THESIS

RESPONSE OF MUNICIPAL WATER USE TO WEATHER ACROSS THE CONTIGUOUS US

Submitted by

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ABSTRACT

RESPONSE OF MUNICIPAL WATER USE TO WEATHER ACROSS THE CONTIGUOUS US

Municipal water demand exhibits seasonal patterns in response to summer withdrawals for landscape irrigation, particularly in dry regions of the western US. Outdoor water use can account for more than half of annual household water use, and therefore is a critical aspect of urban water planning under scarcity. Water use for landscape irrigation is responsive to local weather changes and drought restriction policies and therefore is targeted by demand management programs. Previous studies estimate the impact of climatic, socio-economic, and landscape factors on residential water use, but commonly focus on a single municipality. This nationwide study identified the response of municipal water use to weather variables (i.e., temperature, precipitation, evapotranspiration) using monthly water deliveries for 230 cities in the contiguous US. Using city-level multiple regression and regional-level fixed effects models, we investigated what portion of the variability in municipal water use was explained by weather across cities, and also estimated responses to weather across seasons and climate regions. Our findings indicated that municipal water use was generally well-explained by weather, with median adjusted R^2 ranging from 63 to 95% across climate regions. Weather was more predictive of water use in dry climates compared to wet, and temperature had more explanatory power than precipitation or evapotranspiration. Climate regions and seasons were found to have significantly different water use responses to weather. In regional-level models, we found that relative seasonality in water use across regions corresponds to water use responses to changes in temperature. In response to a 1^0 C change in monthly maximum temperature, municipal water use was shown to increase by 1.1 to 3.9% on average, with greater responses in cold, dry regions and during summer. Climate change and population growth amplify the importance of understanding the impact of climate on water demand in the context of urban water supply.

ACKNOWLEDGEMENTS

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Chapter 1: Introduction

Ensuring resiliency of freshwater resources is a major 21st century challenge. Managing water to meet human and environmental demands has become increasingly difficult under population growth, land use change, and climate change (Brown *et al.*, 2013; MacDonald, 2010; Roy *et al.*, 2012). While solutions to water scarcity previously targeted engineering approaches to increase supply, there has been a recent shift towards conservation to reduce demand (Gleick, 2010; MacDonald, 2010). Even with efficiency advances across sectors, climate change projections suggest that water supplies may be threatened by rising temperatures and often decreasing precipitation, with water supplies for over 70 percent of US counties projected to be at risk by 2050 (Roy *et al.*, 2012). Arid and semi-arid regions of the western US are disproportionately susceptible to water challenges, as limited water resources are often fully appropriated and characterized by extreme drought vulnerability (MacDonald, 2010; Sabo *et al.*, 2010). Furthermore, these arid and semi-arid regions are experiencing rapid population growth, leading municipalities to acquire water rights from agriculture (MacDonald, 2010; Sabo *et al.*, 2010).

Municipal water use is driven by residential use, and in particular residential outdoor use, for landscape irrigation, swimming pools, and car washing. Outdoor water use can account for 22 to 65 percent of annual residential use (DeOreo *et al.*, 2016), and therefore plays a major role in the urban water budget. Municipal conservation initiatives often target reductions in outdoor use, since it is responsive to policy restrictions (Anderson *et al.*, 1980; Kenney *et al.*, 2004, 2008; Mini *et al.*, 2014) and is not vital to sustaining human health.

Understanding water use drivers in urban settings can help inform conservation strategies. Municipal water demand is influenced by a diverse set of climatic, socioeconomic, demographic, and landscape factors. Predictive models typically incorporate combinations of these factors to explain variations in water use across different temporal and spatial scales. However, accurately estimating and forecasting water demand remains elusive due to limitations in data accessibility and difficulty isolating the influence of simultaneous drivers, such as restriction policies and drought conditions.

Weather affects residential water use because of the large fraction of municipal water used seasonally for landscape irrigation. However, there is no consensus on which weather variables are the best predictors across cities. Temperature and precipitation are the most commonly used variables in urban water demand studies, since data are widely available and significantly explanatory, particularly for estimating seasonal or summer-isolated water use (Grimmond and Oke, 1986; Gutzler and Nims, 2005; Maidment and Miaou, 1986)**.** Studies have found that increased water use is related to higher temperatures and lower precipitation (Balling *et al.*, 2008; DeOreo *et al.*, 2016; Grimmond and Oke, 1986; Gutzler and Nims, 2005; Kenney *et al.*, 2008; Mini *et al.*, 2014). Using regression models, temperature and precipitation have been shown to explain 59 to 66% of the variance in residential water use across study sites (DeOreo *et al.*, 2016; Grimmond and Oke, 1986; Gutzler and Nims, 2005).

In addition to weather effects, socioeconomic characteristics and utility-controlled factors within cities or neighborhoods have been shown to influence water demand. Physical characteristics of residences including household size, lot size, presence of a swimming pool, and land cover factors have been shown to have significant effects on water use (Balling *et al.*, 2008; Gage and Cooper, 2015; Mayer *et al.*, 1999; Wentz and Gober, 2007). Water use has been found to have spatial clustered patterns according to household and income characteristics (Gage and Cooper, 2015; Wentz and Gober, 2007). In addition to household characteristics, studies have described the impact of household income, measures of water price, and billing structure-type, with binary variables for restriction periods, rebates, and other utility-controlled factors on water use (Kenney *et al.*, 2008; Zapata, 2015).

Previous work on identifying factors influencing urban water demand has focused mostly on single municipalities, with fewer studies including multi-city or nationwide analyses. DeOreo et al. (2016) assessed outdoor water use drivers across 26 US and Canadian water utilities, determining that annual precipitation alone explained 59% of the variance in total annual water use for single-family homes. Other factors of irrigated area, net evapotranspiration (ET), water price, use of in-ground sprinklers, and excess irrigation together explained 45% of the variation outdoor water use (DeOreo *et al.*, 2016). In nine cities across Texas, Florida, and Pennsylvania, urban seasonal water use was responsive to temperatures above a threshold of 70^0 F and precipitation events greater than 0.05 inches, with precipitation effects that were nearly 6 times greater in Florida and Texas compared to Pennsylvania (Maidment and Miaou, 1986). An analysis using USGS county-level water use data found that climate region groupings were more explanatory than primary economic activity or urban gradient, and emphasized that predictive capabilities of social and environmental variables differ across climate regions (Worland *et al.*, 2018). Mean annual precipitation had the largest effect out of environmental variables included, with an effect in the Southwest three times that of the national average. Water price structure, conservation policies, and a combined aridity index were included in city-level models for 83 cities, which overall improved predictions compared to county-level models.

Overall, the majority of multi-city analyses remain limited to a small number of locations, and often group data into a single model without addressing spatial variation. While focusing on single municipalities is useful to inform city-specific management efforts, regional water management requires quantifying how urban water use drivers vary across broader climatic regimes. City-specific demand models with fine-scale irrigated area information and coefficient estimates can be developed but require significant investments of data collection and time. Patterns of water use response across regions and regionalized coefficient estimates for water use change with weather can be used as a planning-level tool when more detailed demand models are not available. Our approach considers the influence of long-term climate in addition to short-term weather effects on municipal water withdrawals. By taking a national approach, we can learn how urban water use varies across cities based on responses to weather changes. This paper uses a statistical approach to characterize the relationship between weather and municipal water use for 230 cities in the contiguous US and aims to answer the following research questions:

(1) What portion of the variability in municipal water use is explained by weather, and how does this vary across US cities?

