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River-Ditch Flow Statistical Relationships in a Traditionally Irrigated Valley Near Taos, New Mexico

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Abstract: Current and predicted drought and population growth challenge the longevity of irrigation systems of northern New Mexico. Irrigation ditches, also known as acequias, draw runoff directly from rivers without use of storage reservoirs, so it is important to understand the effects of changing river flow on irrigation flow. This study sought to examine river-ditch relationships in an agricultural valley of the region. A first order linear model was used to fit the river-ditch flow relationship on which daily river flow was the explanatory variable and daily ditch flow the response variable. A strong positive relationship between river and ditch flow was observed for all but one of the ditches. Using a statistical model approach that addressed serial autocorrelation, heteroscedasticity, as well as outlier observations, statistical evidence at 5% significance level was found in all ditches but one. The ditch without a positive relationship was at a downstream location, subject to upstream flow diversion that may have influenced river-ditch flow relationships. Results from this study can be used to evaluate the potential effects of changing socioeconomic dynamics and climate change projections in the operations of these irrigation systems to better understand and manage their water resources.

Keywords: *acequia, irrigated agriculture, water sharing, community-managed, mixed model, heteroscedasticity, serial autocorrelation*

Water resources may be greatly affected by climate change, with impacts having broad societal impacts (Hurd et al. 2004; Jimenez Cisneros et al. 2014). Agricultural production, particularly in areas where water is already a concern, is more vulnerable to uncertainty of water availability derived from climate change (Alexandrov and Hoogenboom 2000; Nelson et al. 2009; Fedoroff et al. 2010; Iglesias and Garrote 2015). Climate model projections indicate reductions in snowpack and the associated runoff occur earlier in the year (Barnett et al. 2005; Rauscher et al. 2008; Hurd and Coonrod 2012; Elias et al. 2015). This will likely exacerbate water-scarcity issues in some areas of the southwestern United States, such as in northern New Mexico, where irrigation water is drawn directly from streams without the use of storage reservoirs.

The agricultural sector is now confronted with the challenge of developing and implementing adaptive water management practices and strategies to cope with less water in the future (Barnett et al. 2005; Jimenez Cisneros et al. 2014). In New Mexico and the southwestern United States, agriculture uses roughly 80% of the total water withdrawals (MacDonald 2010; Longworth et al. 2013). Approximately 10% of the total surface water withdrawals for agriculture in New Mexico are used by traditional irrigation systems called acequias (Brown and Rivera 2000; Longworth et al. 2013). Acequias are hand-dug ditches constructed by the Spanish settlers of the late sixteenth century (Rivera and Glick 2002). Most of the estimated 700 acequias in New Mexico are in the north-central part of the state, particularly in small to mid-size tributaries of the Rio Grande watershed in the counties of Rio Arriba, Santa Fe, Mora, and Taos (Ackerly 1996).

Acequia systems, hereafter also referred to as irrigation ditches, were built and continue to harness runoff releases from mountain catchments that are mostly snowpack-dominated. They are located in narrow irrigated valleys just downstream of the sub-basins that produce snowmelt runoff (Steele et al. 2014). Driven by gravity, these irrigation ditches were crafted to divert and distribute river runoff through their valley floodplains for irrigating crops during the snowmelt season. At locations where all water diverted is not consumed for irrigation, the surplus water returns to the source river through the irrigation ditch outflow downstream of the irrigated area. With irrigation ditches so highly dependent on streamflow, changed streamflow amount and timing will directly impact acequia irrigation.

Not only are acequias physical conveyance structures, they are also cultural water management organizations (Rivera 1998). The ditches of northern New Mexico are organized into acequia associations. The acequia associations represent irrigation systems that vary in length, irrigated acreage, and the number of members (Guldan et al. 2013). Each acequia association has a commission that oversees the irrigators' legal matters and a superintendent or *mayordomo* who manages the allocation of water in the irrigation system (Rivera 1998). The ditch associations are recognized as political subdivisions of the state (Rivera and Martinez 2009; New Mexico Office of the State Engineer 2016).

Several studies have shown there are strong linkages between the community ditches of northern New Mexico and aspects of the local economy, society, environment, and hydrology (Rivera 1998; Fernald et al. 2012; Turner et al. 2016). Water supply for crop irrigation and livestock production activities has supported local food, forage, and revenue in historically Hispanic communities. Traditional management of land and water, such as water sharing or *repartimiento*, the annual acequia cleaning or *limpia de la acequia*, and water adjudication to priority crops, has resulted in a continuous interaction and a solid engagement between the community and the irrigation systems, and consolidates the identity of the agricultural communities of northern New Mexico (Rivera 1998; Fernald et al. 2012). The use of the ditches for water distribution has promoted important surface water-groundwater interactions. Seepage from ditches themselves and percolation below flood-irrigated fields have been related to shallow groundwater level rises (Fernald and Guldan 2006; Ochoa et al. 2007). Ditch seepage has been shown to dilute groundwater ion concentrations (Helmus et al. 2009). Spring and summer shallow aquifer recharge from ditch and flood irrigation inputs return to the river in fall and winter as groundwater return flow (Fernald et al. 2010; Ochoa et al. 2013; Guldan et al. 2014).

Under currently projected scenarios of water scarcity that threaten the use of irrigation water in the agricultural sector, more studies are needed to understand the connectivity between the ditches and the environment. Knowledge of the benefits resulting from the use of these irrigation systems, as well as the impacts of limited water in their operations, is crucial for their correct management. The objective of this five-year study was to determine statistical relationships between seasonal river flow and each of the eight community-based irrigation ditches (acequias) in the Rio Hondo agricultural valley in northern New Mexico.

