texas were found. Cropland area planted in the watershed decreased at a rate of 2366 ha yr^{-1}, or 0.32% of the watershed area per year

Specific Aim #2:

Human factors were responsible for more than half (52%-60%) of each of two observed changes in flow (around 1986 and 2000). The recent period of low inflow (2001-2014) corresponded with low precipitation, high ET_0, and a 66% increase in groundwater use for irrigation in the Oklahoma portion of the watershed.

Specific Aim #3:

Precipitation and ET_0 were highly correlated with each flow variable, but several human factors were also important. Of them, lagged and concurrent groundwater use for irrigation in Oklahoma were the most highly correlated with inflow and baseflow, and lagged Oklahoma and Texas irrigation were the only significant human variable in the final inflow multiple regression model. Conversely, cropland area planted was related to neither inflow nor baseflow. A multiple regression model containing precipitation and groundwater use for irrigation explained 81% and 75% of the variability in annual inflow and baseflow, respectively.

The statistical relationships between groundwater use and inflow into Lake Altus-Lugert suggest that ground and surface water interactions help drive streamflow changes and that effective conjunctive water management strategies may be necessary to sustain agricultural productivity in the region. Lake Altus-Lugert and a portion of its watershed have been labeled a water resources "hot spot" because of projected severe water scarcity. While conservation measures may partially improve the water supply outlook, other approaches are likely needed to ensure adequate ground and surface water availability in the region. Water use both upstream of Lake Altus-Lugert and within the LAID need to be critically evaluated. Oklahoma's current water permitting system typically does not recognize connections between ground and surface water, but studies like ours are evidence to the contrary. Effective conjunctive water management strategies may be key to sustaining Lake Altus-Lugert and the irrigated agricultural which depends on it, but a state-mandated conjunctive water use plan could infringe upon property rights of upstream landowners and may be met with resistance. On the other hand, a water conservation district organized by stakeholders in the watershed and focused on developing effective conjunctive management strategies would ensure that important water use decisions were being made by those who depend on water availability for their livelihoods. The difficulties of implementing conjunctive management may be great, but for North Fork watershed, and similar irrigation-dependent regions around the world, the looming prospect of water scarcity may mean that "business as usual" is not a valid option.

Principle Findings in Detail

Specific Aim #1: Quantify changes in streamflow, climate, groundwater use, and land use in the North Fork of the Red River watershed upstream from Lake Altus-Lugert from 1970-2014

The recent severe decline in the level of Lake Altus-Lugert on the North Fork of the Red River in southwestern Oklahoma, USA, caused substantial economic and ecological damage and prompted many in the region to wonder to what extent climate and human factors contributed to the decline. Despite recent annual inflow that was a fraction of its historical average and a lake level that reached an all-time low, we found no significant long-term trends in annual inflow or baseflow. The absence of long-term trends was a consequence of counteracting short-term trends. Two change points were identified for inflow and baseflow, with each variable displaying a pattern of low flow from 1970-1986, high flow from 1987 until 2001 (inflow) or 1999 (baseflow), and low flow thereafter (Fig. 2). The long term annual mean inflow was 17 mm, and long term mean annual baseflow was 10 mm. During the period when flow was high, inflow and baseflow were 16 mm and 12 mm greater, respectively, than during the preceding low-flow period. Average annual inflow then declined by 19 mm and baseflow declined by 11 mm from the period of high flow to the period of low flow from about 2000-2014. During the time of unprecedentedly low lake levels from 2011-2014, annual inflow averaged only 2.2 mm, by far the lowest four-year average for any time during the study, with the next lowest four-year average being 1970-1973 when annual inflow averaged 7.6 mm.

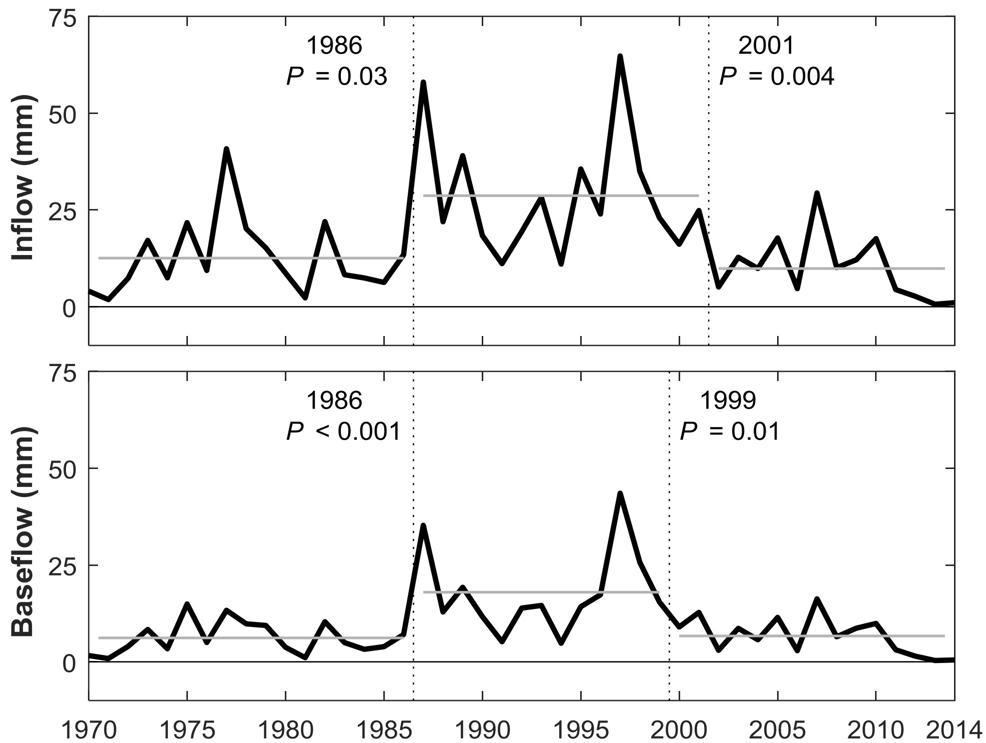

Figure 2. Annual inflow and baseflow for the North Fork watershed from 1970-2014. Year and significance of identified changes are given, with periods separated by vertical lines and period means represented by gray horizontal lines. While there was no long term trend in inflow or baseflow, each flow variable displayed low flow at the beginning and end of the study period, separated by a period of high flow.

