Human factors were dominant drivers of record low streamflow to a surface water irrigation district in the US southern Great Plains

Erik S. Krueger*, Yohannes T. Yimam, Tyson E. Ochsner

E.S. Krueger and T.E. Ochsner, Dep. of Plant and Soil Sciences, Oklahoma State Univ., Stillwater, OK 74078;

Y.T. Yimam, Dep. of Soil and Crop Sciences, Texas A&M Univ., College Station, TX 77843-2474

**Corresponding author (erik.krueger@okstate.edu).*

Abstract

Irrigated agriculture in the North Fork of the Red River watershed in western Oklahoma and the Texas Panhandle depends on groundwater upstream of Lake Altus-Lugert and surface water from the lake, but like much of the world, the region is prone to water scarcity. During a severe drought from 2010-2015, streamflow into the lake reached record lows, and the lake was depleted until no water remained for the surface water irrigation district. Area residents were left wondering whether drought or human factors were primarily responsible for the reduced streamflow and the four years of crop failures that resulted. We aimed to clarify climate and human influences on streamflow in the North Fork of the Red River watershed by (1) quantifying changes in annual streamflow, climate, groundwater use, and land use upstream from Lake Altus-Lugert from 1970-2014, (2) determining the relative contributions of climate and human factors to changes in streamflow, and (3) developing statistical models describing the relationships of climate and human variables with streamflow. We found a counteracting increase (around 1986) and decrease (around 2001) in streamflow, with human factors being responsible for slightly more than half (51%-56%) of each change. There were no long-term trends in precipitation and reference evapotranspiration (ET_0), but low streamflow from 2002-2014 coincided with a period of low precipitation, high ET_0 , and a 75% increase in groundwater withdrawal for irrigation in the Oklahoma portion of the watershed. A multiple regression model containing only precipitation and groundwater withdrawal for irrigation explained 81% of annual streamflow variability. These statistical relationships suggest that upstream groundwater use was an important driver of streamflow changes. Our results indicate that sustained agricultural productivity near Lake Altus-Lugert may require the adoption of

conjunctive water management strategies, and our methods offer a framework for similar assessments in other water-scarce regions.

Keywords: Groundwater; Drought; Climate; Conjunctive water management;

Climate elasticity

1. Introduction

Approximately two thirds of the people in the world live in regions facing severe water scarcity at least one month out of the year (Mekonnen and Hoekstra, 2016), which causes a wide array of harmful effects including lost crop production, decreased food security, degraded ecosystem health, and increased infant mortality (Ejaz Qureshi et al., 2013; Ibáñez and Ciaola, 2013; Meng et al., 2016; Rocha and Soares, 2015). Water scarcity is essentially a spatial or temporal mismatch between the availability and demand for freshwater and thus can result from transient climate factors, such as drought, or from potentially longer time-scale human factors, such as demand growth (Martin-Carrasco et al., 2013). Recurring drought is part of the climate of many water-scarce regions, and its impacts on water availability and demand are somewhat inescapable. Human factors such as groundwater withdrawal and changes in land use, on the other hand, can potentially be managed to mitigate water scarcity, but the individual effects of climate and human factors on water availability are often difficult to discern. To alleviate or prevent water scarcity, there is a need to differentiate the relative influences of climate and humans on water availability (Renner et al., 2014); a challenging task because human activities can mimic, exacerbate, counteract, or mask climate effects (Jones et al., 2012).

In this study, we seek to clarify the influences of climate and human factors on water availability (in the form of streamflow) within the context of irrigated agriculture in the southern Great Plains of the

United States, a region noted for high levels of water scarcity (Mekonnen and Hoekstra, 2016). From late 2010 through early 2015, a particularly severe instance of reduced streamflow affected the North Fork of the Red River (North Fork hereafter) in Texas and Oklahoma, a river that supports one of the few surface water irrigation districts in the southern Great Plains (Fig. 1). The surface water irrigation district, called the Lugert-Altus Irrigation District (LAID), draws water from Lake Altus-Lugert, which was formed by the impoundment of the North Fork in 1945 (Kent, 1980; Smith and Wahl, 2003). In 2010, water release from the lake to the irrigation district was 89 million m³ (USDOI-BOR, 2015), making the district the largest surface water irrigation user in Oklahoma (Tortorelli, 2009). That water was primarily used to irrigate cotton, and the county in which the district is located produced ~36,600 Mg (168,000 bales) of cotton worth ~\$83 million USD that year (USDA-NASS, 2015a). But in October 2010, Oklahoma and Texas entered a period of unprecedented drought (Hoerling et al., 2012), with annual precipitation in 2011 that was the lowest on record near the North Fork in the Texas Panhandle (< 250 mm) (TWDB, 2016c) and the lowest since 1970 in west central Oklahoma (< 450 mm) (OCS, 2015). During the summer of 2011, streamflow into the lake was < 0.1 mm (2% of long-term summer average), and for the first time in the history of Lake Altus-Lugert, irrigation release was terminated (USDOI-BOR, 2015). Water for irrigation did not become available again until mid-2015.