(2) How does the response of municipal water use to weather compare across seasons and climate regions?

We address these questions using city-level multiple regression and regional-level fixed effects modeling approaches to characterize effects of weather on municipal water use. Temperature, precipitation, and actual ET were included as explanatory variables to estimate changes in water use corresponding to weather variability nationwide.

Chapter 2: Data

2.1 Municipal water delivery data

Monthly water deliveries were collected from 232 municipal water suppliers across the contiguous US by Foti et al. (2012). Monthly municipal water deliveries include residential, commercial, and industrial uses. Since the residential sector dominates municipal water use (Maupin *et al.*, 2014), we used total municipal deliveries to estimate weather responses characteristic to the residential sector. The original dataset included 9,118 monthly observations across all cities, with a median value of 24 months of data per city. The majority of city records included 1 to 4 years of data between 2000 and 2007, however, 20 cities contain records from the 1990s that account for more than a quarter of total observations. Records from the 1990s were used only for exploratory analyses, and were omitted from multiple regression models to allow identical temporal scales for all explanatory and response variables. The subset of post-2000 data contained 6,581 observations across 230 cities (Figure 1), and is referred to as the full dataset in this paper.

In the extensive effort to collect water delivery records nationwide, it was difficult to ensure certainty and consistency in recorded units. The full dataset containing cities with both known and unknown units was used in city-level models since model fits but not coefficients were analyzed (more information about models in methods section). Regional-level models, however, required standardization of units across cities since coefficients were directly interpreted to estimate changes in water use corresponding to weather changes. For the regional-level models therefore, we eliminated 33 cities where units were missing, and assessed accuracy of units for remaining cities by computing a standardized z-score for each monthly observation based on the full dataset sample mean and standard deviation. Monthly observations were removed in cases where the absolute value of the z-score was greater than 2, which eliminated 4 additional cities (131 records) from the analysis, leaving 5,518 total observations remaining across 193 cities for regional-level analyses. Despite the limitations discussed, this dataset was uniquely suited to capture seasonal variability in water deliveries across climatically and geographically diverse regions.

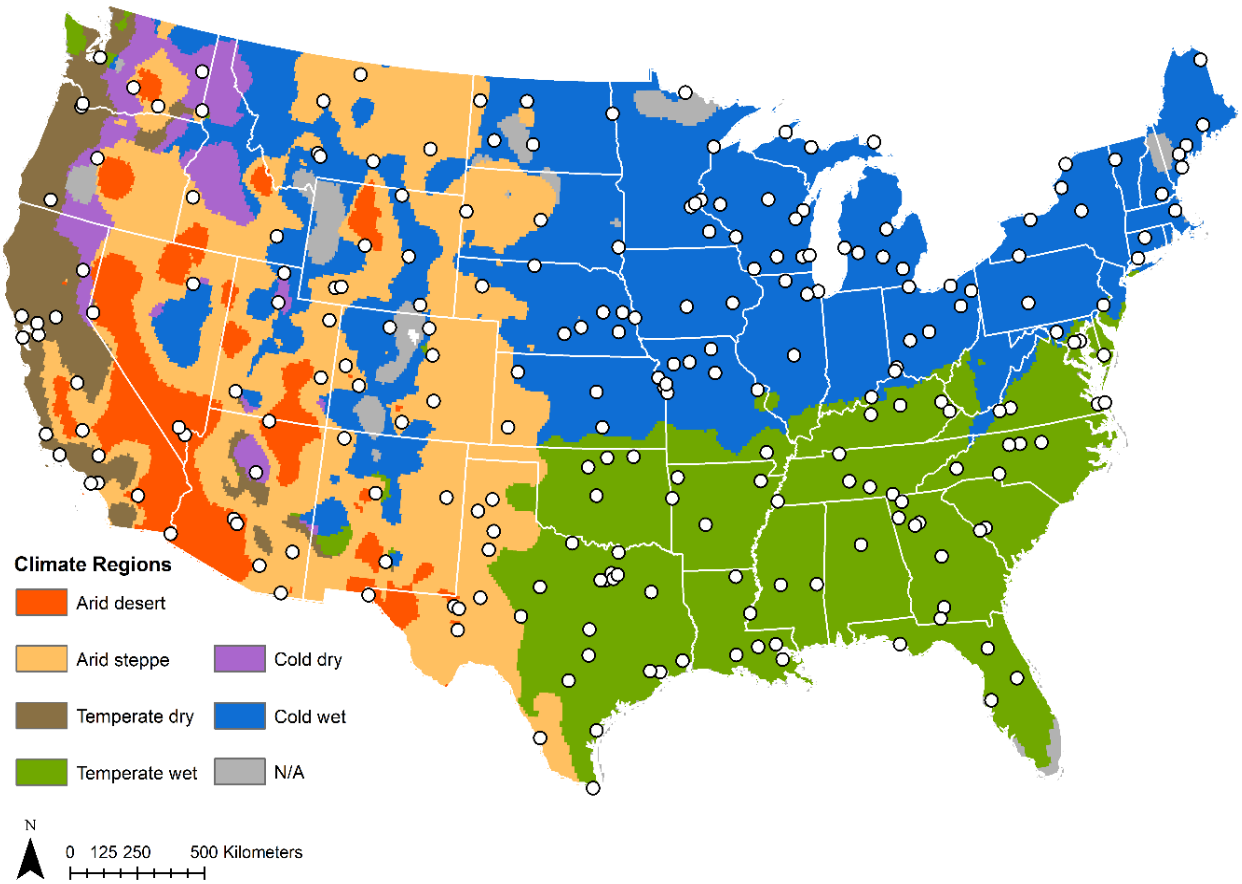


Figure 1. Map of six climate classification groupings and 230 study cities with N/A denoting other climate regions which did not contain study cities

2.2 Temperature, precipitation, and ET_a data

We assessed several measures of each weather variable based on significance in previous studies and to capture the behavioral nature of landscape irrigation, which may be based on perceived weather conditions. Weather variables included temperature (mean, maximum, and difference from 30-year normal), precipitation (depth, number of days, and difference from 30-year normal), and actual ET (details in Table 1). All temperature and precipitation records were obtained from PRISM Climate Group in 4 km monthly grids for 2000 to 2007. Monthly actual evapotranspiration (ET_a) estimates were from the Operational Simplified Surface Energy Balance (SSEBop) model, which provides a robust approach to estimating ET_a by combining remote-sensing thermal imagery, surface-energy-balance, and local weather data (Senay *et al.*, 2013). Each weather variable was obtained in raster format and processed in GIS using Zonal Statistics to obtain monthly averages within each city boundary. Municipal boundaries were used to approximate utility service areas and were represented using shapefiles from TIGER (https://www.census.gov/geo/maps-data/data/cbf/cbf_place.html).

Table 1. Explanatory weather variable short names, description of explanatory variables, variable sources, and time periods.

