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Sensitivity of Urban Water Consumption to Weather and Climate Variability at Multiple Temporal Scales: The Case of Portland, Oregon

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Abstract

The sensitivity of municipal water consumption to climate and weather variability is investigated for Portland's water provider service area between 1960 and 2013. The relationship between detrended seasonal urban water use (the difference between total water use and base use) and weather and climate variables (precipitation, maximum temperature) is examined at daily, monthly, and seasonal scales using stepwise multiple regression and autoregressive integrated moving average (ARIMA) models. At a seasonal and a monthly timescales, interannual variation in maximum temperature is the most important predictor of seasonal water consumption per capita, explaining up to 48% of the variation in seasonal monthly water consumption in June and July. At a daily scale, one-day lagged seasonal water demand and maximum temperature are the variables that are significant in all the daily models. Together with day of the week and precipitation, these variables explained up to 87 % of the variation in seasonal daily water consumption in summer. ARIMA models that take into account temporal autocorrelation explain between 70 and 81% of daily seasonal water consumption in summer months. This study provides useful climate information to urban water resource managers for seasonal water consumption forecasting at multiple temporal scales. Our results demonstrate the sensitivity of seasonal urban water consumption to climate variables as the scale of analysis changes. Urban water managers can use such information to establish proactive seasonal water resource management plans under increasing pressure from potential climate change, as understanding of the climatic sensitivity of seasonal water consumption is necessary for responding to changes.

Keywords

water consumption, weather and climate variability, urban, scale, Portland

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1. INTRODUCTION

Municipal water use has progressively become a greater concern to urban water resource managers as concern over climate variability and change is growing and urban areas have expanded in many parts of the world during the 20th and early 21st centuries. The recent Intergovernmental Panel on Climate Change (IPCC) report also projected an increase in temperature and spatial and temporal variability of precipitation, which may increase water demand but reduce seasonal water supply (Cineros et al. 2014). Although many North American cities have recently implemented conservation measures and consequently seen reductions in water consumption per capita (Gleick 2003), growing municipalities located in arid or semi-arid regions or areas prone to drought are increasingly apprehensive about the sustainability of their water resources (Gleick 2009; Gober 2013; Kenney et al. 2008; Morehouse et al. 2002; Shvarster et al. 1993). Even for cities located in relatively humid temperate climates, such as the Pacific Northwest of North America, potential seasonal changes in runoff due to climate change are posing another stress in the sustainability of water resources (Chang and Jung 2010; Chang et al. 2013; Graves and Chang 2007; VanRheenen et al. 2003). Now, with more attention being paid to how climate change could affect water availability at the local and regional scale (Ellis et al. 2007), there has been a rising focus on the impact of climate on residential water consumption (Parker and Wilby 2013) (see Table 1).

Water use research has long established consumption's positive relationship with temperature and inverse relationship with precipitation (House-Peters and Chang 2011a), but few previous studies have examined how the temporal scale of analysis affects these relations. However, some studies have found that the relation between seasonal consumption and climate can be complex. "Seasonal" water use refers to the mostly outdoor summer water use that is dependent on climate and, together with the climatically-insensitive base use, makes up the total water use. Maidment and Miaou (1986) found that daily base use is sensitive to days of the week and that daily seasonal use exhibits a relation to certain climate thresholds, meaning that there are particular daily maximum temperatures at which water use exhibits a step change. Below these thresholds, however, water use and temperature may exhibit linear relations. They divided water use into base use, defined as primarily indoor use independent of the influence of climate, and seasonal use, which is climate dependant. Seasonal use is calculated by subtracting the base use, often estimated by using the average water use for the lowest-use month, from the total use (Gato 2007a).

Seasonal water use has not been investigated at multiple temporal scales for a single location. Most previous studies have focused on either daily seasonal use (e.g., Maidment and Miaou 1986; Praskievicz and Chang 2009; Wong et al. 2010) or monthly seasonal use only (e.g., Martínez-Espiñeira 2002; Polebitski et al. 2010). Water consumption research is typically constrained by a lack of detailed long-term data to draw from. Many previous studies typically used only a few years of data (Bárdossy et al. 2009; Ghiassi et al. 2008; Zhou et al. 2002), not fully taking into account interannual climate variability. This limits the utility of developed models for forecasting future water demand. However, this study acquired a rich dataset of 54 years of daily water data to analyze, which is not available for many locations.

Table 1. Previous studies modeling municipal water use.

Study/Region	Dependent variable	Independent variables	Model(s)	Results
Maidment and Miaou (1986) Florida, Pennyslvania, Texas (humid)	Daily seasonal use	Tmax, prcp, price, income	A physics-type Transfer function	Model explains up to 99% of variance; Response to rainfall depended on frequency and magnitude A non-linear response of water use to temperature changes
Billings and Agthe (1998) Arizona (arid)	Monthly total household water demand	Tmean, prcp, water price, block rate subsidy, per capita income	State-space, multiple regression	Model error ranged from 7.4-14.8% for multiple regression and 3.6-13.1% for state-space
Morehouse et al. (2002) Arizona (arid)	Winter supply reliability	Precipitation, drought severity	Water budgets	Existing institutions could safeguard supply for a drought of five years' length, but not ten years
Martínez-Espiñeira (2002) Spain (semi-arid)	Average monthly water consumption	Temperature, population density, household size, water &sewer bill, income, marginal price, population, prcp, percentage of housing as main residence dweling tourism index, Nordin-difference.	Instrumental variable models	Significant difference in summer-only elasticities and major impact of climatic variables on monthly consumption.
Campbell et al. (2004) Arizona (arid)	Monthly total household water demand	Price, rules, engineering devices, education, conservation programs, ET, precipitation age/ethicity/income/ education/ethic/ household size, #baths, house value and age, landscape irrigation	Multiple regression	Appropriate regulation and pricing can be effective in managing water demand
Gutzler and Nims (2005) New Mexico (arid)	Daily summer residential demand	Tmax, prcp	Multiple regression	Over 60% of variance in water demand is explained by climate variables