Without irrigation, cotton crops failed, and cotton production in the county from 2011-2014 averaged less than 10% of the production in 2010 (USDA-NASS, 2015a). As a result of these four successive crop failures, agricultural producers in the county received crop insurance payments totaling over \$223 million USD (USDA-RMA, 2016), a fact that gives some idea of the magnitude of the economic impact of the drought. By early 2015, the lake had almost disappeared, falling below 10% of its normal capacity, before heavy spring rains in 2015 finally produced adequate streamflow to refill the lake. This experience of water scarcity had severe local economic and ecological impacts, and the lake and a portion of its

watershed are classified as a water resources “hot spot” because of expected future water shortages (OWRB, 2012).

The question facing the citizens and agricultural producers in the area is unmistakable: was reduced streamflow due solely to the drought, or did upstream factors such as increased groundwater use for irrigation or land-use changes contribute to the lake’s demise? The answer is not obvious because the links between streamflow, climate, and human factors are complex. For example, elevated streamflow in seven Oklahoma watersheds was attributed to increased precipitation when human factors were absent (Garbrecht et al., 2004). But streamflow has also been found unchanged when precipitation increased in a prior study on the North Fork, suggesting human factors can mitigate the impact of precipitation changes (Smith and Wahl, 2003). When streamflow decreased without a change in precipitation, groundwater withdrawal was implicated for streamflow declines in the Beaver-North Canadian River in northwest Oklahoma (Wahl and Tortorelli, 1997). The impact of groundwater withdrawal and other human factors can be large, contributing nearly 50% of the variability in annual streamflow (Dale et al., 2015). In extreme cases, decreased streamflow caused by groundwater withdrawals and climate change can result in unsustainable reservoir storage, or in the Oklahoma Panhandle, complete reservoir failure (Brikowski, 2008).

Land use change can also alter streamflow characteristics, with decreased cropland and increased grassland in north central Oklahoma being associated with increased streamflow (Dale et al., 2015). Conversion from annual cropping systems to grasslands is partly the result of the United States Department of Agriculture (USDA) Conservation Reserve Program (CRP). Since 1986, the CRP has provided financial incentives for farmers to convert cropland to perennial cover, and in western Oklahoma for example, large areas of cropland have been converted to pasture (Rao and Yang, 2010). Increased CRP land in the Oklahoma Panhandle has been correlated with increased groundwater level, and occurred without substantial changes in groundwater use, irrigated area, or precipitation, suggesting increased

groundwater level was due to beneficial impacts of CRP on groundwater (Rao and Yang, 2010) such as reduced runoff and increased infiltration (Gilley et al., 1997). Of the possible human factors that influence streamflow, land use change may be especially important in the southern Great Plains where streams may be less well connected to groundwater and therefore less susceptible to groundwater depletion than streams in the northern Great Plains (Kustu et al., 2010).

To effectively respond to surface water scarcity, it is critical to first understand the relative impacts that climate and humans have on streamflow. The primary goal of this study was to answer the question: to what extent did human factors contribute to the record low streamflow into Lake Altus-Lugert during the drought of 2010-2015? We hypothesized that streamflow into Lake Altus-Lugert was impacted not only by drought, but also by upstream changes in groundwater use and land cover. Our objectives were to (1) quantify changes in annual streamflow, climate (precipitation and ET_0), groundwater withdrawal for irrigation and other uses, and area planted to annual crops (i.e., land use) in the North Fork watershed upstream from Lake Altus-Lugert from 1970-2014, (2) determine the relative contributions of climate and human factors to changes in streamflow using the climate elasticity model, and (3) develop statistical models describing the relationships of climate and human variables with streamflow. Our combination and adaptation of existing methods will serve as a framework for similar assessments in other water scarce regions.

