INFLUENCE OF URBANIZATION AND CLIMATE ON IRRIGATION DIVERSIONS AND RETURN FLOWS IN THE LOWER BOISE RIVER BASIN

by

Bridget Bittmann

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Bridget Marie Bittmann

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The following individuals read and discussed the thesis submitted by student Bridget Marie Bittmann, and they evaluated the student's presentation and response to questions during the final oral examination. They found that the student passed the final oral examination.

Kendra E. Kaiser, Ph.D.	Chair, Supervisory Committee
Alejandro N. Flores, Ph.D.	Member, Supervisory Committee
Michael J. Poulos, Ph.D.	Member, Supervisory Committee
Allison Simler-Williamson, Ph.D.	Member, Supervisory Committee

The final reading approval of the thesis was granted by Kendra E. Kaiser, Ph.D., Chair of the Supervisory Committee. The thesis was approved by the Graduate College.

DEDICATION

To my best friend and life partner, Benjamin – for sharing your love with me and making me laugh daily

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ABSTRACT

The western US is facing both the rapid urbanization of agricultural lands and a changing climate, producing subsequent changes to irrigation water demand and availability. Adaptive water management requires knowledge regarding how and why water usage and availability is changing; however, managers often do not possess the tools or resources for the necessary analysis. These environmental changes are also place-based, meaning that water managers cannot directly use studies from other basins to actively manage theirs. Co-produced, actionable research can help fill this knowledge gap and provide the necessary information for adaptive management. The Lower Boise River Basin (LBRB) in southwestern Idaho is one location that is facing both the pressures of urbanization and climate change and where water managers need the long-term analysis to contextualize how or if these mechanisms are affecting the irrigation system. This research studied both irrigation water diversions and irrigation drain return flow. The goals of this research were to 1) understand how diversions and drains in the LBRB have changed from 1987 to 2020 and 2) to quantify the effects of urbanization, annual weather, and reservoir availability on diversion and drain flows. We used a Mann Kendall test to quantify changes in discharge through time and used variations of a Bayesian Generalized Linear Mixed Effects Model to quantify the effects of predictor variables on annual discharge for both diversions and drains. Generalized linear models were also used for the diversions to understand the effects of predictor variables at the individual diversion scale. Diversions had variable results across the basin with a mix of increasing

(18%), decreasing (35%), and no trend in discharge through time (47%). Forty percent of drains that return irrigation water back to the Boise River had decreasing trends through time while 60% had no significant change. Diversions had variable responses to urbanization, which could be the result of both human decision-making and complex changes in surface water-groundwater interactions associated with urbanization. Drain flows decreased with urbanization more uniformly, which is an indication that drain flows are supplied by discharge from the shallow aquifer system while diversions are more controlled by human decision-making. Increased evapotranspiration increased both diversion and drain discharge while increased temperatures decreased discharge for both, and precipitation played less of a role in the system. Storage water use from the reservoir system had the most consistent positive effect on diversions across models, demonstrating how the reservoir system supplies water during the irrigation season and helps offset the lack of precipitation in this semi-arid region. Increased diversion flows also increased drain flows, demonstrating that seepage loss from canals feeds the groundwater and drain system. This analysis showed complexities across the basin for both drains and diversions and supports the need for localized research to help water managers with adaptive management.

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LIST OF ABBREVIATIONS

AF	Acre-feet
ARMA	Autoregressive—moving average
°C	Degrees Celsius
Daymet	Daily Surface Weather and Climatological Summaries
ET	Evapotranspiration
°F	Degrees Fahrenheit
FAIR	Findable, Accessible, Interpretable, and Reproducible
GLM	Generalized Linear Model
GLMM	Generalized Linear Mixed Effects Model
IDWR	Idaho Department of Water Resources
in	Inches
km	Kilometer
LBRB	Lower Boise River Basin
LCMAP	Land Change Monitoring, Assessment, and Projection
LOOIC	Leave-one-out information criterion
LULCC	Land use and land cover change
MAE	Median absolute error
m	Meter
mm	Millimeter
NHD	National Hydrography Dataset
POD	Point of diversion
POU	Place of use
SSEBop	Operational Simplified Surface Energy Balance model
US	United States
USGS	United States Geological Survey
yr	Year

CHAPTER 1: INFLUENCE OF URBANIZATION AND CLIMATE ON SURFACE WATER DIVERSIONS IN A SEMI-ARID BASIN

Introduction

Arid and semi-arid regions in the United States are rapidly urbanizing, with eleven out of the fifteen fastest growing cities in the US located in the South-Central and Western US (from 2010 to 2020; Friedrich, 2020). These are water-scarce regions where rising populations and associated land use and land cover change (LULCC) are leading to water manager's growing concern about their ability to meet future water demands. Irrigation water is the largest form of consumptive water use in arid regions, making it a particularly important facet of water management to study and understand (St. Hilaire *et al.*, 2008). For example, in Denver, Colorado, outdoor irrigation can comprise up to 50% of a household's water use (Denver Water, 2022) and up to 74% in the Phoenix Metropolitan Area (Balling and Gober, 2007). Because irrigation consumes a large component of water usage in arid and semi-arid regions, understanding how shifts in LULCC changes irrigation water demand is imperative for water managers that are trying to anticipate future demand.

The extent to which irrigation water demand changes with urbanization of agricultural areas is highly variable across studies and is dependent on location-specific variables (Baker *et al.*, 2014; Kliskey *et al.*, 2019). Some irrigation estimates of total water applied remain constant following urbanization (Baker *et al.*, 2014; Crandall, 2019) while other studies show that irrigation demand decreases as a region transitions to an urban environment (Kliskey *et al.*, 2019; Wang and Vivoni, 2022). The variability across the literature makes it challenging for water managers to know what to anticipate in their management area without place-based research.

One reason that LULCC has variable effects on irrigation demand is that urbanization alters multiple parts of the hydrologic system, namely evapotranspiration and infiltration. Urbanization can occur through both urban densification and expansion (Dahal *et al.*, 2017), which have opposing effects the hydrologic system. Urban densification refers to the infill of already urbanized areas, which results in the reduction of outdoor water usage (Polebitski *et al.*, 2011). Expansion or sprawl is defined by low-density housing and large yards on the edges of a city (Dahal and Lindquist, 2018), and how outdoor water usage changes with expansion is less clear. For example, if a 10-acre plot of land in the Boise River Basin was converted from agricultural to urban, about 3.8-acres (38%) of the land would be irrigated in high density urban areas, and 7.6-acres (76%) of the land would be irrigated in low-density areas of urban sprawl (Baker *et al.*, 2014). Turf grass can transpire up to 10% more than some crops (e.g., wheat, barley), meaning that reduction in irrigated acreage due to urbanization may not always result in a net decrease in irrigation water usage (Baker *et al.*, 2014). Urbanization also reduces the amount of permeable surfaces, which can decrease infiltration and impact groundwater table levels (Bhaskar *et al.*, 2016). Decreased infiltration due to a reduction in green spaces and permeable surfaces and increased groundwater pumping to support potable water supplies may lower the groundwater table and result in more seepage from irrigation canal systems (Barlow and Leake, 2012). The variation in how irrigation volumes shift pre- and post-urbanization is, in part, due to spatial non-uniformity of irrigation practices associated with different types of development and highlights the need for place-based research that can take these processes into account.

Annual weather and local climate will also have variable impacts on irrigation water usage, making it challenging or infeasible, to transfer results from one location to another (Abatzoglou *et al.*, 2014). Temperature, precipitation, and evapotranspiration are often used to understand changes in irrigation water demand, but the impacts of these parameters on irrigation demand are highly variable (Balling and Gober, 2007; Breyer *et al.*, 2012; Gage and Cooper, 2015; House-Peters *et al.*, 2010). While it is generally assumed that increases in temperature will require increased outdoor water usage, this response is not always present (Ouyang *et al.*, 2014). For example, how irrigation water usage responded to increases in temperature varied even within Phoenix, Arizona, with some areas increasing water usage, some decreasing, and some remaining constant (Breyer *et al.*, 2012). The lack of, or relatively small, response of irrigation water use to temperature changes in this region has, in part, been explained by human behavior. For example, in urban areas, sprinkler systems are set to irrigate lawns at regular intervals with little change in response to weather conditions (Balling and Gober, 2007). Increased precipitation is generally associated with declining irrigation water usage (Balling and Gober, 2007; House-Peters *et al.*, 2010; Polebitski *et al.*, 2011), but this is not always a significant predictor. The lack of importance of precipitation is due to these urban irrigation studies taking place in semi-arid and arid regions (Balling and Gober, 2007; House-Peters *et al.*, 2010; Polebitski *et al.*, 2011), which receive the bulk of precipitation during the non-irrigation season (Han *et al.*, 2019). Finally, evapotranspiration has been used as a proxy for irrigation water use, as it is the consumptive part of irrigation (Allen *et al.*, 2013). This would indicate that increases in evapotranspiration are correlated with higher irrigation water use (Johnson and Belitz, 2012). The variability of irrigation water usage in response to weather across regions highlights the need for local, actionable research, as managers need location-specific information to adequately adapt to changes in the system.

A changing climate will induce further spatial heterogeneity, making climate impacts on irrigation water demand even less transferrable from one region to another. While climate change will broadly increase temperatures, the extent of increase is non-uniform (Glabau *et al.*, 2020; Mote *et al.*, 2014), and the direction of changes in annual precipitation may increase or decrease depending on the location (Jin and Sridhar, 2012). One commonality in anticipated effects of climate change on precipitation across the West is that higher temperatures during winter months will result in more precipitation falling as rain, and elevated temperatures in the early spring can cause earlier runoff and peak discharge in streams, yielding an overall decrease in water availability for irrigation later in the season (Glabau *et al.*, 2020; Jin and Sridhar, 2012; Steimke *et al.*, 2018; Sterle *et al.*, 2020). Climate change will also increase extreme weather events, such as prolonged droughts or extreme heat events, exacerbating water scarcity (Strzepek *et al.*, 2010). Studying how a specific region's irrigation water usage is currently responding to annual weather variation can help water managers understand how usage might change in the future.

Finally, the source of irrigation water will influence irrigation water demand, and its state-to-state variability in the western US is largely missing from the literature. The majority of studies on irrigation water demand use billing records from public water supply to estimate outdoor water usage (Breyer *et al.*, 2012; House-Peters *et al.*, 2010; Kenney *et al.*, 2008; Sampson *et al.*, 2022). This assumes that outdoor irrigation water in urban spaces is solely sourced from public water supply, but public water is not the only source of irrigation water in all basins. For example, the drinking water supply is used for lawn irrigation in Denver, Colorado (Fillo *et al.*, 2021) while both domestic water and surface water from irrigation canals is used to irrigate lawns in some places in Idaho and Utah (Bjorneberg *et al.*, 2020; Hoekema and Sridhar, 2011; Kliskey *et al.*, 2019). Urban areas that use surface water from irrigation canals for lawn irrigation have less of an incentive to conserve water because of the "use it or lose it" section of water law, and because it is much cheaper than using domestic water (Nampa Meridian Irrigation District; SPF Water Engineering, 2016). Historically, how surface water is used to irrigate urban areas has been minimally studied (Bjorneberg *et al.*, 2020; Goodrich *et al.*, 2020), potentially because it is less common, but this information is necessary for water managers in basins where canal systems are being modernized to deliver pressurized irrigation water to urban areas.

The Lower Boise River Basin (LBRB) is a region that has undergone substantial LULCC over the past few decades and uses an extensive canal system to deliver irrigation water to urbanizing areas that have historical agricultural water rights tied to the land. However, water managers in this region do not currently have tools to explore how urbanization has impacted irrigation water demand from these canals. The goals of this research were to:

1. Quantify the change in irrigation water diversions for 63 diversions in the LBRB from 1987 to 2020, and

2. Determine the effects of urbanization and climate on irrigation water diversions in the LBRB.

We evaluated the effects of predictor variables at the basin-wide scale as well as within individual irrigation districts. We explored the effects of urban area and climate on total irrigation water diversions using repeated observations from 1987 to 2020 with a Bayesian generalized linear mixed effects model (GLMM). We investigated interannual variability of urbanization and climate on irrigation water diversions using a GLMM with an autoregressive-moving average component. We examined the effects of variables at a more local, irrigation district scale to understand basin-heterogeneity using individual generalized linear models (GLMs) for each diversion.

Study area

The LBRB, also known as the Treasure Valley, is in southwest Idaho and has a total area of 3,323 km^2 (Figure 1). This region is home to 40% of the state's total population (Community Planning Association of Southwest Idaho, 2021). The two main counties in the LBRB, Ada and Canyon Counties, had a combined population of 737,790 in 2020 compared to a population of 581,288 in 2010, a growth of 21% in 10 years (Community Planning Association of Southwest Idaho, 2021). By 2100, the area is predicted to double, with a population of approximately 1.5 million (+/- 250,000 people, Narducci *et al.*, 2017). The LBRB has undergone both urban densification and urban expansion into previously agricultural areas (Dahal *et al.*, 2017).

The LBRB has a semi-arid Mediterranean climate, meaning the area receives most of its precipitation during the late fall, winter, and early spring, and the summers are hot and dry. Precipitation is spatially variable across the basin with about 700 mm of precipitation in the Boise foothills and only 200 mm occurring in western cities like Caldwell (Han *et al.*, 2017). The summer irrigation season relies on the snowpack in the Upper Boise River Basin (~800 mm of annual precipitation, Steimke *et al.*, 2018)), which is stored in Anderson Ranch, Arrowrock, and Lucky Peak reservoirs. Stored water in the three reservoirs (949,700 AF) is used to irrigate approximately 1,602 km^2 of land in the LBRB as of 2008 (Reclamation, 2008). The geology in the basin is primarily composed of granodiorite and granite, basalts, and sedimentary rocks (Lewis *et al.*, 2012), all of which have different seepage rates for the canal system (Abdelmoneim, 2021).

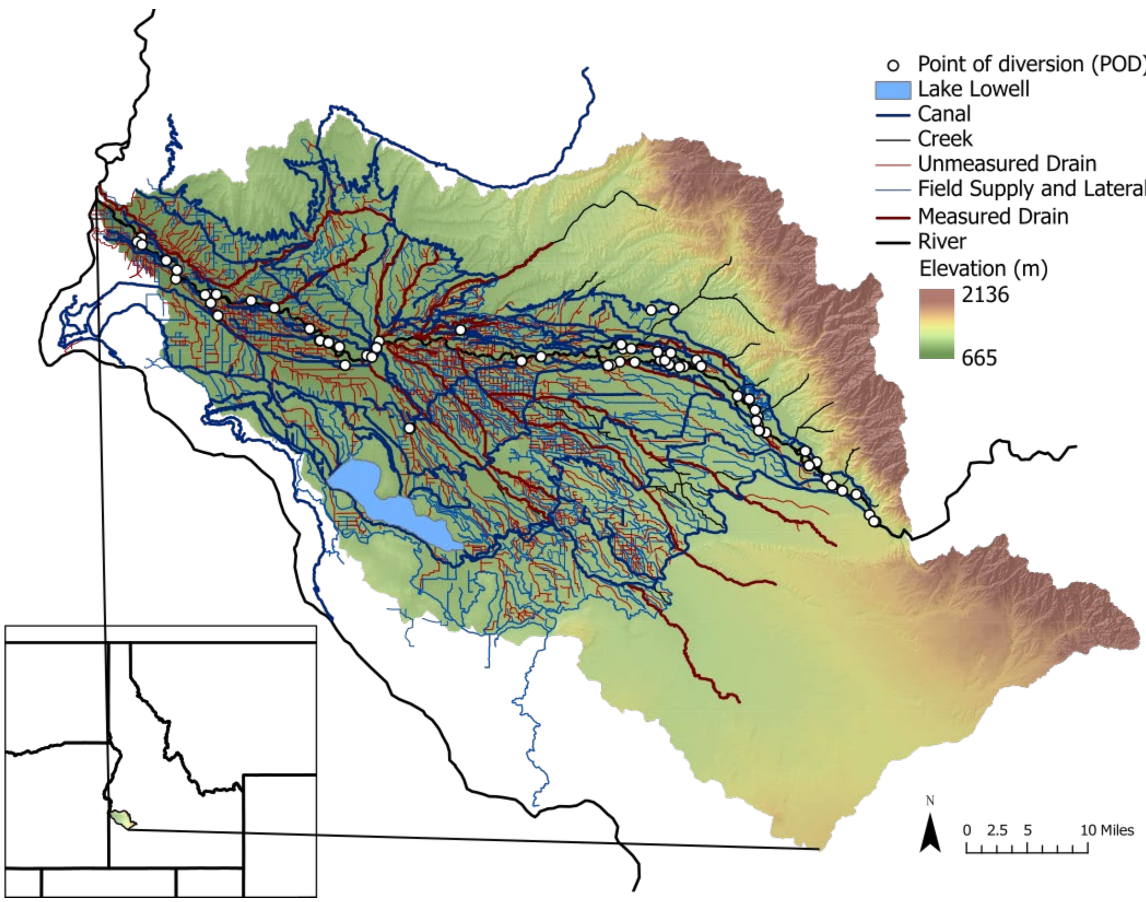

Figure 1.1. Inset and map of the irrigation network in the Lower Boise River Basin.

Data and methods

Data Collection and Preparation

Diversion discharge data.

We obtained daily diversion flow measurements from 1987 to 2020 for 67 points of diversion (POD) from the Boise River from the Idaho Department of Water Resources' (IDWR) Water District Daily Diversion Time Series database (Idaho Department of Water Resources, 2020). The daily flows were summed for each year to calculate a total annual flow for each diversion in acre-feet/year (AF/yr). We calculated the start day of year of the irrigation season, the end day of year of irrigation season, and the length of the irrigation season for each diversion. The start day was the first day of the year with a flow greater than 0 AF, and the end day of year was the date when the diversion reached its cumulative total for the season. Some diversions had earlier start dates or later end dates than the normal irrigation season due to using the canals for transporting storage water. If the start day of year was earlier than March 1, we reassigned the start day for that diversion to the earliest start day of year during March from the other canals. Similarly, if the end day of year was after Nov. 15, we reassigned the end day of year to be the latest end day of the other canals from that irrigation season. For diversions with reassigned start and end date values, we summed the annual diversion total using the new start and end days. Analysis of the timing metrics showed little variability from year to year and did not warrant further modeling (Supplemental Figure 1).

Reservoir Storage data

Many diversions in the upper half of the LBRB (above Middleton, Idaho) have both natural flow and storage water rights. Storage water is often used after the day of allocation, the day of year when curtailments start due to lack of natural flow to support all of the water rights. This is critical information about the actual water availability for an irrigation season. We used IDWR's annual Water Rights Accounting Reports to obtain the storage water used by each diversion (Idaho Department of Water Resources, 2022a). Many diversions in the lower part of the basin do not have storage water rights and instead rely on return flows from drains to the Boise River to offset the water needed after the day of allocation (Figure 1). Because these drains have historically provided surplus water in the river, irrigation users in the lower part of the basin have treated this drain water like their storage water. We assumed the total annual water diverted that surpassed a natural flow right and was not from storage was return flow water. We recorded the value for the associated diversion as the 'storage water' used because return flows in locations with no storage water rights have treated return flow water like storage water.

Table 1.1. Datasets used to understand the relationship of diversions with climate and urbanization and the computed predictor and response variables.

Data Type	Name	Source	Data Output
Hydrologic Flows	Water District Diversion Daily Time Series	Idaho Department of Water Resources (IDWR)	Total Discharge (AF/yr)
	Water Rights Accounting	IDWR	Storage water use (AF/year)
Geospatial Hydrology	National Hydrologic Database (NHD) +2.1	US Geological Survey (USGS)	
	Water Rights Point of Diversion (POD)	IDWR	Linked POD with POU
	Water Rights Place of Use (POU)	IDWR	
	Irrigation Organizations	IDWR	
Geospatial Land Use	Land Change Monitoring, Assessment and Projection (LCMAP)	USGS	Urban Proportion
Geospatial Climate	Daily Surface Weather and Climatological Summaries (Daymet)	Oak Ridge National Laboratory	Avgerage Maximum Irrigation Season Precipitation (mm) Avgerage Maximum Irrigation Season Temperature (°C)
	Operational Simplified Surface Energy Balance (SSEBop) Evapotranspiration	David Ketchum, University of Montana	Avgerage Total Irrigation Season Evapotranspiration (m)

Diversion spatial data

We connected the Water Rights Place of Use (POU), or the designated area where water can be applied for a given water right, with the water rights POD (Table 1) to create a single POU for each of the monitored 67 diversions from the Boise River. One POU for each diversion was needed to calculate associated annual values of land use coverage and climatic variables. We used a spatial join to with the National Hydrologic Database (NHD) +2.1 dataset (U.S. Geological Survey, 2017)to connect the Water Rights PODs to the actual diversions where flow is measured, as discussed in the previous section (Table 1). We verified the spatial join using the measuring site diversion name on the water rights POD file. Many sites' metadata did not include a measuring site name, nor did the spatial join link a POD with a measuring site. As a result, we manually linked the remaining PODs to measuring sites based on the associated POU location. We used the IDWR Irrigation Organization map (Idaho Department of Water Resources) to verify the correct merged POU for each measuring site diversion and met with a IDWR water rights specialist to confirm any remaining PODs and POUs with no associated measuring site. After POUs were established for each POD, we visually analyzed the POUs to check to for complete overlap of the POU. If two POUs were identical, we merged the POUs into one POU, and we summed the two flow values into one flow value. After merging POUs and flow values, we had 63 diversions with an associated POU.