Materials and Methods

Study Site

This study was conducted in the agricultural valley along the Rio Hondo, a perennial tributary to the Rio Grande near Taos, NM (Figure 1). Rio Hondo is located in a semiarid region with mild to moderate summers and cold winters. Obtained from the two closest weather stations, mean annual maximum and minimum temperatures, and mean annual precipitation are as follows: 17.6 °C, -0.6 °C, and 314 mm for Taos (16 km S; period of record 1892-2016); and, 15.6 °C, -1.8 °C, and 323 mm for Cerro (24 km N; period of record 1910-2016) (Western Regional Climate Center 2019a;

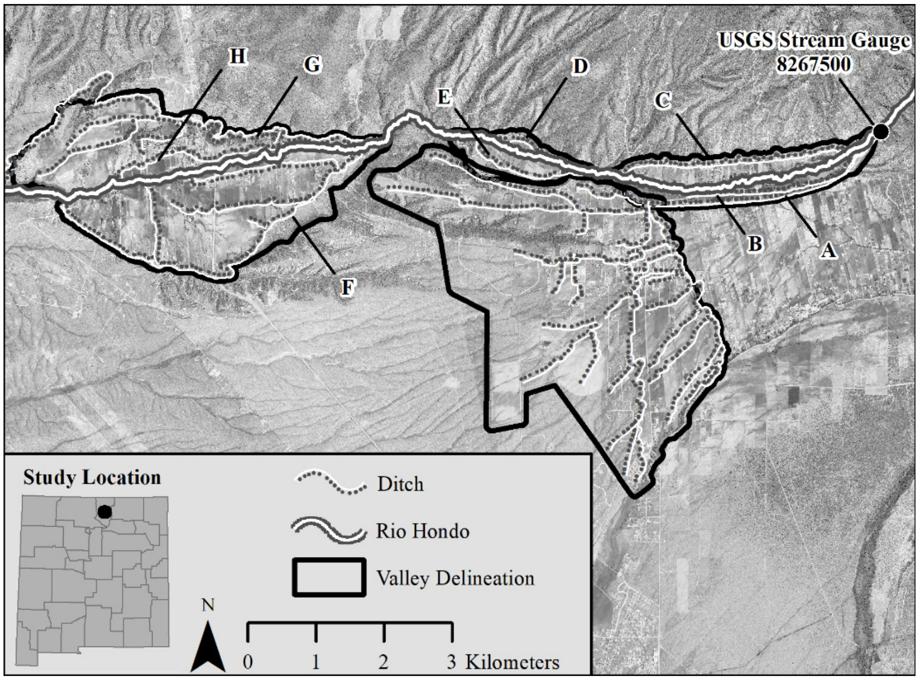

Figure 1. Map of the Rio Hondo Valley (by Robert Sabie Jr., WRRI, NMSU).

2019b). The frost-free period is normally from late May to the end of September and the typical irrigation season is from early April to September.

In the Rio Hondo Valley are the communities of Valdez (3 km^2; elevation 2,265 m), Desmontes (12 km^2; elevation 2,310 m), and Arroyo Hondo (8 km^2; 2,189 m). The area is covered by 70% fallow fields, 22% irrigated pasture (grass and/or alfalfa), 6% roads and structures, 2% riparian vegetation, and only a few scattered orchards (Sabie et al. 2018). Predominant soil textures in the Valdez and Arroyo Hondo communities are clay loam, sandy clay loam, and very gravely sand; soil textures for Desmontes include clay loam, silty clay loam, and silt loam (USDA NRCS 2018).

The Rio Hondo River, 29 km long, rises on the west slope of Wheeler Peak, the highest peak in New Mexico with a summit elevation of 4,012 m. Rio Hondo runs east to west through narrow canyons in the headwaters and merges into the Rio Hondo Valley 14 km downstream. The river then runs through the communities of Valdez and Arroyo Hondo and enters the Rio Grande at John Dunn Bridge (elevation 1,982 m) (New Mexico Office of the State Engineer 1969). Historical (1935-2015) annual flow for the Rio Hondo River is 968 liters per second ($L \cdot s^{-1}$) (United States Geological Survey 2019).

Data Collection and Data Processing

Streamflow and stage data from the Rio Hondo River and the eight main ditches in the valley were collected from March through November, during the years 2011 through 2015. Publicly available streamflow data were obtained from the United States Geologic Survey (USGS), gauging station #8267500, at the Rio Hondo River near Valdez, NM. This USGS station is located 2.5 km east of Valdez, upstream of any irrigation diversions. For the ditches, a gauging station was located downstream of each ditch's head-gate (where water is diverted from the river), before any water diversion to the farms. Each ditch gauging station was equipped with a ramp-type flume (Intermountain Environmental Inc., Logan, UT, USA) and a pressure transducer (Model CS450, Campbell Scientific, Inc., Logan, UT, USA) attached to a datalogger (Model CRX200, Campbell Scientific, Inc., Logan, UT, USA). Manual measurements of streamflow were obtained approximately every two weeks using a portable current meter (Model 2100, Swoffer Instruments, Inc., Seattle, WA, USA).

Manual streamflow measurements and ditch stage data collected by the pressure transducer were used to develop stage-discharge rating curves for each ditch. For ditch B, an additional rating curve was developed for data obtained from August 2013 through 2015. This was necessary because ditch managers had to do some modifications in the ditch that caused backwater to the measuring point. Also, in 2015 equipment at ditch D reported electronic failures from mid-May to mid-June and from the beginning of August to the beginning of September. Electronic failures in ditch E during the same year resulted in missing records from mid-May to the beginning of August. The period of missing records from ditch B in 2013 and those from ditches D and E in 2015 were not included in the analysis for these three ditches.