Variable	Description	Source	Temporal
tmean	Monthly average of daily mean temperatures in ^{0}C	PRISM	2000-2007
tmax	Monthly average of daily maximum temperatures in ^{0}C	PRISM	2000-2007
tmean30	Difference between mean monthly temperature and 30-year monthly normal (1981-2010) temperature in ^{0}C	PRISM	2000-2007
pptdepth	Monthly rainfall as depth in mm	PRISM	2000-2007
pptdaily	Monthly rainfall as percentage of days > 0.1 inch	PRISM	2000-2007
ppt30	Difference between monthly rainfall depth and 30-year monthly normal (1981-2010) rainfall depth in mm	PRISM	2000-2007
ETa	Actual evapotranspiration in mm using Operational Simplified Surface Energy Balance (SSEBop) Approach	SSEBop	2000-2007

Chapter 3: Methods

3.1 Climate classification groupings

Long-term climate regimes are hypothesized to affect water use in addition to short-term weather effects. To identify patterns across broader climatic regimes, cities were grouped based on the Köppen climate classification system, which is an empirical, vegetation-based system with subgroups identified by long-term temperature and precipitation thresholds (Kottek *et al.*, 2006). We grouped cities into six climate regions (Figure 1), based on the first two criteria of the classification system. Table 2 summarizes the method for grouping classifications, including only the climate regions which corresponded to study city locations. Several municipal boundaries fell within two or more climate regions, in which case the classification containing the majority area was chosen.

Table 2. Original Koppen classification groupings (Koppen ID) and descriptions; modified Koppen classification groupings (modified ID) used in this study; and number of cities in each modified ID grouping

Koppen ID	Description	Modified ID	Sample Size
BWh	Arid/Desert/Hot	Arid desert	n=11
BWk	Arid/Desert/Cold		
BSh	Arid/Steppe/Hot	Arid Steppe	n=42
BSk	Arid/Steppe/Cold		
Csa	Temperate/Dry Summer/Hot Summer	Temperate dry	n=14
Csb	Temperate/Dry Summer/Warm Summer		
Cfa	Temperate/Without dry season/Hot Summer	Temperate wet	n=69
Cfb	Temperate/Without dry season/Warm Summer		
Dsa	Cold/Dry Summer/Hot Summer	Cold dry	n=5
Dsb	Cold/Dry Summer/Warm Summer		
Dfa	Cold/Without dry season/Hot Summer	Cold wet	n=88
Dfb	Cold/Without dry season/Warm Summer		

3.2 City-level regression models

City-level regressions were used to determine what portion of the variability in municipal water use was explained by weather at the city-scale (research question 1), and ultimately to inform regional groupings and interaction terms in subsequent regional-level models. City-level regression models for municipal water deliveries were estimated using combinations of six possible explanatory weather variables, as given in Equation 1,

$$y_{i,t} = \beta_0 + \beta_1 tmax_{i,t}^2 + \beta_2 tmax_{i,t} + \beta_3 season * tmax_{i,t} + \beta_4 tnorm_{i,t}$$

$$+\beta_5 pptdepth_{i,t} + \beta_6 pptdaily_{i,t} + \beta_7 pptnorm_{i,t} + \beta_8 ETa_{i,t} + \varepsilon_{i,t} \quad (1)$$

where $y_{i,t}$ is estimated municipal water use (in original units from full dataset) for city *i* in month *t*, β_0 is the intercept, $\beta_{1\text{-}8}$ are coefficients for the weather variables defined in Table 1, *season* is a binary with winter (October-March) as 0 and summer (April-September) as 1, and $\varepsilon_{i,t}$ is the error term. We subsetted the data by city to allow a unique model to represent each location. We observed linear, piece-wise linear (two segments), and quadratic responses to maximum temperature across cities. Therefore to improve residual diagnostic plots, Equation 1 contains linear terms, as well as quadratic and seasonal interaction terms for maximum temperature. The effects of mean temperature were also explored, but were ultimately eliminated from multiple regression models due to extreme collinearity since mean and maximum temperature were over 99% correlated. Maximum temperature was chosen since it is more prevalent in the literature (Kenney *et al.*, 2008; Maidment and Miaou, 1986; Worland *et al.*, 2018). This approach allowed for city-specific models to capture variable responses to weather changes across cities nationwide.

The best multiple regression model for each city was selected to include a subset of the terms in Equation 1 based on the corrected Akaike Information Criterion (AICc), a model selection tool used to balance the tradeoff between model fit and simplicity, with a correction for small sample sizes to prevent overfitting. We tested all possible candidate models for each city using dredge in R (Kamil Bartoń, 2018),providing an iterative, exhaustive approach to select the best model based on the minimum AIC_c. AIC_c values were used only for model selection within a city, and were not compared between cities. Variance inflation factor (VIF) is a diagnostic used to assess collinearity among explanatory variables, an important consideration for weather variables. After selecting models based on minimum AIC_c, models with two or more parameters were tested for collinearity using VIF. There is no standard VIF threshold, but values greater than 10 are of major concern (Helsel and Hirsch, 1992). We used a conservative approach to eliminate variables with VIF greater than 4 using a backwards selection process.

3.3 Regional-level regression models with fixed effects

Regional-level regression models were developed to allow data to be represented by a single model and explore how response to weather varies across climate regions and season (research question 2). These regional-level models included city fixed effects, time trends, interaction terms for climate regions and seasons, and maximum temperature and precipitation depth as explanatory variables. The other weather variables were not included because of their correlation with maximum temperature and precipitation depth. Fixed effects are incorporated to control for endogeneity bias resulting from exclusion of unobserved factors relevant to the regression (e.g., population, infrastructure age, irrigation efficiency, socioeconomic factors) by allowing for city-specific intercepts. Temporal trends were included to account for unobserved factors that may be changing over time. Log-level regression was used to simplify interpretation of coefficients, allowing a one unit change in temperature or precipitation to be interpreted as a fractional change in water use.

We used seasonal and climatic interaction terms to estimate differences in water use response between summer and winter months (Equation 2), across six long-term climate regions (Equation 3), and for wet and dry climate regions (Equation 4), given as:

$$\log(y_{i,t}) = \alpha_i + g(t) + \beta_{a_t,T} tmax_{i,t} + \beta_{a_t,P} pptdepth_{i,t} + \varepsilon_{i,t} \quad (2)$$

$$\log(y_{i,t}) = \alpha_i + g(t) + \beta_{b_i,T} tmax_{i,t} + \beta_{b_i,P} pptdepth_{i,t} + \varepsilon_{i,t} \quad (3)$$

$$\log(y_{i,t}) = \alpha_i + g(t) + \beta_{c_i,T} tmax_{i,t} + \beta_{c_i,P} pptdepth_{i,t} + \varepsilon_{i,t} \quad (4)$$

where $y_{i,t}$ is municipal water use (gallons) for city *i* in month *t*, α_i is the city-specific intercept, *g(t)* is a linear time trend, $\varepsilon_{i,t}$ is the error term, and β_T*'s* and β_P*'s* are a set of maximum temperature (T) and precipitation (P) coefficients with:

a different coefficient for winter and summer, where $a_t = \begin{cases} Winter \\ Summer \end{cases}$ depending on the season of month *t*, with April-September defined as summer and October-March defined as winter (Eq 2);

a different coefficient for each climate region, where $b_i = \begin{cases} Arid\ desert \\ Arid\ steppe \\ Cold\ dry \\ Cold\ wet \\ Temperate\ dry \\ Temperate\ wet \end{cases}$ depending on the climate region of city *i* (Eq 3);

a different coefficient for each grouped climate region of city *i*, where $c_i = \begin{cases} Dry \\ Wet \end{cases}$ (Eq 4), with wet corresponding to cold/wet and temperate/wet; and dry corresponding to arid/desert, arid/steppe, cold/dry, and temperate/dry.