Balling and Gober (2007) Arizona (arid)	Per capita daily total residential demand	Tmean, prcp, mean PDSI	Multiple regression, principal components analysis	Correlations between water use and temp, ,rainfall, and drought index are 0.55, -0.69, and -0.52, respectively
Gato et al. (2007a,b) Australia (semiarid)	Daily total water demand	Tmax, prcp, day of the week	Time series analysis	Model explains up to 83% of variance
Guhathakurta and Gober (2007) Arizona (arid)	Mean June total household water use	Tmin, daily temp range, household income and size, lot size, house age, swimming pool evaporative coolers, vegetation index, percent owner-occupied homes, water source, land value	Multiple regression	1°F increase in temperature results in 290-gallon increase in water use per household
Ruth et al. (2007) New Zealand (humid)	Daily total per capita water demand	Day of the week, Tmax, prcp, # dry days, wind speed, conservation	Multiple regression	Projected climate change and population growth scenarios result in 30-40% probability of water shortages
Ghiasse et al. (2008) Southern California (semi-arid)	Monthly, weekly, daily, hourly water demand	Past 1, 2, 3 days of water use	Artificial Neural Network	Up to 99% of accuracy
Kenney et al. (2008) Colorado (semiarid)	Residential total water demand per billing period	Price, restrictions, length of billing period, outdoor and indoor rebates, water smart readers, irrigation, holidays, Tmax, prcp, household income and size, homeowner age, % homes owner-occupied, age of home, # bedrooms	Fixed effects, instrumental variables	Water use increases 2% for every 1°F rise in temperature and decreases by 4% for every inch of rain
Praskievicz and Chang (2009) Seoul, Korea (humid)	Residential seasonal water use	Tmax Wind speed	Multiple regression ARIMA	Tmax and wind speed explain between 39 and 61% of the variations in seasonal water use

Chang et al. (2010) Portland, humid temperate	Annual water use	Building size, building age, income	OLS regression; Piecewise regression; spatial regression	Size is positively related; age is negatively associated; income threshold identified
Polebitski and Palmer (2010) Seattle, humid temperate	Monthly water use	Density, building area, lot size, household size, income, price, Tmax, prcp, policy	Regression (fixed effects and random effects)	For July and August, a 10% increase in maximum average monthly temperature results in a 10% increase in water consumption; a 10% increase in cumulative monthly precipitation in early summer months results in a 2.5% decrease in total water usage
Wong et al. (2010) Hong Kong (humid-temperate)	Daily water consumption	Trend, seasonality, climate regression, day-of-the week, holiday effect, autoregression	Statistical model composed of base, seasonal, calendrical water use	Explains up to 83% variance with six factors: trend (8%), seasonality (27%), climate regression (2%), day-of-the week (17%), holiday effect (17%), autoregression (12%)
Breyer et al. (2012) Portland, OR and Phoenix, AZ	Temperature sensitivity of monthly water consumption	Housing density, impervious Surface, low vegetation, tree canopy	OLS regression Spatial regression	Temperature sensitive water use is positively related to low vegetation and negatively related to impervious surfaces
Adamowski et al. (2012) Montreal, Canada (humid)	Daily summer water demand	1, 2, 3 previous day's water use and Tmax	Multiple linear regression, nonlinear regression, autoregressive integrated moving average, ANN	Wavelet transformed neural network performed better than other models, explaining up to 90% of variation in daily water demand
Bakker et al. (2014) 6 Netherlands cities(temperate-humid)	Total daily water demand	Daily average temperature, prcp, day of the week	Adaptive heuristic model Transfer/-noisy model, Multiple linear regression	Including weather variables explain up to 11% of variations in water demand

Tmax = maximum temperature; Tmin = minimum temperature; Prcp = precipitation

To draw meaningful inferences on water consumption as it relates to weather and climate variability, multi-scale analysis is needed. Multi-scale temporal analyses allow us to project short-term and long-term water demand based on the fluctuations of climate variables, namely temperature and precipitation. Water resource managers need not only seasonal climate but also daily weather information as they relate to water supply and demand, and may need to identify the most important variables for short-term operational (i.e. daily, weekly) and mid- to long-term tactical or strategic (i.e. monthly, seasonal, yearly) planning (Adamowski 2008; Admowski et al. 2013; Aly and Wanakule 2004; Rufenacht and Gubentif 1997; Steinemann 2006).