Mixed Model and Data Analysis

A statistical model-based and descriptive approach was used to analyze and describe the collected information. A first-order linear model was used to fit the river-ditch flow relationship, in which river flow was the explanatory variable and ditch flow the response variable. Scatter and regression plots of the flow information suggested autocorrelation and heteroscedasticity. Linear mixed models incorporate both fixed effects and random effects to effectively model data with non-constant variability and serial autocorrelation (SAS Institute, Inc. 2015). The fixed effects are related to known explanatory variables and the random effects are associated with unknown random variables that are assumed to impact the variability of the data (Li and Jiang 2013; Hao et al. 2015).

A linear mixed model was the basis to model the river-ditch flow relationship. The flow data were analyzed using the MIXED procedure in SAS (Version 9.4, SAS Institute Inc., Cary, NC, USA). Five models were used, corresponding to five different covariance structures. The model with the lowest Akaike's Information Criterion (AIC) value was selected (Akaike 1974; Stroup 2013, p. 191-194). Four of the five models are the same as models that were described in Cruz et al. (2018). All the models fit a common line to all years in the fixed effects. To account for possible correlations among observations within the same year, along with higher variance at higher river flows, random coefficients fitting random lines to years were included in some models. Also, because daily data values were being analyzed, serial autocorrelation among errors was anticipated and some models incorporated the autoregressive-moving-average model (ARMA) (1,1) serial autocorrelation (Dickey 2008; SAS Institute, Inc. 2014) to account for a possible decreasing correlation among errors farther apart in time but within the same year. In addition to fitting the common fixed line to all years, Model 1 estimated a constant variance and assumed independent errors. Model 2 fitted random coefficients (intercept and slope) to years. Model 3 fitted an ARMA (1,1) serial autocorrelation covariance structure. Model 4 fitted both an ARMA (1,1) serial autocorrelation component and the random coefficients to model the covariance structure. Model 5 was similar to Model 4 but dropped the random intercept from the random coefficients and so fitted only a random slope to years. Logarithmic transformation of the flow data was further explored in all the models.

Residual analysis of the five models indicated a more randomized pattern and fewer outlier (residual values ± 3) frequencies in the logarithmically transformed flow data when compared with the raw flow data; thus, logarithmic transformation was applied to the river and ditch flows in all the models. Under this transformation, Model 3 had the lowest AIC values in six of the ditches (A, C, D, E, F, and G) while Model 4 performed better in the rest (B and H). A 0.05 alpha value was defined as the criteria for significance over the resulting t statistic from the t-test. The resulting covariance parameters from those two models were used to analyze how the model captured the variance and the correlation structure of the data. For Model 4, the following expressions were used:

$$VX_{ij} = \alpha + 2 * \tau * Y_{ij} + \beta * (Y_{ij})^2 + R \qquad (1)$$

where, VX_{ij} = variance of a ditch observation (X) on year ($_i$) and day of the year ($_j$); Y_{ij} = logarithmic river flow observation corresponding to the same year ($_i$) and day of the year ($_j$); α = intercept variance from the random coefficients variance component; τ = intercept-slope covariance from the random coefficients variance component; β = slope variance from the random coefficients variance component; and R = residual variance component.

The covariance of two ditch observations (X's) in year ($_i$) and day of the year ($_j$) at ($_n$) number of time periods (days) apart is as follows:

$$Cov(X_{ij}, X_{ij}\text{-}n) = \alpha + (Y_{ij} + Y_{ij-n}) * \tau + Y_{ij} * Y_{ij-n} * \beta + R_n \quad (2)$$

where Y_{ij} and Y_{ij-n} = logarithmic river flow observations corresponding to the time of the ditch observations; and R_n, as described in Cruz et al. (2018), is the value of the residual component implied by the ARMA (1,1) serial covariance structure. As noted in Cruz et al. (2018), for $_n$ = 1, $R_n = R * \gamma$; for $_n$ = 2, $R_n = R * \gamma * \rho$; for $_n$ = 3, $R_n = R * \gamma * \rho^2$; and so on, where γ = moving average coefficient and ρ = autoregressive coefficient. The implied correlation between two observations within the same year is then $AC(X_{ij,}\ X_{ij-n})$ where:

$$AC(X_{ij}, X_{ij-n}) = Cov(X_ij, X_{ij-n})/\sqrt{}\, VX_{ij} * VX_{ij-n} \quad (3)$$

Regression and residual plots were used to identify high leverage observations and outliers with the logarithmic flow information (Cook 1977; Schutte and Violette 1991). If found, the chosen linear mixed model was used to fit the flow data with and without the high leverage and/or outlier observations. After removing the outliers, some of the river-ditch flow relationship estimates or standard errors (slope SEs) were impacted sufficiently, particularly those of ditches A and B, to justify additional reporting (Ramsey and Schafer 2002).

In the descriptive approach, basic statistics of flow, weather, and river-ditch flow relationships, as well as agricultural and irrigation practices, were used to characterize the Rio Hondo Valley. Streamflow from the Rio Hondo near Valdez gauge station (1935-2015) was analyzed. Maximum and minimum annual temperatures and precipitation records for the same period were also retrieved from the Taos, NM (Lat., 36.45°N; Long., -105.67°W) and Cerro, NM (Lat., 36.75°N; Long., -105.61°W) weather stations located near the Rio Hondo Valley. Only historical data from the two weather stations (Taos and Cerro) with no more than five months missing (World Meteorological Organization 1989) were used in the analysis. Using the software Sigma Plot (Version 13.0, Systat Software, San Jose, CA, USA), Loess smoothing was applied to historical hydrologic and weather records using an alpha window of 0.40 for all available data. This information was used to generate graphics illustrating long-term average and linear trends for streamflow, precipitation, and temperature in the Rio Hondo Valley. Average flow for the March-November 2011-2015 period and average monthly flow for the same period were estimated using the collected raw flow information (i.e., no logarithmic transformation) during the study period. Information about agricultural practices and irrigation management was obtained from field observations and interactions with farmers and ditch superintendents.

