

Article

When Small Is Not Beautiful: The Unexpected Impacts of Trees and Parcel Size on Metered Water-Use in a Semi-Arid City

Shaundra Rasmussen ^{1,2,*} , Travis Warziniack ^{2,3} , Abbye Neel ⁴, Jarlath O'Neil-Dunne ⁵  and Melissa McHale ^{1,2}

¹ Department of Ecosystem Science and Sustainability, Colorado State University, Fort Collins, CO 80523, USA; melissa.mchale@colostate.edu

² Denver Urban Field Station, 240 W Prospect Rd, Fort Collins, CO 80526, USA; travis.w.warziniack@usda.gov

³ Rocky Mountain Research Station, U.S. Forest Service, Fort Collins, CO 80526, USA

⁴ Fort Collins Utilities, Fort Collins, CO 80521, USA; aneel@fcgov.com

⁵ Aiken Center, Rubenstein School of Environment and Natural Resources, University of Vermont, Burlington, VT 05405, USA; Jarlath.ONeil-Dunne@uvm.edu

* Correspondence: shaunie.rasmussen20@alumni.colostate.edu

Abstract: Colorado's water supply is under threat due to climate change pressures and population growth, however Colorado has been recognized to have some of the most progressive water conservation programs in the country. Limiting outdoor water consumption is an increasingly popular approach to conserving water in semi-arid cities, yet in order to implement effective water reduction and conservation policies, more utilities and city managers need a firm understanding of the local drivers of outdoor water consumption. This research explores the drivers of outdoor water consumption in a semi-arid, medium-sized Colorado city that is projected to undergo significant population growth. We used a combination of correlation and linear regression analyses to identify the key descriptive variables that predict greater water consumption at the household scale. Some results were specific to the development patterns of this medium-sized city, where outdoor water use increased 7% for each additional mile (1.6 km) a household was located from the historic urban center. Similarly, more expensive homes used more water as well. Surprisingly, households with a higher ratio of vegetation cover to parcel size tended toward less water consumption. This result could be because parcels that are shaded by their tree canopy require less irrigation. We discuss these results to assist city managers and policymakers in creating water-efficient landscapes and provide information that can be leveraged to increase awareness for water conservation in a growing, semi-arid city.

Keywords: water consumption; water conservation; urban landscapes; tree canopy; lifestyles; urban structure; urban ecology; semi-arid; climate change



Citation: Rasmussen, S.; Warziniack, T.; Neel, A.; O'Neil-Dunne, J.; McHale, M. When Small Is Not Beautiful: The Unexpected Impacts of Trees and Parcel Size on Metered Water-Use in a Semi-Arid City. *Remote Sens.* **2021**, *13*, 998. <https://doi.org/10.3390/rs13050998>

Academic Editor: Giovanni Battista Chirico

Received: 1 January 2021

Accepted: 26 February 2021

Published: 5 March 2021

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.



Copyright: © 2021 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

By the turn of the 20th century, Colorado began to experience a significantly warmer and drier climate compared with the early 20th century [1]. Climate change models predict temperature increases up to 4 °F by 2050, relative to the 1950–1999 baseline; these temperature increases are expected to escalate the severity of droughts and exacerbate their impacts throughout the state [2]. Precipitation patterns remain relatively uncertain in climate projections, while a reduction in snowpack and earlier snowmelt and runoff are already evident [2]. Such climatic changes pose a serious threat to Colorado's water supply, yet water demand is expected to increase as a result of imminent population growth [3]. The pressures of climate change and urbanization underscore the need for innovative and sustainable water management in Colorado cities.

One way to manage urban water supply is by increasing outdoor water efficiency [4,5]. The effectiveness of this strategy was demonstrated by the 2002 drought crisis in Colorado.

In response to the drought, the state imposed temporary water restrictions, curbing overall water consumption by 13–53% across several different municipalities [6]. However, many local water managers are now focusing on more sustainable, long-term strategies to reduce water consumption, such as xeriscape incentive programs [7,8]. Responsive and adaptive conservation efforts will require more programs and policies for water efficiency that can become a regular part of residents' lives [9]. To help estimate the effects of policy changes on residential consumption patterns, cities need to have a firm understanding of the local drivers of urban water consumption [10].

Variables that describe households, neighborhoods, and the overall urban environment can play a significant role in predicting outdoor water consumption [11,12]. In fact, studies have shown bio-physical variables describing land cover and urban structure (e.g., house density, lawn orientation, tree canopy) can impact household-level water use. However, some of these bio-physical variables are also a function of people's decisions and behaviors. Social-demographic descriptors (e.g., income, tenure) and marketing datasets that are meant to characterize lifestyle preferences (e.g., conservation motives, purchasing preferences) can play a role either directly on water use or indirectly through landscape preferences.