Geospatial land use and climate data

We calculated various annual climate and landscape metrics for each POU. We used Daymet data (1 km resolution, Thornton *et al.*, 2020) to calculate the average maximum daily temperature for the irrigation season (°C) and the average total irrigation season precipitation (mm) for each POU (Table 1). Daymet was chosen for precipitation and temperature because this dataset had the highest spatial resolution for the period of record needed. The earliest start day and latest end day of the irrigation season were used to calculate the temperature and precipitation variables. We derived average total evapotranspiration (m) from monthly Simplified Surface Energy Balance (SSEBop) data (30 m resolution, Senay *et al.*, 2022). The entire month of evapotranspiration was included if any water was diverted during that month. For example, we included March evapotranspiration in the total sum even though the start date of the irrigation season was March 15. We analyzed Land Change Monitoring, Assessment, and Projection (LCMAP, US Geological Survey, 2021) to compute the proportion of agricultural land and the proportion of urban land as an annual value for each POU.

Trend Analysis

A Mann-Kendall test was used to test for a significant trend ($p < 0.05$) in the annual volume of water (AF /yr) through time for each diversion. Mann-Kendall trend analysis is a non-parametric test for monotonic trends in a dataset through time (Sang *et al.*, 2014). The period of record needed to be greater than 5 years and have no data gaps for the Mann Kendall test because the test is assuming a continuous period of record. If the diversion had a significant trend, a linear regression was calculated with 95% confidence intervals, and average change through time was calculated. We calculated model fit for the regression using R^2.

Basin Scale Statistical Analysis

Mixed effects model

We constructed a Bayesian Generalized Linear Mixed Effects Model (GLMM) with a lognormal distribution to understand the effect size of urban area and climate on total diversion flow (AF/yr). GLMMs account for data in groups with repeated observations that are not independent of one another and allow for unbalanced datasets (Schreiber *et al.*, 2022). We have 63 diversions, or groups, with most having a full period of record for 34 years but some having less (total observations = 1907).

We constructed a single "full" model containing covariates selected to isolate the effects of urbanization and climate on diversion volumes (Yates *et al.*, 2022; Supplemental Figure 2). A varying intercept was used for the name of each diversion (j = 63) to account for the wide range in baseline diversion volumes (0.83 – 854,000 AF/yr). We allowed for the effect of urban proportion to vary by diversion because irrigation water usage has been shown to vary through space, even within an individual city (Barnett *et al.*, 2020; Wang and Vivoni, 2022). Finally, we included all climate variables—average total irrigation season precipitation, average maximum irrigation season temperature, average total irrigation season evapotranspiration—and storage water use as fixed effects. The general form of the model is as follows:

$$Q_{i,t} = a_j + B_j Urban_{i,t} + B_1 Precip_{i,t} + B_2 Temp_{i,t} + B_3 ET_{i,t} + B_4 Storage_{i,t},$$

for $n = 1, \dots, N$

$$a_j \sim Normal(\gamma_0, \sigma), \text{ for } j = 1, \dots, J, \text{ for } t = 1, \dots, 34$$

where Q is the annual diversion discharge (AF/yr); a_j is the diversion group level intercept with standard deviation, σ; B_j is the parameter coefficient for urban proportion, which is the only diversion level predictor variable; $B_{1, \ldots, 4}$ is the parameter estimate for the given basin level predictors—average total irrigation season precipitation (*Precip*,), average maximum irrigation season temperature (*Temp*), average total irrigation season evapotranspiration (*ET*), and reservoir storage water used (*Storage*, AF).

We fit the model using the *brms* package in R (Bürkner, 2017), which uses a gradient-based Markov chain Monte Carlo sampler. Precipitation, temperature, and storage water use were standardized by subtracting the mean and dividing by two standard deviations while urban area and evapotranspiration were not. Urban proportion only ranged from 0 to 1, and evapotranspiration ranged from 0.29 to 1.56 m. The standard deviation of urban proportion and evapotranspiration was still smaller than that from the other three variables. Precipitation, temperature, and storage water use were scaled to get variables close to the same scale for comparison of effect size. We ran the model with 4,000 iterations (2,000 warm-up iterations and 2,000 sampling events) and used weakly informative priors (Supplemental Table 1). The model was assessed for effective sample size and convergence using visual inspection of chains and confirmation that R-hat values was less than or equal to 1.01. We used visual posterior predictive checks to assess model fit (Supplemental Figure 3). We also calculated model fit using in-sample Median Absolute Error (MAE) and Bayes R^2 (Gelman *et al.*, 2019). The median absolute error was used as opposed to mean absolute error because the median more accurately represents the heavy-tailed distribution of the data.

Mixed effects model with autocorrelated residuals

We used a GLMM with an autoregressive-moving average (ARMA) correlation structure (p = 1, q = 1) to examine how urbanization and climate have impacted diversions through time. We used the same previous model structure in the 'Mixed effects model' section but included an ARMA correlation structure (p = 1, q = 1).

ARMA models assume both response and predictor variable stationarity. We tested for stationarity within each variable for our longitudinal dataset using the Levin-Lin-Chu test (Levin *et al.*, 2002) in the *plm* R package (Tappe, 2022). This test is a variation of the Augmented Dickey Fuller test, adapted for longitudinal datasets (Tappe, 2022). The Levin-Lin-Chu test only allows for balanced datasets; therefore, we used only diversions with consecutive years of data from 1987 to 2020 (t = 34) in this analysis (j = 47, total observations = 1,551). We included all variables previously used in the GLMM with no time component (urban proportion, evapotranspiration, precipitation, temperature, and storage water use). All variables were stationary except for average total irrigation season evapotranspiration, urban proportion, and storage water use. Evapotranspiration, urban proportion, and storage water use were differenced to make the variables stationary using $\Delta x = x(t) - x(t-1)$, where *x* is the variable of interest, *t* is the current time step, and *t-1* is the previous time step. The Levin-Lin-Chu test was used again to confirm that the variables were stationary.

After the data was differenced, we used *brms* to run the GLMM with ARMA correlation. The temperature, precipitation, and storage water use were scaled the same way as the previous model while urban proportion and evapotranspiration were not. The annual diversion volumes were log-transformed because the ARMA structure in *brms* can only account for distributions with a gaussian structure. The log-transformed values were modeled with a student-t distribution to reflect the heavy tails of our response variable's distribution. The general format of the model is as follows:

$$\log(Q_{i,t}) = a_j + B_j Diff.Urban_{i,t} + B_1 Precip_{i,t} + B_2 Temp_{i,t} + B_3 Diff.ET_{i,t} + B_4 Diff.Storage_{i,t} + ARMA(1,1)_j,$$

for $n = 1, \dots, N$

$$a_j \sim Normal(\gamma_0, \sigma), \text{ for } j = 1, \dots, J, \text{ for } t = 1, \dots, 34$$

where log(Q) is the log of annual diversion discharge (AF/yr); $ARMA(1,1)_j$ is the autoregressive-moving average correlation structure in the residuals of the response variable for each diversion, *j*; and all other variables are the same as previously explained. The model used weakly informative priors (Supplemental Table 2). The model was assessed for model convergence and model fit as described in the previous section, including using visual posterior predictive checks (Supplemental Figure 4).

Individual diversion statistical analysis

A generalized linear model (GLM) model with a gamma distribution was fit for each diversion with greater than 5 years of observation, to analyze variable importance at the individual irrigation district level (j = 60). We included all predictor variables (percent urban cover, average total irrigation season evapotranspiration, average total irrigation season precipitation, average maximum irrigation season temperature, and storage water use) in each individual model except for specific scenarios. Urban change and storage water use were excluded from models if there was no variation in their values across the observed time period. No variables were standardized; however, storage water use was now put on the scale of 10,000 AF, and precipitation was converted from millimeters to meters for ease of computation. We used *brms* to run the GLMs with 2,000 iterations, a gamma distribution, and uninformative priors (Supplemental Table 3). Model convergence was assessed with visual inspection of chains and confirmation that R-hat values were less than or equal to 1.01. Effective sample size (> 400) was confirmed for each model. Model fit was calculated using Bayes R^2. Variable coefficients and credible intervals were extracted from each model to understand the direction of effect.

Results

Trends in discharge through time

Nineteen out of 55 (35%) of diversions had significant, negative trends ($p < 0.05$), with the percent of change in discharge through time ranging from 6 to 92% (Figure 1.2). The lowest percent of change is associated with canals that discharge large amounts of water and vice versa. As a result, the diversion with the 6% decrease had a reduction of 9,600 +/- 11,000 AF while the diversion with a 92% decrease had a reduction of 45 +/- 10 AF of water in the diversion. Eleven of the diversions with decreasing trends had greater than 10% increase in the proportion of urban area in a POU over the course of the study. The change in diversion discharge for diversions with greater than 10% urban change ranged from -233 AF/yr (-79%) to -17,000 AF/yr (-13.5%) (Figure 1.2).

Ten diversions had significant, increasing trends in discharge through time (Figure 1.2). Two of the diversions had an increasing trend through time and greater than 10% urban change. The two diversions with greater than 10% change in urbanization had increased diversion volumes of 326 AF (+14.3%) and 491 AF (+204%) from 1987 to 2020. Overall, the change in diversion discharge ranged from 28 +/- 1 AF to 14,000 +/- 5,500 AF (53% and 17.6% respectively). The percent change ranged from 14 to 563%.

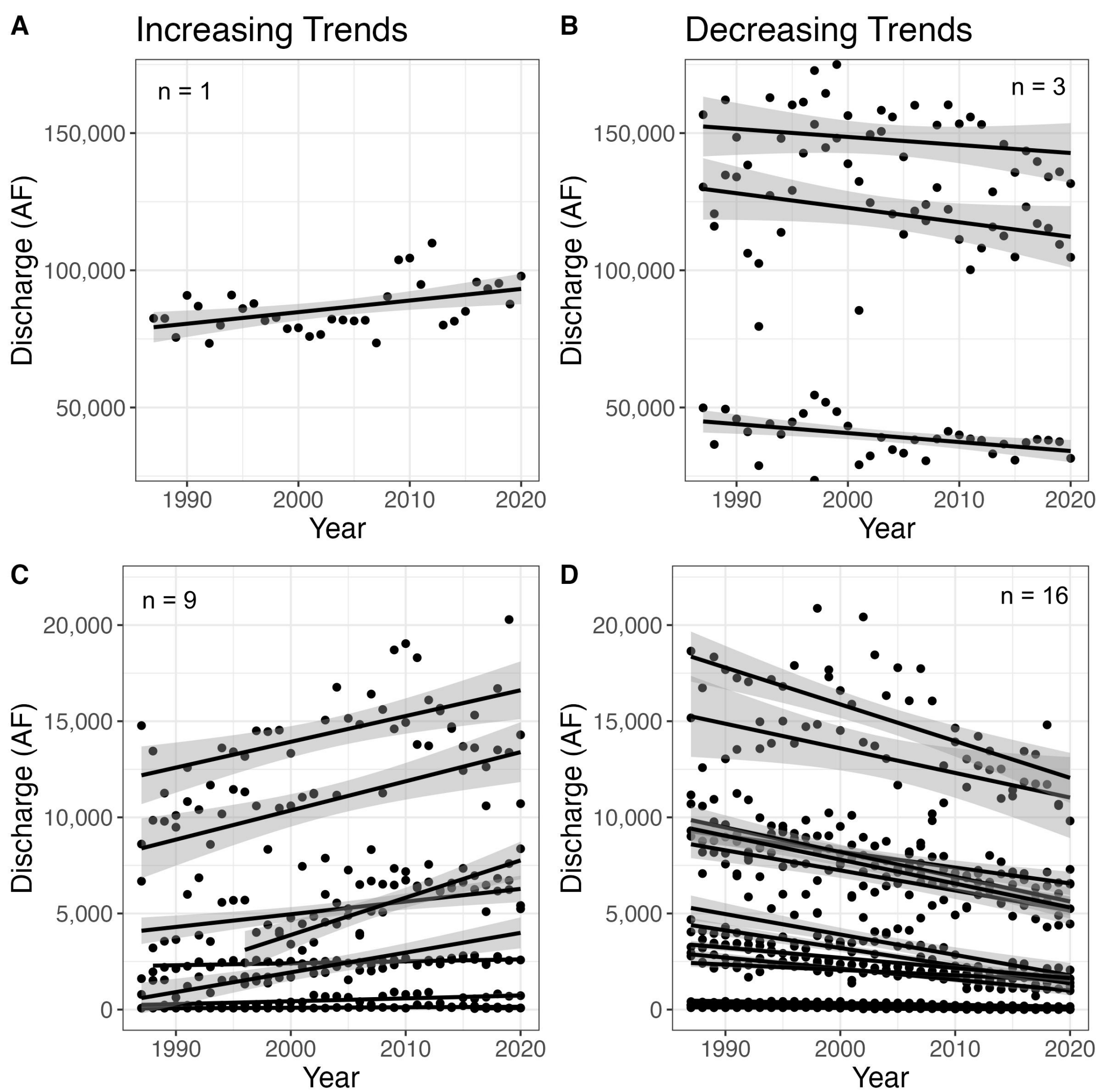

Figure 1.2. Significant (p<0.05) increasing (A, C) and decreasing (B, D) trends through time for diversions with flows greater than 50,000 AF/yr (A,B) and less than 20,000 AF/yr (C,D). Trends were tested for significance by the Mann Kendall trend test.

<u>Mixed effects model</u>

The GLMM with no ARMA, used to understand the effect of predictor variables on total diversion volumes, had nonzero effects for urban proportion, average total irrigation season precipitation, and storage water use (Figure 1.3). The 95% credible intervals for the effects of average maximum irrigation season temperature and average total irrigation season evapotranspiration contained 0 (Figure 1.3). The model had a Bayes R^2 of 0.95 and an MAE of 1,237 AF (Table 1.2).

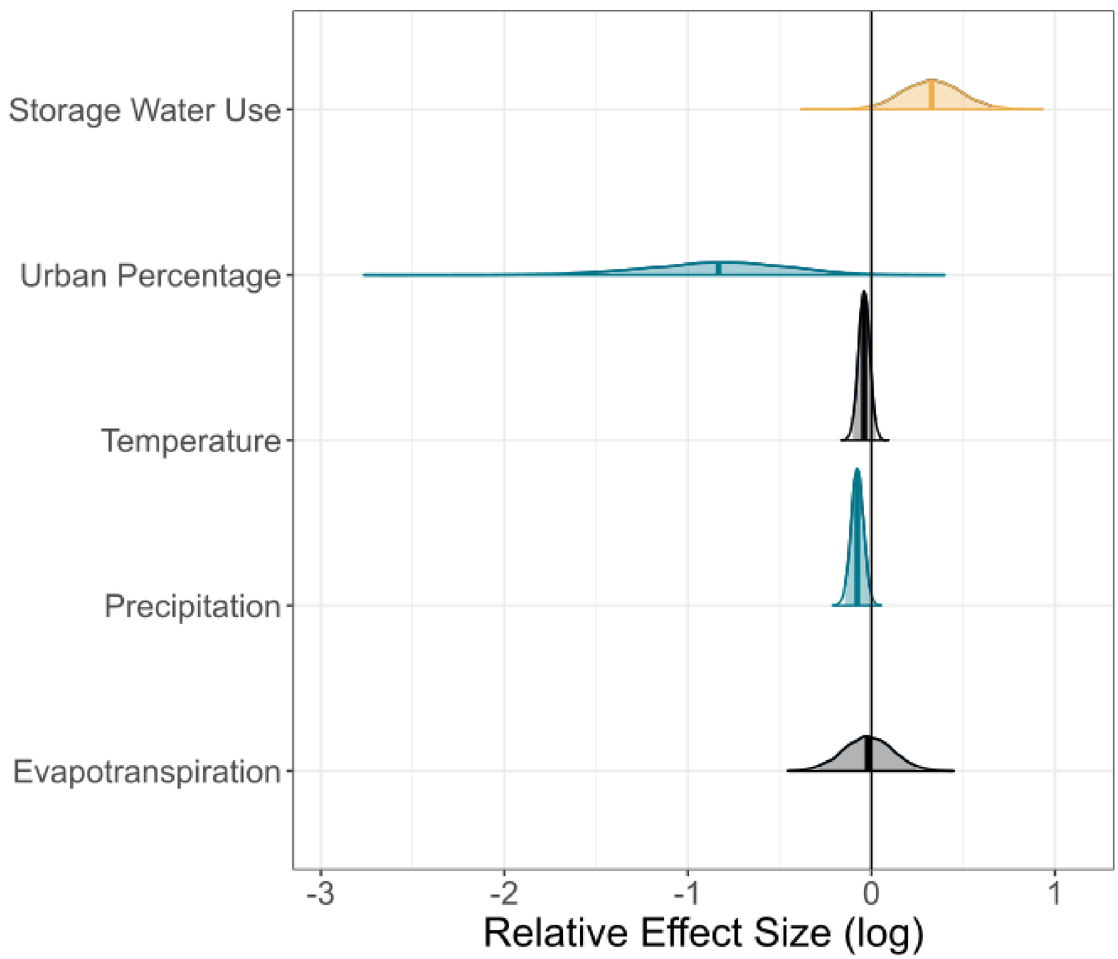

Figure 1.3. Posterior mass distributions on the log scale for a mixed effects model. The model input included storage water use (AF/yr), urban proportion, average maximum irrigation season temperature (℃), average total irrigation season precipitation (mm/yr), average total irrigation season evapotranspiration (m/yr). Decreasing non-zero effects are green while increasing non-zero effects are yellow. Distributions with 95% credible intervals containing 0 are in black.

Urban proportion had a large effect size (average = -0.85, log scale) but also high uncertainty around the effect (Figure 1.3; Figure 1.4). The mean effect of urban cover across diversions was equivalent to a decrease of 135 AF/yr in total discharge for every 10% increase in urban percentage in a POU with a baseline discharge of about 1,650 AF (Figure 1.4A). The standard deviation for the varying slopes for urban area was 1.63 across the 63 diversions included in our analysis (Table 1.2). Four canals' volumes decreased less strongly with increasing urban cover, while two of the canals showed even stronger decreases in discharge with urban growth.

Table 1.2. Model fit and mean intercept and standard deviations of varying components on the log scale with 95% credible intervals for a Generalized Linear Mixed Effects Model with and without an ARMA.

Model	Median Absolute Error	Bayes R^2	Mean intercept (log)	Standard deviation of varying intercept	Standard deviation of varying effect for urban area
GLMM + ARMA	707.6 AF	0.98	7.81 (7.09, 8.44)	2.08 (1.66, 2.63)	0.85 (0.05, 1.93)
GLMM	1,237 AF	0.95	7.25 (6.51, 7.97)	2.52 (2.07, 3.13)	1.63 (1.05, 2.43)

Total diversion discharge decreased with increasing total average irrigation season precipitation (Figure 1.3). The response is relatively small, as increasing precipitation across the entire observed range of precipitation values (42 to 316 mm) decreased discharge from about 1,375 AF to 1,100 AF (Figure 1.4B). Increasing irrigation season precipitation by about 100 mm/yr would result in a net decrease in total diversion volume by 100 AF/yr (Figure 1.4B).

Canal discharge increased when storage water use increased and was a strong, positive effect (Figure 1.3; Figure 1.4C). Not all canals have storage water available to use, which explains the uncertainty in the estimate and the spread in the posterior distribution (Figure 1.3).