Pearson's correlation coefficients (*r*) between the river and ditches' logarithmically transformed flow were also estimated. The strength of the river-ditch flow relationship was defined according to the resulting *r* values. For values of *r* greater than +0.8 or less than -0.8 a strong relationship was called, if *r* was between -0.5 and +0.5 a weak relationship was defined, otherwise it was defined as a moderate relationship (Devore and Peck 1986).

Results

Descriptive Analysis

Long-Term Streamflow, Temperature, and Precipitation. Long-term streamflow, temperature, and precipitation provided insight into the climatic and hydrologic conditions of the Rio Hondo Valley. Long-term annual streamflow (1935-2015) data showed there were two periods (1952-1978 and 1998-2015) with below average streamflow, and two (1935-1951 and 1979-1997) with above average streamflow (Figure 2a). Below average streamflow years were associated with low precipitation years and above average streamflow years were associated with high precipitation years (Figures 2a and 2b). For temperature, one of the two periods with low temperatures (1935-1957) was associated with one of the periods of high flow (1935-1951) while the other (1997-2015) was associated with one of the periods of low flow (1998-2015); the one period with high temperatures (1972-1996) was associated with the other period of high flow (1979-1997) (Figures 2a and 2c).

Our study period (2011-2015) was developed during the second and most recent period of low flow and precipitation (1998-2015). Average flow for 2011 (524 $L \cdot s^{-1}$), 2012 (691 $L \cdot s^{-1}$), 2013 (493

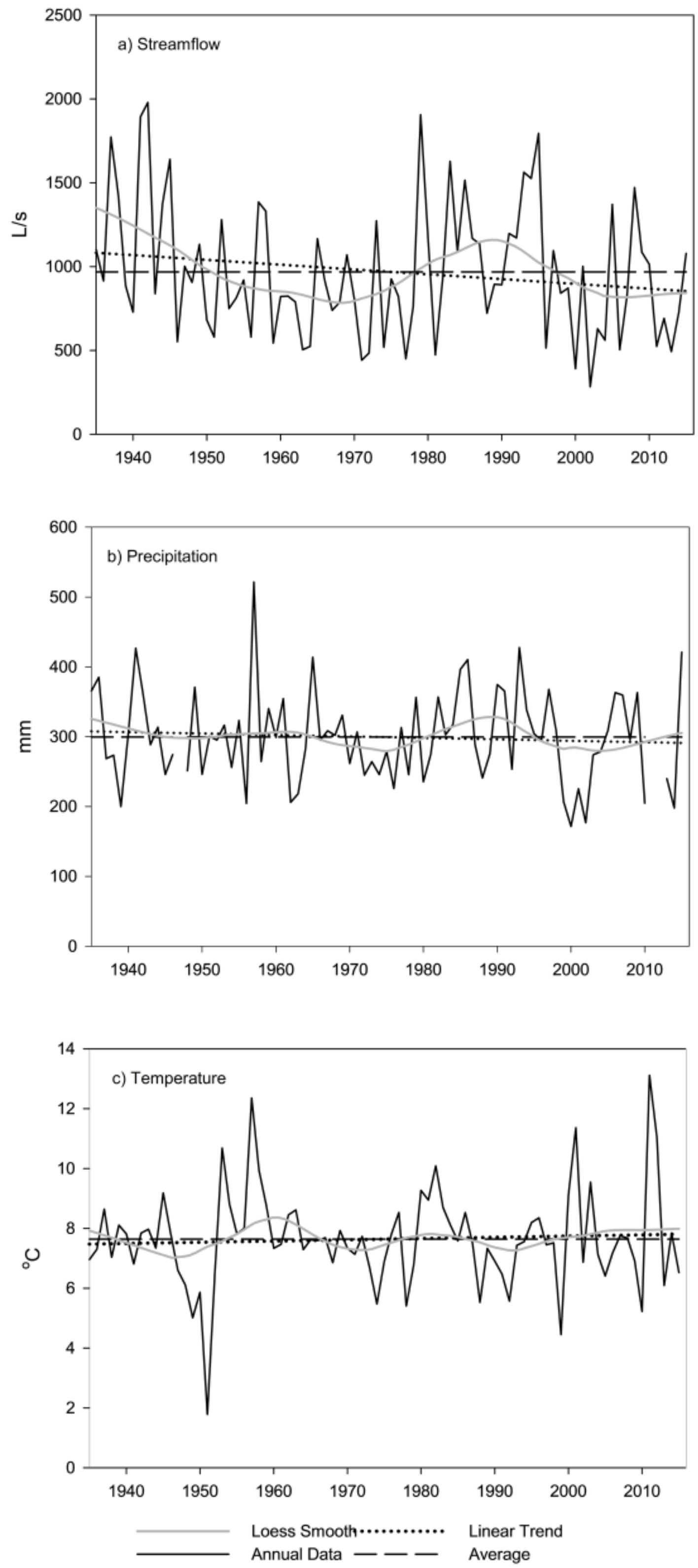

Figure 2. Annual, average, Loess smoothed trend line, and linear trend for (a) Rio Hondo flow from 1935 to 2015; (b) precipitation from Cerro and Taos weather stations from 1935 to 2015 (missing 1947, 2011, and 2012); and (c) temperatures from Cerro, NM and Taos, NM weather stations from 1935-2015.