Seasonal and climate region interaction terms were tested for significance by regression hypothesis tests and ANOVA F-tests for nested models. The significance of results from 2-way interaction models (discussed in the results section) were used to inform 3-way interaction terms used in the final models (Equations 5 and 6), defined as:

$$\log(y_{i,t}) = \alpha_i + g_{b_i}(t) + \beta_{a_t,b_i,T} tmax_{i,t} + \beta_{a_t,b_i,P} pptdepth_{i,t} + \varepsilon_{i,t} \quad (5)$$

$$\log(y_{i,t}) = \alpha_i + g_{c_i}(t) + \beta_{a_t,c_i,T} tmax_{i,t} + \beta_{a_t,c_i,P} pptdepth_{i,t} + \varepsilon_{i,t} \quad (6)$$

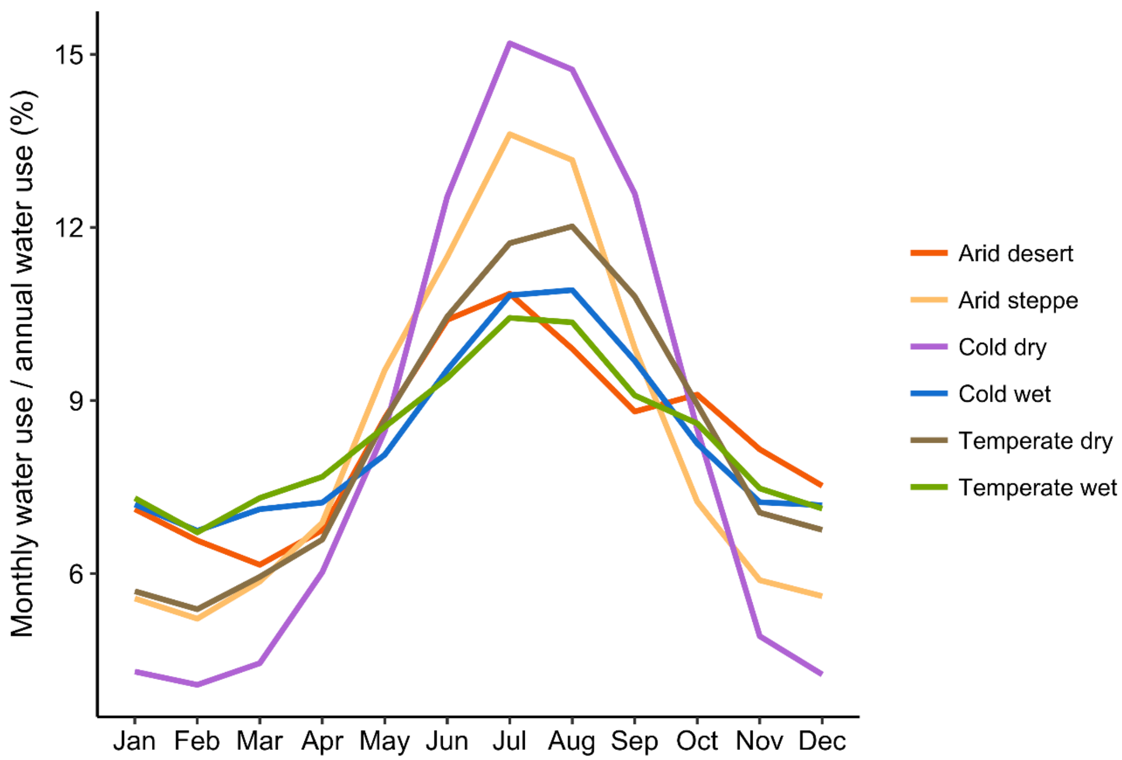
where terms are the same as described for earlier equations. Linear time trends g(t) in Equations 5 and 6 are interacted with regional groupings to allow temporal trends to vary by region. Equation 5 describes average effects for the six climate groupings over two seasons, in this case resulting in twelve β_{a_t,b_i} coefficients for each weather variable. Equation 6 describes average effects for two groupings (wet versus dry regions) over two seasons, resulting in four β_{a_t,c_i} coefficients for each weather variable.

Chapter 4: Results

4.1 Seasonality in municipal water use across climates

Figures 2a and 2b show the relative seasonality in annual water use across climate regions. Seasonal variability in water use was apparent across all regions, with increased withdrawals in the summer months often attributed to outdoor water use. Cold/dry cities had greater seasonality in water use compared to cold/wet cities, and the same pattern can be seen for temperate/dry and temperate/wet. However, arid desert regions showed less seasonality than steppe (or semi-arid) regions. Figure 2b also shows the within-group spread in summer use for individual cities, demonstrating that summer use over six months (April – September) accounted for more than half of total water use in 221 cities. We next investigate whether regions with strong seasonality in water use are more responsive to weather changes.

a.)



b.)

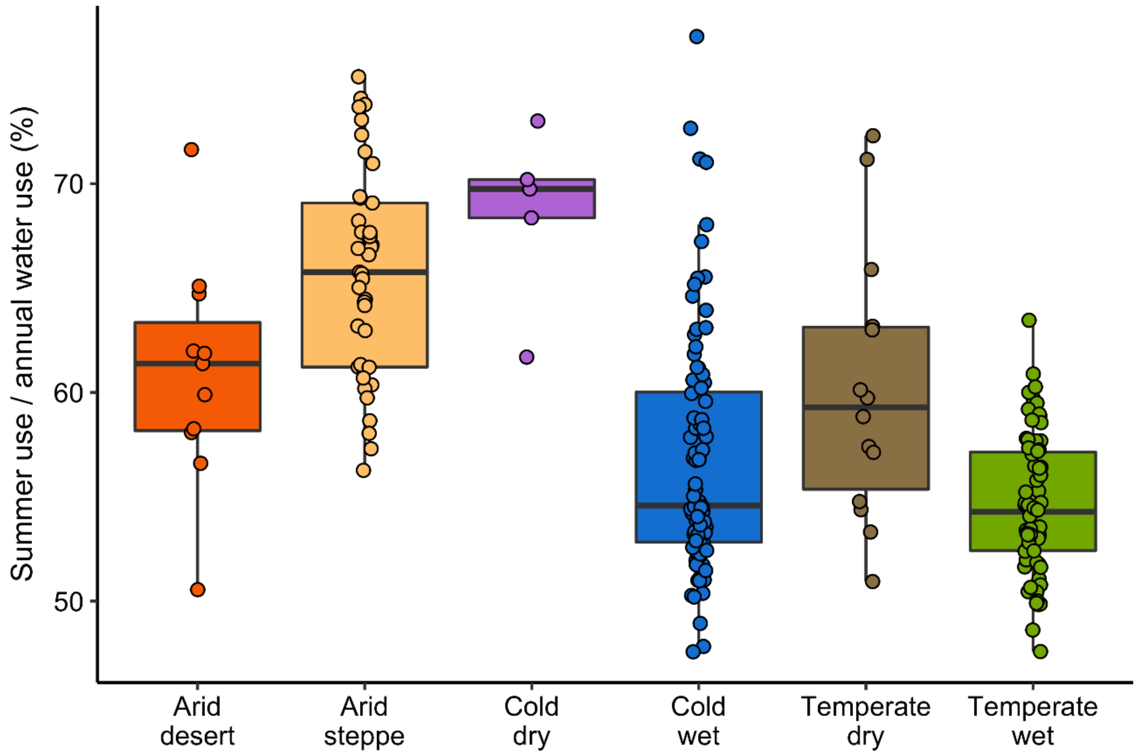


Figure 2. a.) Monthly water use as a percentage of total annual use, averaged by climate region (Table 2). To calculate the percentage of total annual use we retained the most recent records in 12-month increments. b.) Percentage of summer water use (six months of April – September) out of annual water use across climate regions, with points for individual cities.