Long term areal average precipitation was 593 mm, and the corresponding average for ET_0 was 1387 mm. Precipitation and ET_0 trends were similar to those for flow. While long term trends did not exist, annual precipitation increased 71 mm around 1984, and annual ET_0 decreased 46 mm around 1981 (Fig. 3); changes that were conducive to the higher flow that we observed from about 1986-2000. ET_0 then increased 69 mm around 2006, corresponding with the period of decreased inflow and baseflow after 2000. The recent period of extreme low inflow (2011-2014) corresponded with a period when precipitation was 25% below and ET_0 was 5% above their respective long term long term (1970-2014) averages. Four-year average precipitation from 2011-2014 was only 442 mm, 42 mm (9%) lower than the next lowest four-year period in the study (1968-1971). Likewise, four-year average ET_0 from 2011-2014 (1460 mm) was the second highest for any four-year period in the study, falling behind only 2009-2012. These trends suggest a close connection between climate and streamflow, as has been previously reported in Oklahoma (Esralew and Lewis, 2010) and throughout the Great Plains (Garbrecht et al., 2004).

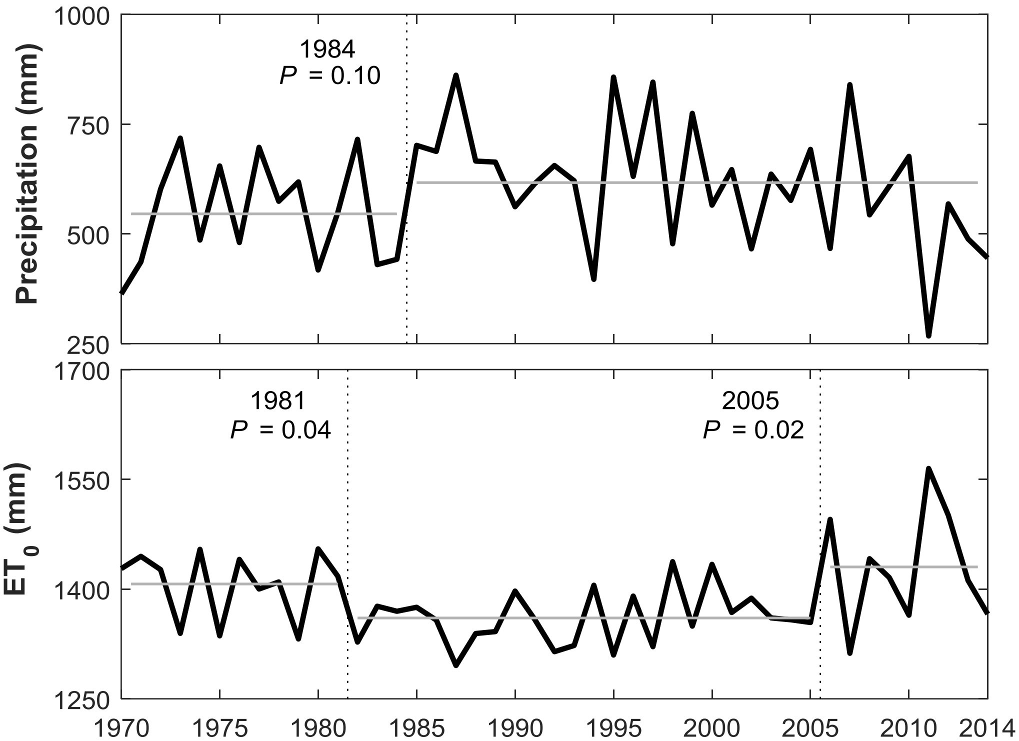

Figure 3. Annual Precipitation and reference evapotranspiration (ET_0) for the North Fork watershed from 1970-2014. Year and significance of identified changes are given, with periods separated by vertical dotted lines and period means represented by gray horizontal lines. While there was no long term trend for either variable, a significant increase in precipitation occurred around 1984, and ET_0 was higher at the beginning and end of the study period.

Unlike flow and climate variables, some human variables displayed significant long term trends. Oklahoma irrigation (i.e. groundwater withdrawal from the North Fork Red River alluvial aquifer for irrigation) increased at a rate of 0.16 million m^3 yr^{-1}, and Oklahoma non-irrigation groundwater use increased at a rate of 0.10 million m^3 yr^{-1} (Fig. 4). Notably, groundwater use was greatest when inflow and baseflow were at their lowest (approximately 2011-2014). Our observed increase in Oklahoma irrigation conflicts with trends reported for Oklahoma as a whole and for alluvial and terrace aquifers within the state. Assessed between 1990 and 2005, statewide groundwater use for irrigation was found to decrease after 1995, and groundwater withdrawal from alluvial and terrace aquifers remained steady or declined slightly (Tortorelli, 2009). Our observed increase was in part a result of the sharp increase after 2010, which had not been previously reported. In Texas, neither irrigation nor non-irrigation groundwater use displayed a significant long term trend, whereas others have reported declines in groundwater use for irrigation in the Texas High Plains beginning in the mid 1970's (Musick et al., 1990). The declines were attributed to a reduction in irrigated area and improved irrigation systems and water management. While our data suggest a similar decline, our inability to detect a statistically significant trend was possibly the result of data gaps before 1985.

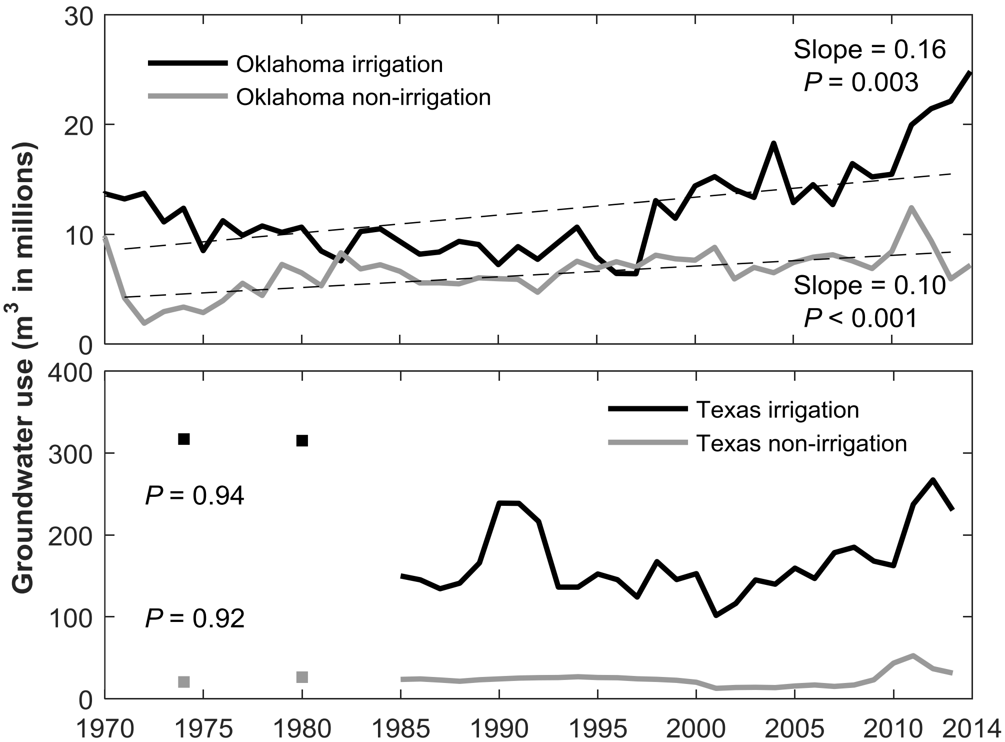

Figure 4. Annual groundwater withdrawals for irrigation and non-irrigation uses in the Oklahoma and Texas portions of the North Fork watershed from 1970-2014. In Oklahoma, groundwater use for irrigation and non-irrigation increased throughout the study (dashed black lines), whereas no significant trends for groundwater use in Texas were identified.