L·s^{-1}), and 2014 (725 L·s^{-1}) were lower than the long-term average (968 L·s^{-1}); only the flow for 2015 (1,079 L·s^{-1}) was higher than the average (New Mexico Office of the State Engineer 1969).

Irrigation and Agricultural Practices, Flow Seasonality, and Descriptive Statistics. Forages are the most common crop grown on irrigated fields in the Rio Hondo Valley. The irrigation season generally ran from April to October and the number of days between irrigations ranged from 11 to 25. Two to three hay cuts occurred during the irrigation season in every year evaluated. Following the last hay cut, there was at least one additional irrigation, then after that, water was used for livestock watering and small backyard garden irrigations.

It was found that the river and the five ditches with the largest average flow for the period of record (March-November 2011-2015) had the same year with the largest average flow; on the other hand, the river and only one of the ditches had the same year with the lowest average flow (Table 1). The five ditches with the largest average flow values for the period of record were ditches A (424 L·s^{-1}), C (119 L·s^{-1}), E (66 L·s^{-1}), F (170 L·s^{-1}), and G (112 L·s^{-1}). The river and these ditches (A, C, E, F, and G) had the largest average flow in 2015 with values of 1,355, 559, 139, 91, 246, and 155 L·s^{-1}, respectively. The river and ditch E had the lowest average flow in 2011 with values of 626 and 51 L·s^{-1}, respectively. It was noticed that during 2013, the year with the second-lowest average flow in the river (643 L·s^{-1}) and the ditches D (45 L·s^{-1}), G (85 L·s^{-1}), and H (33 L·s^{-1}), the ditches A, B, C, and F had the lowest average flow with values of 338, 37, 89, and 98 L·s^{-1}, respectively.

Seasonal similarities were observed on the river and ditch hydrographs during the study period (March-November 2011-2015) (Figure 3). In 90% of the cases, the river and the ditches had a snowmelt peak within the mid-May to mid-June period. Their flow decreased considerably by the end of July or early August. During mid- to late September 2013, heavy rainfall events from storms characteristic of the monsoon season in the region resulted in substantial rises in river flow (NOAA NCEI 2013). Ditch hydrographs promptly responded to those increases in the river flow in the same way.

For the average monthly flow analysis, it was found that the river and most of the ditches had the largest average flow in either May or June (Table 2). The largest average monthly flow was reported in May for the ditches B (60 L·s^{-1}), D (102 L·s^{-1}), F (355 L·s^{-1}), and H (56 L·s^{-1}) while June was the month with the largest average monthly flow for the river (2,059 L·s^{-1}) and the ditches A (639 L·s^{-1}), C (188 L·s^{-1}), and G (191 L·s^{-1}). In the ditches where May was the month

Table 1. Average flow (L·s^{-1}) for the March-November 2011-2015 period in the Rio Hondo Valley.

Year	River	---------- Ditch ----------							
		A	B	C	D	E	F	G	H
2011	626	433	62	126	55	51	168	105	37
2012	803	411	44	130	82	56	182	83	20
2013	643	338	37	89	45	66	98	85	33
2014	836	416	46	120	50	80	199	137	40
2015	1355	559	41	139	35	91	246	155	35
Average	852	424	45	119	56	66	170	112	33