4.2 City-level regression outputs

We analyzed model fit for city-level regressions in two ways. Figure 3 presents adjusted R^2 for each city-level model (Equation 1). Cities with adjusted R^2 greater than 85% were commonly located in the western arid and semi-arid US, which was explored further by grouping cities by climate region (Figure 4). Figure 4 summarizes the variability in adjusted R^2 across regions. Using Tukey-adjusted pairwise comparisons, the differences in mean adjusted R^2 between climate regions were significant at 5% for arid steppe and cold wet, arid steppe and temperate wet, and temperate dry and temperate wet. Median adjusted R^2 values ranged from 63 to 95% across regions, with higher values in dry climates than wet. Thirteen cities were not appropriately explained by weather according to the AIC_c selection criteria, therefore these cities are represented by negative or zero values in Figures 3 and 4. Notable differences in weather responses between dry and wet regions were used to inform climatic interaction terms used in regional-level models.

In addition to evaluating model fit, we also assessed which weather variables were most commonly chosen in regression models based on AIC_c selection (Figure 5). Maximum temperature (as linear, quadratic, or seasonal) was selected for over 80% of cities, whereas temperature differences from normal and actual ET were only selected for 17 and 22% of cities, respectively. Differences from normal precipitation (pptnorm) was the most commonly selected precipitation variable, and was included in models for 23% of cities. Precipitation represented as depth and percentage of days were included for 13 and 16% of cities, respectively.

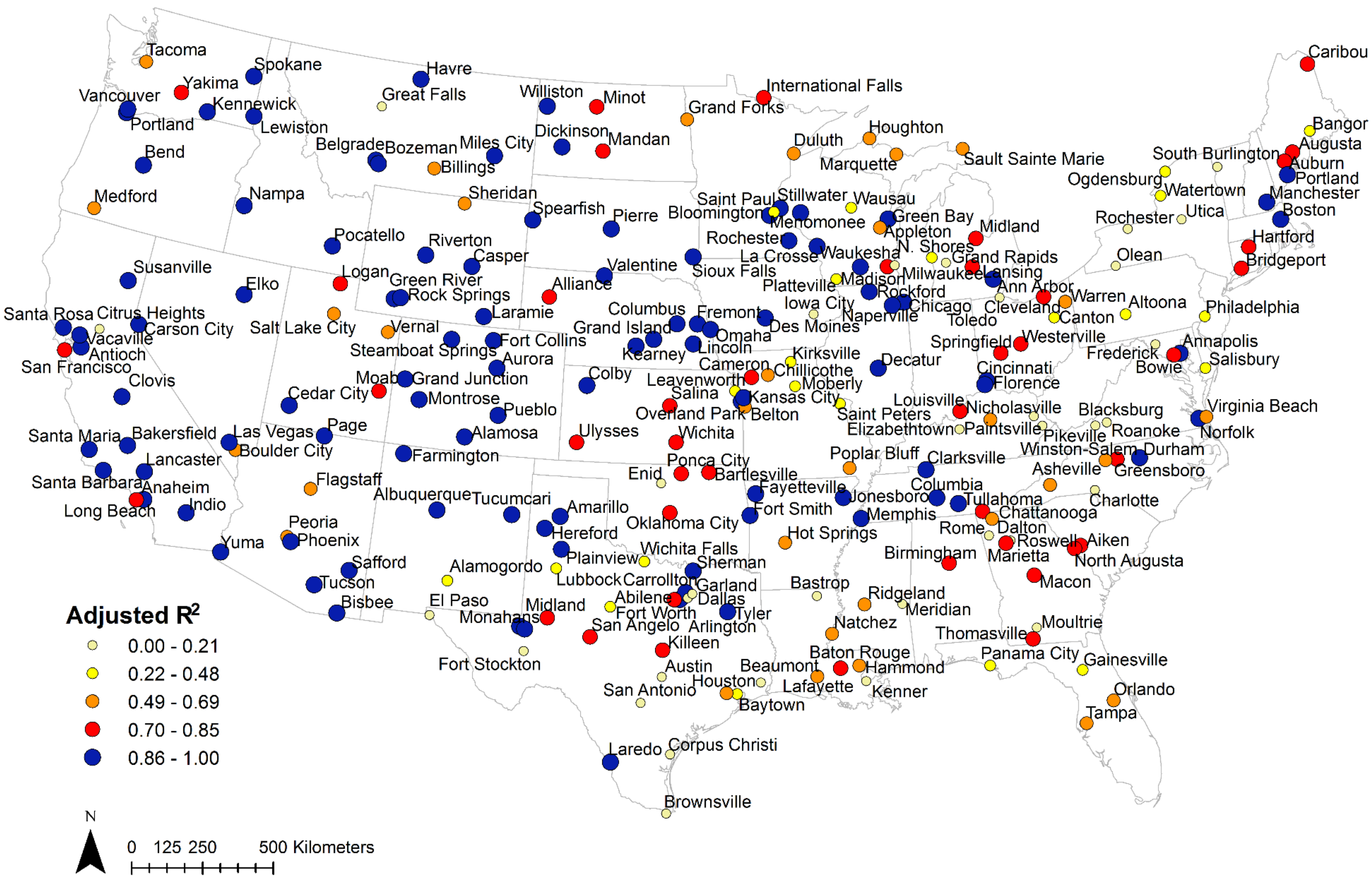


Figure 3. City-level adjusted R^2 model fit (Equation 1) across the contiguous US