Cropland area planted in the watershed decreased at a rate of 2366 ha yr^{-1}, or 0.32% of the watershed area per year (Fig. 5). The proportion of the watershed planted to crops was at its maximum from the mid-1970's to the mid-1980's, before declining thereafter, with land enrolled in the conservation reserve program (CRP) likely accounting for much of the decline. CRP land area averaged 48,083 ha (6.5% of the watershed area) from 1986-2014, but decreased slightly over the study period ($P = 0.06$) (222 ha yr^{-1} or 0.03% of the watershed area per year). Our observed trend in planted cropland corroborates trends reported throughout the Great Plains, with agricultural land area reaching its maximum about 1980, before declining as land was converted to grassland in conjunction with the CRP (Drummond and Auch, 2013).

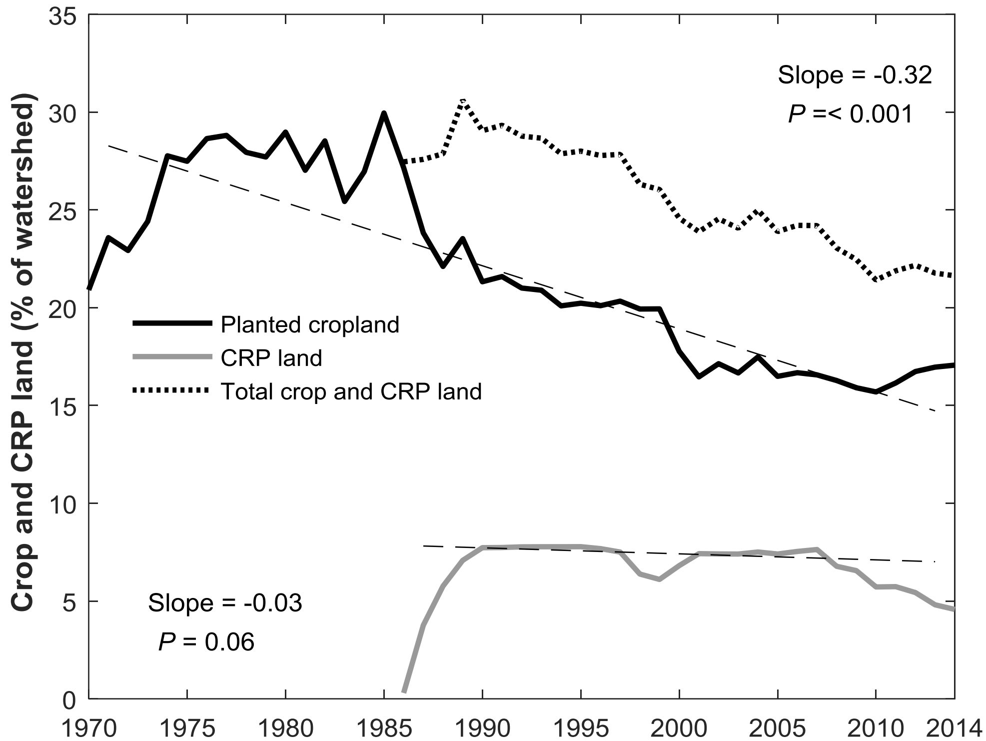

Figure 5. Cropland area planted and land in the conservation reserve program (CRP) as percentage of watershed area in the North Fork watershed from 1970-2014. Cropland area planted decreased from 1970-2014, and a slight decrease (*P* = 0.06) was detected for CRP land from 1986-2014.

Trends in climate and human factors suggested that each contributed to low inflow into Lake Altus-Lugert, with periods of low precipitation, high ET_0, and high irrigation corresponding with low flow. To more rigorously assess these relationships, we compared flow, climate, and human factors for each of the high and low flow periods (1970-1986, 1987-2000, and 2001-2014), and statistical comparisons (Table 1) reflect observed temporal trends (Figs 2-4). Average annual inflow, baseflow, and precipitation were highest from 1987-2000 when ET_0 and groundwater use for irrigation in Oklahoma and Texas were at their lowest (Table 1). Oklahoma irrigation was 66% higher during the low flow period from 2001-2014 than during previous periods, and Texas irrigation was 52% higher during the low flow period from 1970-1986 than during subsequent periods. Oklahoma non-irrigation increased each period, but the magnitude of water use averaged only 6.5 million $m^3\ yr^{-1}$ compared with Oklahoma and Texas irrigation, which averaged 12.3 and 170 million $m^3\ yr^{-1}$, respectively. Texas non-irrigation groundwater use did not change. The large volume of groundwater use in the Texas compared with the Oklahoma portion of the watershed was likely a reflection of differing groundwater resources. In 1974, the estimated combined groundwater storage for Carson, Gray, and Wheeler counties in Texas, which are underlain by the High Plains aquifer, was 24,000 million m^3 (Bell and Morrison, 1979; Bell and Morrison, 1980; Bell and Morrison, 1982). This is nearly 8-fold greater than the 1973 estimated groundwater storage in the alluvial aquifer (3,200 million m^3) from which groundwater is drawn in Oklahoma portion of the watershed (Kent, 1980).

Table 1. Average annual flow, climate, and human factors (groundwater use for irrigation and non-irrigation and cropland area planted) during periods identified by the change point analysis in the Oklahoma (OK) and Texas (TX) portions of the North Fork watershed from 1970-2014.