As shown in Table 1, most previous studies used diverse methods ranging from regression-based analysis to artificial neural network. While some of these sophisticated methods may provide accurate water demand forecasting, they are mathematically complex and require fine scale weather data (e.g., sub-daily). Additionally, some of these studies heavily rely on detailed socioeconomic characteristics of customers (e.g., household income, size of house, etc.) to derive the parameters of water demand model coefficients. Moreover, since water use can fluctuate day by day, using the raw water use data may not be suitable for identifying the determinants of water use at a finer temporal scale. We attempt to overcome these methodological issues by using readily available weather data and using the residuals of water use derived from the locally weighted scatterplot smoothing (LOWESS) model in constructing regression-based models (see the method section).

Here we examined the relation between urban seasonal water consumption and climate variables at daily, monthly, and summer (June to September) scales using 54 years of historical data from Portland, Oregon (OR), USA. This study is a unique investigation concerning the sensitivity of urban seasonal water consumption to climate variables as the temporal scale of analysis changes. We also generated autoregressive integrated moving average (ARIMA) models and compared their results to traditional multiple regression because previous studies show that daily water consumption is highly associated with previous day’s water consumption (Praskievicz and Chang 2009).

Urban water managers often require short-term demand forecasting as well as seasonal demand forecasting (Ghiassi et al. 2008) for establishing proactive plans under increasing pressure from climate change. Knowing which climatic variables are most deterministic at different scales is necessary for short- and long-term planning (Miller and Yates 2006; Ruth et al. 2007). While this is a case study in a temperate climate, our work adds to a growing body of literature on the relationship between climate variables and seasonal water demand, mostly currently focused on dry or semi-arid climates. Results of our study will provide a basis for future comparison of how the climate-modulated consumption varies (or is similar) across different climatic regimes, in terms of whether water use is more sensitive to temperature or precipitation or other variables.

2. WATER USE IN PORTLAND

Portland is supplied by water from reservoirs in the Bull Run Watershed. The 262 km^2 watershed is located 48 km east of downtown Portland. Mean annual precipitation is approximately 330 cm, with rain providing 90-95 % of the water in the watershed. Mean annual streamflow measured at the mouth of the basin (USGS #14140000) between 1960 and 2013 is 16.05 m^3/sec, with the lowest flow occurring in August (0.69 m^3/sec) (USGS 2014). Water from the Bull Run Watershed has flowed into Portland water taps since 1895. The Portland Water Bureau provides water resources to approximately 860,000 Oregonians in 19 of the region's 24 water providers. In FY 2011-2012, the Bureau served approximately 60% of its retail demand to both single family and multi-family residential customers. On average these single family residential houses have smaller lots with older buildings (Portland Water Bureau 2013).

As shown in Figure 1, water use per capita declined since the late 1980s as a result of various conservation programs adopted by water providers in the region. These conservation and education programs include developing wise watering schedules using local weather information and planting water-efficient native plants (Regional Water Providers Consortium 2014). However, a considerable part of reduction in consumption is due to the new building code change in 1992, which required use of water efficient fixtures. In addition, smaller lot sizes in the new developments along with increase in multifamily dwellings have reduced the amount of water required for lawn irrigation and landscaping (Breyer and Chang 2014). Although these conservation efforts have contributed to the efficient use of water in the metro area, growing municipalities are currently facing challenges obtaining scarce water resources in summer when multiple water users compete (Larson et al. 2013). According to a forecast by Metro (2009), population in the Portland-Beaverton-Vancouver areas is projected to increase from 1.9 million in 2000 to 5.6 million in 2060, based on the region's average annual growth rate of 1.8 % between 1980 and 2000. A recent study showed that most new urban development in the Portland metro area is likely to occur in the urban-rural fringe area (Hoyer and Chang 2014).

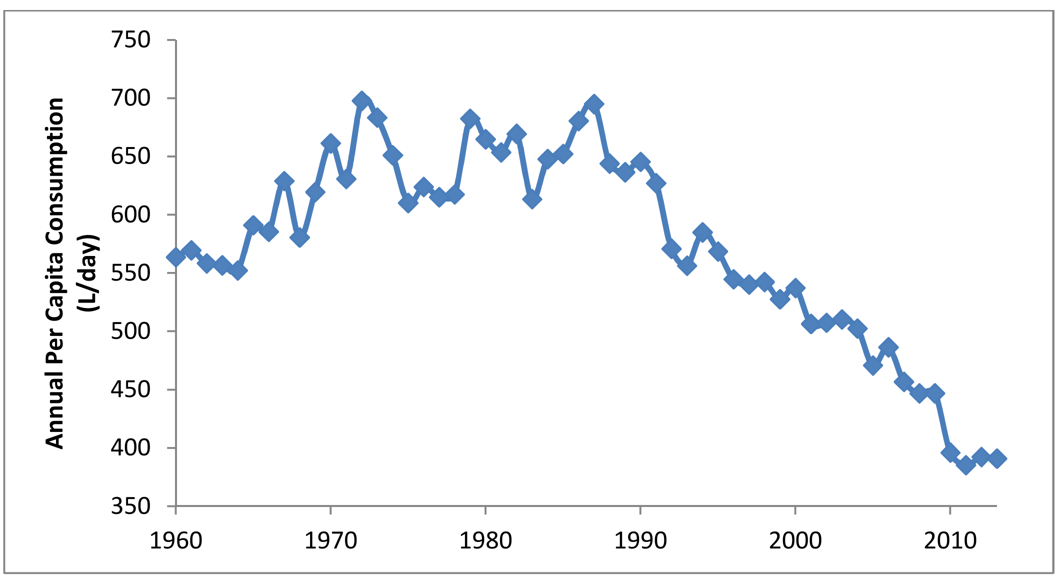

Figure 1. Annual per capita total water consumption (L day^{-1} per capita), Portland, 1960-2013