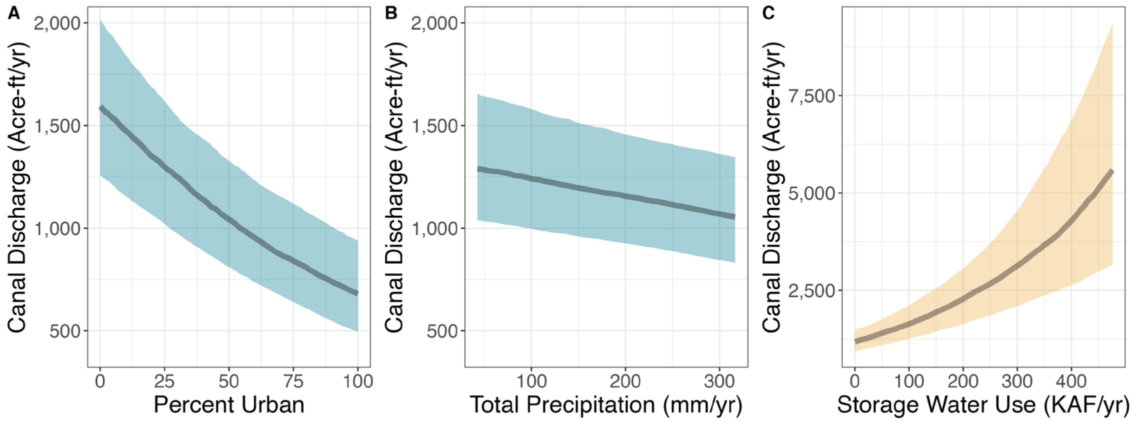

Figure 1.4. The effects of urban area (A), average total irrigation season precipitation (B), and storage water use (C) on diversion discharge from a generalized linear mixed effects model with no time component. Positive effects are in yellow while negative effects are in blue. Shading shows 50% credible intervals for predictions of canal discharge, while holding all other variables at their mean.

<u>Autoregressive- moving average mixed effects model</u>

All variables except urban proportion had nonzero effects in the GLMM with an ARMA term. Increased annual changes in evapotranspiration and annual changes in storage water use both increased diversion discharge while increases in average maximum temperature and average total precipitation both decreased diversion discharge (Figure 1.5). Changes in storage water use and evapotranspiration produced larger changes in annual discharge when compared to the effects of precipitation and temperature (Figure 1.6).

Differences in urban proportion had no effect basin-wide, shown by a mean effect size of 0.01 and the distribution overlapping 0 (Figure 1.5). The distribution of the effect was wide and flat compared to all other effects (Figure 1.5), and the standard deviation on the varying effect of urban area was 0.85 (Table 1.2). The wide, flat distribution indicates high variability across the basin. Urban proportion was allowed to vary by diversion, but no diversion had a significantly different effect size.

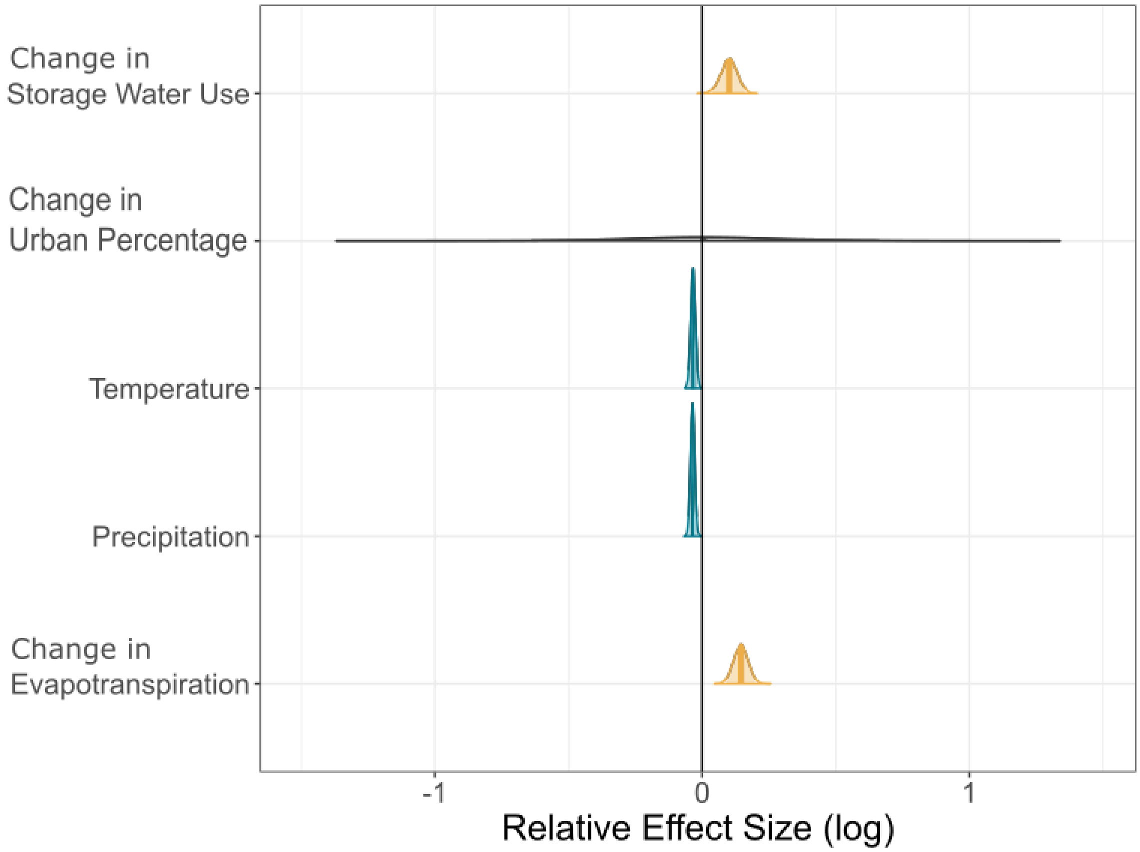

Figure 1.5. Posterior distributions for parameters from a generalized linear mixed effects model with an autoregressive moving-average component. Nonzero negative effects (based on 95% credible intervals) are blue while nonzero, positive effects are yellow.

The GLMM with the ARMA produces greater variability around estimates than the model without the time component (Figure 1.4; Figure 1.6). The underlying structure of the ARMA highlights incremental changes through time, which increases the importance of understanding initial conditions of a given canal when interpreting the results and increases uncertainty in individual effects basin-wide (Figure 1.6).

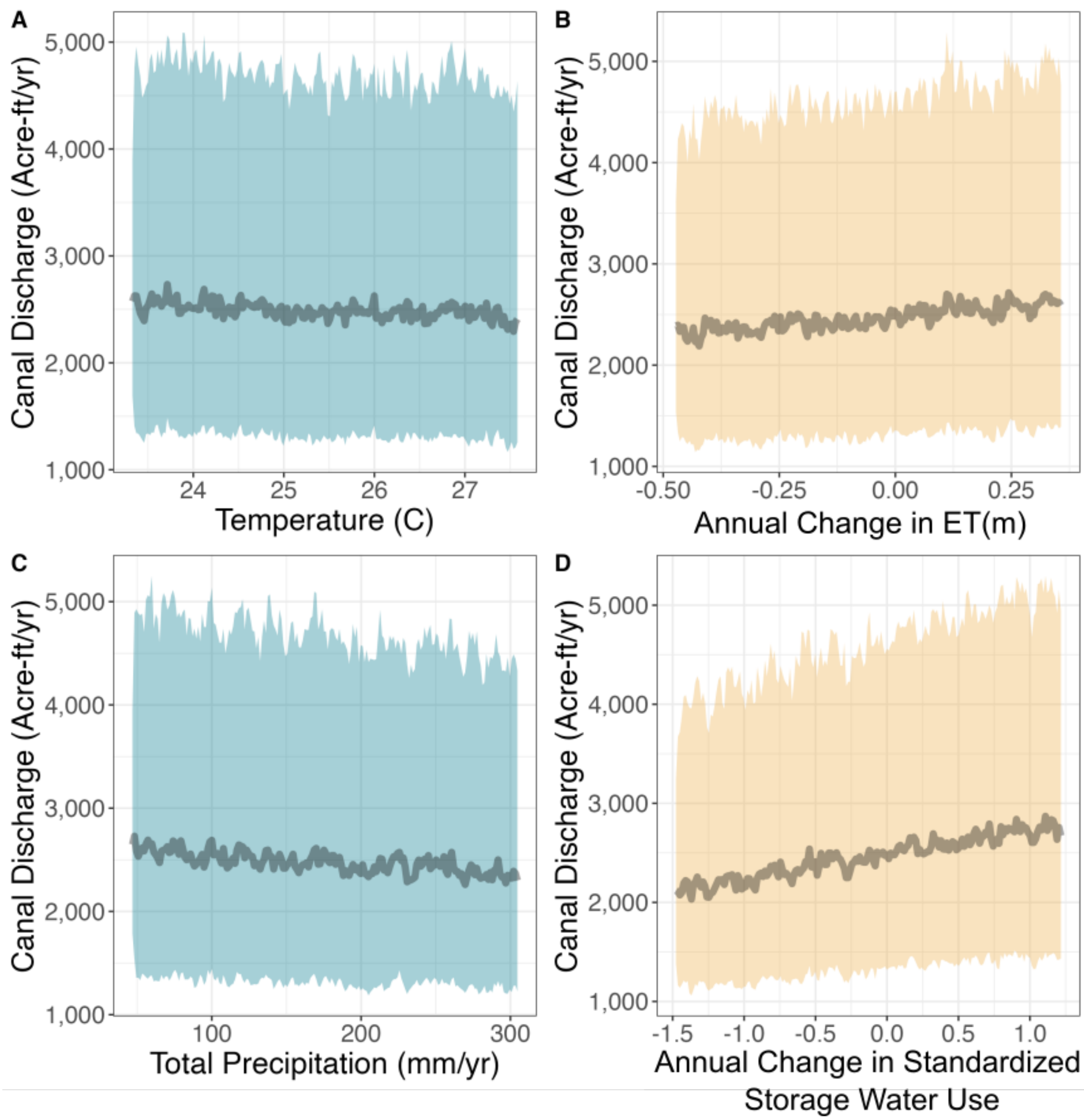

Figure 1.6. The effects of average maximum irrigation season temperature (A), annual change in evapotranspiration (B), average total irrigation season precipitation (C), and annual change in standardized storage water use (D) from a generalized linear mixed effects model with an autoregressive moving-average component. Positive effects are yellow while negative effects are blue. Shading shows 50% credible intervals when all other variables are held at their mean.

<u>Individual generalized linear models</u>

GLMs for each diversion (n = 60) showed variable directions and strength of effect across parameters (Figure 1.7). Urban area had a relatively strong effect across many diversions; however, the direction of effect varied across diversions. Seventeen of the diversions had a nonzero effect for urban area with 6 of them being a positive effect and 11 of them being a negative effect (Figure 1.7). Evapotranspiration also had a variable effect across diversions both in terms of the direction and magnitude of the effect, but the effect of evapotranspiration was only non-zero for 7 diversions, with 2 having a negative direction and 5 having a positive effect (Figure 1.7). Storage water use had an overwhelmingly positive effect on diversion volumes, and the magnitude of the effect was large for many diversions, with 16 diversions have an effect size greater than 10 on log scale (Figure 1.7). Precipitation tended to have a negative effect across diversions, but the effect was only nonzero for 3 diversions. Temperature had a small (-0.1 to 0.1) effect size across most diversions (Figure 1.7).

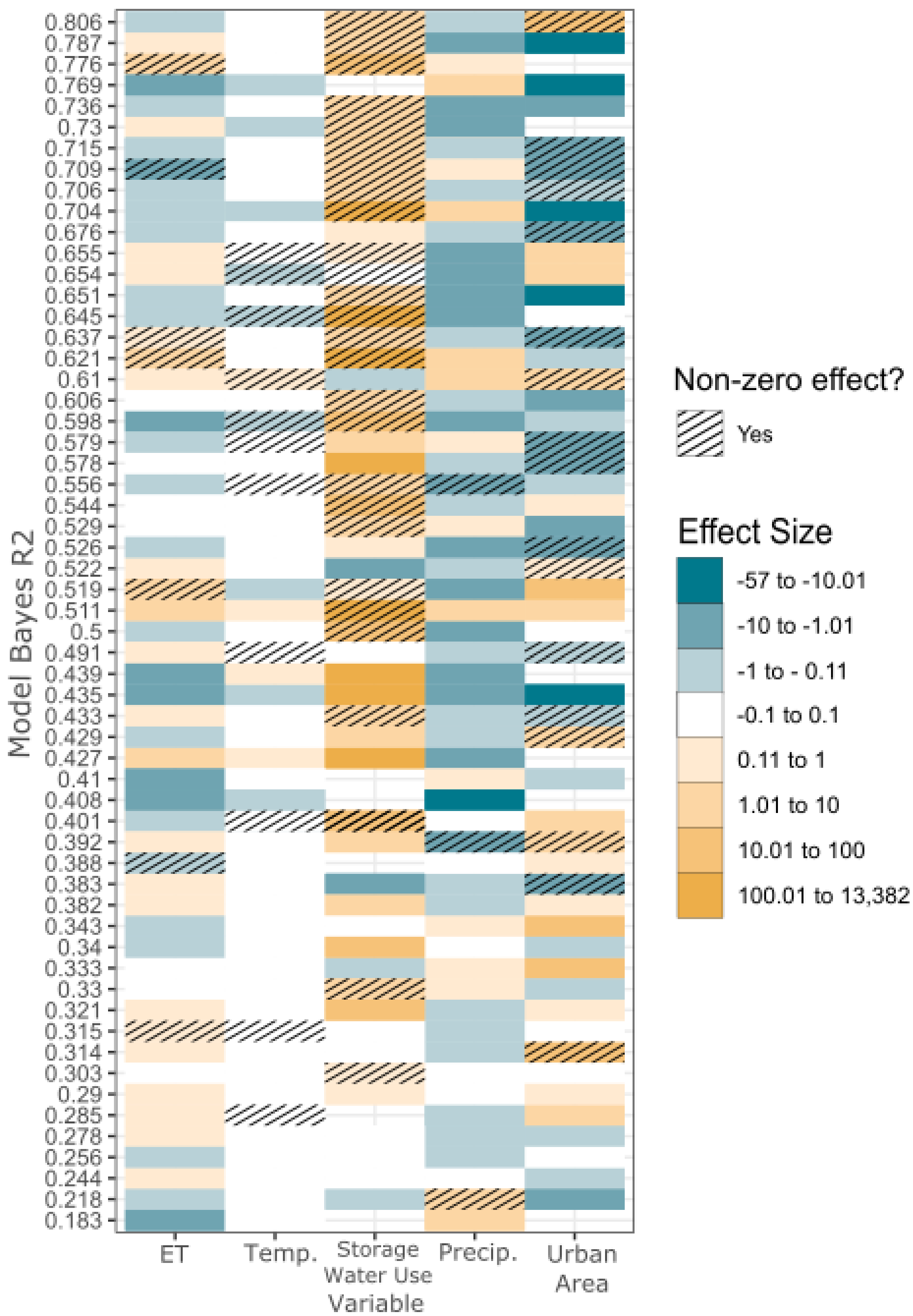

Figure 1.7. A heatmap showing direction and size (log) of effect for each variable for each diversion's generalized linear model (n = 60) Positive effects are yellow while decreasing effects are blue. A nonzero effect, indicated by 95% credible intervals not overlapping zero, are marked with slanted lines to the right.

Discussion

The goals of this research were to understand how diversion volumes in the LBRB have changed from 1987 to 2020 and to quantify the effects of urban area and climate variables on annual diversion volumes. We used multiple models to understand these relationships across spatial and temporal scales, and the analyses revealed variable results across the basin. Existing water law and politics (SPF Water Engineering, 2016), the uncertainty with human decision-making at the scale of individual diversions (Kaiser *et al.*, 2020), and undocumented irrigation efficiency improvements across the basin (Elkamhawy *et al.*, 2021; Kendy and Bredehoeft, 2006) all contribute to this basin-wide heterogeneity and provide insight into why establishing basin-wide relationships is difficult. The results of this analysis demonstrate differences in response to changing conditions even within a basin and highlight the need for localized research in order to help water managers respond to their changing environment.

Differences in model structure to quantify effects

The GLMM with no ARMA examined correlations between urbanization and climate on total diversion volume in each annual timestep without considering temporal structure, whereas the GLMM with an ARMA (for volume in the preceding year) examined the association between annual change in diversion volume and patterns of urbanization and climate. The ARMA accounts for temporal autocorrelation between observations (Benson *et al.*, 2007) while the GLMM with no ARMA does not. Weather impacts had nonzero effect in the GLMM with the ARMA while urbanization did not have a measurable effect (Figure 1.5). Urban change happens on a slower progression, highlighting a reason why many land use change studies look at 5-year or decadal differences (Dahal *et al.*, 2018; Mirhosseini *et al.*, 2018). Furthermore, annual changes in irrigation demand may respond to urbanization on timescales greater than 1 year, which may provide insight as to why urbanization did not have an effect in the model with the ARMA. Urbanization had a negative effect on diversion discharge in the GLMM with no time component, meaning that diversions serving a more urbanized place of use tend to have smaller diversion volumes. Urban area also had a larger effect than weather variables in the GLMM with no time component. Because the two different GLMMs are inherently answering different questions and modeling different response variables, we would expect that these models would have different results, and each individual model shows insight into different aspects of irrigation deliveries.

Effect estimates within each GLMM had high uncertainty (Figure 1.3; Figure 1.5). Individual GLMs for each diversion help explain why there was uncertainty for each effect size. Individual GLMs aid in showing basin-wide heterogeneity because the GLMs explained the effects at the individual irrigation scale, and effects were highly variable across GLMs, particularly for urban area and evapotranspiration (Figure 1.7).

<u>Differences in volume through time</u>

Canals exhibited high variation in time trends (Figure 1.2). The difference in changes through time from canal to canal shows the variability across the basin and highlighted the need for a further explanation of why diversions have or have not changed. While the trend analysis does not provide insights as to why some diversions are changing while others have not, possible mechanisms for change include urbanization (Bigelow *et al.*, 2017), crop rotations (Schilling *et al.*, 2008), changing temperatures (Jin and Sridhar, 2012), and processes that lead to no changes in diversions despite a changing landscape or climate include a lack of incentivize to conserve and water law that promotes full usage of a water right (SPF Water Engineering, 2016). These mechanisms are evaluated further in subsequent sections that examine individual predictor effects from GLMMs and GLMs.

Urbanization and diversion volumes

While many assume that the urbanization of agricultural landscapes will result in a net decrease in irrigation water usage due to the loss of green space (Bigelow *et al.*, 2017; Wang and Vivoni, 2022), our analysis shows that this assumption may not be universal, and that urbanization has variable effects (Figure 1.3; Figure 1.5; Figure 1.7). The GLMM with no ARMA had a nonzero, negative effect for urbanization, suggesting that areas with more urbanization have smaller total diversions, and the magnitude of the effect was large compared to other predictor variables (Figure 1.4). The GLMM with the ARMA takes into account changes from year-to-year in terms of both diversions and urbanization, and urbanization had no effect, showing that change in urban proportion from year-to-year does not lead to a change in diversion volumes at the annual scale. Both GLMMs had wide credible intervals around the effect estimate, which indicates variability around the mean effect at the basin scale (Figure 1.3; Figure 1.5). The GLMs showed that individual diversions responded non-uniformly to urban area but that the effect of urban area was large in magnitude relative to other variables for many diversions (Figure 1.7). These results illustrate that urbanizing agricultural landscapes can but does not always result in net reduction in irrigation water usage and, in some cases, produces an increase in irrigation diversions. This poses the question, why are not all diversions decreasing their irrigation water usage with urbanization as other studies have found?