	Inflow[1]	Baseflow	P	ET_0	Irrigation		Non-Irrigation		Planted
					OK	TX	OK	TX	
	mm				million m^3				%
1970-1986	12.6 a	6.2 a	563 a	1394 b	10.7 a	220 b	5.2 a	25 a	27 c
1987-2000	29.0 b	17.3 b	656 b	1358 a	9.7 a	140 a	6.6 b	24 a	21 b
2001-2014	10.9 a	6.5 a	566 a	1407 b	16.9 b	149 ab	7.8 c	24 a	17 a

1 Values within a given column followed by the same lower case letter are not significantly different at P < 0.1.

Cropland area planted showed no obvious relationship to inflow or baseflow, with low flow periods occurring when area planted was at its highest (1970-1986) and at its lowest (2001-2014). While others have found that streamflow was negatively related to cropland area and positively related to grassland area (Dale et al., 2015), the relationship is complex. An increase in CRP land can result in decreased runoff (Lindstrom et al., 1998) and increased evapotranspiration (Khanal et al., 2014), thereby decreasing streamflow. On the other hand, increased infiltration on CRP land can lead to increased groundwater levels (Rao and Yang, 2010), which in turn support increased baseflow (Barlow and Leake, 2012). The absence of a relationship in our study may have resulted because of these counteracting influences or because cropland was a relatively minor land use in our study, averaging < 22% of watershed area.

Specific Aim #2: Determine the relative contributions of climate and human factors to changes in flow.

Greater than 50% of each change in inflow and baseflow was attributable to human factors, but climate also contributed significantly to each change (Table 2). Average inflow increased by 16.4 mm and average baseflow increased by 11.2 mm around 1987, with changes in flow due to climate being 7.9 mm (48% of the total change) for inflow and 4.5 mm (40%) for baseflow. Inflow and baseflow then respectively decreased by 18.0 and 10.8 mm around 2000, with changes in flow due to climate being 7.9 mm (44% of the total change) for inflow and 4.8 mm (44%) for baseflow. Flow variables were related positively to precipitation and negatively to ET_0, and each flow variable was more sensitive to precipitation than ET_0. The proportional change in inflow, for example, was 2.37 times the change in precipitation but -1.23 times the change in ET_0. That is, a 10% increase in precipitation resulted in a 23.7% increase inflow, whereas a 10% increase in ET_0 resulted in a 12.3% decrease in streamflow. Our calculated precipitation elasticity of inflow is similar to that reported by Sankarasubramanian et al. (2001), which ranged from 1.5-2.5 for western Oklahoma and the Texas Panhandle, although values as high 3.0 have been reported for the area (Khanal et al., 2014).

Our observation that climate was responsible for less than half of each change in inflow and baseflow underscores the control humans can have on streamflow in the region. While previously unquantified, the importance of human influences on streamflow in the North Fork Red River watershed has been reported by others. Esralew and Lewis (2010), for example, found a significant decline in precipitation-adjusted streamflow in the North Fork Red River, and they suggested that human factors such as changes in water use and water-management practices were likely responsible for the decline. Likewise, Smith and Wahl (2003) reported an increase in watershed precipitation without an accompanying increase in streamflow, with human factors possibly counteracting the influence of increased precipitation. In the Cimarron river watershed in north central Oklahoma, Dale et al. (2015)

found that nearly half (48%) of streamflow variability was attributable to human factors. Among the human factors they studied, increased groundwater use was associated with decreased streamflow, and conversion of cropland to grasslands was associated with increased streamflow. Zume and Tarhule (2008) found a simulated 47% decline in streamflow due to groundwater pumping from the terrace and alluvial aquifer along the Beaver-North Canadian River in northwest Oklahoma. The decline was due to a reduction in baseflow and a reversal of the stream-aquifer hydraulic gradient, or stream leakage.

Table 2. Precipitation (P) and reference evapotranspiration (ET_0) elasticity of inflow and baseflow for the North Fork watershed from 1970-2014. Absolute and percentage changes in flow and climate are reported, as well as the percentage of each change in flow attributable to climate (C) and human (H) factors. Human factors explained >50% of both the first (around 1987) and second changes (around 2000).

	Climate Elasticity		Change 1			Change 2		
Variable	P	ET_0	mm	%C	%H	mm	%C	%H
Inflow	2.37	-1.23	16.4	48.4	51.6	-18.0	43.8	56.2
Baseflow	2.34	-1.48	11.2	40.0	60.0	-10.8	44.0	56.0

Our results and the results of these prior studies suggest that groundwater use was potentially an important human factor contributing to changes in inflow in our study. Groundwater use for irrigation and non-irrigation in the Oklahoma portion of the watershed were 74% and 18% higher, respectively, during the low flow period from 2000-2014 than during the previous high flow period. These increases occurred at the same time that the climate elasticity model indicated that human contribution to the change in inflow was at its greatest (57%), which is consistent with a connection between groundwater use and inflow. The connection may be especially strong in the Oklahoma portion of the watershed because of the close proximity of the alluvial aquifer (and therefore groundwater withdrawal) to the stream. By contrast, the High Plains aquifer that underlies the Texas portion of the watershed spans the entirety of some counties, and the distance between groundwater wells and the river can be large, which would reduce their impact on streamflow (Barlow and Leake, 2012).

We emphasize, however, that the relative contributions of climate and human factors to changes in flow are dependent on the elasticities assigned to climate variables, which can be calculated by a number of different techniques that give different results (Khanal et al., 2014; Zheng et al., 2009). Our methodology (Ma et al., 2010; Zheng et al., 2009) has been shown to produce slightly lower estimates of precipitation elasticity of streamflow compared with other methods. This uncertainty has implications when determining the contributions of climate and human factors on changes in streamflow. For example, a precipitation elasticity of inflow that is 20% higher than our value of 2.37, as has been found when comparing the methods of Zheng et al. (2009) and Sankarasubramanian et al. (2001), would reduce the calculated human contribution to our second observed change in inflow from 57% to 48%. This small change in precipitation elasticity of inflow would lead to the conclusion that climate factors, not human factors, were responsible for the largest portion of the change. Nonetheless, our calculated elasticities are typical of those for western Oklahoma and the Texas Panhandle (Khanal et al., 2014; Sankarasubramanian et al., 2001), and despite possible uncertainties regarding elasticities, we conclude that climate and human factors were each important drivers of changes in flow in our study.

<u>Specific Aim #3: Develop statistical models describing the relationships of climate and human variables with flow.</u>

The climate elasticity analysis showed that both human and climate factors were important drivers of inflow and baseflow in the North Fork Red River watershed, and the comparison of variables for each sub-period suggested that groundwater use was potentially an important human factor influencing inflow into Lake Altus-Lugert. Next, correlation was used to determine which climate and human factors were most closely related to annual flow, and multiple regression models were developed using significantly correlated variables.