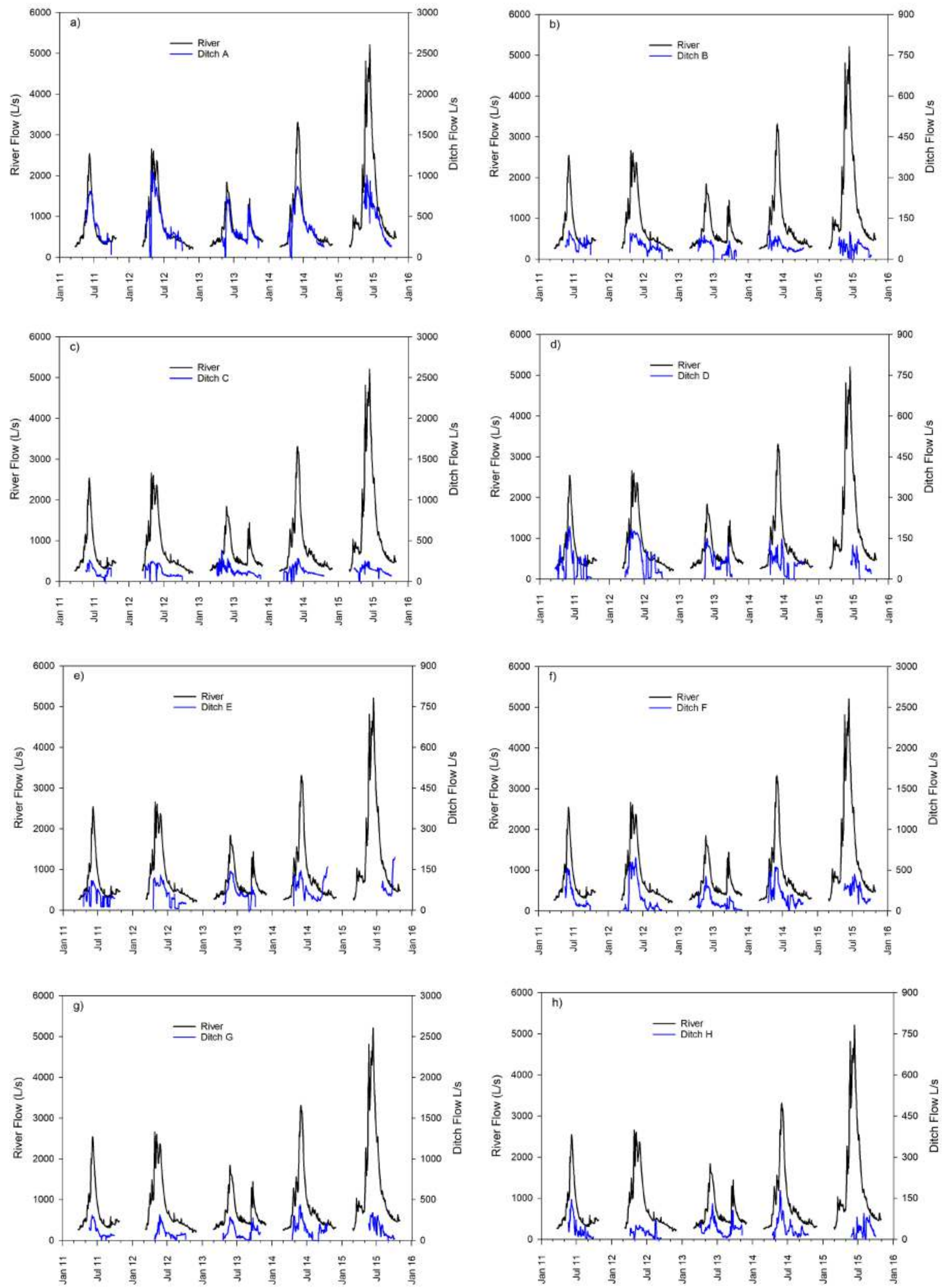

Figure 3. River-ditch flow seasonality for the March-November 2011-2015 period in the Rio Hondo Valley. (a) ditch A, (b) ditch B, (c) ditch C, (d) ditch D, (e) ditch E, (f) ditch F, (g) ditch G, and (h) ditch H.

Table 2. Average monthly flow ($L \cdot s^{-1}$) for the period of record (March-November 2011-2015) in the Rio Hondo Valley.

Location	March	April	May	June	July	August	September	October	November
River	380	738	1721	2059	865	573	525	459	360
A	--	327	599	639	407	325	293	263	239
B	--	57	60	58	39	42	35	21	--
C	148	128	179	188	102	79	85	51	18
D	29	69	102	91	37	37	31	21	5
E	--	73	92	87	50	41	55	117	--
F	24	205	355	294	146	99	73	75	8
G	--	110	168	191	81	47	87	116	--
H	--	22	56	53	26	22	22	23	36

with the largest flow, June was the second and vice versa. Ditch E showed its largest average monthly flow in October (117 $L \cdot s^{-1}$), followed by May (92 $L \cdot s^{-1}$) and June (87 $L \cdot s^{-1}$).

Only positive associations between the logarithmically transformed river and ditch flows were found in the study (Table 3). The positive river-ditch flow associations ranged from 0.22 to 0.65. Moderate associations ($r > 0.50$ to 0.80) were calculated for the ditches E (0.54) and F (0.65) and weak associations ($r \leq 0.50$) for the ditches A (0.36), B (0.22), C (0.45), D (0.43), G (0.50), and H (0.39). A larger r-value was observed in four (C, E, F, and G) out of the five ditches with the largest average flows; ditch A also had the largest average flow although its r-value was 0.36 (Table 1).

Model-Based Analysis

Model Selection. Models 3 and 4 were chosen from the five proposed models to fit the river-ditch flow relationship with logarithmically transformed flow values (Table 3). Logarithmic transformation accounted for some heteroscedasticity observed in the flow information. In Model 1, the simple linear regression, the independence of errors assumption was violated by the time series nature of the flow data. Violation of this assumption led to underestimated SEs resulting in inflated rates of Type I errors invalidating the test based on this model. Models 2, 4, and 5, with the use of random lines, accounted for variations among years from unknown random variables. They also accounted for changing variance at different river flow magnitudes. Models 3, 4, and 5 used an ARMA (1,1) structure to address serial correlation across time. The AIC values dropped substantially on these last three models, indicating a better performance by accounting for the serial autocorrelation. Model 3 had the lowest AIC values in six ditches (A, C, D, E, F, and G) while Model 4 had the lowest AIC values in the remaining two (B and H). Model 3 used the ARMA (1,1) structure and Model 4 combined the ARMA (1,1) structure and the random lines, resulting in a more complex model. Both models approximated well to the variance and led to approximately unbiased SEs as a base for inference.

River-Ditch Flow Relationship Parameters. The resulting linear model parameters (intercept and slope) of the logarithmically transformed flow data from Models 3 and 4 quantified the ditches' overall responses to changes in river flow during the study period (Table 3). While the intercept has no meaningful interpretation, the value of the slope represents the increase in ditch flow ($L \cdot s^{-1}$) to every unit increase in river flow ($L \cdot s^{-1}$). This parameter showed that ditch response to every unit of river flow increase ranged from 0.5320 (H) to 1.1821 (G) and was statistically significant ($p<0.05$) in all the ditches but two (B and H) (Table 3). Like the correlation coefficient or r, larger slope values were estimated in four out of five of the ditches with the largest average flow (C, E, F, and G) with the exception of ditch A (Table 1).