Multiple mechanisms exist that could lead to a constant irrigation diversion rate despite losing green space. These processes include increased seepage to the shallow aquifer due to a declining shallow aquifer (Elkamhawy *et al.*, 2021), a lack of incentive to conserve water due to existing water law (Nampa Meridian Irrigation District; SPF Water Engineering, 2016), different evapotranspiration rates between crops and turf lawns (Baker *et al.*, 2014), and longer growing seasons (Hoekema and Sridhar, 2011). The Treasure Valley has a shallow aquifer system that has historically been elevated due to canal and irrigation seepage (Urban, 2000). However, the water table in the shallow aquifer has been declining over the past decade (Idaho Department of Water Resources, 2023), which has resulted in some wells going dry (Kerndl, 2022). In conjunction, irrigation diversions may not be declining uniformly because of existing water law that disincentivizes water conservation. Under Idaho statute 42-222, water rights will be forfeited if they are not used to their full beneficial use for 5 consecutive years, creating an incentive for water users to use their full water right even if it is not necessary for their land cover (Idaho Legislature, 2022) Furthermore, in Idaho, the volume of water that a parcel of land can use for irrigation does not decrease when the land is converted from an agricultural to urban land use (Fereday, 2016); therefore, urban water users are incentivized to use the water right past down from the agricultural lands (SPF Water Engineering, 2016). Along with disincentive to conserve due to law, surface irrigation water is much cheaper than domestic, potable water (Nampa Meridian Irrigation District), again, creating a lack of incentive to conserve. Urban water users may also be using the same amount of water despite a loss in green space because turf grass transpires 10% more water per unit area than crops like wheat or barley (Baker *et al.*, 2014; Crandall, 2019). Urban water users are often ignorant of irrigation requirements based on evapotranspirative demand, which leads to over-watering of lawns in semi-arid and arid regions (Litvak and Pataki, 2016). Finally, the growing season could be extending (Jin and Sridhar, 2012); however, there has been little change in the number of days a canal is delivering water based on preliminary analysis of the data (Supplemental Figure 1). Lack of changes in water demand is likely due to a combination of these mechanisms. Identifying which factors are the main drivers for a lack of changes to diversions with urbanization can support policy development towards water conservation.

Our findings also show a significant, negative relationship between diversion discharge and urbanization in the GLMM with no ARMA (Figure 1.3) and in 48% of the canals based on individual GLMs (Figure 1.7). These relationships can be caused by a decreased green footprint (Bigelow *et al.*, 2017; Wang and Vivoni, 2022), improved delivery efficiency (Elkamhawy *et al.*, 2021), and more efficient irrigation systems (Blount *et al.*, 2021). Urban areas converted from historically agricultural land cover in the LBRB can maintain anywhere from 38 to 78% of their original irrigated acreage, with this green footprint decreasing as urban areas become more dense (Baker *et al.*, 2014). This decrease in irrigated acres is typically associated with a reduction in irrigation usage (Bohn *et al.*, 2018). As regions urbanize, historically open ditches and laterals are now being piped, resulting in a reduction in seepage (Jadhav *et al.*, 2019). This increase in water delivery efficiency can result in a net reduction in the volume of water diverted. The land use transition from agricultural to urban also can result in more efficient irrigation practices, with the conversion from flood irrigation to pressurized sprinkler systems (Bjorneberg *et al.*, 2020; Nampa Meridian Irrigation District). Combined, these systems could result in net diversion reductions in urbanizing regions.

Our analysis provides a unique contribution to the existing literature because few studies have analyzed how irrigation water use changes with urban expansion into agricultural lands, and all of these studies have shown that irrigation water use decreases with this conversion (Bigelow *et al.*, 2017; Bohn *et al.*, 2018; Wang and Vivoni, 2022). Much of the other literature focuses on water use in areas of urban expansion that were previously undeveloped and shows that water usage will increase with this type of development (Heidari *et al.*, 2021; Hepinstall-Cymerman *et al.*, 2013). Our study incorporates urban expansion at the loss of agricultural land and shows that urbanization has non-uniform impacts on irrigation diversions (Figure 1.3; Figure 1.7). Agricultural land has been established to have a higher irrigation demand than urban areas because urban areas have impervious surfaces and less green space than agricultural lands (Bigelow *et al.*, 2017; Wang and Vivoni, 2022). However, our study provides unique insight that irrigation requirements are not the only factor influencing irrigation demand in urban areas, and universal assumptions that irrigation use will decrease after LULCC may not be appropriate.

<u>Reservoir Storage for Irrigation</u>

Reservoir systems in the Western US were designed to hold surface runoff for irrigation during the dry, growing months (Stevens, 2015). We expected that irrigation water diversions would increase with increased storage water usage for this reason, and this relationship is present in both GLMMs (Figure 1.3; Figure 1.5). The positive effect from the GLMM with no time component means that diversions that use larger volumes of storage water also have larger diversion volumes while the positive effect in the GLMM with the ARMA shows that when more storage water is used, this leads to greater annual changes in diversion volume. Furthermore, storage water use had consistently positive effects across diversions (Figure 1.7). Some diversions do not use storage water because they do not have storage water rights. Despite not all diversions having storage water available, this was still a basin-wide effect, highlighting the importance of the reservoir system and the influence of water management on the basin as a whole. However, a changing climate may begin to alter reservoir water availability. Changes in precipitation during the winter and early spring months due to climate change may have large impacts on the water availability during the irrigation season by altering storage water availability (Steimke *et al.*, 2018); however this was beyond the scope of this study.

Climate effects on diversion volume

Temperature, precipitation, and evapotranspiration are all commonly used to understand variation in irrigation water usage; however, effects of these variables on actual irrigation water usage differed from place to place (Balling and Gober, 2007; Blount *et al.*, 2021; Breyer *et al.*, 2012; Haque *et al.*, 2015). In this study, temperature had a small, nonzero, negative effect in the model with the ARMA and tended to have a negligible effect for individual GLMs, after accounting for evapotranspiration (Figure 1.5; Figure 1.7). The effect was not meaningful in the GLMM with no ARMA (Figure 1.3). The GLMM model with the ARMA is explaining that on a year-to-year basis increased temperatures result in a small reduction in irrigation diversions after accounting for evapotranspiration. The temperature effect in these models is the effect after accounting for evapotranspiration (Supplemental Figure 2), which could possibly explain why temperature had an unexpected, negative effect. While variability exists across studies, increasing temperatures are often linked to increases in irrigation water usage, rather than declining or unchanging usage (Blount *et al.*, 2021; Haque *et al.*, 2015; Wang and Vivoni, 2022). The presence of a small decreasing effect or no effect across models shows that the Lower Boise River Basin may be less sensitive to increasing temperatures than originally thought because water usage is already high, so temperature changes produce small variation in water usage (Stoker and Rothfeder, 2014). Part of the reason that irrigation water diversions may already be high is that the volume in the canal is pre-determined by water rights, and water rights users are incentivized to use their full water right (Idaho Legislature, 2022). Another reason that temperature might have a negative effect at the basin-wide scale or no effect is that hotter temperatures can be associated with the day of allocation, or the day that junior water rights holders are cut back, occurring sooner in the season (Garst, 2017). An earlier day of allocation results in less natural flow being available for water users and a reduction in annual volumes (Steimke *et al.*, 2018). While the negative temperature effect at the basin scale was unexpected, water policy and management of the LBRB could contribute to direction of effect.

Increases in precipitation led to decreases in irrigation water diversions in both the GLMM with and without the ARMA; however, the effect size was small, relative to other variables in both models (Figure 1.3; Figure 1.5). Precipitation generally had negative effect sizes in individual GLMs as well. While precipitation was a nonzero effect for the basin-scale models, the small effect size is consistent with urban irrigation water use studies in semi-arid and arid regions that receive the bulk of their precipitation during the non-irrigation season (Balling and Gober, 2007; Han *et al.*, 2019; Stoker and Rothfeder, 2014). The region relies on the reservoir and canal system created to offset the lack of runoff during the growing season (Han *et al.*, 2017). The annual time step in this study may also be lacking in the ability to understand the effect of precipitation. For example, spring precipitation during March and April may heavily drive irrigation demand during the early irrigation season (Bigelow *et al.*, 2017), but diversions during this time are already low compared to summertime irrigation diversions, meaning that changes in discharge during the spring would not greatly affect the total annual diversions. The effect of precipitation across the valley appeared to be less important than other variables in the models.

Evapotranspiration is often used as a proxy for irrigation water usage, as it is the consumptive use component of irrigation water usage (Crandall, 2019; Johnson and Belitz, 2012). Therefore, we would have expected irrigation water diversions to increase with increasing evapotranspiration, as evapotranspiration represents the total consumptive use of the total applied irrigation water. A positive relationship with evapotranspiration and discharge was illustrated in the model with the ARMA in our study (Figure 1.5), which we used to show interannual variability, but we did not see this effect in the GLMM with no ARMA (Figure 1.3), which is not surprising based on differences in model structure discussed earlier. Individual GLMs with evapotranspiration as a predictor variable were split on the direction and magnitude of effect (Figure 1.7). We assumed in this model that surface water irrigation would be a good proxy for irrigation demand because surface water diversions are primarily used for irrigation in the LBRB (SPF Water Engineering, 2016); however, hydrologic processes within the canals and data limitations may result in the evapotranspiration and irrigation diversions not being tightly coupled. Hydrologic processes that may lead evapotranspiration to not be as correlated with irrigation diversions as originally thought could include seepage and evaporation from canal systems and other sources of irrigation water (Shakir *et al.*, 2010, J. Barnes, personal communication, 2023). In the LBRB, approximately 30 to 40% of irrigation water is lost to seepage (Urban, 2000), and water evaporated from the canal system itself (Reclamation, 2008), which could lead to irrigation diversions not being completely representative of the on-farm irrigation. Evapotranspiration may also not be as correlated with irrigation water diversions as originally thought because irrigation diversions may not be the only source of irrigation water, both for agricultural and urban areas. This is particularly relevant during low water years when irrigators may rely on groundwater because surface water rights are cut back early in the irrigation season (Hoekema and Sridhar, 2011). While many studies use evapotranspiration to infer irrigation water usage (Allen and Robinson, 2006; Nisa *et al.*, 2021; Poudel *et al.*, 2021), evapotranspiration is not the only component of the water balance for irrigation. Irrigation water is comprised of seepage and overland runoff as well (US Bureau of Reclamation, 2008). Depending on the magnitude of these two other components and the annual fluctuations, evapotranspiration may not be as correlated with total irrigation water applied. Data limitations are another reason that evapotranspiration may not be strongly correlated with irrigation diversions. The SSEBop evapotranspiration estimates were derived from Landsat imagery (30 m resolution); however, 30-meter resolution imagery may not adequately capture irrigation practices in urban regions

(Crandall, 2019). While evapotranspiration was positively correlated with irrigation diversions in one model, the others show greater variations or no coupling. Our results contribute to the greater understanding about the relationship of climate and irrigation water usage, as results again were non-uniform across the basin.

Study Limitations

While this analysis helps reveal how and why diversions may be changing in the LBRB, data resolution adds unquantifiable uncertainty to the model, and limited data availability restricted the variables that we could include in the model. The data used for this project was diversion discharge measurements from IDWR, which have historically been measured by the water district watermasters weekly. Weekly measurements are then interpolated to daily data by IDWR (Idaho Department of Water Resources, 2020), which may be either over- or underestimating the daily measurements and adds unquantifiable uncertainty in our analysis. Furthermore, we assumed that diversions were an adequate proxy for irrigation water demand, knowing that some of the water in the canals would be lost to seepage and evaporation (SPF Water Engineering, 2016; Urban, 2000). Diversions do not represent total on-farm delivery or total water usage, which would provide better understanding of the actual irrigation used. On-farm deliveries would also provide insight into the water lost through seepage and evaporation as it moves through the canal system and could aid in better understanding the connection between the groundwater and surface water systems in the LBRB. Groundwater was not incorporated into this model due to both data and time limitations but would be useful to understand if greater seepage is occurring due to declining groundwater tables in urban areas (Urban, 2000). Another component that could impact irrigation diversions but did not have data available for the whole period of record was crop rotations (Reclamation, 2019). Crops have variable irrigation demands, based on evapotranspirative demand (Allen and Robinson, 2006). Therefore, in both urbanizing and predominantly agricultural irrigation districts, crop rotations could impact the total diversion volumes. Incorporating groundwater and crop rotations into a subsequent study would be useful for better understanding the various mechanisms in the system.

Irrigation diversion volumes are, almost fully, controlled by human decision-making (Khatri, 2018; Stevens, 2015). While changes in climate and land use are projected to alter irrigation water usage in a uniform way, humans may not be responding to these natural phenomena consistently (Balling and Gober, 2007; Kaiser *et al.*, 2020). One example of decision-making that would cause non-uniform response is a lack of knowledge in urban water users regarding irrigation requirements for different plants, which can result in over-watering (Litvak and Pataki, 2016). Farmers introduce additional variability through their choices on the types of crops they plant or the volume and frequency they irrigate (Sarku *et al.*, 2020). Because the water that flows down irrigation canals is ordered by irrigation districts or individual water users, variability exists in the data that cannot be described by the variables in this model. Human decision-making contributes to the complex surface water – groundwater interactions that are highly variable across this urban gradient.

Conclusion

We used both basin-scale and individual diversion analyses to understand how and why diversions in the LBRB have changed through time and in response to LULCC and climate. The different model structures and approaches in the analysis allow us to understand the complexities of the system and provide more insight than any of the individual models. The GLMM with no time component allowed us to see that areas with more urbanization had decreased diversion volumes; however, urbanization was less important in the GLMM with the ARMA, as this signified changes from year to year. Instead, climate variables have stronger effects on inter-annual variability of diversion volumes as seen in the model with the ARMA. Increased precipitation and temperature led to decreased irrigation diversions, but the effects were small, and increased evapotranspiration led to increased diversion volumes in the GLMM with the ARMA. Both models highlighted that increased storage water use results in higher diversion volumes, indicating the importance of the reservoir management system in this basin. The direction and magnitude of urban and climate effects varied from other urban water usage studies, which could stem from systematic or model structure differences, suggesting the need for further review across urban irrigation water usage studies. While the direction of effect from the GLMMs was clear, the effect sizes across predictor variables, particularly for urbanization, had high uncertainty. The individual diversion analysis using GLMs highlights why the basin-scale analysis had high variability across the effects because the factors affecting diversion discharge differed from place to place. Diversions in the LBRB are managed by individuals or an irrigation district, and while seeking to understand how canals are responding at a basin-scale may be informative, it does not account for individual management and decisions at a more local scale.

CHAPTER 2: HOW IS THE AMOUNT OF IRRIGATION WATER DRAINING TO THE BOISE RIVER CHANGING WITH URBANIZATION AND CLIMATE CHANGE?

Executive Summary

The Treasure Valley of Idaho also known as the Lower Boise River Basin has been rapidly urbanizing over the past few decades, not only resulting in substantial land use and land cover change, but also creating shifts in irrigation water usage and irrigation return flows to the river. Simultaneously, the area is also facing increasing pressure from a changing climate, which will likely lead to earlier runoff in the region, hotter summer months and greater water demand for crops, and more frequent and prolonged drought. Combined, these changes in the system will alter water availability in the region.

The watermasters of the Lower Boise River Basin are tasked with allocating irrigation water to water users throughout Water District 63. Historically, users in the downstream half of the basin have relied on irrigation return flows from drains to support their irrigation demand; however, both the watermasters and irrigation district managers have noticed changes to multiple of the main drains through time. The goals of this study were to 1) analyze changes in the irrigation season drainage flows from 1987 to 2020, and 2) to quantify the effect of urbanization and climate on irrigation season discharge in 15 major drains in the Lower Boise River Basin using a statistical model.

Key results

- Trend analysis showed that 6 of the 15 (40%) drains have decreased significantly ($p < 0.05$) from 1987 to 2020, with decreases in annual flow ranging from 26 to 66%.
- Urbanization had the greatest impact on drainage flows compared to all climate variables and canal flows.
- Increased urbanization decreased drain flows. The magnitude of decrease was larger in watersheds that were still in the early stages of urbanization (10-30% urban area) as opposed to watersheds with urban areas already comprising 75% of the land.
- Increased average maximum irrigation season temperature led to decreased drain flows.
- Increased evapotranspiration and canal inflows in a watershed had a significant, positive impacts on drain flows.

Future Considerations and Suggestions

- Trend analysis results quantitatively show that less water exists in the river for downstream water users who have historically relied on the specific drains with decreasing flows. The extent of decrease should be shared with individual irrigation districts who have relied on this water, so irrigation districts can relay this information to farmers.
- Future drain measurements can and should be incorporated into the trend analysis because the drains will likely continue to change with increased urbanization.

- Increasing communication between land use planners and water managers (e.g. irrigation districts) could help bring awareness to land use planners of how urbanization impacts the hydrology of the drains. Potential planning efforts could go into creating urban areas that help reduce impacts on drains.
- Convening a meeting with various scales of water management (IDWR, watermasters, irrigation district managers) to discuss how farmers will continue to have access to sufficient water for crops may be necessary as the basin continues to urbanize.

Introduction

The Treasure Valley has been urbanizing over the past few decades, growing by 45% from 1990 to 2010 and by 21% from 2010 to 2020. Currently, about 738,000 people live in the valley, but by 2100, the population is predicted to be around 1.5 million individuals (+/- 250,000; Narducci et al. 2017). This has, and will continue to, create unique pressures for irrigation water managers as they begin to serve less agricultural landscapes and more urban areas. Systematic differences between delivering irrigation water to agricultural and urban irrigation systems include pressurized irrigation, piping or lining canal systems, and increased impervious surfaces on the landscape. Population growth will alter demand for surface water irrigation, groundwater levels, and the amount of water returning to the Boise River.

The watermasters for the Boise River Basin (Water District 63), located in the Treasure Valley, allocate irrigation water to water users throughout the basin (Figure 2.1). Idaho allocates water based on the Doctrine of Prior Appropriation, which states that those who established their water right first and continue to use the water for a beneficial use will receive their water before those who established their right later, colloquially known as “first in time, first in right” (IDWR, 2021). Irrigation districts are sub-level management systems that oversee the maintenance, upkeep, and water allocation from a given set of canals or ditches to a specified place of use. The irrigation district managers place their order for the daily volume of water needed with the watermasters, who request the total amount of water needed for the Lower Boise River Basin (LBRB) to be released from Lucky Peak reservoir. All water users will receive their full water requests until the day of allocation (Steimke *et al.*, 2018), at which point water rights start to be curtailed, or cut back, based on priority date, by the Stewart and Bryan Decrees (Fereday and Creamer, 2010). The day of allocation occurs after the maximum reservoir fill date and once the water demand of irrigators is greater than the “natural” flow in the Boise River (Cresto, 2013), which is an estimate of the natural inflow to Lucky Peak by the US Bureau of Reclamation .

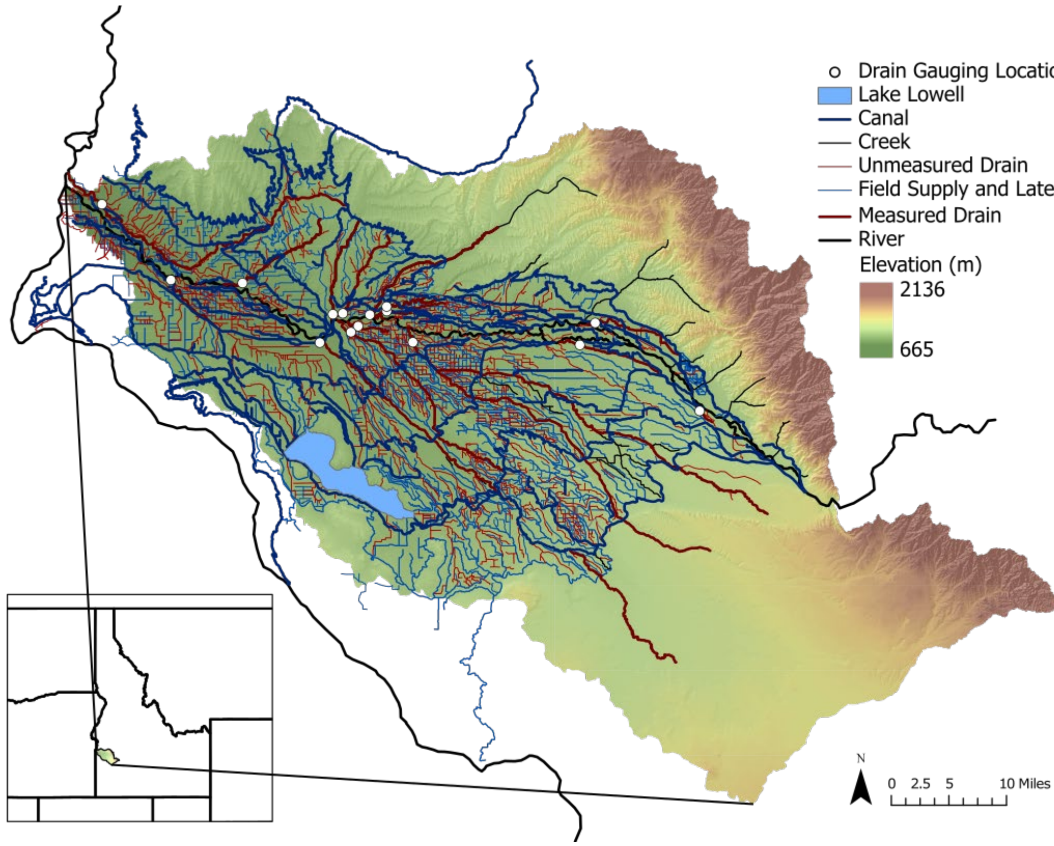

Figure 2.1. Inset and map of the irrigation system and drain gauges in the Lower Boise River Basin.