Like most urban areas, Portland's water consumption exhibits seasonal patterns (see Figure 2). During the wet, cooler period (November to April), monthly average water consumption is fairly constant and low with the lowest consumption occurring in February. During the dry warm period (May to October), monthly average water consumption is high. The average monthly water consumption of July, the peak month, is approximately 2/3 (66 %) higher than that of February. The water consumption during the summer months (from June to September) is nearly 41 % of annual water consumption. Palmer and Hahn (2002) projected that by 2040, Portland's water demand will increase by 8 % during the summer season, while the region's rivers will be experiencing historically low flows in summer. Climate-induced water consumption is projected to increase by 8 % in summer based on average monthly changes in precipitation and temperature. The Palmer and Hahn (2002) study, however, was conducted solely with monthly data and did not examine any temporal scale effects.

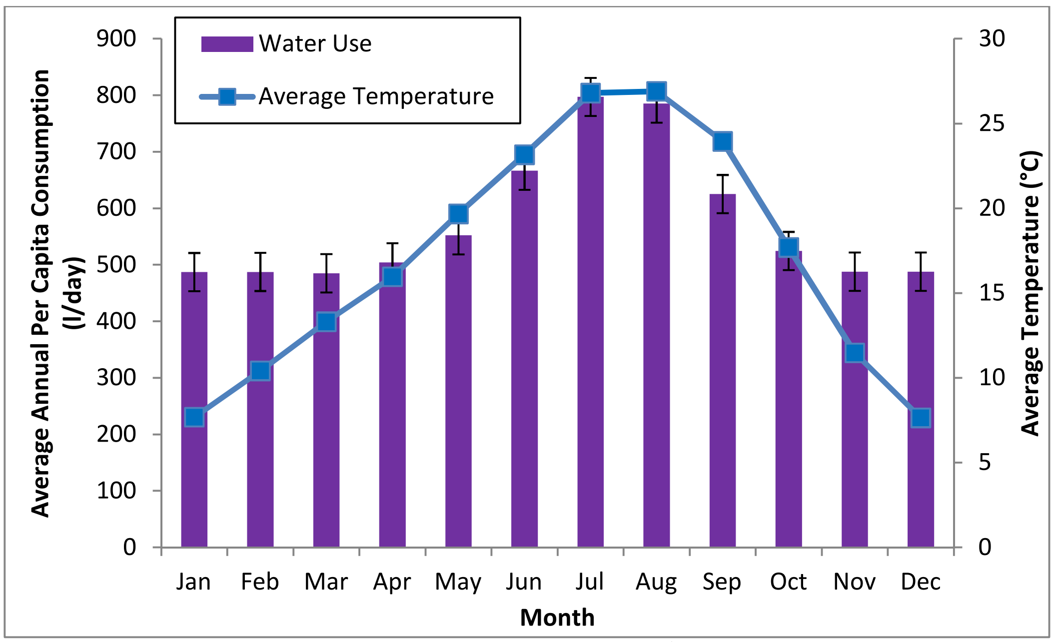

Figure 2. Distribution of monthly water consumption (L day^{-1} per capita) and average maximum temperature (°C), Portland, 1960-2013

3. DATA AND METHODS

3.1 DATASETS

Data used in this study were obtained from various sources. Water consumption and annual population data for the Portland metropolitan area between 1960 and 2013 were provided by the Portland Water Bureau. Daily precipitation and daily maximum temperature data were obtained from the National Weather Service station located at the

Portland airport (station number #356751). The water consumption values were normalized by population to obtain (1) average daily summer (June through September) consumption per capita (liters (L) day^{-1} person^{-1}) for each summer season and (2) average daily summer consumption per capita for individual summer months. Weather data – daily maximum temperature (^{o}C) and daily precipitation (mm) – were used for daily analysis. For monthly and seasonal analysis, also done only for the summer season, average maximum temperature and total precipitation were calculated for each individual summer month and season.

In order to separate the base use, the climatically-insensitive, mostly indoor water use that occurs year-round at a fairly constant rate, from climatically-sensitive mostly outdoor summer use, we determined the month with the lowest average daily water use in each water year, and subtracted that amount from the average daily use in each summer month. This difference is the seasonal use for each month, which we averaged accordingly to estimate seasonal use at the monthly and summer scales.

3.2 Statistical Analysis

Before any inferential statistical analysis, all the datasets (daily, monthly, summer) were evaluated for normality using the Kolmogorov-Smirnov one-sample test. We used the Pearson's parametric correlation coefficient and the Spearman's rho non-parametric correlation coefficient to estimate the association between seasonal per capita water consumption and each of the climate variables at the summer and monthly scale.