2. Materials and methods

2.1. Watershed description

The North Fork rises near Amarillo, Texas and flows eastward across the Texas Panhandle and into southwest Oklahoma before being impounded behind Altus dam near Altus, Oklahoma (Fig. 1). The dam was completed in 1945 to form Lake Altus-Lugert, which has total capacity of 190 million m³ (USDOI-BOR, 2015). The lake is used for irrigation across more than 19,000 ha in the Lugert-Altus Irrigation District (LAID) and is a supplemental water source for the city of Altus. The watershed area upstream of the dam is 7335 km², of which 5835 km² (80%) contributes to streamflow (USGS-WR, 2015). The river is intermittent across the western two-thirds of its watershed (west of the Oklahoma-Texas state line) (Parsons Engineering Science, 1999), which is approximately the portion underlain by the unconfined High Plains aquifer (Smith and Wahl, 2003; TWDB, 2016a) (fig. 1). Depending on time of year, the river may either gain water from or lose water to the High Plains aquifer (Parsons Engineering Science, 1999). The unconfined North Fork Alluvial Aquifer occurs primarily east of the Oklahoma-Texas state line (OWRB, 2016a) where it underlies approximately 19% of the total watershed area and sustains the North Fork most of the year (Kent, 1980) (fig. 1). The alluvial aquifer likely extends across the state line into southeastern Wheeler County, Texas (Ryder, 1996), but boundary data for this portion of the alluvial aquifer were not available. Baseflow index (BFI), the proportion of streamflow that comes from baseflow (i.e., groundwater discharge), can be used as an indicator of primary streamflow mechanisms within the watershed. Annual BFI from 1992-1999 measured 25 km upstream of Lake Altus-Lugert was > 0.5, indicating that during that time more streamflow came from groundwater discharge than from surface runoff (Smith and Wahl, 2003).

The watershed climate varies approximately from west to east, with a semi-arid climate over its western two-thirds and a temperate climate in the east (Peel et al., 2007). Average annual precipitation (1970-2014) ranges from 489 mm at Amarillo in the west to 727 mm at Lake Altus-Lugert in the southeast (NOAA-NCEI, 2015), and a majority of precipitation (69%) falls from May through October. Average annual air temperature increases from 13.8°C in the northwest to 16.4°C at Lake Altus-Lugert in the southeast, and average monthly temperatures range from 3°C in January to 27°C in July. Land cover in the watershed is predominantly grassland and pasture, which together in 2014 made up 54% of the watershed area, while cropland and shrub made up 20% and 18% of the watershed area, respectively (USDA-NASS, 2015b). The major annual crops in the watershed are wheat, sorghum, and cotton, which respectively accounted for 65%, 18%, and 11% of the annual planted area from 1970-2014, with minor crops including rye, corn, oats, and barley (USDA-NASS, 2015a).

2.2. Streamflow and Climate

Streamflow into Lake Altus-Lugert is calculated monthly by United States Army Corp of Engineers using changes in reservoir storage volume, determined from reservoir elevation and area (USDOI-BOR, 2007), and losses via seepage, evaporation, and discharge (USDOI-BOR, 2015). Streamflow data were obtained for 1970-2014 because groundwater and land use datasets prior to 1970 were incomplete. Streamflow was reported on a water year basis (1 October – 30 September) as a depth of water (water volume divided by watershed area).

Weather data (monthly precipitation and monthly minimum, maximum, and mean temperature) were retrieved from weather stations within or near the watershed (NOAA-NCEI, 2015). Areal annual average precipitation and ET_0 for each water year were calculated using the Thiessen polygon method (Thiessen, 1911), a commonly used area-weighted average technique (Wang, 2014). Averages were

calculated by weighting data from each station by the proportion of its Thiessen polygon within the watershed, multiplying values at each station by its weight, and summing values across all stations. To fill missing data, monthly data from each station were correlated against data from all other stations, and missing data were filled using data from the station with the highest correlation (Peel et al., 2010). The correlation coefficients of stations used to fill missing data ranged from 0.70-0.92 for precipitation and were > 0.99 for temperature. Prior to filling, 98% of data were present for precipitation and 95% for ET_0 . The spatial measurement density was one station per 668 and 816 km² for precipitation and ET_0 , respectively.

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., 1998). Reference evapotranspiration was calculated as:

$$ET_0 = 0.0023 R_a (T_{mean} + 17.8)(T_{max} - T_{min})^{0.5} \quad [1]$$

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. (1998) 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.