To date, many studies have found inconsistent results in the relative importance of bio-physical variables and social-demographic characteristics when trying to understand water consumption. Some of these differences in results could be a function of both scale and resolution of the data and analyses. For instance, some social-demographic data are only available at the scale of a neighborhood, or what the US Census Bureau defines as a "Block Group" [13]. Neighborhood or block group level data can be subsidized with other household level explanatory variables of social-demographic characteristics, like housing prices, yet these data are not entirely indicative of household socio-economic status either. On the other hand, because of advances in remote sensing techniques, scientists often have access to very high-resolution land cover data for cities (e.g., imagery with sub-meter resolution) so that it is possible to distinguish between different vegetation types, and map every single tree around each residence; therefore, the bio-physical data can be analyzed at high resolution across multiple scales, from the entire city, to one or more neighborhoods, to a single individual parcel surrounding one home.

Due in part to the availability of fine-resolution data on urban structure and form, many studies have shown that bio-physical variables are important predictors of water consumption. Most of these findings indicate that parcel size, the presence of swimming pools, home age, and building size are important variables, but the direction and degree of these relationships differ across studies [14–16]. For example, Stoker and Rothfeder [14] found newer homes use more water in Salt Lake City, Utah, while Chang et al. [16] found that older homes use more water in Portland, Oregon. Further, Sanchez et al. [17] found that while spatial patterns of structural development drive water consumption in North Carolina, they also noted that the bio-physical landscape was a key component in understanding consumption patterns.

In particular, tree canopy cover is a widely studied bio-physical characteristic of cities, and there has been a lot of interest in the relationship between tree cover and water consumption in the context of residential landscaping preferences [8,18]. While urban trees are associated with several ecological, physical, and social benefits, these benefits may be offset by their potential cost in water consumption, especially in arid or semi-arid landscapes where water is already scarce [19]. If trees are associated with more water consumption in arid and semi-arid urban landscapes, cities may want to consider promoting alternative, water-efficient residential landscapes; however, the studies on residential landscaping and its impacts on outdoor water consumption are also inconclusive. For instance, Olmost and Loge [20] studied landscaping techniques in Davis, California, and found that increasing the cover of drought-tolerant grass could reduce water use by up to 40%. Alternatively, Wentz and Gober [10] found that xeric landscaping in Phoenix, Arizona did not explain as many residential consumption patterns as they expected, concluding that residents may not

be adjusting their water practices to coincide with different seasonal water requirements of their new water-efficient landscapes.

Wentz and Gober's [10] findings exemplify the complex interplay between urban characteristics, residents' behaviors, and their impact on water consumption. Despite testing for the effects of the bio-physical landscape, they found social and lifestyle watering practices to significantly affect their results. Many studies have further investigated the role of social characteristics on water consumption, and often they find similar trends. One common trend is that households of higher socio-economic status use more water to maintain lawns, gardens, swimming pools, and other water features [11,12,21]. Additionally, homeowners tend to use more water than renters [21]. The age of household members and household size can also influence water consumption due to differing daily household choices, including the fact that, families with young children or teenagers may be more likely to install swimming pools [22].

Some of these household-level decisions are influenced by lifestyle choices. Lifestyles are a more complex facet of social characteristics, encompassing attitudes, opinions, values, feelings, intentions, and habits [23]. Jorgensen et al. [21] found that consumer conservation motives were highly impacted by perceptions of how other people behaved, indicating social norms and "trust in others" play a significant role in conservation behavior. Bollinger et al. [24] analyzed peer effects on water conservation in Phoenix and found that households are more likely to switch to water-efficient landscapes if their peers do the same, supporting the notion that the perception of others' behavior may be important for understanding water consumption patterns.

It is indisputable that a wide range of variables influence water consumption, as identified by previous studies. The complex nature of these studies suggests that trends in outdoor water consumption will be dependent on the study region as well as the unique bio-physical, social-demographic and resident lifestyle characteristics exhibited by households in that city. Furthermore, many of the studies investigating water consumption drivers have been conducted in highly developed urban systems such as Phoenix, Arizona [25] and Los Angeles, California [26]. Few studies have investigated water consumption drivers in growing, semi-arid cities where increased population is expected to exert substantial stress on local water supplies [27], and where there is the opportunity to improve water efficiency and literacy in the local community during the urbanization process. To better understand the drivers of water consumption and compare across cities, scientists must analyze more cities of different sizes and development stages.