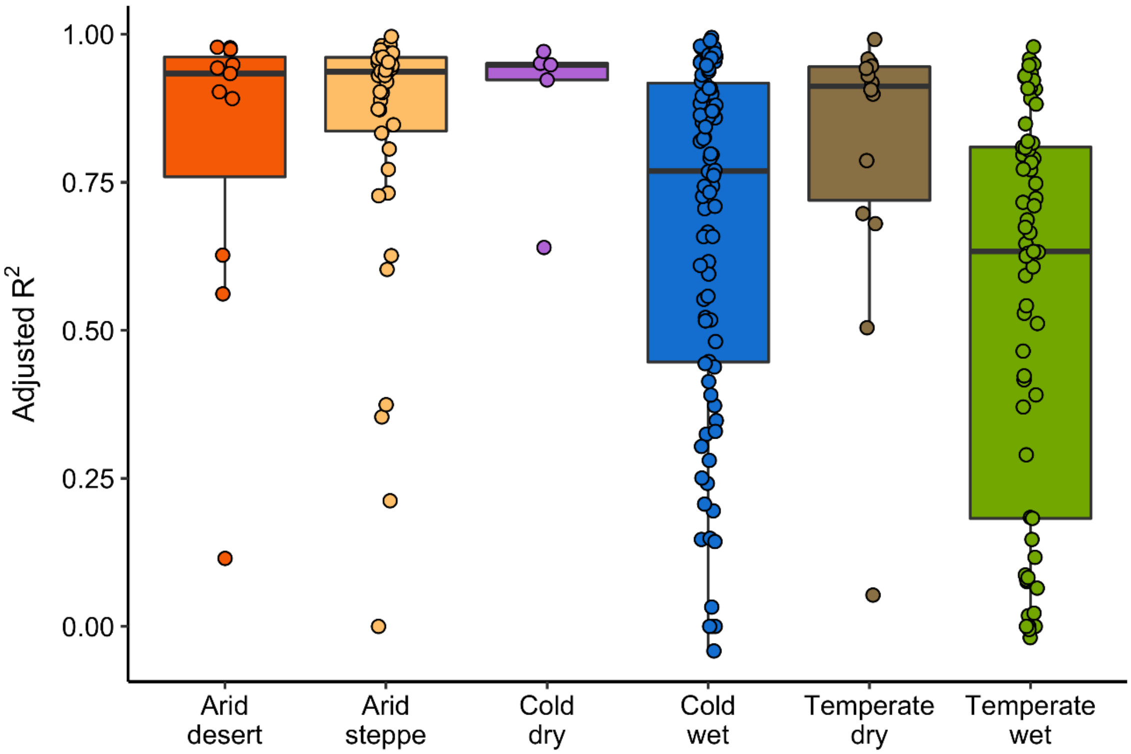


Figure 4. Adjusted R^2 across 6 climate regions, with points for individual cities.

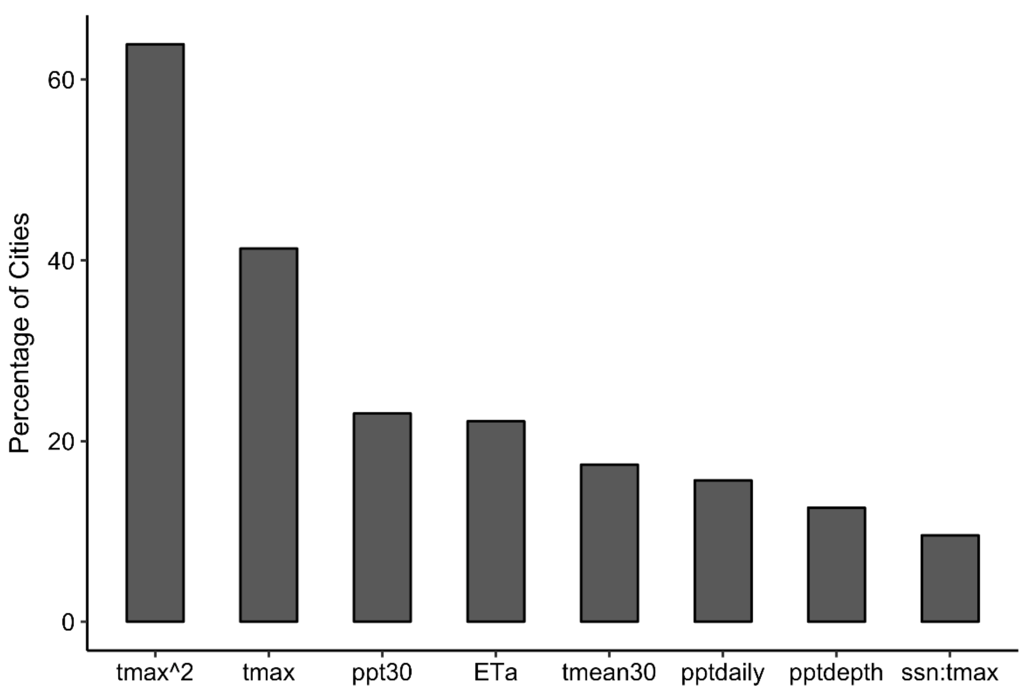


Figure 5. Percentage of cities with variable selected in city-level regression models, with ssn:tmax representing an interaction with a seasonal binary

4.3 Regional-level regression outputs

Seasonal and climatic interaction terms were found highly significant in regional-level fixed effects models based on regression hypothesis testing and ANOVA F-tests (Table 3). Interaction terms for summer/winter (Equation 2) and wet/dry (Equation 4) were found significantly different from zero at 5% based on regression outputs, and were also found significant when testing nested interaction versus non-interaction models using ANOVA F-tests. Regional interactions including six levels for climate regions (Equation 4) could only be appropriately tested using ANOVA F-tests, which showed highly significant differences in models with and without climate region interactions (F=33.83, p≈0***). These significance tests were used to inform 3-way interactions used in subsequent regional-level models.

Table 3. Coefficients for tmax, pptdepth, and differences from winter (summer:tmax and summer:pptdepth for Equation 2) or wet regions (dry:tmax, dry:pptdepth for Equation 4), standard errors, and significance tests (indicates significance at 1% and *** at 0.1%) for 2-way interaction models represented in Equations 2 and 4. The intercept is not given since it was locational, seasonally, and regionally dependent.**

Summer/winter interaction (Equation 2)		**Wet/dry interaction (Equation 4)**	
intercept	N/A	intercept	N/A
tmax	0.0159(0.011)***	tmax	0.0160(0.0007)***
pptdepth	0.0005(0.0002)***	pptdepth	-0.0002(0.0001)
summer:tmax	0.0174(0.0015)***	dry:tmax	0.0215(0.0012)***
summer:pptdepth	-0.00189(0.0002)***	dry:pptdepth	-0.0008(0.0003)**
ANOVA F-test for nested models with and without seasonal terms gives F=74.13, p≈0***		ANOVA F-test for nested models with and without regional terms gives F=156.89, p≈0***	

The results from regional regression models given by Equation 5 and 6 are summarized in Table 4, and also represented visually in Figures 5a and 5b. In the majority of cases, coefficients showed the expected patterns in terms of sign and magnitude. The coefficients for maximum temperature were in all cases positive and greater in summer months than winter months (within groups). Across six climate regions, maximum temperature had the largest coefficient value in the summer within cold dry regions, with a 1^{0} C increase corresponding to a 5.3% increase in water use. The smallest effect of maximum temperature occurred in cold wet regions during winter, with a 1^0 C increase corresponding to 0.71% increase in water use.