2.3. Groundwater and land use

Groundwater use data in the Oklahoma portion of the watershed were obtained from the Oklahoma Water Resources Board from 1970-2014. Data included estimated annual water use for each permitted well drawing from the North Fork Alluvial Aquifer and were separated by use: irrigated agriculture, public, industrial, commercial, mining, power generation, and recreation. These data are self-reported estimates from well owners, and data quality is therefore dependent on the accuracy with which users report groundwater use. 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 streamflow into the lake (OWRB, 2016b; 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, 2016b). Approximately 98% of groundwater use by volume in the Texas portion of the watershed came from the High Plains Aquifer. Data included estimated groundwater use for irrigated agriculture (1985-2013), 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 identical 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, 2016b).

Unlike streamflow 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, 2015a) and Conservation Reserve Program (CRP) data from 1986-2014 (USDA-FSA, 2015). 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 or other reasons. Annual data were area weighted by multiplying county level values by the proportion of the county within the watershed and then summing across counties to get watershed totals (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. 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).

2.4. Statistical Analysis

2.4.1. Long-Term Trends and Change Points

Long-term trends in streamflow, 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). While no variables displayed significant negative autocorrelation, positive autocorrelation ($P < 0.05$) was observed for planted crop area and Oklahoma and Texas irrigation and non-irrigation. 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 counteracting changes could exist. Therefore, potential 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, and a significance level $P \leq 0.10$ was used to detect changes. The time series was then divided at the point of the significant change, and the analysis was repeated. This approach is an alternative to the commonly used Pettitt method for change point detection (Wang, 2014), which is incapable of detecting multiple changes (Rodionov, 2005).

Streamflow, climate, and human variables were then compared between three sub-periods defined based on the results of the change point analysis (1970-1986, 1987-2001, and 2002-2014). Data between sub-periods were compared using either analysis of variance (ANOVA) for normally distributed data or Kruskal-Wallis analysis for non-normally distributed data. Normality was determined using the Lilliefors test ($P = 0.05$), with non-normally distributed data including streamflow and Texas irrigation and non-irrigation. With the exception of Texas non-irrigation, between period differences were found for all variables, although the difference for precipitation was significantly different only at $P = 0.11$. 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.

2.4.2. Climate elasticity model

We quantified the relative effects of climate (precipitation and ET_0) and human factors on streamflow by (1) using the climate elasticity of streamflow model to estimate the response of streamflow 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 (e.g., precipitation and ET_0) will produce a corresponding change in streamflow, and for a two parameter model (Zheng et al., 2009), is described by:

$$\frac{\Delta Q}{\bar{Q}} = \varepsilon_P \frac{\Delta P}{\bar{P}} + \varepsilon_{ET_0} \frac{\Delta ET_0}{\bar{ET}_0} \quad [2]$$

where $\Delta Q/\bar{Q}$, $\Delta P/\bar{P}$, and $\Delta ET_0/\bar{ET}_0$ are proportional changes in streamflow, precipitation, and reference evapotranspiration relative to the pre-change period, respectively, ε_P is the precipitation elasticity of streamflow, and ε_{ET_0} is the reference evapotranspiration elasticity of streamflow. Elasticities can be interpreted as the degree of sensitivity of streamflow to a change in a climate variable. For $\varepsilon_P = 2$ in equation 2, for example, the proportional change in streamflow is twice the proportional change in precipitation.

Climate elasticities 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. 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:

$$\frac{\Delta Q_i}{Q_{mean}} = \varepsilon \frac{\Delta X_i}{X_{mean}} \quad [3]$$

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 distinguish from the direct effect of precipitation (Chiew et al., 2014). In our study, precipitation and ET_0 had a Pearson correlation coefficient of -0.75 ($P < 0.001$). Thus, we used multiple regression to estimate the elasticities because any correlation between independent variables is incorporated into the 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:

$$\frac{\Delta Q_i}{\bar{Q}} = \varepsilon_P \frac{\Delta P_i}{P_{mean}} + \varepsilon_{ET_0} \frac{\Delta ET_{0i}}{ET_{0mean}} \quad [4]$$