Inflow and baseflow tended to be higher when precipitation was high and ET_0 was low (Table 3), and the directions of these relationships were also reflected in the signs of precipitation and ET_0 elasticities. Concurrent values of precipitation and ET_0 showed stronger linear relationships to flow than their values lagged by one year, with for example, the correlation between precipitation and inflow being more than double for concurrent compared with lagged precipitation (r = 0.67 vs. 0.32) (Table 3). Our observed correlation coefficients between concurrent climate variables and flow were consistent with previous reports for western Oklahoma and the Texas Panhandle, which have ranged from 0.3 to 0.7 for precipitation (Dale et al., 2015; Khanal et al., 2014) and from -0.2 to -0.6 for ET_0 (Dale et al., 2015). Of the human factors, concurrent and lagged Oklahoma irrigation had the strongest correlations to each flow variable. Neither concurrent nor lagged cropland area planted were significantly correlated to the flow variables (Table 3).

Table 3. Correlation coefficients for inflow and baseflow with concurrent and one year lagged precipitation (P), reference evapotranspiration (ET_0), groundwater use for irrigation and non-irrigation in Oklahoma (OK) and Texas (TX), and cropland area planted for the North Fork watershed from 1970-2014.

	Flow Variables		Climate		Irrigation		Non-Irrigation		Cropland
	Inflow[1]	Baseflow	P	ET_0	OK	TX	OK	TX	Planted
Baseflow	**0.98**								
P	**0.67**	**0.66**							
P -1 yr.	**0.32**	**0.36**	-0.15	0.07	-0.16	-0.11	0.05	-0.10	-0.07
ET_0	**-0.55**	**-0.53**	**-0.75**						
ET_0 -1 yr.	**-0.30**	**-0.32**	0.23	0.01	**0.34**	0.13	0.00	0.18	-0.11
OK irrigation	**-0.65**	**-0.62**	**-0.45**	**0.46**					
OK irrigation -1 yr.	**-0.60**	**-0.57**	-0.17	0.26	**0.84**	0.14	0.19	0.12	**-0.54**
TX irrigation	**-0.43**	**-0.46**	**-0.40**	**0.46**	0.18				
TX irrigation -1 yr.	**-0.46**	**-0.47**	-0.20	0.05	0.08	**0.61**	-0.30	0.24	**0.37**
OK non-irrigation	-0.05	-0.02	-0.19	0.26	**0.34**	-0.19			
OK non-irrigation -1 yr.	**-0.31**	-0.25	-0.11	0.29	**0.37**	-0.02	**0.50**	0.24	**-0.51**
TX non-Irrigation	-0.26	-0.25	-0.29	**0.40**	0.23	0.25	**0.45**		
TX non-irrigation -1 yr.	**-0.40**	**-0.40**	-0.27	**0.42**	0.33	**0.50**	**0.37**	**0.79**	0.02
Area planted	0.14	0.05	0.05	-0.13	**-0.57**	0.31	**-0.52**	-0.02	
Area planted -1 yr.	0.20	0.13	0.08	-0.19	**-0.62**	0.17	**-0.48**	-0.05	**0.95**

[1] Bold font indicates statistical significance at $P = 0.05$

Increased groundwater use was associated with decreased inflow and baseflow for all groundwater use variables (irrigation and non-irrigation in both states), and most of these correlations were stronger than those reported elsewhere in Oklahoma. For example, our observed correlation between inflow and Oklahoma irrigation was -0.66, whereas the streamflow-consumptive water use correlation (which incorporates groundwater use for irrigation) in the Cimarron River watershed ranged from -0.19 to -0.38 (Dale et al., 2015). The high correlation that we observed suggests that the North

Fork Red River may be more susceptible to alluvial aquifer withdrawals than is the Cimarron River, possibly because of the greater extent of the Cimarron River alluvial aquifer (Ryder, 1996).

Relationships among climate and human variables were also evaluated in order to understand their interrelations. For example, precipitation and concurrent irrigation were negatively related, which is expected since increased irrigation would likely be required during dry years. We considered the possibility that the correlation between Oklahoma irrigation and streamflow was a spurious relationship resulting from the fact that both low streamflow and high levels of irrigation were caused by low precipitation. However, precipitation and lagged irrigation were not significantly correlated, yet lagged Oklahoma irrigation was almost as strongly related to flow as concurrent irrigation (Table 3). This is evidence that groundwater withdrawal itself impacted inflow and baseflow and that streamflow changes were not simply the result of variable precipitation.

While many climate and human variables were significantly correlated with inflow and baseflow (Table 3), of these candidate variables, only precipitation, Oklahoma irrigation -1 year, and Texas irrigation -1 year were retained in the final multiple linear regression model for each flow variable (Table 4). Even with this limited number of predictor variables, our models explained 81% of annual inflow variability and 75% of annual baseflow variability. These results apply only to the period when data for each input parameter were available (1986-2014). Our results are similar to those of Burt et al. (2002) who found that precipitation, lagged precipitation, and the number of groundwater wells explained between 64% and 94% of the streamflow variability in southwest Nebraska. Unlike their study where lagged precipitation was important, precipitation -1 year was not significant in the regression models for inflow of baseflow. The importance of concurrent precipitation is not surprising, but it is important that Oklahoma and Texas irrigation -1 year were the only other significant variables, which is perhaps evidence of the negative impact that groundwater withdrawal can have on streamflow and lake levels as has been reported elsewhere (Brikowski, 2008). Groundwater withdrawal can reduce groundwater levels, thereby decreasing the amount discharging to streams, and when depletion is severe, groundwater withdrawal can reverse the hydraulic gradient causing recharge from the stream to the aquifer (Barlow and Leake, 2012).

Table 4. Stepwise multiple regression of inflow and baseflow against significantly correlated concurrent and one year lagged precipitation (P), reference evapotranspiration (ET_0), groundwater use for irrigation and non-irrigation in Oklahoma (OK) and Texas (TX), and cropland area planted for the North Fork watershed from 1970-2014. Variables retained by the stepwise procedure are displayed.

	Inflow				Baseflow			
	Parameter		Model		Parameter		Model	
Variable	Estimate	P value	Adj. R^2	P value	Estimate	P value	Adj. R^2	P value
Intercept	3.0	< 0.001	0.81	< 0.001	2.6	0.001	0.75	< 0.001
P	0.004	< 0.001			0.003	< 0.001		
OK irrigation -1 yr.	-0.122	< 0.001			-0.122	< 0.001		
TX irrigation -1 yr.	-0.008	0.003			-0.008	0.007		

We emphasize, however, that our analyses describe statistical associations, and unlike hydrologic modeling, they do not represent mechanistic controls that climate and human factors can have on flow. That is, our results are not evidence of cause and effect. We also acknowledge that there are factors for which we did not account. For example, increased forest and urban lands have been correlated with increased streamflow (Dale et al., 2015), whereas the proliferation of floodwater retarding structures can reduce streamflow (Van Liew et al., 2003). Likewise, salt cedar encroachment, a common problem throughout much of the southwestern United States, can result groundwater depletion and reduced streamflow (Di Tomaso, 1998). Irrigation itself can alter streamflow characteristics because it dictates antecedent soil moisture content, which can influence infiltration and runoff during precipitation events (Castillo et al., 2003), irrigation return can promote streamflow and recharge (Barlow and Leake, 2012), and large-scale irrigation can alter climate (Sacks et al., 2008). Furthermore, our analyses were restricted to available data, and may have been improved with a more complete groundwater use record for Texas or improved groundwater use data for Oklahoma, which were self-reported by users. The difficulty in untangling the effects of individual climate and human factors on streamflow is obvious.