We developed three sets of ordinary least square (OLS) multiple regression models for each summer month (June through September), one for the summer season, one for monthly, and one for daily consumption. For the daily, monthly, and summer models, we first generated Locally Weighted Scatterplot Smoothing (LOWESS) models (Cleaveland 1979), with year of record as independent variable, to non-linearly detrend separate time-series of seasonal water use (shown in Figure 1), precipitation and temperature data (Maidment and Parzen 1984; Balling and Gober 2007). After detrending, we checked the time-series using with scatterplots and determined, based on non-significant correlation coefficients, that the distribution of each variable was random and that the association between the seasonal water use and maximum temperature residuals is approximately linear (Figure 3). The dependent variable in our final regression models was the LOWESS residual of monthly average per capita seasonal use (U_{mon}). The independent variables were the LOWESS residuals from the 1960-2013 mean monthly temperature (t) and LOWESS residuals of total monthly precipitation (p). The monthly models take the form:

$$U_{\mathrm{mon}} = b_1 t + b_2 p + \mathrm{a} \tag{1}$$

where a, b_1, and b_2 are regression coefficients, and the remaining variables are as defined above.

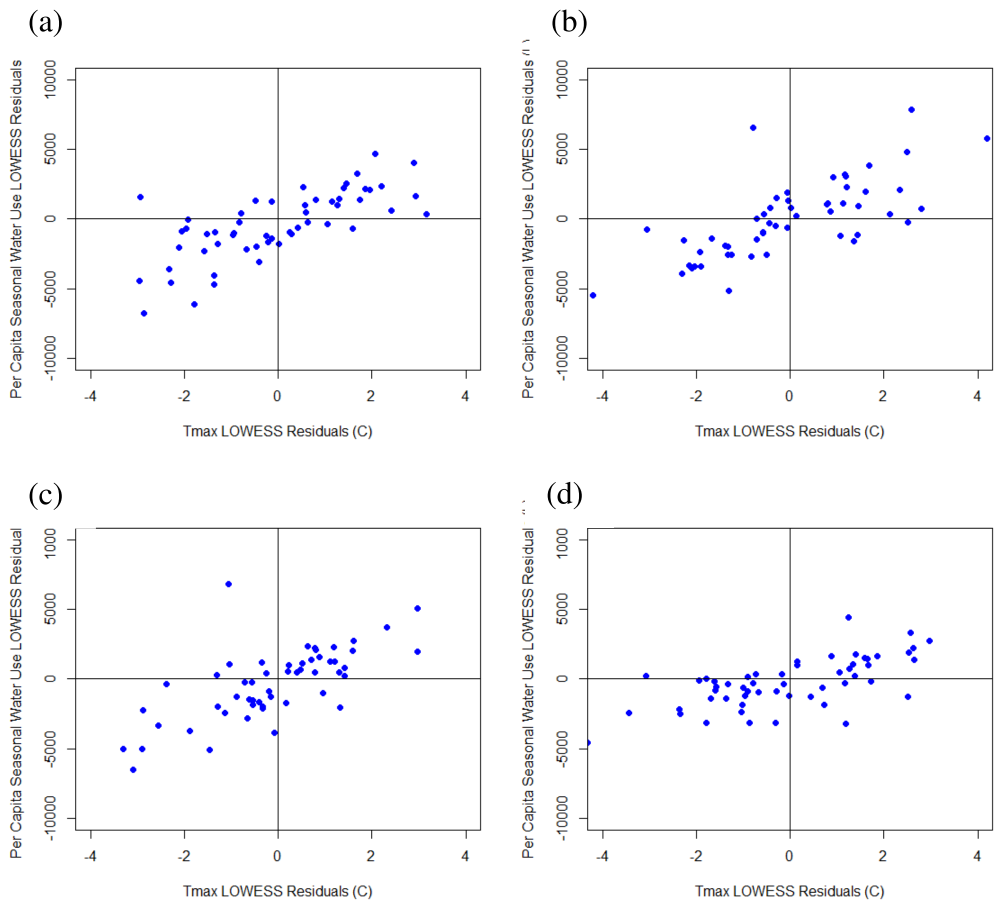

Figure 3. LOWESS residuals of maximum temperature and per capita seasonal water use for monthly data (a) June; (b) July; (c) August; (d) September

For the second set of regression models, those modeling daily use, we used only the last ten years of data (1999 to 2009), because this represents a sufficiently large sample size (at least 300 samples for each month) with relatively homogeneous climatic and socioeconomic conditions. The dependent variable was again the residual use (U_{day}), calculated from the LOWESS models. The independent variables included in the daily models were maximum temperature LOWESS residuals (t), total daily precipitation LOWESS residuals (p), and the previous day's seasonal water use LOWESS residuals (d_1) (see Figure 4). Use of this lagged variable allowed us to take into account the temporal autocorrelation of the consumption time series, as recommended by previous studies (Aly and Wanakule 2004; Gato et al. 2007a, b; Maidment and Parzen 1984; Zhou et al. 2000) and based on strong correlation coefficients between current day and previous day's demand. The final variable included in the daily models was a binary dummy variable (w) with 0 representing weekdays and 1 representing weekend days, thus allowing us to take into account within week variations in the intensity of water use, because Maidment and Miaou (1986) and Wong et al. (2010) found that such within week variations are significant for both base and seasonal use. The daily models take the form:

$$U_{\text{day}} = b_1 t + b_2 p + b_3 d_1 + b_4 w + \text{a} \tag{2}$$

where the variables are as defined above, and only statistically significant variables based on stepwise-regression method are included in the final models.