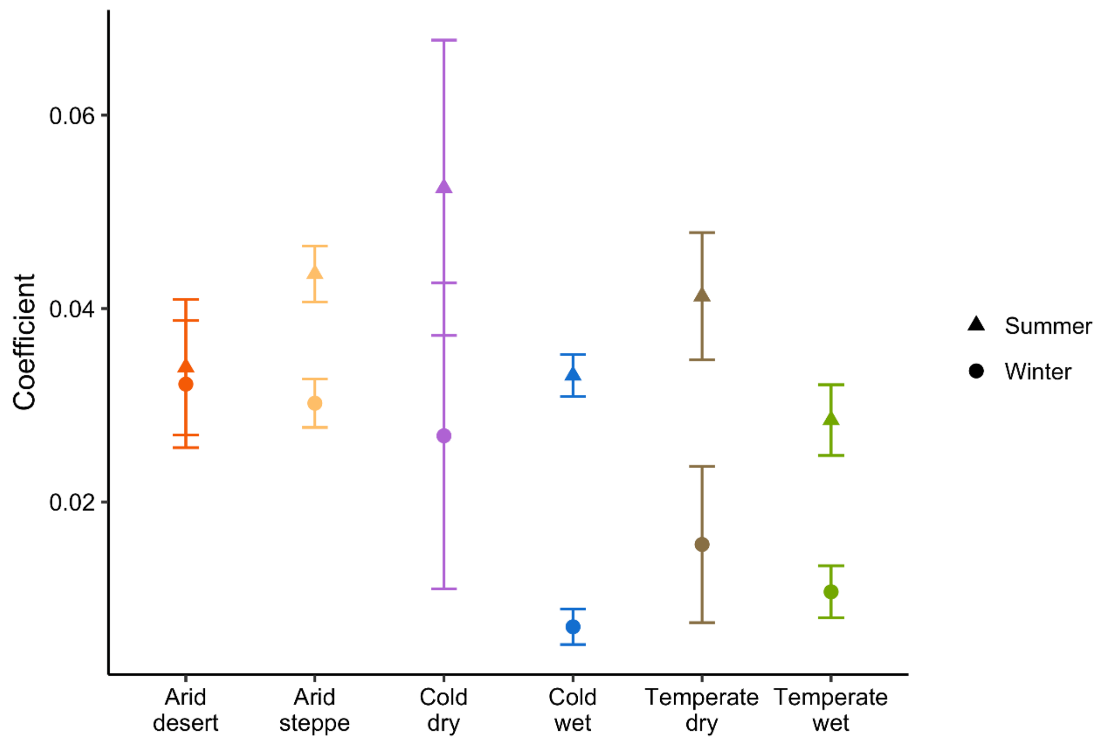
Maximum temperature responses across dry/wet regions (Equation 6) showed that average coefficients in dry regions in both summer and winter are greater than wet regions. On average in dry regions, a 1^0 C increase in maximum temperature accounted for a 3.2 and 3.9% increase in winter and summer months, respectively. Wet regions showed comparatively smaller responses to maximum temperature, with a 1.1 and 3.0% increase in winter and summer months.

Coefficients for precipitation exhibited the expected sign (negative) in the majority of cases, however, positive coefficients were observed in the winter months in cold/dry, cold/wet, and temperate/wet regions. A 1 mm increase in precipitation had the greatest effect on water use in cold dry regions (-0.33%) in the summer. Focusing on summer precipitation effects, which exhibited the expected coefficient sign in all cases, a 1 mm increase in precipitation corresponded to a 0.06 and 0.15% decrease in water use in wet versus dry regions, respectively.

Table 4. Coefficients and standard errors for regional-level regression models. Coefficients for six climate regions from Equation 5, dry/wet coefficients from Equation 6

	tmax		pptdepth	
	Summer	**Winter**	**Summer**	**Winter**
Arid desert	0.0339 (0.0070)	0.0322 (0.0066)	-0.0009 (0.0018)	-0.0021 (0.0015)
Arid steppe	0.0436 (0.0029)	0.0302 (0.0025)	-0.0016 (0.0005)	-0.0008 (0.0007)
Cold dry	0.0525 (0.0153)	0.0268 (0.0158)	-0.0033 (0.0031)	0.0012 (0.0026)
Cold wet	0.0331 (0.0022)	0.0071 (0.0018)	-0.0011 (0.0002)	0.0006 (0.0003)
Temperate dry	0.0413 (0.0066)	0.0156 (0.0081)	-0.0018 (0.0009)	-0.0008 (0.0005)
Temperate wet	0.0285 (0.0037)	0.0107 (0.0027)	-0.0002 (0.0002)	0.0005 (0.0002)
Dry	0.0388 (0.0023)	0.0319 (0.0020)	-0.0015 (0.0004)	-0.0007 (0.0003)
Wet	0.0297 (0.0018)	0.0113 (0.0013)	-0.0006 (0.0002)	0.0007 (0.0002)

a.)



b.)

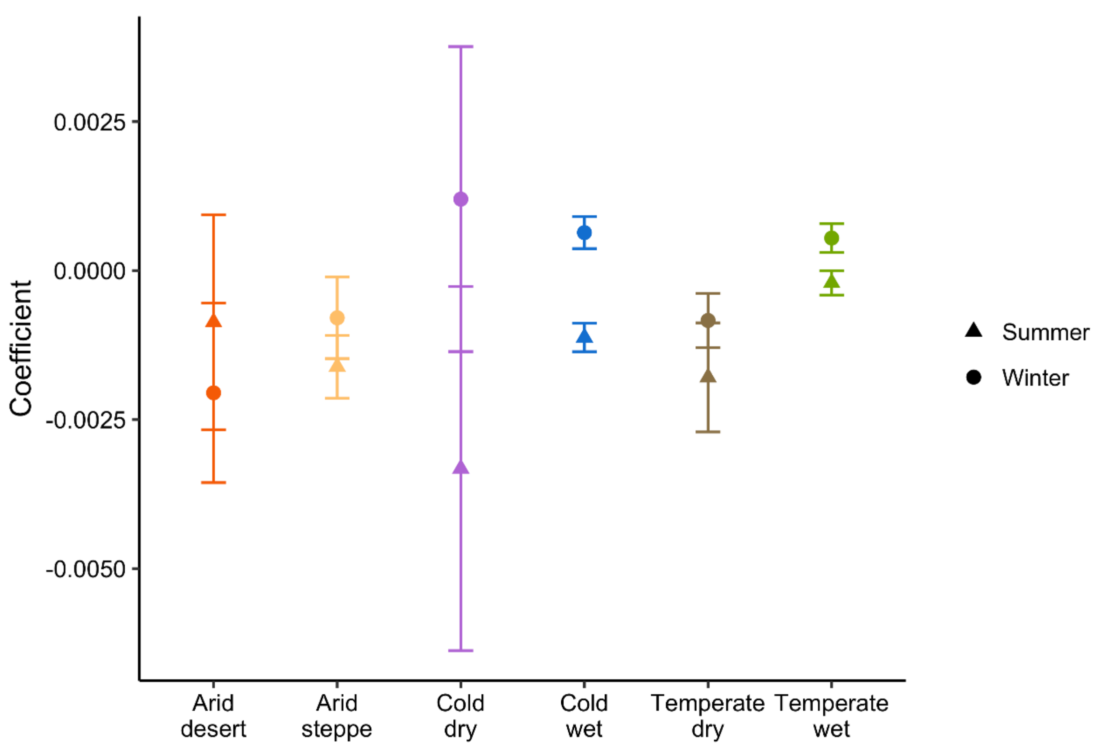


Figure 6. a.) Maximum temperature coefficients, and b) precipitation coefficients (Table 4) across six climate regions and two seasons, with bars representing standard errors

Chapter 5: Discussion

Seasonality in municipal water use is driven by withdrawals for outdoor water use and landscape irrigation. In general, dry regions of the US exhibited greater seasonality in water use (Figure 2), which is expected in areas where existing green urban landscapes would have large summertime water deficits without irrigation. We found that regions with more seasonal water use (Figure 2) also had larger responses to summertime changes in maximum temperature (Table 4; Figure 6a). The exception in relative ordering of climate regions between Figure 2b and Figure 6a is arid desert, which is discussed below. The correspondence between seasonality and water use response to maximum temperature would be expected in areas with large differences between summer and winter temperatures. Therefore, relative differences in seasonal municipal water use may be used to infer to the magnitude of water use change in response to weather changes.