Nevertheless, the results of each of our analyses suggest that streamflow in the North Fork Red River watershed has been substantially impacted by human factors. Without question, drought was a major contributing factor to the extremely low inflows to Lake Altus-Lugert in recent years, but humans, likely in part through groundwater withdrawals from the North Fork Red River alluvial aquifer, also contributed to the demise of the lake. The connection between groundwater use and inflow and baseflow is evidenced by the high correlation between these variables and the importance of lagged Oklahoma and Texas irrigation in the inflow and baseflow regression models. Moreover, Oklahoma irrigation was highest during the period from 2000-2014 when inflow was low, reaching its maximum during the extreme low flow years after 2010. This was also the time when the climate elasticity model suggested that the human contribution to the inflow change was largest. Our results suggest that if precipitation and groundwater use for irrigation remain near levels seen during 2000-2014, severe water scarcity will be an ongoing challenge for the region served by Lake Altus-Lugert.

Surface water supply shortages and groundwater depletion in the North Fork Red River watershed are projected to grow as demand for water increases (OWRB, 2012), and at the same time, climate change models suggest precipitation in the Texas Panhandle and western Oklahoma will become less frequent (Shafer et al., 2014). With these increased pressures on water resources, irrigation release from Lake Altus-Lugert at the levels that were typical before the 2010 drought may be impossible. Producers in parts of the Oklahoma Panhandle and western Kansas have faced just these circumstances, with dwindling reservoir storage resulting from groundwater withdrawal and changing climate (Brikowski, 2008). Projected water shortages in the North Fork Red River watershed may be partially addressed through conservation measures (OWRB, 2012), and improvements in irrigation efficiency have been credited with decreasing groundwater use elsewhere in Oklahoma (Tortorelli, 2009). But conservation will likely fill only a portion of the projected water supply gap, and other measures such as increased development of the North Fork Red River alluvial aquifer have also been suggested (OWRB, 2012).

Our results, however, suggest that increased groundwater development in the North Fork Red River alluvial aquifer could have negative consequences for Lake Altus-Lugert and for producers in the Lugert-Altus Irrigation District (LAID). For this reason, other innovative strategies to address water scarcity in the region are needed. The construction of new reservoirs and the sourcing of out-of-basin water are possible alternatives (OWRB, 2012), or perhaps the problem calls for a fundamental change in farming strategies in the region (Iglesias and Garrote, 2015). A transition from irrigated agriculture to rainfed ranching would be more in synch with the natural vegetation in the region both upstream and downstream of Lake Altus-Lugert. This transition may offer long term sustainability, but there are currently significant economic incentives for producers to continue growing irrigated crops (Conner et al., 2001). Unfortunately, these are potential long-term solutions to a problem that may demand attention in the near term.

Implementing conjunctive management of ground and surface water has been suggested as an important step toward meeting Oklahoma's water needs (OWRB, 2010), and based on our results, conjunctive management may be necessary to sustain irrigated agriculture in the North Fork Red River watershed. Currently, surface and groundwater are treated and permitted as separate and unrelated resources in Oklahoma water law and policy, with the exception of one isolated aquifer where conjunctive management is required (OWRB, 2012). This artificial separation in law and policy does not provide a suitable management framework for locations where surface and groundwater interact. For example, in the permitting process for wells in the North Fork Red River alluvial aquifer, current policy does not consider the potential impact of the proposed wells on the flow in the river. If groundwater pumping is impacting flows in Oklahoma rivers, as our results and others suggest, then there is a need for increased conjunctive management of surface and groundwater within the state.

One possible approach to implementing conjunctive water management would be the creation of a water conservation district (Blomquist et al., 2001) charged with developing conjunctive use strategies for the North Fork watershed. Our work has shown that people, as much as climate, dictate changes in water availability in the region. Concentrating decision making ability within the people dependent upon the watershed would entrust them to develop strategies to sustain it. The effort would require tremendous cooperation among stakeholders, decisions would unlikely be unanimous, and winners and losers would be almost unavoidable. Still, by banding together and using information from studies like ours, stakeholders in such a water conservation district would have the opportunity to cooperatively make conjunctive water management decisions and could avoid having decisions imposed upon them.

These findings will be disseminated to the broader scientific community through a peer reviewed journal article. Our manuscript is in preparation and will be submitted to Agricultural Water Management. We have also presented preliminary results to stakeholders in the LAID. This project has furthered our understanding the diverse factors that affect irrigation water quantity in the Lake Altus-Lugert watershed and our results will be a valuable tool to inform irrigation planning, water permits, and conservation measures throughout the watershed.

Literature Cited:

Allen, R., R. Bosecker and G. Hanuschak. 1998a. Policy issues associated with the utilization of geographic information systems (GIS) in the U.S. National Agricultural Statistics Service (NASS). USDA-NASS. Washington, D.C.

Allen, R.G., L.S. Pereira, D. Raes and M. Smith. 1998b. Crop evapotranspiration: Guidelines for computing crop water requirements, FAO Irrigation and Drainage Paper No. 56. Food and Agriculture Organization of the United Nation. Rome, Italy.

Barlow, P.M. and S.A. Leake. 2012. Streamflow depletion by wells—Understanding and managing the effects of groundwater pumping on streamflow: U.S. Geological Survey Circular 1376. U.S. Geological Survey, Reston, Virginia.

Bayazit, M. and B. Önöz. 2007. To prewhiten or not to prewhiten in trend analysis? Hydrolog. Sci. J. 52:611-624. doi:10.1623/hysj.52.4.611.

Bell, A.E. and S. Morrison. 1979. Analytical study of the Ogallala aquifer in Carson County, Texas. Projections of saturated thickness, volume of water in storage, pumpage rates, pumping lifts, and well yields. Report 242. Texas Water Development Board, Austin, TX.

Bell, A.E. and S. Morrison. 1980. Analytical study of the Ogallala aquifer in Gray County, Texas. Projections of saturated thickness, volume of water in storage, pumpage rates, pumping lifts, and well yields. Report 243. Texas Water Development Board, Austin, TX.