Irrigation water returns to the Boise River via drains throughout the canal network. The drains are fed by discharge from groundwater due to an elevated water table into the drains, direct irrigation runoff from fields, and remaining canal water at the end of the canal line (Reclamation, 2008). The Water District 63 Watermasters redistribute water that returns to the Boise River from the irrigation network to downstream surface water users in the basin. These water users typically do not have storage water rights and rely upon "natural" flow, making them vulnerable to declining drainage flows.

Urbanization changes irrigation practices, delivery, and the ability for water to infiltrate the ground surface. Historically, farmers used flood irrigation which created elevated groundwater levels, and the groundwater discharged into the drainage system (Baker *et al.*, 2014). Urban areas have less irrigated acres and generally use sprinkler systems, which could decrease the total volume used to irrigate and increase evaporative losses when compared to historical flood irrigation (Kliskey *et al.*, 2019; Ward *et al.*, 2007). In conjunction, this will decrease groundwater discharge to the drains. Transitioning from agricultural to urban land uses increases the total amount of impervious surface, which decreases the area of land over which water can infiltrate (Bhaskar *et al.*, 2016). For example, ~38% of a plot of land remains available for irrigation in dense urban areas closer to Boise while more rural subdivisions converted from croplands have up to 76% of the area remain irrigated after conversion (Kliskey *et al.*, 2019). Finally, urbanization is leading to extensive lining and piping of the existing canal system, cutting off recharge to the groundwater from this surface water system (Johnson and Tracy, 2014). Given the complexities of urban growth, water usage, and return flows, water managers to understand how drains may continue to change with projected growth in the area, and one step to achieve this is to examine how drain flows have responded to urbanization in the Treasure Valley thus far.

In addition to rapid urbanization, the Treasure Valley experiences variation in precipitation and temperature from year-to-year and is also facing long-term climate change. While there is consensus that the region will experience increasing temperatures with climate change, the outlook for precipitation is less clear (Mote *et al.*, 2014). Some reports state that precipitation will slightly increase during the winter months for the region, but there is uncertainty around these estimates (Glabau *et al.*, 2020; Han *et al.*, 2019; Jin and Sridhar, 2012). Even though precipitation during the winter months may increase, the increased temperatures are projected to result in more winter precipitation falling as rain, leading to earlier runoff and earlier peak natural streamflow (Garst, 2017; Steimke *et al.*, 2018). Increasing temperatures are likely to lead to increased water demand during the irrigation months (Han *et al.*, 2019; Wang and Vivoni, 2022). Finally, the region will likely experience more frequent and prolonged drought (Strzepek *et al.*, 2010). Combined, the effects of climate change are likely to alter both water availability and demand.

The following analysis was completed to inform the Water District 63 watermasters on how drain flows have changed in the Lower Boise River Basin (LBRB) from 1987 to 2020 and to help the watermasters to identify particularly vulnerable downstream water users. The goals of this analysis were to 1) identify how the drain flows in the LBRB have changed through time, and 2) quantify the impacts of urbanization and climate on changes in drainage flows.

Methodology and Model Fit

Overview

We gathered return flow data for 15 drains in the LBRB, computed annual total return flow values (AF/yr) from 1987 to 2020, and analyzed changes in flows through time. We created drainage areas for each drain to then calculate annual zonal statistics for precipitation (in), temperature (°F), evapotranspiration (in), percent of urban area in the catchment, and the total canal flow contribution (AF). Zonal statistics were used as predictor variables in a Generalized Linear Mixed Model (GLMM), which is a type of regression that helps account for individual differences across drains (Harrison *et al.*, 2018). We used the GLMM to describe annual drainage discharge changes over the time period.

Data collection, preparation, and analysis

We gathered daily flow measurements from 1987 to 2020 for 15 drains across the LBRB from the Idaho Department of Water Resources' Water Rights Accounting page (Idaho Department of Water Resources, 2022b) and the USGS National Water Information System (USGS, 2023). Multiple drains were historically monitored by the Idaho Water District 63 watermasters from 1987 to 2016, and the USGS installed continuous monitoring stations in late 2016. We summed the daily flow values during the irrigation season to obtain an annual total flow (AF/yr). The length of irrigation season was defined by when the first canal in the LBRB started diverting water to the last day that a canal in the LBRB diverted water. Therefore, the length of the irrigation season varies from year to year.

We used the Hydrologic Unit Map watershed boundaries, StreamStats watershed delineation (USGS, 2019a) and a Digital Elevation Model of the Boise River Basin (10 m resolution) (USGS, 2019b) to create drainage areas for each of the 15 drains in the Boise River Basin. Given the lack of relief across the Treasure Valley and the manmade canal structures, which move water across the valley in ways that don't always align with topographic gradients, we verified the drainage area for each drainage basin with the watermasters (Figure 2).

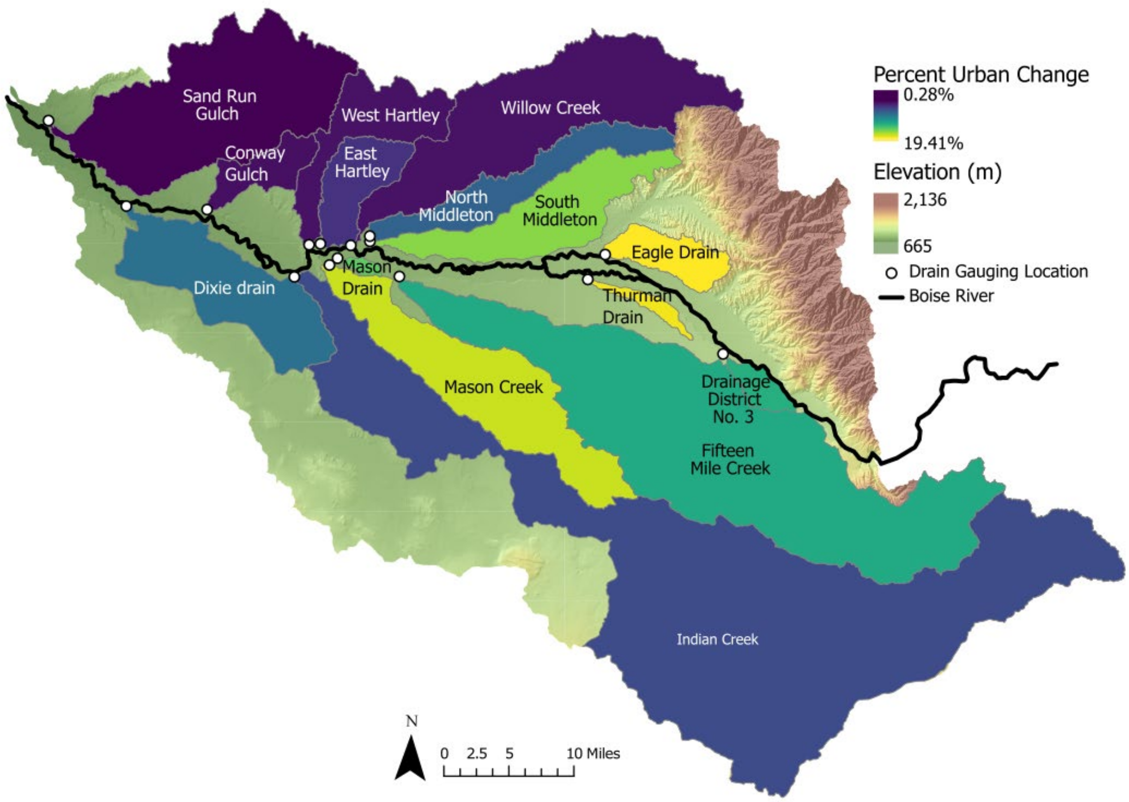

Figure 2.2. Map of drainage delineations for each measured drain in the Lower Boise River Basin. The color of the drain is associated with the percent of urban change in the watershed from 1987 to 2020.

Using the drainage area boundaries, we calculated annual average zonal statistics across the irrigation season for each drain. The start and end days of the irrigation season were defined by the earliest date any canal in the valley started diverting water to the last day any of the canals in the valley stopped diverting water, making the irrigation season length annually variable. We calculated average total irrigation season precipitation (in) and average maximum irrigation season temperature (°F) from Daymet (1-km resolution) (Thornton *et al.*, 2020) using the start and end dates for each year. The annual urban proportion was derived from the Land Change Monitoring, Assessment, and Projection dataset (LCMAP; 30-m resolution, US Geological Survey, 2021). We calculated the average total evapotranspiration (in) across a drainage area using outputs from the Simplified Surface Energy Balance model (30-m resolution, Senay *et al.*, 2022).

We determined canal inputs into each drain by linking the drainage area with the associated canals' places of use. If a canal passed through multiple drainage areas, it was considered to contribute to each of the associated drains. We gathered diversion flows from the IDWR Water Rights Accounting database (Idaho Department of Water Resources, 2022b), and we summed the total canal diversions for each drain and used this as a predictor variable in the model.

Model development and fit

A Mann-Kendall test was used to calculate if there had been a significant ($p < 0.05$) change through time with the annual discharge in the drains. If the change was significant, we used a linear regression to calculate, on average, how much each drain has changed across the whole time period. All drains with the full period of time were summed to create a basin-wide total drainage value and a Mann Kendall test was used again to test for a significant trend through time.

We then created a Generalized Linear Mixed Effects Model (GLMM) with autoregressive—moving-average (ARMA) errors (Harrison *et al.*, 2018). GLMMs allow for repeated observations through time at each of the drain sites. We used a varying intercept by drain name to account for the repeated observations and the different sizes in drains across the basin. The ARMA uses the previous year's information to help inform the next year's estimate and helps to better account for changes through time in the data. We fit the GLMM model with urban area, climate (average total irrigation season precipitation, average maximum irrigation season temperature, and average total evapotranspiration), and canal contributions as predictor variables to understand how drainage discharge has changed through time. The predictor variables were chosen based on both data availability and our understanding of the system, to identify the effect of urban cover on drain volumes (Supplemental Figure 5).

We compared the full model to a subset of models with different predictor variables using MAE, as a metric of model fit, and Leave-one-out information criterion (LOOIC) to ensure that the included variables did not result in overfitting (Appendix III). MAE reflects the disparity between the model's prediction and the actual data, on the scale of the response (AF). The LOOIC is a relative metric used to compare the estimated out-of-sample predictive accuracy of models.

We used the *brms* package in R to fit the GLMMs (Bürkner, 2017). We standardized precipitation, temperature, and canal inflows by subtracting the mean and dividing by two standard deviations. We did not standardize evapotranspiration or urban proportion in the same way because urban proportion only ranged from 0 to 1, and evapotranspiration ranged from 0.19 to 1.02 m. Both ranges for urban proportion and evapotranspiration were smaller than the other scaled variables. None of the variables were differenced in this model. All models were run with 4 chains with 4,000 iterations and weakly informative priors (Supplemental Table 4). We assessed model convergence using effective sample size, visual analysis of chain convergence, and confirmation that the R-hat value was less than or equal to 1.01 (McElreath, 2018). We compared the observed and predicted values using posterior predictive checks (Supplemental Figure 6). We calculated the median absolute error (MAE) to understand the uncertainty in the model.

Modeling Results

<u>Overview</u>

The trend through time analysis showed that six of the fifteen drains had significant decreases in drainage flows from 1987 to 2020. The variables included in the full model improved estimated predictive accuracy, relative to reduced models (Table AIII-1). The GLMM showed that increasing urbanization and temperature leads to decreases in drain flows while increasing evapotranspiration and total canal flows increases drain flows.

<u>Changes in drainage flows through time</u>

Six of the fifteen drains had significant changes through time (p-values < 0.05). The six drains, which included Conway Gulch, Eagle Drain, Fifteen Mile Creek, Mason Drain, South Middleton, and Thurman Drain, all exhibited negative trends through time (Figure 2.3). The remaining nine drains exhibited annual variability but did not have a significant trend (Supplemental Figure 7). There was no significant, basin-wide trend when all fourteen drains with complete periods of record were summed and fit with a Mann Kendall test.

The two drains with the largest percent decrease over time were Conway Gulch (64.1%) and Mason Drain (66.9%) and the remaining drains decreased by at least 26%. From 1987 to 2020, Conway Gulch decreased from 26,258 AF (+/- 2,971) to 9,435 AF (+/- 2,971) in 2020 and Mason Drain decreased from 11,231 AF to 3,713 AF (+/- 1,219). Combined, the six drains with decreasing trends present a net loss of 63,688 AF of drainage water returning to the Boise River from 1987 to 2020; however, the basin-wide flow does not decrease through time when adding all 15 drains together.

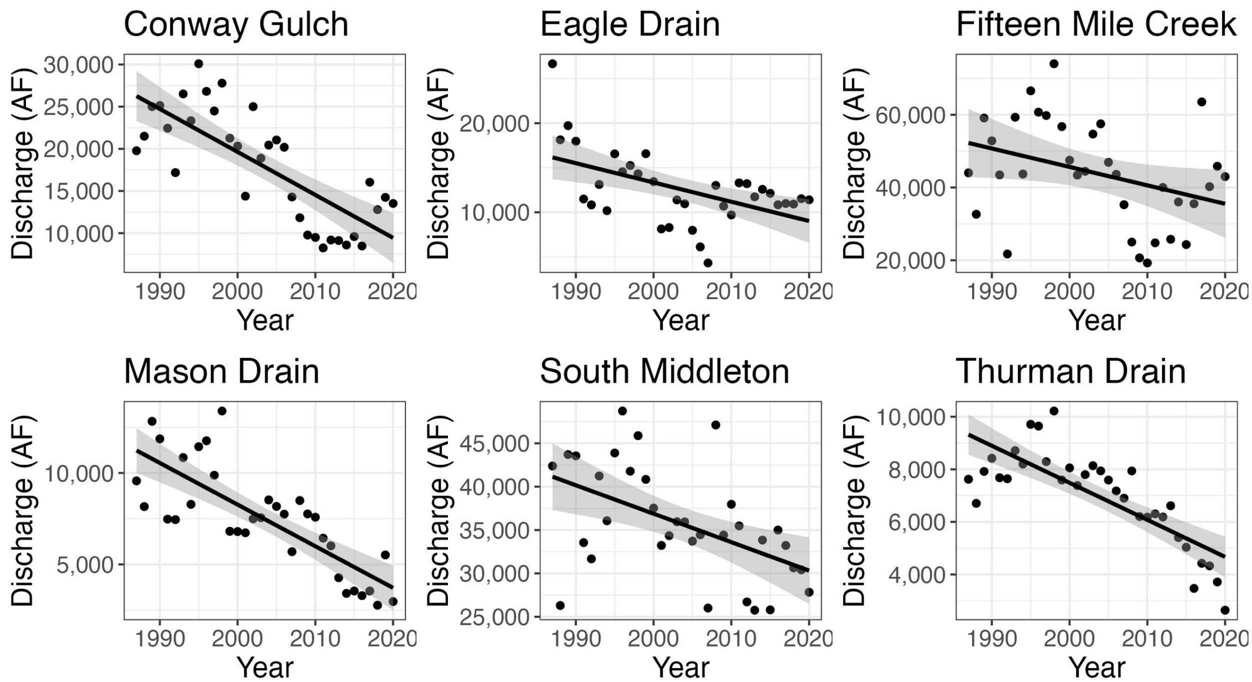

Figure 2.3. Plots of discharge (acre-feet) as a function of year for six of the fifteen measured drains in the Lower Boise River Basin. These drains exhibited a significant trend ($p < 0.05$) with the Mann Kendall trend test. The black line is the average trend line while the grey region is the 95% confidence intervals.

<u>Impact of urbanization on drainage flows</u>

Drainage discharge decreased drastically with increased urbanization (Figure 2.4; Figure 2.5). The confidence in direction of effect is shown by the 95% credible intervals of the posterior distribution not overlapping zero (Figure 2.4). When urban area increased from 10 to 20% of a drainage watershed, drain discharge decreased by approximately 4,010 AF when it started at about 24,500 AF with no urban area. However, this relationship was not linear (Figure 2.5). When urban area increases from 75 to 85% in a drainage watershed, this only decreases the drainage discharge by about 764 AF/yr. More drastic shifts in drain discharge are seen during the early stages of urbanization, and as urban area increases, the rate of change in discharge is lower.

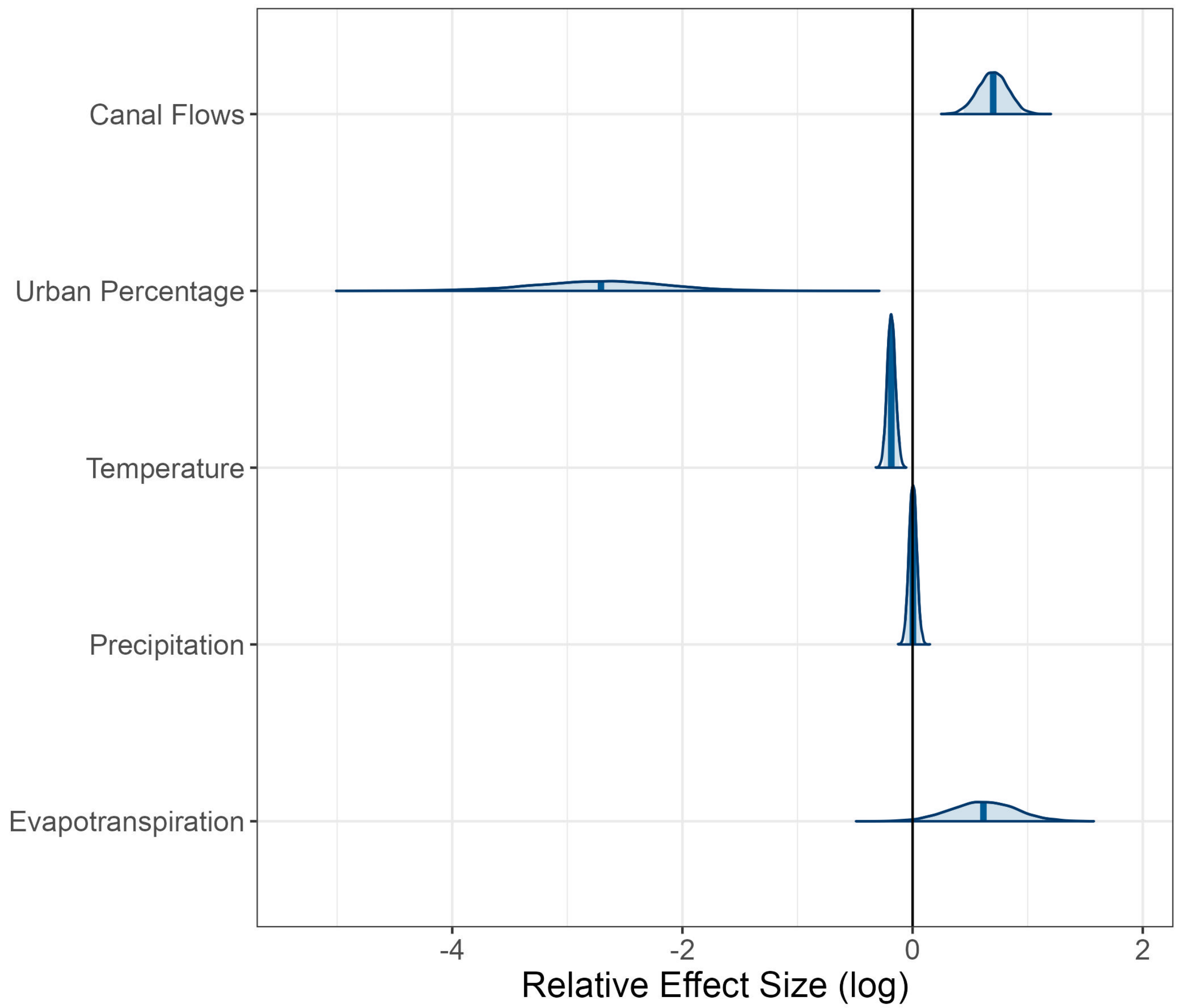

Figure 2.4. Density plots of the posterior mass distribution of the effects for canal flows, urban percentage, irrigation season temperature, irrigation season average total precipitation, and irrigation season evapotranspiration on drainage flows. Light blue shading represents 95% credible intervals while the dark blue center line represents the median value.