Except for arid desert cities, we observed a consistent pattern in the relative ordering of climate regions in terms of water use seasonality (Figure 2b), explanatory power of weather (Figure 4), and responses to changes in maximum temperature (Table 4; Figure 6a). For cold and temperate areas, drier regions had greater seasonality and response to temperature changes. In contrast, in arid climates, steppe regions had greater seasonality (Figure 2b) and water use response to changes in temperature (Table 4) compared to arid desert regions. The regions with the lowest seasonality in water use were arid desert, cold wet, and temperate wet regions. Low seasonality in water use could be caused by either year-round irrigation, or adequate summer precipitation to support lawns without irrigation. Year-round irrigation is more likely in areas with warm winters and desert climates. Another noteworthy result within arid regions is the small difference in summer and winter responses to maximum temperature (Table 4; Figure 6a), especially for arid desert regions. The responsiveness of water use to weather all year in desert and steppe climates provides support that lack of seasonality in desert regions is likely driven by year-round irrigation, rather than absence of irrigation. To best separate outdoor use in areas of year-round irrigation, dual-metering of indoor and outdoor water use would be needed.

City-level regression models selected by AIC_c indicate the relative importance of weather variables in predicting water demand nationwide. In general, maximum temperature had the most explanatory power and was selected in over 80% of cities. Actual ET did not provide much additional explanatory power, and was often eliminated from city-level regressions due to high collinearity with temperature. Precipitation was much less important for explaining variability than temperature, which was also observed in regional-level models, where responses to precipitation were less predictable, and in several cases, exhibited an unexpected positive relationship with water use. In regional-level models, all summer precipitation coefficients were negative, with relative magnitudes (Figure 6b) that again seem to be related to seasonality (Figure 2b). Arid desert cities, however, had a negligible response to precipitation, possibly due to extremely low summer precipitation or automated sprinkler systems. Overall, the importance of temperature over other weather variables in explaining water use may be due to seasonality in temperature, suggesting that irrigators are more likely to respond to seasonal, continuous changes in temperature than stochastic, discrete precipitation events. The finding that temperature had the most substantial effect on water use is consistent with other studies using monthly data (Zapata, 2015), however, precipitation has been shown to be more important when modeling daily data (Gutzler and Nims, 2005).

In addition to determining the relative importance of weather variables, city-level regression results showed that water use was generally well-explained by weather, particularly in the western US (Figures 3 and 4), with median adjusted R^2 ranging from 63% (temperate wet) to 95% (cold dry). The lower end of this range is comparable with R^2 from other water demand studies (Anderson *et al.*, 1980; DeOreo *et al.*, 2016; Grimmond and Oke, 1986; Gutzler and Nims, 2005), and improvements in upper range values in this study may be attributed to allowing city-specific models, predictions of aggregated municipal use, and the application to many locations. Cities with low adjusted R^2 indicate areas in which urban irrigation was minimal, or irrigation occurred irrespective of weather changes. The within-region variability in adjusted R^2 between cities implies that other factors in addition to weather, such as socioeconomic, demographic, household, and landscape characteristics, have variable levels of explanatory power for water use within a climate region.

Responses to weather would be expected to be different for daily water use as compared to monthly water use as presented here. For example, lag responses to previous day's weather has been found to be important (Anderson *et al.*, 1980; Maidment and Miaou, 1986). We used total, monthly municipal deliveries to characterize weather responses driven by the residential sector, therefore, a limitation of this dataset is that monthly water deliveries were not separated by residential, commercial, and industrial uses. Deliveries in some cases also may include significant leakage that is not use. Changes in service area population and land use over the study period were not accounted for, but are assumed to be uncorrelated with stochastic weather changes. Water price was also not included due to data limitations, however, if utilities respond in similar ways in the future as in the past, our results would still be applicable.

Chapter 6: Conclusions

This study used a nationwide approach to characterize municipal water use drivers at both city- and regional-level scales. Using monthly municipal water deliveries, temperature, precipitation, and ET, we demonstrated that variability in water use was generally better explained by weather in dry regions of the western US. In addition, we estimated average responses to weather across seasons and climate regions, concluding that water use changes to weather are typically higher in summer months in dry climates. Noteworthy conclusions from this study are as follows:

1. Seasonality in water use across climate regions was generally related to summertime changes in temperature. Climate regions with increased summer withdrawals (Figure 2), which can be mainly attributed to landscape irrigation, had greater changes in water use in response to summer changes in monthly maximum temperature (Table 4; Figure 6a).
2. Weather variables alone (temperature, precipitation, and ET) explained most of the variation in monthly municipal water use across the US, with median adjusted R^2 ranging from 63% (temperate wet) to 95% (cold dry) (Figure 4). Adjusted R^2 was generally higher in dry climates than wet, indicating that weather was more predictive of water use in areas that irrigate to reduce water deficit under high temperatures and low precipitation.
3. City-level regression models suggest that maximum temperature was highly predictive of water use compared to other weather variables (selected in models for over 80% of cities). Actual ET and precipitation variables were much less explanatory in comparison, with each included in less than ¼ of city-level models (Table 5).
4. The response to temperature and precipitation variations was found to significantly change across seasons and climate regions of the US (Table 3).
5. Across all climate regions, water use increased with maximum temperature. Furthermore, water use responses to maximum temperature increased in the summer months, and were greater in dry climates compared to wet (Table 4; Figure 6a). On average in dry regions, a 1^{0}C increase in

maximum temperature accounted for a 3.2 and 3.9% increase in water use in winter and summer months, respectively. Comparatively in wet regions, a 1^{0}C increase corresponded to a 1.1 and 3.0% increase in water use in winter and summer months, respectively.

6. Water use responses to precipitation were less predictable, especially in winter where increases in water use was sometimes observed with increased precipitation (Table 4; Figure 6b). Summer responses to precipitation exhibited the expected sign in all but one region (arid desert), with a 1 mm increase in precipitation corresponding to a 0.06 to 0.15% decrease in summertime water use in wet and dry regions, respectively (Table 4).
7. Arid regions of the US were found to be distinct from others in a few ways. First, arid desert regions exhibited less water use seasonality than steppe (semi-arid) regions (Figure 2), and second, desert and steppe regions showed the smallest differences in summer and winter water use responses to maximum temperature (Figure 6a). Both of these results indicate arid regions have cities where irrigation is occurring year-round and therefore have similar responses to weather in both seasons.

While management efforts have previously focused on predicting and securing municipal water supplies, the effects of climate change and population growth require a better understanding of urban water use drivers to inform conservation efforts. Results from this study can be used to inform management decisions on water use variation with weather and initial coefficient estimates when more detailed models are not available. Future work in modeling urban water demand could be improved by incorporating more recent datasets covering drought and normal periods, including variables in addition to weather, and separating indoor vs. outdoor use quantities for a subset of locations. Using weather to describe water use variability and response differences in city-and regional-level water use habits raises additional questions about water demand. For example, what other factors are contributing to variability within regions or neighboring cities? Such future work could inform regional-level water management with improved predictive capabilities for demand to complement supply predictions.

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