Bell, A.E. and S. Morrison. 1982. Analytical study of the Ogallala aquifer in Wheeler County, Texas. Projections of saturated thickness, volume of water in storage, pumpage rates, pumping lifts, and well yields. Report 266. Texas Water Development Board, Austin, TX.

Blomquist, W., T. Heikkila and E. Schlager. 2001. Institutions and conjunctive water management among three western states. Nat. Resources J. 41: 653.

Brikowski, T.H. 2008. Doomed reservoirs in Kansas, USA? Climate change and groundwater mining on the Great Plains lead to unsustainable surface water storage. J. Hydrol. 354:90-101. doi:http://dx.doi.org/10.1016/j.jhydrol.2008.02.020.

Burt, O.R., M. Baker and G.A. Helmers. 2002. Statistical estimation of streamflow depletion from irrigation wells. Water Resour. Res. 38:1296. doi:10.1029/2001WR000961.

Chiew, F.H.S., N.J. Potter, J. Vaze, C. Petheram, L. Zhang, J. Teng, et al. 2014. Observed hydrologic non-stationarity in far south-eastern Australia: implications for modelling and prediction. Stoch. Environ. Res. Risk Assess. 28:3-15. doi:10.1007/s00477-013-0755-5.

Dale, J., C.B. Zou, W.J. Andrews, J.M. Long, Y. Liang and L. Qiao. 2015. Climate, water use, and land surface transformation in an irrigation intensive watershed—Streamflow responses from 1950 through 2010. Agric. Water Mange. 160:144-152. doi:http://dx.doi.org/10.1016/j.agwat.2015.07.007.

Di Tomaso, J.M. 1998. Impact, Biology, and Ecology of Saltcedar (Tamarix spp.) in the Southwestern United States. Weed Technol. 12: 326-336.

Drummond, M.A. and R. Auch. 2013. Land-cover change in the United States Great Plains. US Geological Survey, Land Cover Trends Project. US Department of the Interior. U.S. Geological Survey, Washington, DC. (4 January 2016). http://landcovertrends.usgs.gov/gp/regionalSummary.html

Esralew, R.A. and J.M. Lewis. 2010. Trends in base fow, total flow, and base-flow index of selected streams in and near Oklahoma through 2008. Scientific Investigations Report 2010–5104. U.S. Department of the Interior. U.S. Geological Survey, Reston, VA.

Garbrecht, J., M. Van Liew and G. Brown. 2004. Trends in precipitation, streamflow, and evapotranspiration in the Great Plains of the United States. J. Hydrol. Eng. 9:360-367. doi:10.1061/(ASCE)1084-0699(2004)9:5(360).

Hargreaves, G. and R. Allen. 2003. History and evaluation of Hargreaves evapotranspiration equation. J. Irrig. Drain. Eng. 129:53-63. doi:10.1061/(asce)0733-9437(2003)129:1(53).

Hyndman, R.J. and G. Athanasopoulos. 2013. Forecasting: principles and practice. OTexts: Melbourne, Australia. (7 April 2016). http://otexts.org/fpp/.

Iglesias, A. and L. Garrote. 2015. Adaptation strategies for agricultural water management under climate change in Europe. Agric. Water Mange. 155:113-124. doi:http://dx.doi.org/10.1016/j.agwat.2015.03.014.

Kendall, M.G. 1970. Rank correlation methods. Griffin, London.

Kent, D.C. 1980. Evaluation of aquifer performance and water supply capabilities of alluvial and terrace deposits of the North Fork of the Red River in Beckham, Greer, Kiowa and Jackson Counties, Oklahoma. Oklahoma Water Resources Board. Oklahoma City, OK.

Khanal, S., R.P. Anex, C.J. Anderson and D.E. Herzmann. 2014. Streamflow impacts of biofuel policy-driven landscape change. PLoS ONE 9:e109129. doi:10.1371/journal.pone.0109129.

Lindstrom, M.J., T.E. Schumacher, N.P. Cogo and M.L. Blecha. 1998. Tillage effects on water runoff and soil erosion after sod. J. Soil Water Conserv. 53:59-63.

Ma, H., D. Yang, S.K. Tan, B. Gao and Q. Hu. 2010. Impact of climate variability and human activity on streamflow decrease in the Miyun Reservoir catchment. J. Hydrol. 389:317-324. doi:http://dx.doi.org/10.1016/j.jhydrol.2010.06.010.

Mann, H.B. 1945. Nonparametric tests against trend. Econometrica 13:245-259.

Menard, S. 2001. Applied logistic regression analysis. 2nd ed. Sage University paper series on quantitative applications in the social sciences, 07-106. Sage, Thousand Oaks, CA.

Musick, J.T., F.B. Pringle, W.L. Harman and B.A. Stewart. 1990. Long term irrigation trends in the Texas High Plains. Appl. Eng. Agric. 6:717-724.

Nathan, R.J. and T.A. McMahon. 1990. Evaluation of automated techniques for base flow and recession analyses. Water Resour. Res. 26:1465-1473. doi:10.1029/WR026i007p01465.

NOAA National Centers for Environmental Information. 2015. Climate Data Online. NOAA NCEI. Washington, DC. (18 September 2014). http://www.ncdc.noaa.gov/

OCS. 2015. Precipitation history - Annual, West Central. Oklahoma Climatological Survey Norman, OK. (10 December 2015). http://climate.ok.gov/index.php/climate/climate_trends/

OWRB. 2010. Oklahoma comprehensive water plan. 2011 Update. Technical memorandum: Conjunctive water management in Oklahoma and other states. Oklahoma Water Resources Board. Oklahoma City, OK.

OWRB. 2012. Oklahoma comprehensive water plan. Executive report. Oklahoma Water Resources Board. Oklahoma City, OK.

OWRB. 2016. Water Use permitting. Oklahoma Water Resources Board. Oklahoma City, OK. (7 April 2016). http://www.owrb.ok.gov/supply/watuse/permitting.php

Parsons Engineering Science. 1999. Surface water/groundwater interaction evaluation for 22 Texas river basins. Prepared for Texas Natural Resource Conservation Commission, Austin, TX.

Peel, M.C., T.A. McMahon and B.L. Finlayson. 2010. Vegetation impact on mean annual evapotranspiration at a global catchment scale. Water Resour. Res. 46:1-16. doi:10.1029/2009wr008233.

Potter, N.J., C. Petheram and L. Zhang. 2011. Sensitivity of streamflow to rainfall and temperature in south-eastern Australia during the Millennium drought. 19th International Congress on Modelling and Simulation. Perth, Australia. p. 3636–3642.

Rao, M.N. and Z. Yang. 2010. Groundwater impacts due to conservation reserve program in Texas County, Oklahoma. Appl. Geogr. 30:317-328. doi:http://dx.doi.org/10.1016/j.apgeog.2009.08.006.