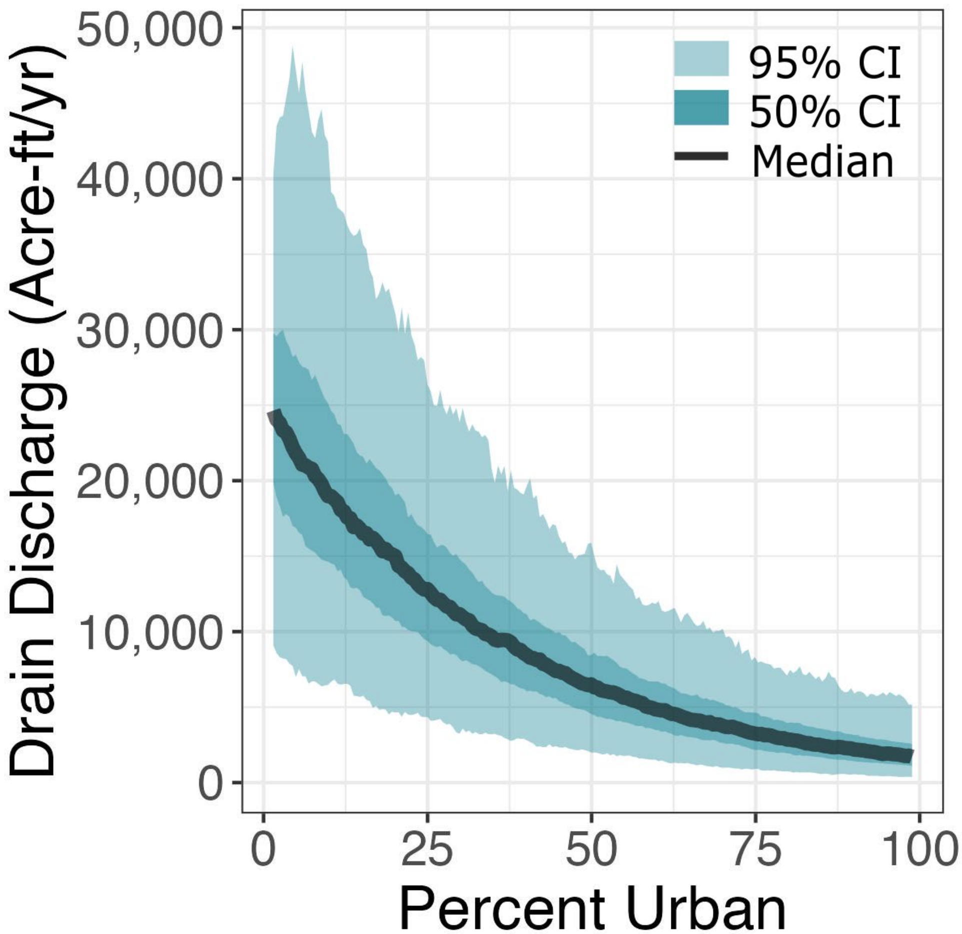

Figure 2.5. Plot of drain discharge (Acre-feet / year) as a function of percent urban with 50 and 95% credible intervals (CI). This is the effect of urban area on drain discharge when holding all other variables in the model at their mean.

<u>Impact of climate on drainage discharge</u>

Evapotranspiration and average maximum irrigation season temperature had inverse effects on one another while precipitation had no measurable effect on the drainage discharge (Figure 2.4). The effect of evapotranspiration was marginally larger than temperature; however, the 95% credible intervals for the effect of evapotranspiration were larger than the credible intervals for temperature, indicating greater likelihood of the mean effect for temperature (Figure 2.4). Increasing evapotranspiration by 5 inches annually created an increase of about 1,031 AF/yr in return flows annually for drains with average volume (Figure 2.6A). Increasing the average maximum temperature during the irrigation season by 1°F will decrease return flows by about 773 AF/yr (Figure 2.6B).

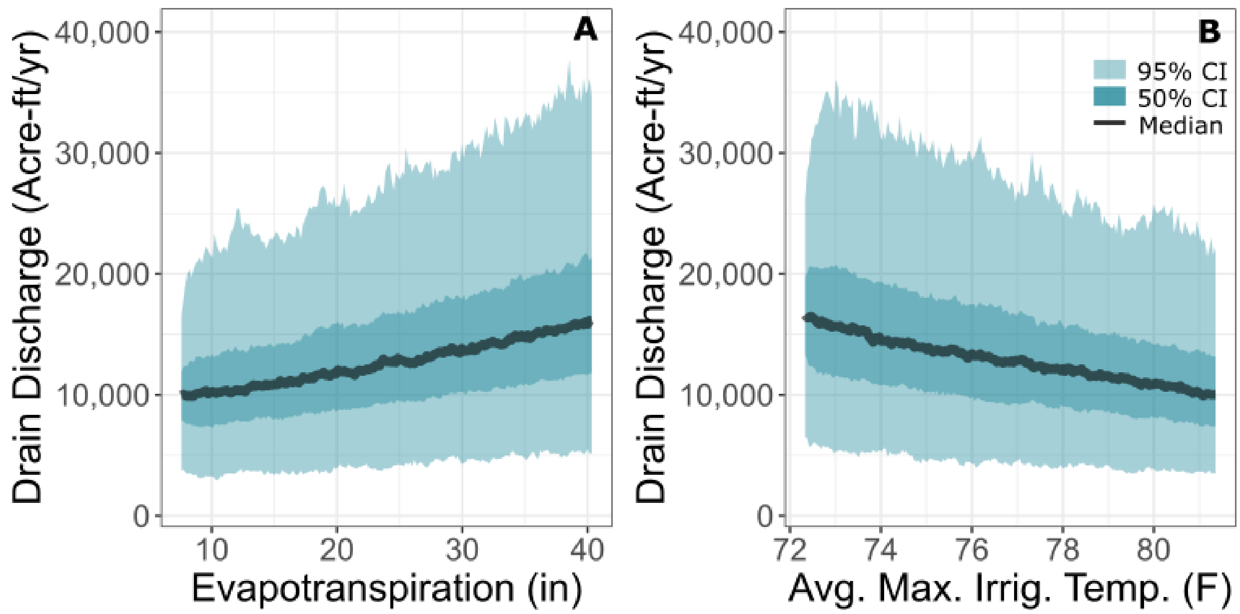

Figure 2.6. Plots of the effect of (A) evapotranspiration and (B) average maximum irrigation season temperature (°F) on drain discharge. This is the effect of each variable on drain discharge when holding all other variables in the model at their mean. 'CI' in the legend is a credible interval.

Impact of canal contributions on drainage discharge

Increased canal flows entering a drainage watershed increased drainage flows (Figure 2.4; Figure 2.7). On average, drain discharge increases by approximately 495 AF/yr in a given irrigation season for every 50,000 AF increase in canal flow that contributes to the drains (Figure 2.7). For example, if one drain receives input from 5 different canals, with a cumulative increase of 50,000 AF in flow in these 5 canals, we would expect to see about 495 AF/yr increase in the corresponding drain for a drain with average discharge.

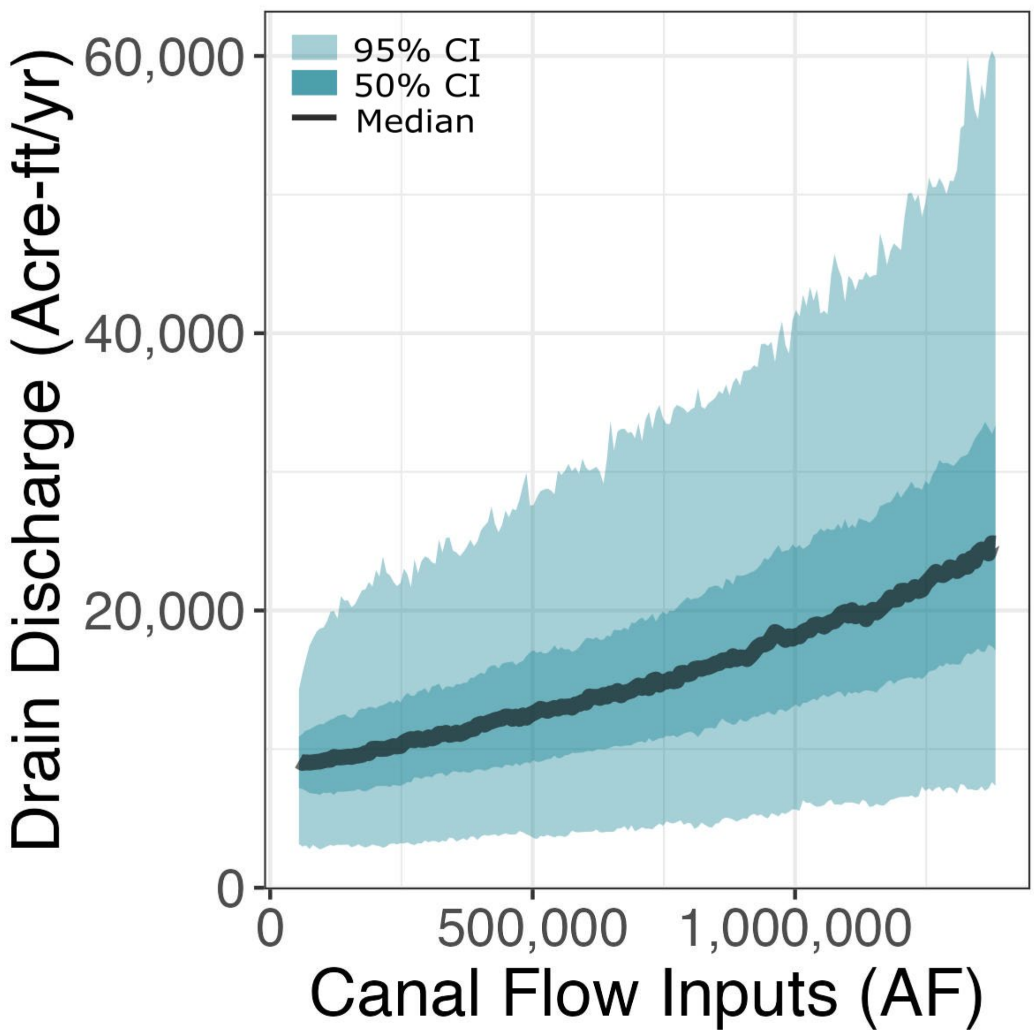

Figure 2.7. Plot of the effect of canal contributions (AF) on drain discharge (AF) on an annual time scale. This is the effect of canal flows on drain discharge when holding all other variables in the model at their average. 'CI' is a credible interval.

Discussion and Implications

The goals of this study were to 1) identify drains in the Lower Boise River Basin with significant changes in discharge from 1987 to 2020 and 2) quantify the effects of urbanization and climate on drainage flows. The trend analysis showed that 6 of the 15 drains have had substantial decreases in annual flows by at least 26% from 1987 to 2020 (Figure 2.3). The models showed that increases in urban area and average maximum irrigation season temperature decrease drainage flows (Figure 2.5; Figure 2.6), and increased evapotranspiration and contributing canal flows result in increased annual drainage flows (Figure 2.6; Figure 2.7).

When all fifteen drains were summed and analyzed for a trend, there was no significant trend through time, showing little basin-wide changes to drainage. Interestingly, no individual drains had significant increasing trends through time, but the annual variability in the drains with no trend through time (Supplemental Figure 7) must be making up for the deficit from the drains that are decreasing through time (Figure 2.3) when all the drains are summed together. Similarly, the year-to-year variability at the basin scale may mask shifts in mean volume over time. Decreasing drain discharge through time in 6 of the drains shows that less water is available for downstream water users who rely upon those specific drains, highlighting localized impacts from changes in drainage flows as opposed to basin-wide implications. If drain flows continue to decline in these 6 drains or begin to decline in any of the other 9 drains that did not currently have a significant trend, water users who rely upon these return flows as ‘storage water’ may need to find new sources of storage water, such as water banking. Implementing continuous monitoring stations at smaller drains in the 6 drainage watersheds that have already seen decreasing flows could be useful for these vulnerable water users to understand what sections of the watershed are contributing to lower flows. The 9 drains that had not seen significant changes in the flow still need to be monitored into the future, as flows may shift as the LBRB continues to urbanize and feel the effects of climate change. Therefore, continuous monitoring of the 15 drains in this study combined with annual trend analysis is necessary for water users to understand how localized drainage flows have and will continue to change.

Our models found that increased urban area in a drainage watershed resulted in decreasing drainage flows. Urbanization is a complex sociopolitical process that can affect multiple mechanisms driving streamflow (Bhaskar *et al.*, 2016), including reducing infiltration rates (Price *et al.*, 2010), increasing impervious surface cover (Kauffman *et al.*, 2009), increasing groundwater pumping from the shallow aquifer, shifting water sources, and changing irrigation practices (Ward *et al.*, 2007). The drains in the LBRB were created to help reduce elevated water tables from flood irrigation in the agricultural sector (Baker *et al.*, 2014); therefore, reduction in drain flows is likely linked to declining water tables through the processes previously mentioned. Urbanization of agricultural lands can reduce infiltration rates through a combination of changes, one of which is compaction of soils and infill on construction sites using material with different hydrologic properties. Compaction of soil decreases soil infiltration rates, which controls how quickly water will enter the subsurface and recharge the shallow aquifer (Yang and Zhang, 2011). Infiltration is also decreased by the lining and piping of canals and laterals throughout the valley during the process of urbanization (Jadhav *et al.*, 2019). While lining and piping canals improves conveyance efficiency, this can negatively impact return flows and downstream water users who relied on those return flows (Meeks, 2021). Increasing impervious surface cover by replacing fields with roads and areas of pavement creates an overall reduction in total area for water to infiltrate, again decreasing the total recharge to the groundwater. Increased groundwater pumping from the shallow aquifer could also create local drawdown in these newly urban areas (Kendy and

Bredehoeft, 2006; Sekhar *et al.*, 2013). While we know some water is currently pumped from the shallow aquifer for domestic water supplies, further analysis needs to explore if new subdivisions are supported by public water supply or by newly drilled wells. If all new subdivisions were using public supply water rather than private wells, increased domestic water supply would not cause the shallow aquifer to decline because domestic water in the Treasure Valley comes from Boise River water and deep groundwater wells (USGS and Idaho Department of Water Resources 2017). This issue could be mitigated by having land use planners consult with water managers in the valley. While this exchange has not historically occurred, recent Treasure Valley Water Summits are seeking ways to increase coordination across interest groups. If more groundwater is being pumped, we also need to understand if that water is being used for irrigation or domestic purposes, as the fate of the water could be substantially different. Using groundwater for irrigation could result in less water needed in canal systems, which may adversely impact the shallow groundwater table and drainage flows (Kendy and Bredehoeft, 2006). Finally, changes in drainage rates may be linked to differences in irrigation practices between urban and agricultural regions. Historically, the Treasure Valley used flood irrigation in agricultural practices (Kliskey *et al.*, 2019). However, urban areas predominantly use sprinkler systems, which can diminish recharge rates (Grafton *et al.*, 2018). The processes that lead to declining drain flows with urbanization are linked to declining recharge and shallow aquifer water levels; therefore, increased data accessibility regarding domestic water supply and shallow groundwater levels would enhance water managers abilities to grapple with the changes in their region of the

LBRB. Currently, no centralized hydrologic database exists for the LBRB, but this information would be useful for many sectors.

Increased temperatures resulted in declining drainage flows while increased evapotranspiration resulted in increased drain flows (Figure 2.6). While we may expect these two to have the same directional effect, the Treasure Valley is a water limited environment, meaning that the rate of the evapotranspiration is lower than the potential evapotranspiration based on temperature alone (Mcvicar *et al.*, 2012). Increasing evapotranspiration linked with increasing drain flows may be an indicator that water users are applying more water to the landscape in general. If we assume recharge rates do not change, the increase in irrigation application would result in both higher evapotranspiration and higher water table levels, resulting in higher drain flows (Bhaskar *et al.*, 2016). Increasing temperatures may be related to less water making it to the drainage systems because of increased evaporation from canals during conveyance from the reservoir system all the way to a drain. During hot periods, more water is required to be released from Lucky Peak reservoir to offset any increased evaporation from the Boise River before entering a diversion (personal communications, Mike Meyers). While more water is being released to offset losses in the Boise River, canals may not be compensating for increased losses, resulting in less water making it to the drain systems.

Increasing flows in the canals contributing to a given drain led to increased annual drainage flows through multiple mechanisms (Figure 2.7). Increased volumes of water in the canals could produce more seepage to the groundwater, creating an elevated groundwater table and more discharge to the drain (Meredith and Blais, 2019; Urban, 2000). Similarly, more water in the canals may also mean that water users are calling for more water and are applying more water to crop fields or lawns, again leading to more infiltration and recharge of the groundwater table. Another mechanism is that more water may be moving through the canal, but not all the water gets used by water users, so extra water at the end of the canal empties to one of the drains. Canal flows were an important predictor in this model for increasing drain flows, but increased piping and lining of canals and laterals to improve conveyance efficiency may mean that canals may play less of a role in recharging the shallow aquifer and maintaining drain flows in the future (Meeks, 2021). Canal flows in this model demonstrate an important groundwater – surface water connection, which should be taken into consideration with conveyance updates.

Limitations

While this model provides valuable insight into the mechanisms that are impacting drain flows, this model does have limitations, including data availability for both drain discharge and irrigation and conveyance efficiency improvements. First, most of the flow measurements used in this analysis are from IDWR's Water Rights Accounting database (Idaho Department of Water Resources, 2022b). These historical measurements were measured weekly by the Idaho Water District 63 watermasters, and IDWR has interpolated the data to obtain daily flow data. Therefore, the true variability in flow may not be fully captured. Additionally, the 15 monitored drains are a subset of the total number of drains in the LBRB and, as a result, provide only a snapshot of the total change in drainage flows across the basin.

The drains are not only influenced by all the mechanisms previously discussed, but on-field irrigation and conveyance efficiency improvements will also decrease groundwater recharge and drain discharge (Grafton et al., 2018; Malek et al., 2021). We do not currently have data on irrigation efficiency improvements, but this could explain why more agricultural regions, like Conway Gulch (Figure 2.2; Figure 2.3), are seeing declining drainage flows. Similarly, piping and lining canals increases conveyance efficiency, but also cuts off seepage, leading to less recharge to the shallow groundwater table. However, the extent to which the canals have been lined or piped has not been mapped across the valley. These two efficiency improvements could also be altering drain flows, calling for a need to collect and digitize this data.

Conclusions

The goal of this research was to identify changes in drainage discharge in the LBRB from 1987 to 2020 and to understand how climate, urbanization, and canal flows affect changes in the discharge through time. This analysis showed drain discharge was decreasing locally, with 40% of drains decreasing through time, but there has been no significant change in drain discharge across the LBRB as a whole. The main driver for declining drainage flows was increased urban area in a drainage watershed, which is likely linked to decreased infiltration with urbanization and declining shallow groundwater tables. The connection between the surface water and groundwater system is further demonstrated by the model showing that increased canal flows lead to increased drainage flows. The shallow groundwater table will likely shift as more canals are piped and lined, and less seepage enters the aquifer. A centralized hydrologic data management system is needed for water managers to assess how groundwater and surface water systems in their region of the basin are changing, as the irrigation system and shallow aquifer are extensively connected. Furthermore, this analysis highlights the need for increased partnership between water managers and land use planners, and a centralized data management system could help facilitate part of this necessary collaboration.

Climate played less of a role in why the drains have changed when compared to canal inputs or urbanization, but evapotranspiration and temperature did impact drainage discharge. Increased evapotranspiration led to increased drainage flows and is likely a reflection of more water being applied to the landscape, and, in turn, more recharge. Increased temperature led to decreased drain discharge, which may need to be further investigated as temperatures in this region will continue to increase with climate change. While this analysis increases our understanding of the drain system in the LBRB, water managers would benefit from continued research to help management adapt to a changing environment.