After estimating elasticities, we calculated the relative effects of climate and human factors on streamflow between periods, which were determined using the Taylor change point analysis above. The predicted change in streamflow due to climate factors was calculated by rearranging equation 2 as

$$\Delta Q_C = \left(\varepsilon_P \frac{\Delta P}{\bar{P}} + \varepsilon_{ET_0} \frac{\Delta ET_0}{\bar{ET_0}} \right) \bar{Q} \quad [5]$$

where ΔQ_C , ΔP , and ΔET_0 are changes in streamflow, precipitation, and ET_0 between periods, respectively (Zheng et al., 2009). $\bar{Q}$, $\bar{P}$, and $\bar{ET_0}$ 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). This was necessary because our data display multiple change points, whereas the climate elasticity model is typically used to determine the climate and human contributions to a single change (Wang, 2014). The overbar notation was used to distinguish these means from long-term means in equations 3 and 4. 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

$$\Delta Q_H = \Delta Q - \Delta Q_C \quad [6]$$

where ΔQ_C was calculated using equation 6 and ΔQ is the total observed change in each streamflow between periods.

2.4.3. Correlation and Multiple Regression

Relationships between streamflow, 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 (Vogel and Wilson, 1996), our data 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. We did not assess longer lags 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 streamflow patterns using climate and human variables. Candidate variables were those that were significantly ($P < 0.05$) correlated with streamflow. 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). The BIC was calculated as

$$BIC = -2(\log L) + k(\log n) \quad [7]$$

where k is the number of parameters and n is the sample size. L is the likelihood function, with the BIC therefore being minimized when the likelihood is maximized (Hyndman and Athanasopoulos, 2013). The variance inflation factor (VIF) was used to assess collinearity among included variables and was calculated as:

$$VIF = \frac{1}{1-R^2} \quad [8]$$

where R^2 is the coefficient of determination of a multiple linear regression of each independent variable against all other independent variables (O'Brien 2007). A VIF of 1 represents no collinearity, values > 5 indicate collinearity may be a problem, and values > 10 are strong evidence of the presence of collinearity (Menard 2001). We found VIF values of < 1.1 for each model. Multiple regression results apply only to the period when data for each input parameter were available (1986-2014). All statistical analyses were conducted with Matlab R2012a (The MathWorks, Inc., Natick, MA).

3. Results and discussion

3.1. Trends in streamflow, climate, and human factors

The recent severe decline in the level of Lake Altus-Lugert on the North Fork of the Red River in southwestern Oklahoma, 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 streamflow into the lake 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 streamflow. Long-term streamflow averaged 17.2 mm, but it underwent two opposing changes, with a period of low streamflow from 1970-1986 (12.6 mm), high streamflow from 1987 until 2001 (28.7 mm), and low streamflow thereafter (9.9 mm) (Fig. 2). During the time of unprecedentedly low lake levels from 2011-2014, annual streamflow 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 streamflow averaged 7.6 mm. Long-term areal average precipitation and ET_0 were 593 mm and 1387 mm, respectively, and, like streamflow, 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 streamflow that we observed from

1987-2001. ET_0 then increased 69 mm around 2005, corresponding with the period of decreased streamflow after 2001. The recent period of extreme low streamflow (2011-2014) corresponded with a period when precipitation was 25% (151 mm) below and ET_0 was 5% (74 mm) above their long-term (1970-2014) averages. These trends corroborate the close connection between climate and streamflow that has been previously reported in Oklahoma (Esralew and Lewis, 2010) and throughout the Great Plains (Garbrecht et al., 2004).

Unlike streamflow and climate, some human variables displayed significant long-term trends. Oklahoma irrigation (i.e. groundwater withdrawal from the North Fork alluvial aquifer for irrigation) averaged 12.1 million $m^3\ yr^{-1}$ but increased at a rate of 0.16 million $m^3\ yr^{-1}$, and Oklahoma non-irrigation groundwater use averaged 6.4 million $m^3\ yr^{-1}$ but increased at a rate of 0.10 million $m^3\ yr^{-1}$ (Fig. 4). Notably, annual Oklahoma irrigation averaged 22.1 million m^3 from 2011-2014 when streamflow was lowest, nearly double the long-term average. This 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 has 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). While our data suggest a similar decline, our inability to detect a statistically significant trend was possibly the result of data gaps before 1985.

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 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).

3.2. Linking streamflow changes to climate and human factors

Trends in climate and human factors suggested that each contributed to low streamflow into Lake Altus-Lugert, with periods of low precipitation, high ET_0 , and high irrigation corresponding with low streamflow. To more rigorously assess these relationships, we compared streamflow, climate, and human factors for each of the high and low streamflow periods, and then quantified the relative contribution of climate and human factors to each change in streamflow. We divided the study period into three sub-periods based on identified change points (1970-1986, 1987-2001, and 2002-2014) and found that precipitation was lower and ET_0 higher during times of low streamflow, while groundwater use in Oklahoma was highest during the recent low streamflow period (2002-2014) (Table 1). We then quantified the relative contribution of climate and human factors to each streamflow change using the climate elasticity model (Eq. 2) and found that human factors were responsible for more than half of each identified change (Table 2).