Our study adds to the scientific literature by investigating the relationships between single-family households and outdoor water consumption in a growing, semi-arid Colorado city, hereafter known as the "City". The objectives of this study were to (1) determine which bio-physical, urban structural, social-demographic and lifestyle variables may be driving outdoor water consumption and compare their importance; and (2) discern relationships between vegetation type (trees vs. herbaceous cover) and outdoor water consumption at a single-family residential parcel scale. We expected water consumption in this City to be predominantly driven by bio-physical characteristics, as it is a water-limited landscape that is sensitive to vegetation preferences. Specifically, we hypothesized that the presence of trees would decrease outdoor consumption due to tree shading and evaporative cooling effects, whereas herbaceous cover would increase consumption because people tend to prefer, and therefore water, green and thriving grass. We then discuss our results in context of planning and policy for municipalities and local government.

2. Materials and Methods

2.1. Study Area

This growing city in northern Colorado is a vibrant community transitioning from a large, suburban town to a small urban city [28]. Currently, the population is 174,871 [29], but it is expected to experience significant population growth and development in the coming decades. Located at the base of the Rocky Mountains of the northern Front Range, it

lies approximately 5000 ft (1524 m) above sea level. It sits about an hour north of Denver via a major interstate (I-25), and 40 min northeast of Boulder. The region is semi-arid, receiving an average of about 14.44 in (36.68 cm) of precipitation per year from 2016–2019 [30]. The area is primarily dominated by grassland east of the foothills, but the City itself contains an extensive urban forest. Near the north-central part of the City is a historic urban center comprised of natural open spaces, tourist attractions, restaurants, and retail and novelty shops. This historic center regularly attracts many residents and tourists alike [31] and serves as an important place for the community in the City.

The local municipality also prioritizes the well-being of the community through proactive and informed urban planning. For decades, the municipal water utility has promoted innovative water policies that focus on conservation and efficiency. Recognizing local population growth, the municipal water utility seeks to develop and promote water-efficient landscapes that will support long-term water availability for all residents, reflect its semi-arid climate, and encourage greater integration of water efficiency into land use planning and building codes [32]. To encourage sustainable living at the personal and community level, this City hopes to leverage metered water use data to communicate better and increase awareness of consumption and to help promote water literacy in the community.

Due to the preferences of the local utility, we performed this analysis using English units; however, we have added metric conversions in parentheses.

2.2. Water Consumption Data

Metered household-level water consumption data were provided by the local municipality. In the original dataset, all households had different billing dates, resulting in billed monthly consumption data that did not align with the calendar months. To make all the household level data comparable, we standardized water use according to the calendar month (Table 1).

Table 1. Average monthly consumption across all single-family parcels in total gallons (liters) and gallons per day (liters per day), provided by the utilities department in a semi-arid city in Northern Colorado.

Time Period	Total Gallons (L)	Gallons/Day (L/Day)
January	3983.36 (15,078.66)	128.50 (486.43)
February	3724.79 (14,099.86)	128.44 (486.20)
March	4088.88 (15,478.09)	131.90 (499.30)
April	4314.89 (16,333.64)	143.83 (544.46)
May	6968.23 (26,377.62)	224.78 (850.88)
June	13,211.25 (50,010.02)	440.38 (1667.02)
July	16,032.09 (60,688.06)	517.16 (1957.66)
August	14,151.63 (53,569.75)	456.50 (1728.04)
September	11,229.00 (42,506.39)	374.30 (1416.88)
October	7108.23 (26,907.58)	229.30 (867.99)
November	4461.60 (16,888.99)	148.72 (562.97)
December	4177.59 (15,813.90)	134.76 (510.12)

Once we had corrected the metered water use for each calendar month, we isolated outdoor water use, as our primary goal was to identify the characteristics that may explain outdoor irrigation. To distinguish between indoor and outdoor use, we used the following formulas:

$$C_s = \text{Jun}_T + \text{Jul}_T + \text{Aug}_T \quad (1)$$

$$C_w = \text{Dec}_T + \text{Jan}_T + \text{Feb}_T \quad (2)$$

$$C_o = C_s - C_w \quad (3)$$

where C_s refers to total summer consumption (indoor and outdoor), C_w refers to winter consumption (indoor) and C_o is the resulting summer outdoor consumption. Jun_T , Jul_T , and Aug_T denote the total gallons/liters used in June, July and August, while Dec_T , Jan_T , and Feb_T denote the total gallons/liters used in December, January and February. C_w represents indoor consumption because we assumed that no one waters outdoor landscapes in Colorado during the winter months. Across all households, the average winter indoor use was approximately 4000 gallons (15,000 L)/month (Figure 1) and the average summer use was approximately 14,000 gallons (53,000 L)/month.