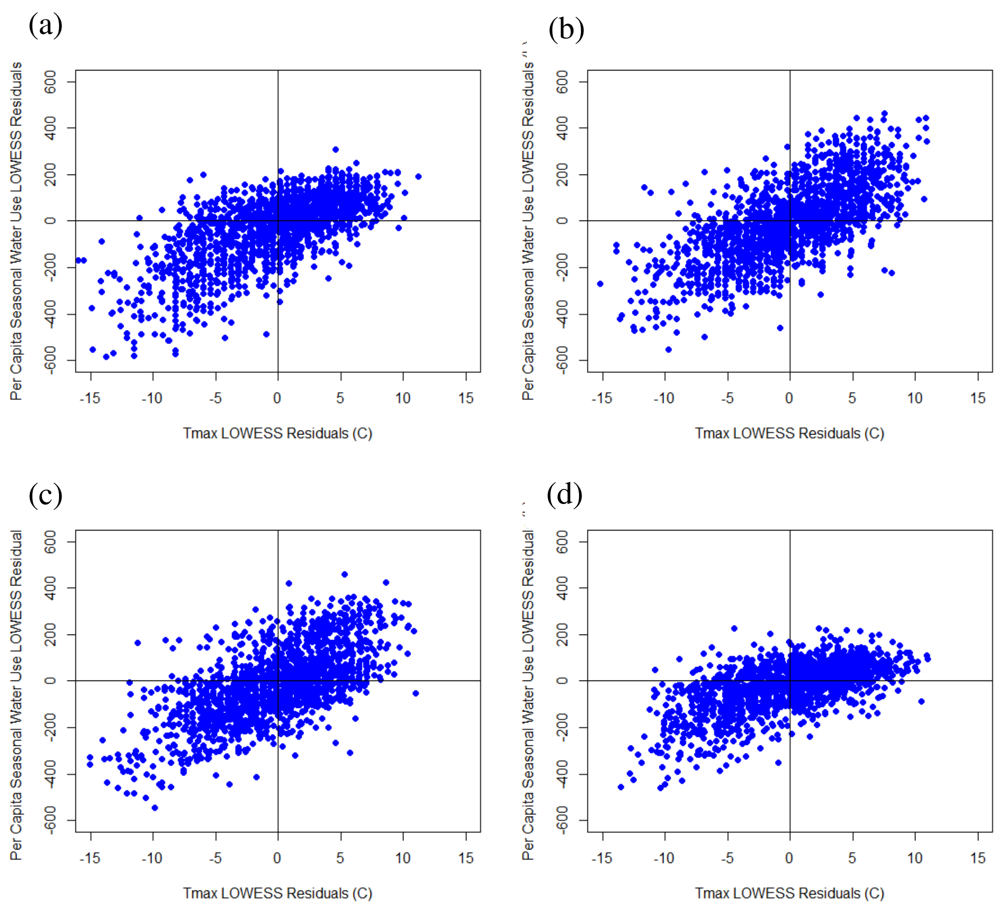

Figure 4. LOWESS residuals of maximum temperature and per capita seasonal water use for daily data (a) June; (b) July; (c) August; (d) September

In addition to ordinary least square regression (OLS) models, we also estimated an ARIMA model for daily seasonal water use in each summer month for the dependent variable, selecting with the Akaike information criterion. This allowed us to compare traditional multiple regression analysis with the time series analysis method of ARIMA, for data with significant temporal autocorrelation in the dependent variable. In the

ARIMA models, we used the raw rather than the detrended data, because it is inappropriate to apply ARIMA to detrended data. We used the freely available software R (R core team 2013). The program contains algorithms for selecting the best-fit ARIMA model for a time series using the Akaike information criterion. ARIMA models are characterized by the subscript (p,q) in which p represents the autoregressive coefficient and q represents the size of the moving average window. The general form of our ARIMA models is:

$$Y_t = \theta_p(B)Z_t + Y_{t\text{-}1} + X \tag{3}$$

where Y_t = per capita seasonal water use at time t; Z_t = parameters of the autoregressive part of the model at time t; B = lag operator; $\theta_p(B)Z_t$ = the series of the autoregressive component of order p of the time series Z_t; $Y_{t\text{-}1}$ = per capita seasonal water use at time t-1; and X = the set of all independent variables.

The coefficient of determination (r^2) was used to statistically estimate how much of the consumption was explained by the climate variables. All of the regression models satisfied an F-test for overall significance at the 5 % level.

4. RESULTS AND DISCUSSION

4.1 SUMMER SEASONAL AND MONTHLY ANALYSIS, 1960-2013

The correlation between temperature and water consumption is consistently higher than that between precipitation and water consumption. Temperature and water consumption shows slightly stronger correlation in June (r = 0.66) and August (r = 0.55) than in July (r = 0.44) and September (r = 0.50). The association between precipitation and water consumption is stronger in June (r = -0.41) and July (-0.43) than in August (-0.30) and September (-0.06). The relationship between water consumption and climate variables shows weaker correlation in summer than in individual months.

Our results are similar to other studies that found significant relations between water consumption and climate variables (namely negative relation with precipitation and positive relation with temperature) in arid-climates (Balling and Gober 2007). Balling and Gober, however, found the strongest correlations between water use and total annual precipitation (r = -0.69) in Phoenix, AZ. It appears that limited water supply is a major factor in determining water consumption in Phoenix, while evaporative demand in summer, driven by high temperatures and little precipitation, has more influence than precipitation on water consumption in Portland, OR. This finding is similar to the results of Maidment and Miaou (1986), who found that municipal water use in Pennsylvania was more sensitive to temperature than precipitation, compared to the hotter climates of Texas and Florida.