3.2.1. Comparison of climate and human factors for each streamflow period

Statistical comparisons of streamflow, climate, and groundwater use for each sub-period (Table 1) reflect observed temporal changes (Figs 2-4). Average annual streamflow and precipitation were highest from 1987-2001 when ET_0 and groundwater use for irrigation in Oklahoma and Texas were at their lowest (Table 1). Oklahoma irrigation was 75% higher during the low streamflow period from 2002-2014 than during previous period, and Texas irrigation was 52% higher during the low streamflow period from 1970-1986 than during subsequent periods. Oklahoma non-irrigation was lowest from 1970-1986, but the magnitude of non-irrigation groundwater use averaged only $6.5 \text{ million m}^3 \text{ yr}^{-1}$ compared with Oklahoma and Texas irrigation, which averaged 12.3 and 170 million $\text{m}^3 \text{ yr}^{-1}$, respectively. Texas non-irrigation groundwater use did not change.

Cropland area planted showed no obvious relationship to streamflow, with low streamflow periods occurring when area planted was at its highest (1970-1986) and at its lowest (2002-2014). 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 groundwater levels have been associated with CRP land possibly due to increased infiltration (Rao and Yang, 2010), and increased groundwater levels in turn could support increased streamflow (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.

3.2.2. Climate elasticity of streamflow

Greater than 50% of each change in streamflow was attributable to human factors, but climate also contributed significantly to each change (Table 2). Average annual streamflow increased by 16.1 mm around 1986, with changes in streamflow due to climate being 7.9 mm (49% of the total change). Average annual streamflow then decreased by 18.8 mm around 2001, with the change in streamflow due to climate being 8.4 mm (44% of the total change). Streamflow was related positively to precipitation and negatively to ET_0 and was more sensitive to precipitation. The proportional change in streamflow, for example, was 2.37 times the change in precipitation but -1.23 times the change in ET_0 . Our calculated precipitation elasticity of streamflow 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).

The influence humans can have on North Fork streamflow is highlighted by our observation that climate was responsible for less than half of each change. While unquantified, this human influence on streamflow in the North Fork watershed has been previously reported. Esralew and Lewis (2010), for example, found a significant decline in precipitation-adjusted streamflow in the North Fork, 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. In the Cimarron river watershed in north central Oklahoma, which like the Oklahoma portion of the North Fork Watershed is underlain by an alluvial aquifer, 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 groundwater discharge to streams and a reversal of the stream-aquifer hydraulic gradient, or stream leakage.

Our results and the results of these prior studies suggest that groundwater use was potentially an important human factor contributing to changes in streamflow in our study. Groundwater use for irrigation in the Oklahoma portion of the watershed was 75% higher during the low streamflow period from 2002-2014 than during the previous high streamflow period. This increase occurred at the same time that the climate elasticity model indicated that human contribution to the change in streamflow was at its greatest (56%), which is consistent with a connection between groundwater use and streamflow. 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 (Fig. 1). 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 streamflow 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 method has been shown to produce slightly lower estimates of precipitation elasticity of streamflow compared with other methods (Zheng et al., 2009). This uncertainty has implications when determining the contributions of climate and human factors on changes in streamflow. For example, a precipitation elasticity of streamflow 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 streamflow from 56% to 47%. This small change in precipitation elasticity of streamflow would lead to the conclusion that climate factors, not human factors,

were responsible for a majority 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 can be certain that climate and human factors were each important drivers of changes in streamflow in the North Fork watershed.

3.3. Relating annual streamflow to climate and human factors

The climate elasticity analysis showed that both human and climate factors were important drivers of streamflow in the North Fork watershed, and the comparison of variables for each sub-period suggested that groundwater use was potentially an important human factor influencing streamflow into Lake Altus-Lugert. Next, correlation was used to determine which climate and human factors were most closely related to annual streamflow, and multiple regression models were developed using significantly correlated variables. Precipitation was the variable most highly correlated with streamflow, but the relationships between streamflow and concurrent and lagged Oklahoma irrigation were nearly as strong (Table 3). Precipitation and irrigation -1 year in the Oklahoma and Texas portions of the watershed were retained in the final multiple regression model, which explained 81% of annual streamflow variability.