Ryder, P.D. 1996. Ground water atlas of the United States: Oklahoma, Texas. HA 730-E. U.S. Geological Survey, Reston, VA.

Sacks, W.J., B.I. Cook, N. Buenning, S. Levis and J.H. Helkowski. 2008. Effects of global irrigation on the near-surface climate. Clim. Dyn. 33:159-175. doi:10.1007/s00382-008-0445-z.

Sankarasubramanian, A., R.M. Vogel and J.F. Limbrunner. 2001. Climate elasticity of streamflow in the United States. Water Resour. Res. 37:1771-1781. doi:10.1029/2000wr900330.

Schaake, J.C. 1990. From climate to flow. In: P. E. Waggoner, editor Climate Change and U.S. Water Resources. John Wiley, New York. p. 177– 206.

Senay, G.B. and R.L. Elliott. 2000. Combining AVHRR-NDVI and landuse data to describe temporal and spatial dynamics of vegetation. For. Ecol. Manage. 128:83-91. doi:http://dx.doi.org/10.1016/S0378-1127(99)00275-3.

Shafer, M., D. Ojima, J.M. Antle, D. Kluck, R.A. A. McPherson, S. Petersen, et al. 2014. Ch. 19: Great Plains. Climate Change Impacts in the United States: The Third National Climate Assessment, J. M. Melillo, Terese (T.C.) Richmond, and G. W. Yohe, Eds., U.S. Global Change Research Program, 441-461. doi:10.7930/J0D798BC.

Silver, N.C. and W.P. Dunlap. 1987. Averaging correlation coefficients: Should Fisher's z transformation be used? J. Appl. Psychol. 72:146-148. doi:10.1037/0021-9010.72.1.146.

Smakhtin, V.U. 2001. Estimating continuous monthly baseflow time series and their possible applications in the context of the ecological reserve. Water SA 27:213-218.

Smith, J. and K.L. Wahl. 2003. Changes in streamflow and summary of major-ion chemistry and loads in the North Fork Red River basin upstream from Lake Altus, northwestern Texas and western Oklahoma, 1945–1999. Water-Resources Investigations Report 03–4086. United States Geological Survey, Reston, VA.

Taylor, W.A. 2000. Change-point analysis: a powerful new tool for detecting changes. (22 October 2015). http://www.variation.com/cpa/tech/changepoint.html

Thiessen, A.H. 1911. Precipitation averages for large areas. Mon. Weather Rev. 39:1082-1089.

Tomer, M.D. and K.E. Schilling. 2009. A simple approach to distinguish land-use and climate-change effects on watershed hydrology. J. Hydrol. 376:24-33. doi:http://dx.doi.org/10.1016/j.jhydrol.2009.07.029.

Törnqvist, L., P. Vartia and Y.O. Vartia. 1985. How Should Relative Changes be Measured? Am. Stat. 39:43-46. doi:10.1080/00031305.1985.10479385.

Tortorelli, R.L. 2009. Water Use in Oklahoma 1950–2005. Scientific Investigations Report 2009–5212. U.S. Department of the Interior U.S. Geological Survey, Reston, VA.

TWDB. 2015. Historical Groundwater Pumpage. Texas Water Development Board. Austin, TX. (7 October 2015). http://www.twdb.texas.gov/waterplanning/waterusesurvey/historical-pumpage.asp

TWDB. 2001. Inventories of irrigation in Texas 1958, 1964, 1969, 1974, 1979, 1984, 1989, 1994 and 2000. Report 347. Texas Water Development Board. . Austin, TX.

USDA-Farm Service Agency. 2015. CRP enrollment and rental payments by county, 1986-2014. USDA-FSA, Washington, DC. (18 September 2015). http://www.fsa.usda.gov/programs-and-services/conservation-programs/reports-and-statistics/conservation-reserve-program-statistics/index

USDA-National Agricultural Statistic Service. 2015. Data and statistics-Quick Stats. USDA-NASS, Washington, DC. (18 September 2015). http://quickstats.nass.usda.gov/

USDOI Bureau of Reclamation. 2015. W.C. Austin Project. USDOI BOR. Washington, D.C. (15 October 2015). http://www.usbr.gov/projects/Project.jsp?proj_Name=W.C.+Austin+Project

USGS Water Resources. 2015. National Water Information System: Web Interface. Washington, DC. (11 October 2015). http://waterdata.usgs.gov/nwis

Van Liew, M.W., J.D. Garbrecht and J.G. Arnold. 2003. Simulation of the impacts of flood retarding structures on streamflow for a watershed in southwestern Oklahoma under dry, average, and wet climatic conditions. J. Soil Water Conserv. 58:340-348.

Vogel, R. and I. Wilson. 1996. Probability distribution of annual maximum, mean, and minimum streamflows in the United States. J. Hydrol. Eng. 1:69-76. doi:10.1061/(ASCE)1084-0699(1996)1:2(69).

Vogel, R.M., I. Wilson and C. Daly. 1999. Regional regression models of annual streamflow for the United States. J. Irrig. Drain. Eng. 125:148-157.

Wahl, K.L. and R.L. Tortorelli. 1997. Changes in flow in the Beaver-North Canadian River basin upstream from Canton Lake, western Oklahoma. Water-Resources Investigations Report 96-4304. United States Geological Survey, Reston, VA.

Wang, X. 2014. Advances in separating effects of climate variability and human activity on stream discharge: An overview. Adv. Water Resour. 71:209-218. doi:http://dx.doi.org/10.1016/j.advwatres.2014.06.007.

Xu, X., B.R. Scanlon, K. Schilling and A. Sun. 2013. Relative importance of climate and land surface changes on hydrologic changes in the US Midwest since the 1930s: Implications for biofuel production. J. Hydrol. 497:110-120. doi:http://dx.doi.org/10.1016/j.jhydrol.2013.05.041.

Yue, S. and C.Y. Wang. 2002. Applicability of prewhitening to eliminate the influence of serial correlation on the Mann-Kendall test. Water Resour. Res. 38:4-1-4-7. doi:10.1029/2001WR000861.

Zheng, H., L. Zhang, R. Zhu, C. Liu, Y. Sato and Y. Fukushima. 2009. Responses of streamflow to climate and land surface change in the headwaters of the Yellow River Basin. Water Resour. Res. 45:1-9. doi:10.1029/2007wr006665.

Zume, J. and A. Tarhule. 2008. Simulating the impacts of groundwater pumping on stream–aquifer dynamics in semiarid northwestern Oklahoma, USA. Hydrogeol. J. 16:797-810. doi:10.1007/s10040-007-0268-8.