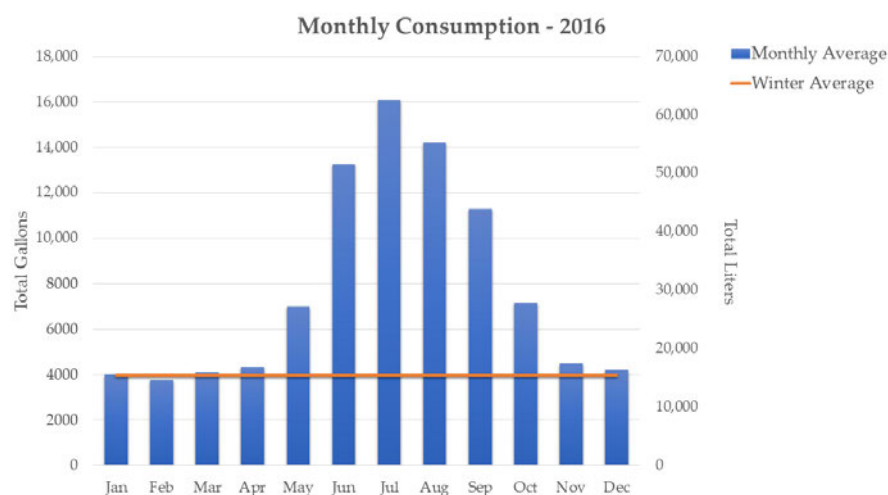


Figure 1. Metered water consumption. Blue bars represent the average household monthly consumption trends (total gallons/liters) across all single-family parcels, while the orange line represents winter monthly average.

2.3. Response Variable

Given that the size of each parcel can directly influence the amount of water needed during the summer season, we normalized outdoor water use by the amount of available irrigatable space within each parcel. We assumed that people are not intentionally watering impervious surfaces, such as driveways or patios, but rather they are only watering the pervious area within the parcel boundary (e.g., lawns, trees).

We used high-resolution raster land cover data (1 m²), derived from a combination of WorldView-2 satellite imagery and LiDAR using object-based feature extraction techniques [33,34] to distinguish irrigatable space from non-irrigatable space. This land cover dataset consisted of seven classes: trees, herbaceous vegetation, bare soil, water, buildings, roads and railroads, and “other” paved surface cover (e.g., driveways, parking lots, sidewalks, etc.) (Figure 2). The overall accuracy of the land cover dataset was calculated to be 95% based on a hybrid stratified-random accuracy assessment using 2400 points [35]. We used the ArcGIS Pro (Version 2.5.1) Erase tool to remove buildings and other paved surfaces from each parcel, leaving only the area of irrigatable space (Figure 3).