Covariance Parameters for the River-Ditch Flow Relationships. The ARMA (1,1) covariance structure in Model 3 and the combined ARMA (1,1) and random coefficients parts in Model 4 modeled the covariance and correlation structure of the logarithmically transformed flow data (Table 4). For Model 3, the ARMA (1,1) covariance structure implied strong correlations among ditch observations at consecutive time points in an exponentially decaying function. For Model 4, the random coefficients portion of the variance (α, τ, and β) modeled a fraction of the estimated variability in the ditch observations that, when combined with the ARMA (1,1) covariance structure, implied a correlation between ditch flow at different time points within a year that decayed over time at a slower rate than that of Model 3 (Equations 2-3). While the model parameters for the river-ditch flow relationship (Table 3) indicate that ditch and river flow are positively related, the covariance parameters indicate that errors from one day to another are highly correlated. Therefore, ditch flow observations at a current point in time are best understood as a function of both recent past ditch flow and current and recent past river flow.

Ditches B and H, for which a positive relationship with river flow was not statistically demonstrated, had large slope SE and large year to year variability (Tables 3 and 4**).** The SE indicates the amount of variability or error that can be expected in an estimate (slope); slope estimate is more reliable if the SE is small (Harding et al. 2014). Large sample sizes and small variances lead to more reliable estimates of the SE (Harding et al. 2014). The number of observations used for ditches B and H were 811 and 851, respectively. For ditch B, the number of observations (811) was below the average observations used in the ditches (850) but larger than ditch E (752). For ditch H, the number of observations (851) was above the average (850). In both ditches B and H we found large year to year variability ($\alpha = 8.3238$ in ditch B and $\alpha = 23.651$ in ditch H) in the random effects portion of the variance. Thus, the large slope SE values found in ditches B and H were not attributed to the sample size but to the greater year to year variability in those ditches (Table 4).

Outlier Effect on the River-Ditch Flow Relationship Parameters. A total of 147 out of 6,798 observations from all the ditches were considered outliers. After their removal, the number of observations in the ditches decreased from 0 (ditch D) to 38 (ditch C); 0.0 to 4.0%, respectively, (Tables 3 and 5). As expected, in all the ditches with outliers removed, the strength of the river-ditch flow association, r, increased, and the slope SE decreased (Osborne and Overbay 2004; Cousieau and Chartier 2010). Similarly, lower values of the year to year variability as well as the R variance component were obtained (Table 6). Ditch A, the ditch with the largest average flow for the period of record, had the largest increase in r (from 0.36 to 0.89) and largest decrease in slope SE (from 0.1228 to 0.0453). While the value of the slope in all the ditches remained within the confidence limits of the raw flow data once the outliers were removed (Tables 3 and 5), the relationship for ditch B changed from being not statistically significant ($p>0.05$) to being statistically significant ($p<0.05$). However, that of ditch H remained not statistically significant ($p>0.05$).

Discussion

In this study, we analyzed the statistical relationships between river flow and community irrigation ditch flows in an agricultural valley in northern New Mexico. River and ditch flow levels during most of the years evaluated (2011-2014) represented below average streamflow conditions. This was in part due to the prolonged drought conditions prevalent in the region (Cayan et al. 2010; Garfin et al. 2013), which resulted in reduced snowpack depths and lower river flow.

Study results show that for every unit increase in river flow ($L \cdot s^{-1}$) there was an increase in ditch flow that ranged from 0.5320 to 1.1821 $L \cdot s^{-1}$ depending on the particular ditch evaluated. Results indicated that ditch flow was related to both current river flow and recent past river and ditch flow conditions. Stronger streamflow associations with the river were observed on the ditches that diverted the largest amount of water. Ditch H, located at the downstream end of the valley, showed a weak streamflow relationship related to the river flow. This was particularly evident toward the end of the ditch flow season. It is possible that the weak relationship observed between river and ditch H flow was in part due to the late-season operations made in upstream ditches.

Social and climate-related changes can negatively influence some of the ditch-river flow relationships observed in these traditional irrigation systems. The population of residents new to the area has increased, and the proportion of local Hispanic families, largely responsible for maintaining community-ditch traditions (such as equal water distribution regardless of river flow), has decreased. It is possible that some of these traditions may be lost if they are not embraced by the newcomers. Another threatening factor is related to the ongoing changes in land use observed in many acequia communities in northern New Mexico. These communities are facing reductions in irrigated land due to residential development (Ortiz et al. 2007; Llewellyn and Vaddey 2013) and increasing demands for water from other sectors (e.g., urban), which may result in reductions of land and water flow for agricultural activities. In previous studies, we documented important hydrological benefits associated with the use of these traditional irrigation systems in northern New Mexico. For instance, during the irrigation season, water diverted from the river is distributed in the irrigated valley moderating streamflow extremes. Ditch seepage and field irrigation deep percolation inputs help recharge the aquifer, which then releases water late in the season when baseflow decreases, resulting in substantially extended hydrographs (Fernald et al. 2010; Ochoa et al. 2013; Gutierrez-Jurado et al. 2017). Under predicted scenarios of water scarcity, climate change adaptation strategies consistently point to reduced surface irrigation (Pamuk-Mengu et al. 2011; McDonald and Girvetz 2013; Xu et al. 2013; Varela-Ortega et al. 2016; Rey et al. 2017). While these measures could in fact reduce water demands, it is possible they may disrupt benefits such as the recharge of local aquifer systems or the delayed return flows and environmental benefits associated with the use of these community-based irrigation ditches.

This research increases knowledge of traditionally managed irrigation ditches and their relationships with society and the environment. In particular, this study contributes important statistical understanding of the seasonality of river and community ditch flow relationships in a natural river flow regime system. Over the centuries, agricultural communities in Rio Hondo and in northern New Mexico at large have adapted to cope with the high and low river flows resulting from winter precipitation and snowmelt runoff conditions. This is different from many other surface-irrigated agriculture regions where river systems are controlled with man-made reservoirs that modulate streamflow deliveries to satisfy irrigation and community water needs.