Table 2 shows the monthly model parameters for June, July, August, and September. For all individual months except for July, monthly temperature LOWESS residual is the only significant variable included in all regression models. The importance of this variable is highest at the beginning of the summer, as indicated by larger standardized

regression coefficients in June and July. As shown in the slope of regression coefficients in the regression models, the influence of monthly maximum temperature residuals on monthly water consumption is highest in June. In other words, 1°C increases in temperature residuals in June temperature would lead to an increase of 20.7 L day^{-1} per capita water consumption. While it is not as important as temperature, precipitation is also a significant predictor of monthly demand residuals in June, July, and August with the highest influence on August water consumption. In September, temperature is the only significant variable. At the summer seasonal scale, both temperature and precipitation are significant; however, together they only explain approximately a third of the variation in water consumption characteristics during the study period ($r^2 = 0.33$).
Our results are somewhat comparable to the findings of a previous study that examined the influence of monthly climate on summer months' water use in Seattle, Washington (Polebitski & Palmer 2010). Like our study, they identified temperature elasticities were higher in July than in September. With the same 10% increases in maximum average monthly temperature, July water consumption increased 10%, while September water consumption only increased 4%.

Table 2. Coefficients of stepwise linear regression models for LOWESS residuals of seasonal water consumption per capita during the summer months and summer season between 1960 and 2013. Models are derived from LOWESS residuals of average maximum temperature (*Tmax*) and total precipitation. Only significant independent variables are included in the regression model; non-significant variable contain no values in the table.

	June	July	August	September	Summer
Tmax	20.7(35.2)**	23.7(36.5)**	20.8(31.5)**	14(32.2)**	21.1(53.3)**
Precipitation	-1.2(1.5)**	-5.1(-3.5)**	-5.5(-5.3)**		-1(-1.8)*
R^2	0.48	0.48	0.43	0.39	0.33

Numbers in parenthesis are t values. ** Significant at the 0.05 level, * significant at the 0.10 level.

Our monthly scale analysis suggests that other hydroclimatic variables such as evpotranspiration or soil moisture - might explain additional variations in monthly water use since precipitation and maximum temperature only explain less than half of the variation in water use. The lower R^2 values in August and September clearly suggest that, as summer progresses, soils get dry and evaporative demand increases. Typically, one can hypothesize higher water demand as summer progresses since residents are likely to irrigate lawns more as the grass turns into yellow. However, in our study, the opposite case is observed since August and September show lower temperature elasticities. While this at first glance may be surprising, considering that an increasing number of Portland residents let their lawns turn into brown or converted their lawn grasses to water efficient native plants or simple gravel gardens that do not require any irrigation (Breyer and Chang 2014), they may have effectively reduced water demand. Breyer et al. (2012) found that census block groups that have a higher proportion of low vegetation (e.g., lawn grasses) used more water in summer, while the opposite is observed for census block groups that have a higher proportion of impervious surfaces.

Our findings illustrates that other non-climate factors should be considered in estimating urban water demand. These non-climate factors can be used as a room for possible climate adaptation. As reported in a previous study (Breyer and Chang 2014), significant water reductions since the late 1980s are attributed to the densification of lands or continuous water conservation efforts. These efforts have also reduced the temperature sensitivity, the response of summer water consumption to temperature variability. Yet, since some suburban residents still have higher temperature sensitivity than inner city residents, suburban residents can be targeted for further conservation efforts. The lowest R^2 in the seasonal analysis indicates that other non-climatic factors become even more important for seasonal water demand.

4.2 DAILY DATA ANALYSIS USING MULTIPLE REGRESSION AND ARIMA MODELING

Table 3 shows the daily model parameters for June, July, August, September, and summer. The highest model fit was found for summer (R^2 = 0.87), followed by June, July, August, and September. As shown in t-test statistical values, the most important determinants of seasonal water use at a daily timescale is one-day lagged use, followed by temperature anomaly, precipitation anomaly, and the day of the week. All variables are significant in the daily models. All variables have a positive relation with seasonal water use except precipitation (p) and day of the week (w) for the daily models, meaning wetter days and weekends are likely to have lower seasonal water use.

Table 3. Stepwise linear regression models for daily seasonal water consumption per capita (U_{day}) during the summer months and summer season between 1999 and 2009. Models are based on LOWESS-filtered time series of maximum temperature (*Tmax*), total current day precipitation (*Prcp*), and the previous one day's use (U_{day1}); and the day of the week (*w*).

	June	July	August	September	Summer
Tmax	6.1(14.3)**	6.2(14.9)**	4.6(12.0)**	4.5(11.3)**	4.3(20.0)**
Prcp	-1.3(-2.6)**	-3.9(-3.4)**	-3.8(-5.7)**	-0.8(-2.1)**	-1.5(-5.1)**
U_{day1}	0.7(30.6)**	0.7(31.7)**	0.7(31.0)**	0.6(23.5)**	0.8(100.4)**
W	-16.7(4.4)**	-17.2(4.8)**	-12.2(3.7)**	-15.5(4.3)**	-14.2(7.2)**
R^2	0.81	0.8	0.77	0.7	0.87

Numbers in parenthesis are t values.
** Significant at the 0.05 level, * significant at the 0.1 level.