3.3.1. Correlation

Streamflow tended to be higher when precipitation was high and ET_0 was low (Table 3). Concurrent values of precipitation and ET_0 showed stronger linear relationships to streamflow than their values lagged by one year, with for example, the correlation between precipitation and streamflow 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 streamflow 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 with streamflow, but neither concurrent nor lagged cropland area planted were significantly correlated with streamflow (Table 3).

Increased groundwater use was associated with decreased streamflow 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 streamflow 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 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). Unsurprisingly, precipitation and concurrent irrigation were negatively related. We considered the possibility that the correlation between Oklahoma irrigation and streamflow was a spurious relationship resulting because 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 streamflow

as concurrent irrigation (Table 3). This is evidence that groundwater withdrawal itself impacted streamflow and that changes were not simply the result of variable precipitation.

3.3.2. Multiple Regression

While many climate and human variables were significantly correlated with streamflow (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 (Table 4). Even with this limited number of predictor variables, our model explained 81% of annual streamflow variability. 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. The importance of concurrent precipitation is not surprising, but it is noteworthy that Oklahoma and Texas irrigation -1 year were the only other significant variables, which is consistent with the hypothesis that groundwater withdrawals are negatively impacting streamflow and lake levels, a phenomenon reported in other portions of the southern Great Plains (Brikowski, 2008).

We emphasize, however, that our analyses describe statistical associations, and unlike hydrologic modeling, they do not represent mechanistic controls that climate and human factors have on streamflow. Our results, by themselves, are not proof of cause and effect (Devi et al., 2015), and there are potentially important factors for which we did not account. For example, a proliferation of floodwater retarding structures (Van Liew et al., 2003) and salt cedar encroachment, a common problem throughout much of the southwestern United States, can result in 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.

Nevertheless, the results of each of our analyses suggest that streamflow in the North Fork watershed has been substantially impacted by human factors. Without question, drought was a major contributing factor to the extremely low streamflow into Lake Altus-Lugert in 2011-2014, but humans also contributed to the demise of the lake, and that human contribution was likely due, in part, to upstream groundwater withdrawals. Oklahoma irrigation was highest during the period from 2002-2014 when streamflow was low, reaching its maximum during the extreme low streamflow years from 2011-2014. This was also the time when the climate elasticity model suggested that the human contribution to the streamflow change was largest. Our results suggest that if precipitation and groundwater use for irrigation remain near levels seen during 2002-2014, 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 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, sustained irrigation release from Lake Altus-Lugert at the levels that were typical before 2010 may become impossible. Producers in 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 watershed may be partially addressed through conservation measures (OWRB, 2012; Tortorelli, 2009), but conservation will likely fill only a portion of the projected water supply gap.

Increased development of the North Fork alluvial aquifer has also been suggested as a means to offset water supply shortages (OWRB, 2012). Our results, however, suggest that such increased groundwater

development would likely 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 agricultural strategies in the region (Iglesias and Garrote, 2015). Reducing the region's reliance on irrigated agriculture and increasing rainfed farming and ranching might offer better long-term sustainability, and this potential change could be evaluated using multi-objective optimization (e.g. Lautenbach et al., 2013). But such a change in agricultural systems is a long-term solution to a problem that may demand attention in the near term, and meanwhile there are significant economic incentives for producers to continue growing irrigated crops (Conner et al., 2001)-

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 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 does not provide a suitable management framework in areas where surface and groundwater interact. For example, in the permitting process for wells in the North Fork alluvial aquifer, current policy does not consider the potential impact of the proposed wells on streamflow. 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 could empower 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 would then have the opportunity to cooperatively make conjunctive water management decisions and could avoid having external decisions imposed upon them.

4. Conclusions

We found no long-term trends in streamflow in the North Fork of the Red River upstream of Lake Altus-Lugert, but identified two counteracting changes in streamflow, with a period of high streamflow occurring between low streamflow periods. Human factors accounted for slightly larger proportions (51-56%) of the observed changes in streamflow than did climate factors (44-49%). As expected, precipitation and ET_0 were highly correlated with streamflow, but several human factors were also important. Of them, lagged and concurrent groundwater use for irrigation in Oklahoma were the most highly correlated with streamflow, and lagged Oklahoma and Texas irrigation were the only significant human variables in the final multiple regression model. Conversely, cropland area planted was not related to streamflow. Our results suggest interaction between ground and surface water was an important driver of streamflow upstream of Lake Altus-Lugert, with increased groundwater withdrawal associated with decreased streamflow into the lake. The suite of tools that we used to assess human impacts on streamflow can be used as a framework for similar assessments in other water scarce regions because it does not require technical expertise in hydrologic modeling and is applicable to time series with multiple changes, whereas prior use of change point and climate elasticity analyses were limited to time series with only one change point.