CHAPTER 3: CONCLUSIONS AND FUTURE WORK

The goal of this study was to co-produce research to help water managers in the LBRB understand how both irrigation diversion volumes and irrigation drainage flows have changed through time and what the drivers of change have been. This research was necessary for water managers in the LBRB because the region has been urbanizing, similar to other major cities across the western US (Dahal *et al.*, 2018; Friedrich, 2020). While existing literature explains that urbanization affects hydrologic systems and irrigation water demand in other major cities in the western US (Baker *et al.*, 2014; Bhaskar *et al.*, 2016; Kliskey *et al.*, 2019), water managers in the LBRB did not have the information available to understand the specifics of how and why local diversion and drain volumes were changing. Simultaneously, annual weather impacts the irrigation water availability and demand, and providing information to water managers about which variables are most influential on the system can help them prepare for future change. Co-producing this research with water managers in the basin was necessary for us to incorporate institutional knowledge into model formation and to make the results of this research actionable. Together, this work disentangles the influence of climate and urbanization impacts on the LBRB irrigation demand and return flows, which can be used for future studies in the region. Water budgets that have been created for the LBRB employ basin-wide assumptions about the behavior of drains and diversions (Reclamation, 2008; Urban, 2000); our work suggests that basin-wide assumptions could be leading to an oversimplification of the system and high uncertainty in the estimates.

We used both basin-wide and local statistical models to understand the complexity of the system and answer our questions. Two different model structures asking inherently different questions were used at the basin scale, and each model provided unique insight into how different predictor variables impacted flows, suggesting that only using the outputs of one model may lead to an incomplete understanding of the system (Sterman, 2002). Employing models and trend analysis at local scales helped show that individual diversions and drains are changing at variable rates through time and that individual diversions are influenced by decision-making and complexities that are not captured by basin-wide models.

Trend analysis for drain and diversion volumes showed non-uniformity across the basin. While 40% of the drains were decreasing through time, only 35% of diversions were decreasing, and 18% of diversions were increasing through time. Future work with trend analysis could include integrating the diversion and drain datasets to understand if drains are decreasing in the same places that diversions are decreasing. The drain model showed a strong, positive relationship between drainage flows and canal inflows (Figure 2.7), and combining the changes through time with the canals and drains could provide more insight into the connectivity. If drain and diversion discharge are changing in the same locations, water managers could use this information to divert more water down the canals that are heavily influencing groundwater levels and drainage flows as a form of managed aquifer recharge and increased water delivery (Hipke *et al.*, 2022).

The model outputs for diversion and drain flows showed a disconnect in the system in response to urbanization but similarities with climate impacts. Urbanization had a negative effect on total diversion volume at the basin scale, but the effect size was variable (Figure 1.3), and individual MLRs showed that some diversions have increasing diversion volumes with urbanization while others are decreasing (Figure 1.7). Drain discharge decreased with increased urbanization more uniformly than the diversions (Figure 2.5). This highlights that while drains are influenced by humans, the mechanisms that drive flow (e.g., elevated shallow groundwater tables) are more physically based hydrologic processes compared to the drivers of flow in the diversions (e.g., human decision-making). Climate impacted annual diversion and drain volumes more uniformly than urbanization (Figure 1.5; Figure 2.4). Temperature and evapotranspiration had the same direction of effect for both diversions and drains, which was surprising as the diversions are an inflow into the surface water – groundwater system while drains are an outflow. For example, we anticipated that increased temperature would increase diversion volumes but decrease drain flows because irrigation demand typically increases with rising temperatures (Breyer *et al.*, 2012; House-Peters *et al.*, 2010), but less water would make it to the drains due to evaporative losses and less water entering the groundwater system. The same directionality in these effects warrants further research. The effect of precipitation on the diversions and drains was small or non-existent, demonstrating the lack of precipitation during the irrigation season and the importance of the reservoir system to support irrigation. Drain and canal systems throughout the valley and in the western US are interconnected surface water – groundwater systems (Baker *et al.*, 2014; Ward *et al.*, 2007); however, the disconnect in the system in response to urbanization calls for further work to understand these differences and the conceptualization of the mechanisms that may be leading to these differences.

Future Work

While this study provides insights about the irrigation demand and return flows in the LBRB, this research highlights the need for further research on connections between diversions, drain flows, and urbanization to aid water managers in understanding how this system will continue to change. Groundwater pumping, canal seepage rates, and irrigation efficiency improvements are three large components that were missing from this study and could provide further insight into why diversions and drains are showing differences in response to urbanization. Pumping from the shallow aquifer system in the LBRB could cause local drawdown and, in turn, lower flows in the drains even if diversion discharge remains constant. Given this importance, groundwater data from IDWR (Idaho Department of Water Resources, 2023) should be evaluated for potential inclusion in future statistical modeling efforts. Groundwater levels control discharge to the drain system (Baker *et al.*, 2014; Reclamation, 2008) and also alter vertical hydraulic gradients (Abdelmoneim, 2021), which could lead to greater seepage from the canal system. Seepage from canals is variable through both time and space due to differences in lithology and perched aquifer systems (Abdelmoneim, 2021); however, there are limited measurements of seepage rates, leading to large uncertainty in any seepage calculated through water budgets for the region (US Bureau of Reclamation, 2008; Urban, 2000). As urbanization increases, more canals and laterals are being piped or lined, which will drastically alter seepage, but no database contains this information. Finally, data that was missing from both the drain and diversion analysis was changes in irrigation efficiency, and many of the farms throughout the LBRB have transitioned from flood irrigation to drip or sprinkler systems, which will again impact recharge to the aquifer (Fillo *et al.*, 2021; Malek *et al.*, 2021). Together, characterizing these components with new or existing data would help improve our understanding of the mechanisms that are producing changes in surface flows in the LBRB irrigation system.

Predicting irrigation diversion and drain flows would be another useful addition for basin scale water management, and future analysis could use the knowledge gained from this study in combination with predictions of future water availability to do so. While the models in this study were not built for, and are likely not appropriate for, predictive purposes (Yates *et al.*, 2022), other model structures, such as random forests and artificial neural networks, may be better suited for prediction (Donkor *et al.*, 2014). Future irrigation diversion demand and drain flows can serve as inputs for other basin-wide predictive models, such as the US Bureau of Reclamation RiverWare model (Meeks, 2021), and could be useful for understanding how water diversions and drain flows will shift as the LBRB continues to change.

This research highlighted the need for a centralized data management system that follows FAIR (Findable, Accessible, Interpretable, Reusable) data principles (Wilkinson *et al.*, 2016) for both geospatial and flow data for Idaho. Some data was available from IDWR (Idaho Department of Water Resources, 2020, 2021, 2022b); however, both data and metadata were often incomplete and required extensive engagement with IDWR staff to obtain. The error on flow measurements was not available, making it difficult to quantify measurement uncertainty for this analysis. Data also exists at the individual irrigation district level; however, this data is not public and not always archived. Having a centralized database that all water agencies have access to in the LBRB would promote more communication and collaboration between entities. A data system where flow and geospatial data are connected and easily accessible could also help land use planners consider the impacts on hydrologic systems as the valley continues to urbanize. Improved data harmonization and management will aid water management and researchers as the LBRB continues to grow and change.

This research created fundamental, baseline information on how and why irrigation flows have changed from 1987 to 2020 in the LBRB. Next steps in progressing both our essential understanding of the hydrologic response to LULCC and the actionable knowledge on how to adaptively manage this system in the future will require a better characterization of how groundwater-surface water interactions are shifting with LULCC, predictions for future diversion and drain volumes using information gained from this study, and the creation a centralized data management system for the LBRB.

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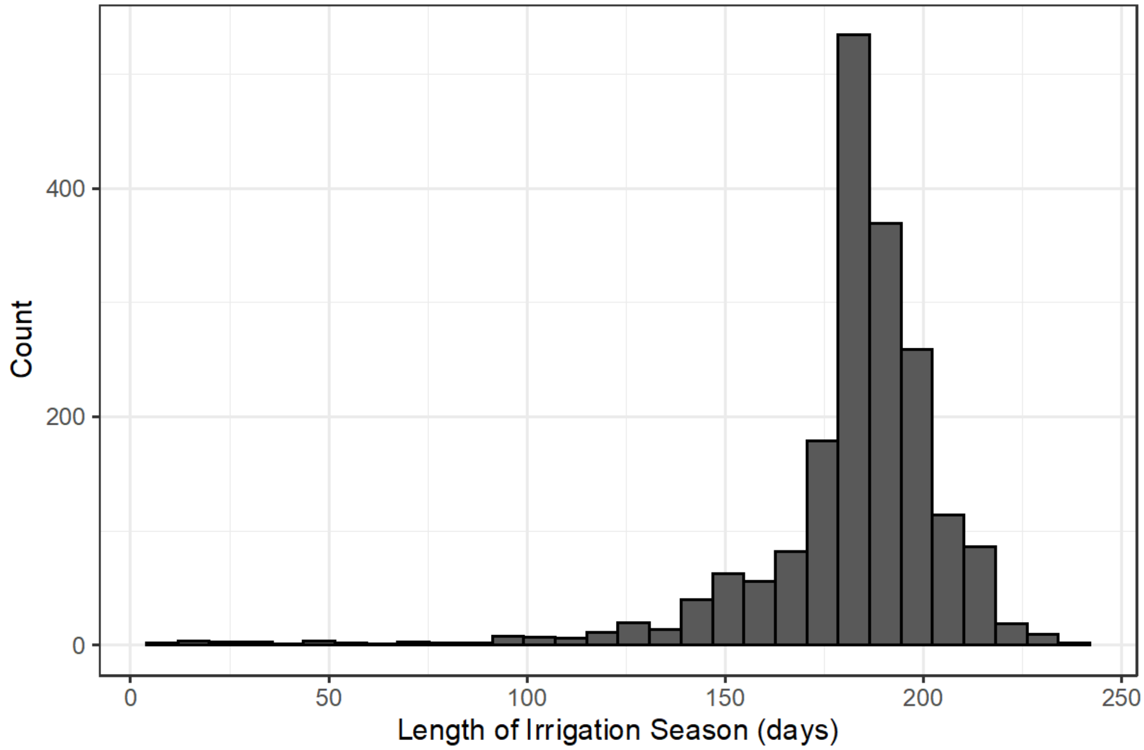
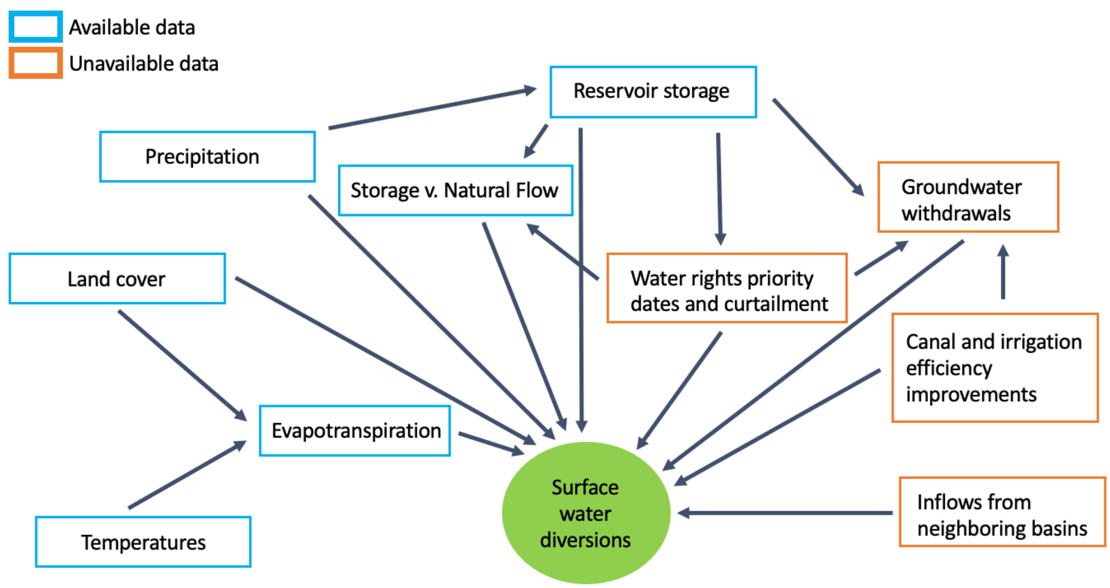
APPENDIX I: SUPPLEMENTAL TABLES AND FIGURES

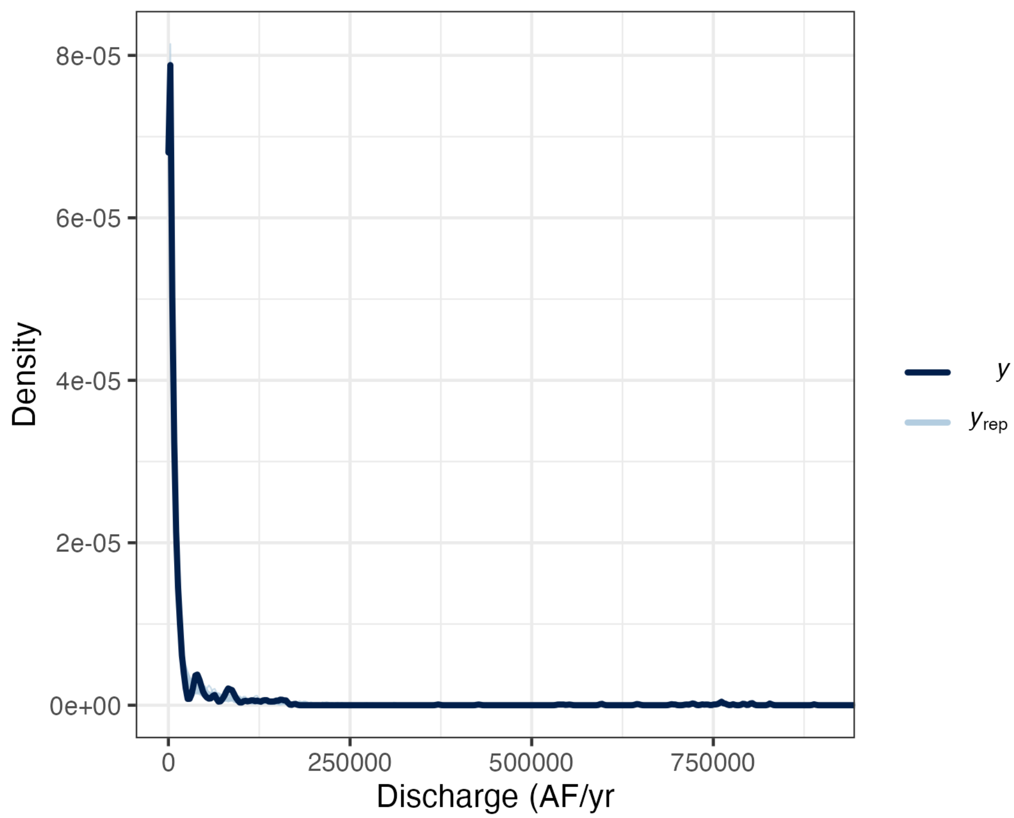
Supplemental Figures



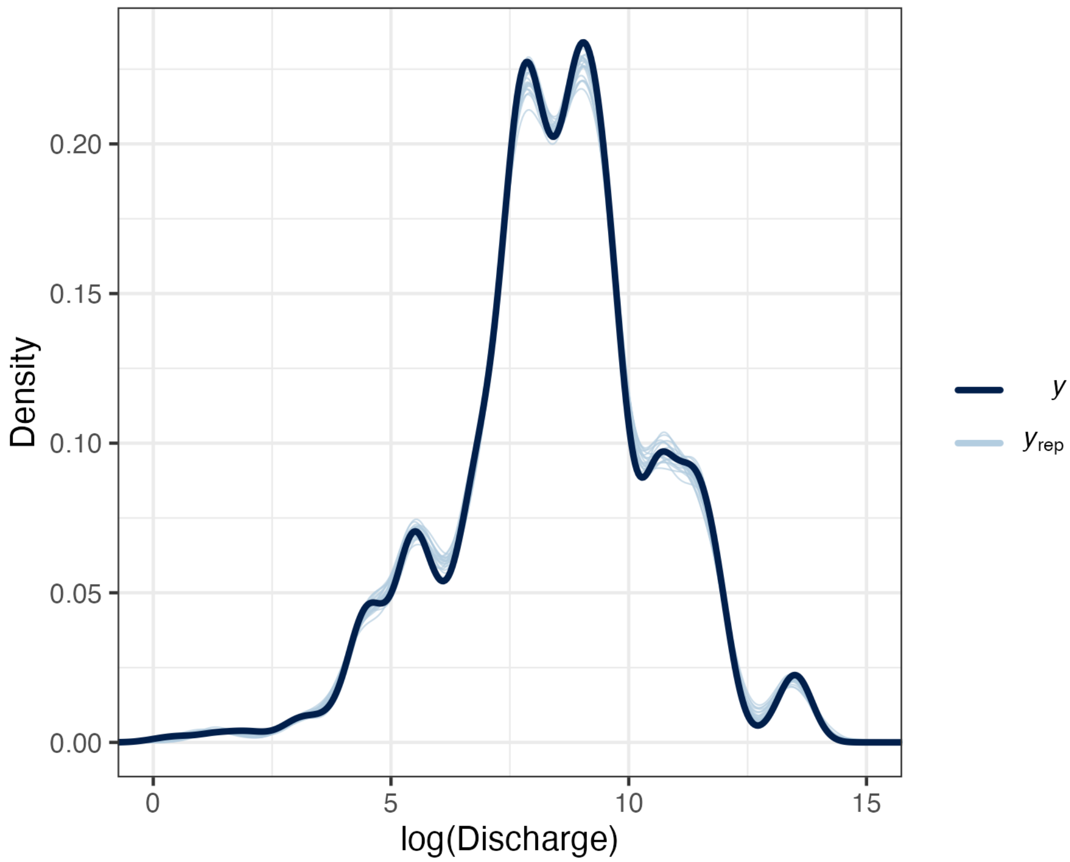
Supplemental Figure 1. Histogram of the length of the irrigation season for all diversions (n= 63). The length of irrigation season for each diversion was calculated using the first day it diverted water and the day it reached its cumulative flow for the season.



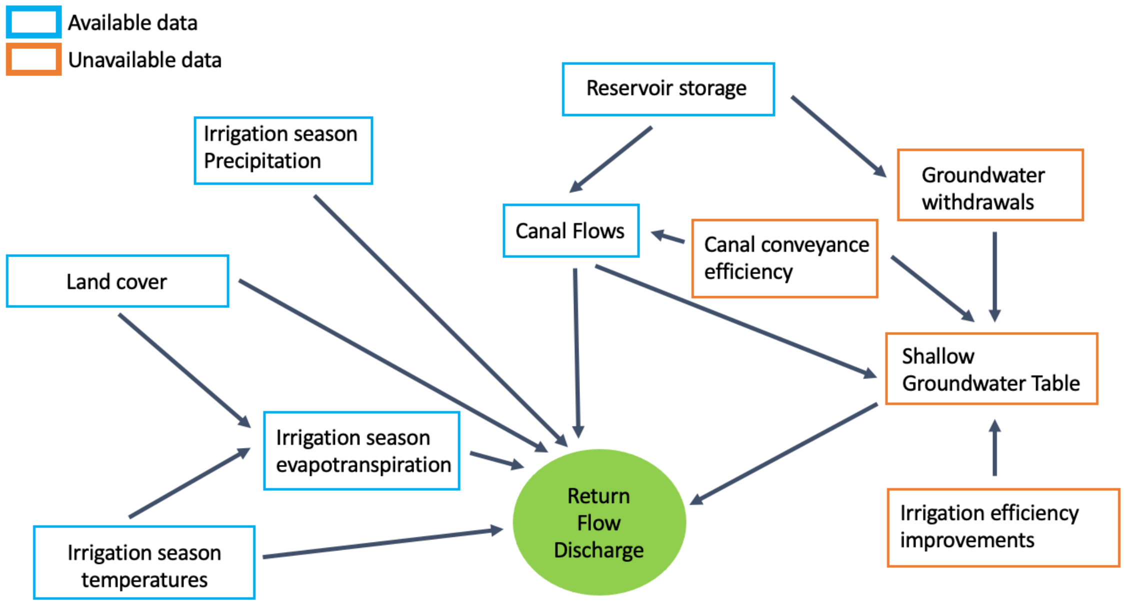
Supplemental Figure 2. The directed acyclical graph (DAG) of the variables that impact surface water diversions in the Lower Boise River Basin. Blue boxes represent available data while orange boxes show unavailable data.