Summer rainfall can cause an immediate drop in seasonal water use followed by a gradual increase until, after a period of time, there is no further effect of that particular summer rainy period on seasonal water use (Maidment and Miaou 1985). The negative relation of the day of the week dummy variable with daily seasonal water use indicates that more climate-sensitive water is used on weekdays than weekends, probably because of closed businesses on weekends. Commercial, industrial, and other nonresidential water consumption comprise of more than 40% of total water consumption in the Portland Water Bureau service area in the 2000s (PWB 2013). Since a considerable portion of water is consumed is by these nonresidential sectors, especially office buildings are closed on weekends, lower water consumption occurs on weekends. Our findings confirm the findings of earlier studies by Maidment and Miaou (1986) and Shvarster et al (1993) who reached the same conclusion for seasonal use in representative cities across continental USA. Similarly, Adamowski (2008) identified that peak demand from the previous day, maximum temperature, and the five-day rainfall occurrence were the most predictive variables for summer total peak water demand in humid temperate climate in Ottawa, Canada. In a follow-up study, Adamowski et al. (2013) found that summer urban water demand in three Canadian cities are only sensitive to daily temperature when mean daily temperature are higher than 10 to 12 °C, while also identifying a weekly cycle in urban water demand. Wong et al. (2010) also reported negative coefficients for weekend days but positive effects for weekdays when examining day-of-the-week effect in Hong Kong.

Table 4 compares the model fit of the OLS and ARIMA models that take into account temporal autocorrelation in seasonal water use for each month. The ARIMA models were based on the raw daily seasonal water use time series. All models use a one-day moving window except June, which uses a two-day window. This suggests that the memory in the seasonal water use time series is quite short. In the June model, the OLS and ARIMA fits are approximately the same. In the other months, the ARIMA model significantly improves the model fit, particularly toward the end of the summer. Other studies found similar higher predictability in ARIMA models over OLS models in water consumption, as time-series memory is more pronounced than the weather dependence in summer water use (Aly and Wanakule 2004). Our results suggest, although a significant amount of the variance in Portland's seasonal water use at various timescales is explained by temperature and precipitation variables, at the daily timescale, memory in the water use time series is more significant than climatic variation.

Table 4. Comparison of OLS and ARIMA model fit.

Month	OLS R^2	ARIMA Model	ARIMA R^2
June	0.81	(2,2)	0.81
July	0.80	(2,1)	0.84
August	0.77	(2,1)	0.86
September	0.70	(2,1)	0.80
Summer	0.87	(2,1)	0.90

In the ARIMA model, numbers in parenthesis represent the autoregressive coefficient and the size of the moving average window, respectively.

5. SUMMARY AND CONCLUSIONS

Statistical analysis of seasonal water consumption per capita for 1960-2013 shows that determining which climate and weather factors are the most influential to consumption per capita is greatly dependent on the scale of temporal aggregation. We found that the influence of maximum temperature is stronger than that of precipitation on water consumption at the monthly scale. Changes in climate from previous year's summer months and season show significant associations with water consumption. The relation between weather and climate variables and seasonal water consumption is stronger at the beginning of the summer months than the later summer months. This suggests that non-climatic variables could be significant, or that other hydroclimatic variables such as relative humidity and evaporative demand could be also potential factors that affect the variations in water consumption during later summer months. Additionally, as soil moisture depends on both precipitation and evaporation, it is important to include soil-water content as part of water demand modeling, particularly outdoor water use such as lawn irrigation and recreational activities. Changes in lawn irrigation behavior thus can also be an important factor that might influence irrigation water demand (Halper et al. 2012), although such data were not available for our study area. Our monthly analysis suggests that other landscape management factors than climate variables may explain the remaining variations in monthly water demand. This implies that, from a policy perspective, society has a window of opportunity to adapt to future climate change by manipulating existing landscapes (Gober et al. 2013). A few examples of such adaptation plans include the densification of existing urban areas (House-Peters and Chang 2011b) and planting water efficient species (Middel et al. 2011).

At a daily scale, one-day lagged seasonal water use (the previous day's water use) and temperature LOWESS residuals are the variables that are significant in all the daily seasonal use models. These variables explained 81% and 80 % of daily seasonal water consumption in June and July, respectively. Our findings suggest that seasonal daily water consumption has a memory effect (affected by previous day's water usage). If confidence in summer weather forecasts is improved, consumers could use such information for water use planning several days in advance rather than using water insensitive to weather variations. Growing conservation efforts, such as smart lawn watering programs based on soil conditions and plant needs (Regional Water Providers Consortium 2008), appear to have contributed to weather-sensitive water use. In other words, instead of constantly using an automatic timer for lawn irrigation, residents can modify water consumption in response to weather variations.

This study is unique in that it examined the role of climate variables with multiple timescales on seasonal water consumption. The regression coefficients derived from multiple regression models can be used to estimate potential water consumption rate due to changes in total precipitation and maximum temperature, although at the daily scale memory in the water use time series is more significant. This multi-scale analysis of urban water consumption illustrates different relationships between urban water consumption and climate variables depending on the scale of analysis. It demonstrates that for long-term (monthly, seasonal) planning, maximum temperature and precipitation forecasts can be of use to water managers, but in the short-term (daily), memory in the water use time series is likely to be more significant. Urban water resource managers can use such information for establishing proactive water resource management strategies under increasing pressure from potential climate variability and change, because understanding of which variables are significant is a necessary prerequisite for planning.

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