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 strategies are likely needed to ensure adequate ground and surface water availability in the region. Water use 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 provide evidence that this connection exists. 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 the 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.

Acknowledgments

The authors would like to thank the staff of the Texas Water Development Board and Derrick Wagner of the Oklahoma Water Resources Board for providing groundwater water use data. We would also like to thank Chris Zou and Garey Fox of Oklahoma State University for their review comments that greatly improved the manuscript. Funding for the project was provided by Oklahoma Water Resources Center through the USGS 104(b) grants program and the Oklahoma Agricultural Experiment Station.

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Figure 1. The North Fork watershed and underlying portions of the High Plains and North Fork Alluvial aquifers upstream from Lake Altus-Lugert stretch from the central Texas Panhandle to southwest Oklahoma, covering 7,335 km². The Lugert-Altus Irrigation District (LAID) is downstream (south) of Lake Altus-Lugert.

Figure 2. Annual streamflow 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, periods of low streamflow at the beginning and end of the study period were separated by a period of high streamflow.

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.

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.

Figure 5. Cropland area planted and Conservation Reserve Program (CRP) land as a percentage of watershed area in the North Fork watershed from 1970-2014. Cropland area planted decreased from 1970-2014, and CRP land decreased slightly from 1986-2014.

Table 1. Average annual streamflow, 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.

	Stream flow ¹	P	ET ₀	Irrigation		Non-Irrigation		Planted
				OK	TX	OK	TX	
	mm			million m ³				%
1970-1986	12.6 a	563 a	1394 b	10.7 a	220 b	5.2 a	25 a	27 c
1987-2001	28.7 b	656 b	1359 a	9.7 a	136 a	6.7 b	23 a	21 b
2002-2014	9.9 a	560 a	1410 b	17.0 b	154 ab	7.7 b	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.								

Table 2. Precipitation (P) and reference evapotranspiration (ET₀) elasticity of streamflow for the North Fork watershed from 1970-2014. Changes in streamflow are reported, as well as the percentage of each change in streamflow attributable to climate (C) and human (H) factors. Human factors explained >50% of both the first (1986) and second changes (2001).

Variable	— Climate Elasticity —		—Change 1 —			— Change 2 —		
	P	ET ₀	m m	%C	%H	mm	%C	%H
Streamflow	2.37	-1.23	16 .4	49	51	-18.0	44	56

Table 3. Correlation coefficients for streamflow with concurrent and one year lagged precipitation (P), reference evapotranspiration (ET₀), 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.

	Streamflow ¹	Climate		Irrigation		Non-Irrigation		Cropland
		P	ET ₀	OK	TX	OK	TX	Planted
P	0.67							
P -1 yr.	0.32	-0.15	0.07	-0.16	-0.11	0.05	-0.10	-0.07
ET ₀	-0.55	-0.75						
ET ₀ -1 yr.	-0.30	0.23	0.01	0.34	0.13	0.00	0.18	-0.11
OK irrigation	-0.66	-0.45	0.46					
OK irrigation -1 yr.	-0.60	-0.17	0.26	0.84	0.14	0.19	0.12	-0.54
TX irrigation	-0.43	-0.40	0.46	0.18				
TX irrigation -1 yr.	-0.46	-0.20	0.05	0.08	0.61	-0.30	0.24	0.37
OK non-irrigation	-0.05	-0.19	0.26	0.34	-0.19			
OK non-irrigation -1 yr.	-0.31	-0.11	0.29	0.37	-0.02	0.50	0.24	-0.51
TX non-Irrigation	-0.26	-0.29	0.40	0.23	0.25	0.45		
TX non-irrigation -1 yr.	-0.40	-0.27	0.42	0.33	0.50	0.37	0.79	0.02
Area planted	0.14	0.05	-0.13	-0.57	0.31	-0.52	-0.02	
Area planted -1 yr.	0.20	0.08	-0.19	-0.62	0.17	-0.48	-0.05	0.95

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

Table 4. Stepwise multiple regression of streamflow 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.

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