Some of the statistical relationships observed in this study can be incorporated into simulation frameworks aimed to investigate water resources management at a larger scale. For example, natural river flow and community irrigation relationship metrics derived from this study can be used to parametrize regional water resource models such as the Snowmelt Runoff Model (Rango et al. 2017) and the Acequia System Dynamic Model (Turner et al. 2016), which are being used to evaluate the effects of climate variations and community-based management practices in water availability in the southwestern United States.

Conclusions

Community ditch flows in the Rio Hondo Valley are highly correlated to the natural river flows observed. Climate change-driven projections of reduced snowpack levels and earlier spring flow in the southwestern United States may significantly

Table 3. Model parameters and statistical components for the river-ditch flow relationship with flow values logarithmically transformed.

Ditch	Obs	Model	Intercept	Slope	Slope SE	------ Slope CL ------ Lower	Upper	*r*
A	851	3	2.1619	0.5431*	0.1228	0.3020	0.7841	0.36
B	811	4	-0.7247	0.6521	0.2261	-0.0014	1.3056	0.22
C	959	3	-0.6169	0.7622*	0.1081	0.5499	0.9744	0.45
D	872	3	-0.2180	0.5351*	0.1448	0.2509	0.8193	0.43
E	752	3	-1.2391	0.7768*	0.1021	0.5764	0.9773	0.54
F	890	3	-0.7143	0.7793*	0.1396	0.5052	1.0533	0.65
G	812	3	-3.7436	1.1821*	0.1898	0.8095	1.5548	0.50
H	851	4	-0.4348	0.5320	0.3380	-0.4246	1.4886	0.39

Note: Obs = number of observations; Slope SE = slope standard error; Slope CL = slope confidence limits (95%); *r* = Pearson's correlation coefficient; *Significant at the 0.05 probability level.

Table 4. Covariance parameters for the river-ditch flow relationship with flow values logarithmically transformed.

Ditch	Model	α	τ	β	ρ	γ	R
A	3	-----	-----	-----	0.8124	0.8673	0.8007
B	4	8.3238	-1.2087	0.1771	0.8437	0.8465	0.6211
C	3	-----	-----	-----	0.7005	0.8003	0.9213
D	3	-----	-----	-----	0.9356	0.9606	1.4289
E	3	-----	-----	-----	0.9107	0.9504	0.5916
F	3	-----	-----	-----	0.9290	0.9507	1.1136
G	3	-----	-----	-----	0.9348	0.9309	1.5360
H	4	23.651	-3.3284	0.4691	0.8518	0.9015	0.8348

Note: α = intercept variance for the random coefficients' variance component; τ = intercept and slope covariance for the random coefficients' variance component; β = slope variance for the random coefficients' variance component; ρ = autoregressive component of the ARMA (1,1) covariance structure in the residual component; γ = moving average coefficient of the ARMA (1,1) covariance structure in the residual component; R = residual variance component.

Table 5. Model parameters and statistical components for the river-ditch flow relationship with flow values logarithmically transformed and outliers removed.

Ditch	Obs	Model	Intercept	Slope	Slope SE	------ Slope CL ------		*r*
						Lower	Upper	
A	834	3	1.4057	0.6670*	0.0453	0.5782	0.7558	0.89
B	783	4	-2.1153	0.8705*	0.2020	0.3087	1.4324	0.40
C	921	3	-0.0589	0.7015*	0.0584	0.5868	0.8161	0.70
D	872	3	-0.2180	0.5351*	0.1448	0.2509	0.8193	0.43
E	749	3	-1.2072	0.7718*	0.0995	0.5765	0.9672	0.55
F	875	3	-1.1353	0.8485*	0.1208	0.6114	1.0856	0.74
G	783	3	-3.6767	1.1874*	0.1608	0.8716	1.5031	0.58
H	834	4	-0.8149	0.5885	0.3322	-0.3576	1.5346	0.54

Note: Obs = number of observations; Slope SE = slope standard error; Slope CL = slope confidence limits (95%); *r* = Pearson's correlation coefficient; *Significant at the 0.05 probability level.

Table 6. Covariance parameters for the river-ditch flow relationship with flow values logarithmically transformed and outliers removed.

Ditch	Model	α	τ	β	ρ	γ	R
A	3	-----	-----	-----	0.9170	0.9197	0.0880
B	4	6.7577	-1.0232	0.1553	0.9416	0.9349	0.3475
C	3	-----	-----	-----	0.7801	0.8621	0.2177
D	3	-----	-----	-----	0.9356	0.9606	1.4289
E	3	-----	-----	-----	0.9172	0.9537	0.5803
F	3	-----	-----	-----	0.9312	0.9507	0.8152
G	3	-----	-----	-----	0.9081	0.9071	1.0369
H	4	23.535	-3.2764	0.4560	0.8887	0.9162	0.7052

Note: α = intercept variance for the random coefficients' variance component; τ = intercept and slope covariance for the random coefficients' variance component; β = slope variance for the random coefficients' variance component; ρ = autoregressive component of the ARMA (1,1) covariance structure in the residual component; γ = moving average coefficient of the ARMA (1,1) covariance structure in the residual component; R = residual variance component.

impact water resources management in the community-based irrigation systems of northern New Mexico. The river-ditch flow relationships observed were affected by ditch location along the agricultural valley. Also, the volume of water diverted influenced the strength of the river-ditch flow relationship. Future research would benefit from an enhanced understanding of river flow and ditch flow change between wet and dry years, and from improved knowledge of the influence of upstream ditch return-flow to the river.

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