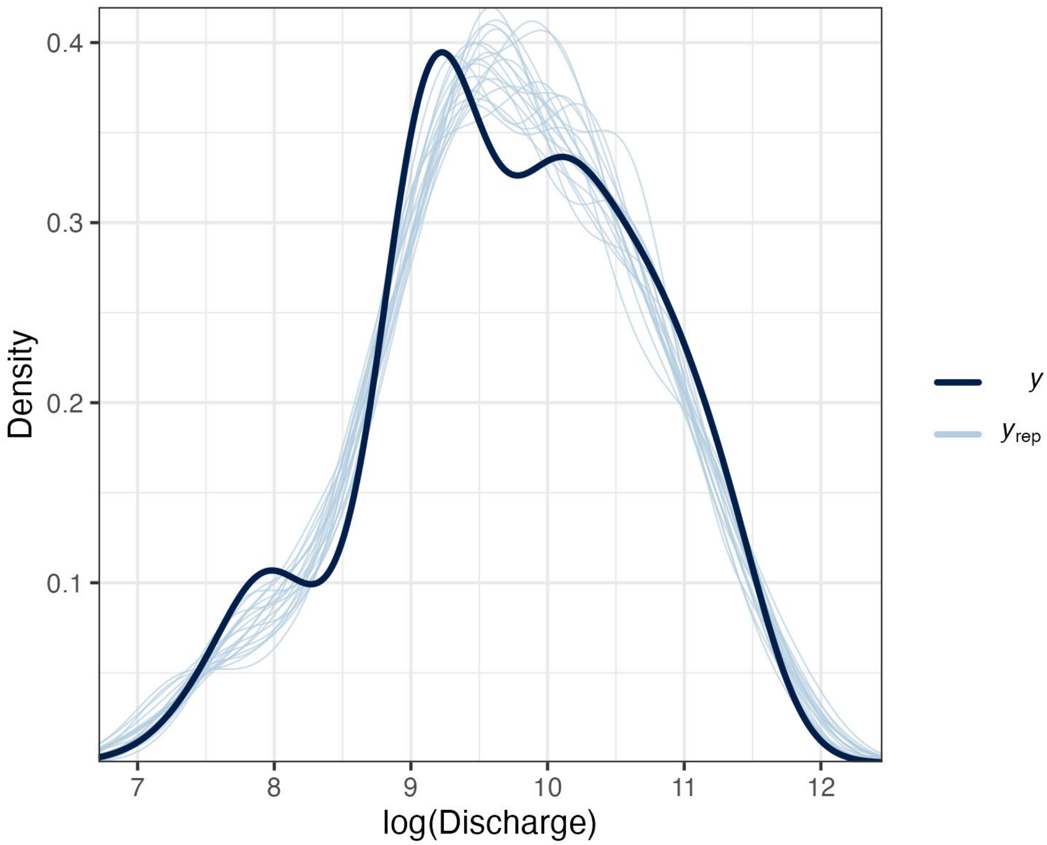
Supplemental Figure 3. The posterior predictive check for a Generalized Linear Mixed Effects Model with no time component modeling the effects of different predictor variables on surface water diversions in the Lower Boise River Basin. The observations (y) are in dark blue while the 20 samples from the posterior (y_{rep}) are shown in light blue.



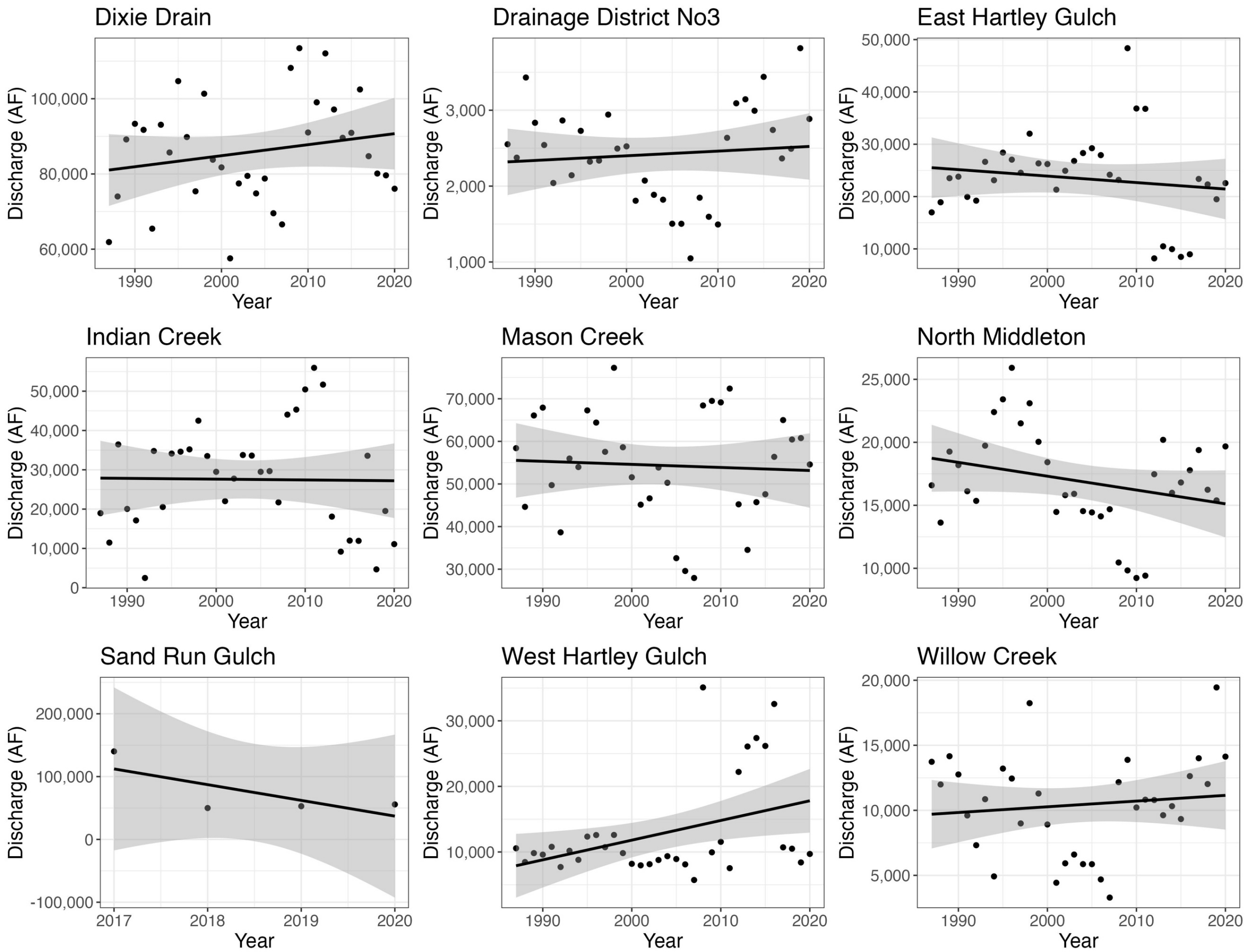
Supplemental Figure 4. The posterior predictive check for a Generalized Linear Mixed Effects Model with an autoregressive-moving average term that models the effects of different predictor variables on surface water diversions in the Lower Boise River Basin. The observations (y) are in dark blue while the 20 samples from the posterior (y_{rep}) are shown in light blue.



Supplemental Figure 5. The directed acyclical graph (DAG) of the variables that impact return flow discharge in the Lower Boise River Basin. Blue boxes represent available data while orange boxes show unavailable data.



Supplemental Figure 6. Posterior predictive check of a Generalized Linear Mixed Effects model with an autoregressive-moving average term with urban area, precipitation, temperature, evapotranspiration, and canal inflows as predictor variables to explain return flow discharge in the Lower Boise River Basin. The observations (y) are in dark blue while the 20 samples from the posterior (y_{rep}) are shown in light blue.



Supplemental Figure 7. The change in flow from 1987 to 2020 for drains in the Lower Boise River Basin with no significant trend, based on a Mann Kendall test.

Supplemental Tables

Supplemental Table 1. The priors for the Generalized Linear Mixed Model with no time component to understand the effect of variables on surface water diversions in the Lower Boise River Basin.

Variable	Prior
Evapotranspiration	Normal (0,1)
Storage water use	Normal (0,1)
Urban Area	Normal (0,1)
Temperature	Normal (0,1)
Precipitation	Normal (0,1)
Intercept	Normal (0,1)
Intercept level by diversion name	Cholesky LKJ Correlation (1)
Standard deviation	Gamma (1,1)
Sigma	Student T (3, 0, 2.5)

Supplemental Table 2. The priors for the Generalized Linear Mixed Effects Model with an autoregressive-moving average term to understand the effect of predictor variables on surface water diversions in the Lower Boise River Basin.

Variable	Prior
Change in Evapotranspiration	Normal (0,1)
Change in Storage water use	Normal (0,1)
Change in Urban Area	Normal (0,1)
Temperature	Normal (0,1)
Precipitation	Normal (0,1)
Intercept	Normal (0,1)
Intercept level by diversion name	Cholesky LKJ Correlation (2)
Standard deviation	Gamma (1,1)
Sigma	Student T (3, 0, 2.5)
Autoregressive term	Flat (-1,1)
Moving average term	Flat (-1,1)
Degrees of freedom	Gamma (2, 0.1)

Supplemental Table 3. The priors for individual Generalized Linear Models for each diversion to understand the effect of predictor variables in individual diversion volumes in the Lower Boise River Basin.

Variable	Prior
Evapotranspiration	Uniform $(-\infty, \infty)$
Storage water use	Uniform $(-\infty, \infty)$
Urban Area	Uniform $(-\infty, \infty)$
Temperature	Uniform $(-\infty, \infty)$
Precipitation	Uniform $(-\infty, \infty)$
Intercept	Student T (3, 8.5, 2.5)
Shape	Gamma(0.01, 0.01)

Supplemental Table 4. The priors for the Generalized Linear Mixed Effects Model with an autoregressive-moving average term to understand the effect of predictor variables on return flow discharge in the Lower Boise River Basin. Predictor variables in this model include average daily maximum irrigation season temperature, irrigation season precipitation, irrigation season evapotranspiration, urban area, and canal inflows to a drainage watershed.

Variable	Prior
Evapotranspiration	Normal (0,5)
Storage water use	Normal (0,5)
Urban Area	Normal (0,5)
Temperature	Normal (0,5)
Precipitation	Normal (0,5)
Intercept	Normal (2,1)
Autoregressive term	Flat (-1,1)
Moving average term	Flat (1-,1)
Standard deviation	Normal (0,1)
Sigma	Student T (3, 0, 2.5)

APPENDIX II: ADDITIONAL DIVERSION ANALYSES

Chapter 1 of this thesis presents the conclusions from the diversion analysis; however, additional models and statistical analyses were explored in the process of this work. The additional response variables, predictive parameters, and models will be shared here. However, the results will not be interpreted.

Timing Metrics

Response variables of both volume and timing were calculated as explained in Chapter 1. Timing metrics included start day of year of the irrigation season, end day of year of the irrigation season, and length of irrigation season. We used a GLMM with no ARMA to try to explain how the length of the irrigation season was changing for across the basin; however, the MAE of the model was about equal to the standard deviation of the variable, likely because not enough variability is present in the data, as shown by the peaked distribution in Supplemental Figure 2. Furthermore, the irrigation season cannot extend beyond certain dates, as the irrigation season follows the growing season. Some of the GLMMs showed that certain predictor variables would increase the length of the irrigation season past the bounds of the year, which is not possible. The constraints of the calendar year make modeling the changes in timing metrics difficult.

Survival analysis was also used to model the length of the irrigation season, as survival analysis is a type of model used to represent time to an event (Clark *et al.*, 2003). The time to event in this analysis was the time to the end of an irrigation season. Survival analysis did not yield better results than the GLMM analysis.

Individual trend analysis using a Mann Kendall test for each timing metrics was explored for each diversion. Trend analysis for the length of irrigation season included 55 of the diversions. The trend analysis showed that 17 diversions had a significant ($p <$

0.05), increasing length of irrigation season while 7 had a significant, decreasing trend in the length of irrigation season (Figure AII-1). The increasing length of the irrigation season stems primarily from an earlier start date, where 17 of the diversions had an earlier start date of the irrigation season and 5 had a later start date. Finally, 7 diversions were ending the irrigation season later in the year, and 7 were ending earlier in the year (Figure AII-1). One diversion that does not primarily serve irrigation purposes was diverting year-round (Figure AII-1).

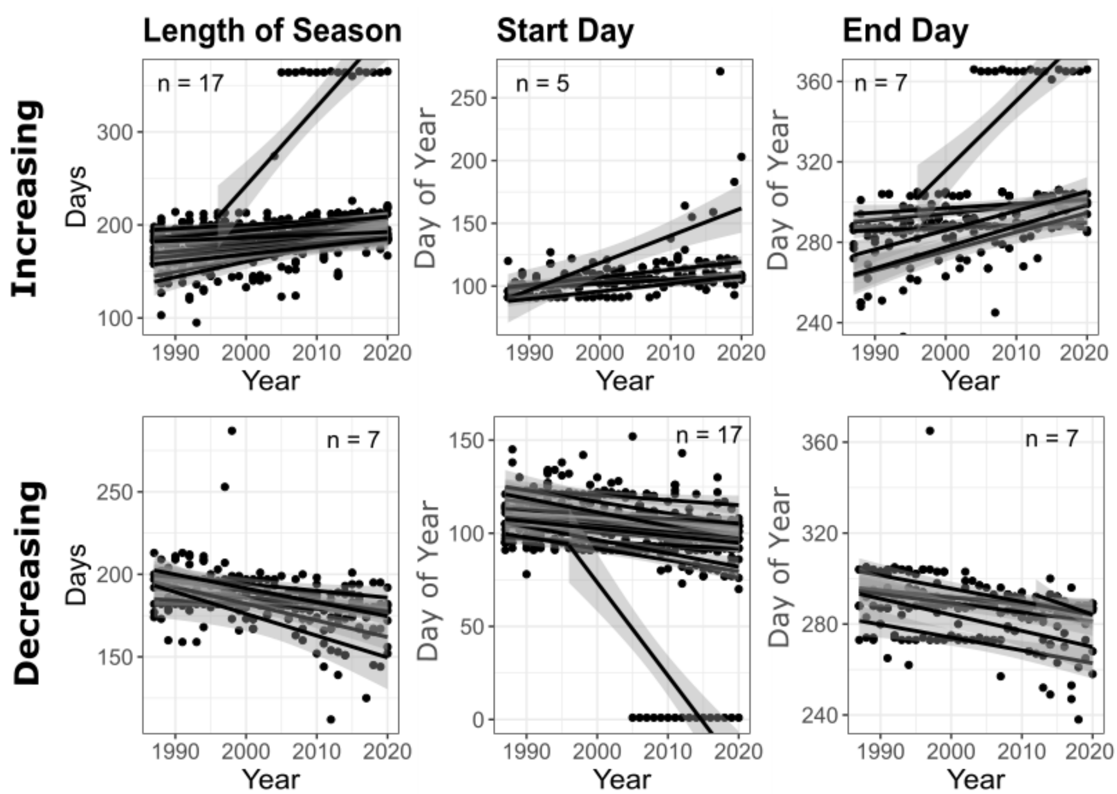


Figure AII-1. Increasing and decreasing trends for the length of the irrigation, season start day of the irrigation season, and the end day of the irrigation season across 55 diversions in the Lower Boise River Basin.

Additional Predictor Variables

Many additional predictor variables were calculated in the process of conceptualizing what variables to include in the model. Ultimately, the models included predictor variables that matched our understanding of the system (Supplemental Figure 2; Supplemental Figure 5). Additional calculated or recorded potential predictor variables were maximum reservoir storage, reservoir carryover from the previous water year, storage water available, proportion of agricultural area, precipitation prior to the irrigation season, average maximum June through August temperatures, and inflows to Lucky Peak reservoir. Annual cumulative maximum reservoir storage across Anderson Ranch, Arrowrock, and Lucky Peak reservoirs will influence the available storage water for each canal, but storage water use, which was included in the models, explained more individual behavior for canals. Reservoir carryover from the previous water year was not included because it does not represent the full amount of water available for the current water year. Available storage water for each canal was not incorporated in the models because it had a 0.98 correlation with storage water used. Similarly, the proportion of agricultural area had a -0.97 correlation with the proportion of urban area and was, therefore, not incorporated in the model. Precipitation prior to the irrigation season was considered but ultimately not used because precipitation during the irrigation season was deemed a better variable for understanding demand during the irrigation season. Average daily maximum June through August temperature was not incorporated in the models because the response variable was at the whole length of the irrigation season while this temperature variable only represents one fraction of the whole period. While all these metrics were not included in the model, they could potentially be used in future models focused more on prediction rather than causal inference.

Additional predictor parameters considered for timing models were March total precipitation, March total evapotranspiration, and March average daily maximum temperature. The March variables were calculated for the models regarding the length of irrigation season and start day of irrigation season because March weather are an indicator for when the canals will start diverting water. The March variables were not used in the models for total diversion volume.

Additional Model Runs

The two GLMMs presented on diversion volumes in the paper were carefully considered as two models to explain two different questions in which we were interested. As the predictor variables included in the model will alter the inference of each coefficient (Yates *et al.*, 2022), predictor variables were chosen to best represent the system and were based on discussions with stakeholders and previous literature. Additional models were considered and run during this study, primarily because the models presented here were time intensive to fit. Model structures all followed the general GLMM structure; therefore, the differences in models considered were primarily due to additions to the general structure or subsets of the data. One model structure difference was including an offset for the diversion size, which is used to provide the diversion volume as a ratio to the size of the area it serves (Stijnen *et al.*, 2010). Additional models that were run included subsets of the full dataset. These models included subsets as follows:

1. Excluding the largest canal from the dataset

2. Diversions with less than 10% urban change and greater than 10% urban change
3. Diversions with an average discharge less than 20,000 AF and greater than 20,000 AF

Excluding the largest canal from the dataset was considered because water from this canal also delivers water to a small reservoir and not just irrigation, and this canal's discharge was, on average, 4.7 times larger than the next biggest canal. Splitting the dataset into two datasets, one with diversions that have had greater than 10% urban change and one with less than 10% urban change, was considered because of the difference in the magnitude of urban growth. However, this subset did not account for the starting urban area (e.g., 10% versus 60% urban area in 1987), which could alter the total amount of water being used at the beginning of the period of study. Finally, we explored dividing diversions into large (greater than 20,000 AF average discharge) and small discharge groups to explore if different size diversions responded differently to the predictor variables and for computational efficiency. While separating the data into different groups provided unique insights, this addressed a different question than our intended basin-wide response to these different predictor variables. Therefore, all diversions were kept in the model as long as they met the requirements for the model.

APPENDIX III: ADDITIONAL DRAIN MODELS

Model Comparison for Overfitting

For the drains, we ran various individual GLMMs for the different predictor variables, adding one variable at a time to the model. The combination of predictor variables included in the models were as follows:

1. Urban area
2. Climate variables
3. Urban area and climate variables
4. Urban area, climate variables, and canal contributions.

One model was run with all predictor variables but without the ARMA component that all other models included.

Model comparison

The model comparison on the basis of LOOIC revealed that including all predictor variables in the model with an ARMA term did not overfit the model (Table AIII-1). The model with the best fit (lower MAE and LOOIC) included urban area, all climate variables, and canal contributions, had a varying intercept by drain, and included an ARMA average term (Table AIII-1). Models with an ARMA term performed better than models without the term, illustrating that information about the previous year can help inform the discharge at the current time step. In the case of using all predictor variables, the MAE for the model with the ARMA and all predictor variables was 900 AF less than the model with all predictor variables and no ARMA.

Table AIII-1. Comparison of model fit (MAE and LOOIC) among models with different predictor variables, grouping structure, and the inclusion of an autoregressive moving average term.

Model Variables	Grouped variables by drain name	Autoregressive term?	MAE (AF)	LOOIC
Urban + climate + canals	Intercept	Yes	4,045	213.0
Urban + climate + canals	Intercept, Urban	Yes	4,051	212.9
Urban + climate	Intercept, Urban	Yes	4,157	237.0
Climate	Intercept	Yes	4, 247	250.6
Urban	Intercept	Yes	4,413	283.7
Urban + climate + canals	Intercept, Urban	No	4,952	-