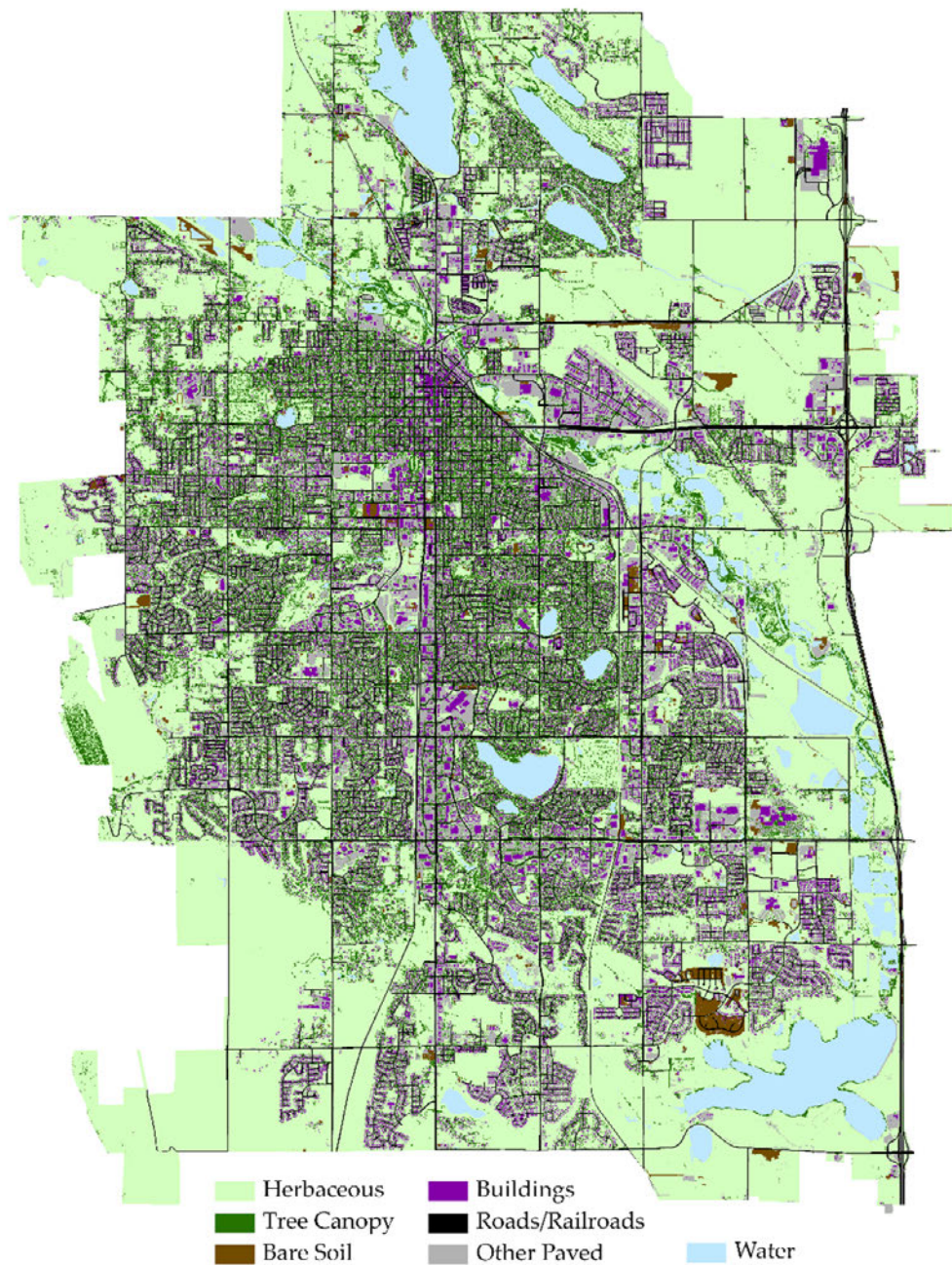


Figure 2. Land cover classes (1 m²).

Our final response variable was calculated by taking summer water use (total gallons) and dividing it by the amount of irrigatable space (ft²) on each parcel, resulting in summer water use that ranged from approximately 0–218 gallons/ft² (0–8883 L/m²) (Figure 4). Since the response was heavily skewed, we performed a log-transformation to meet normality assumptions for analysis.

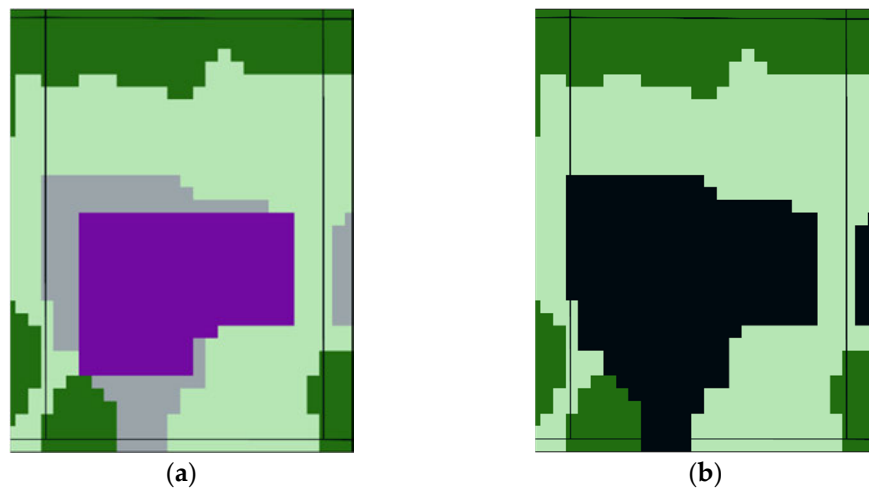


Figure 3. The process of removing impervious cover from parcels: (a) displays all land cover within the parcel, with purple representing the house and gray representing other impervious cover (e.g., driveway, patio). The pervious cover within the parcel is divided into tree cover (dark green) and herbaceous cover (light green); (b) represents the parcel after erasing the impervious cover, leaving only the irrigatable space.

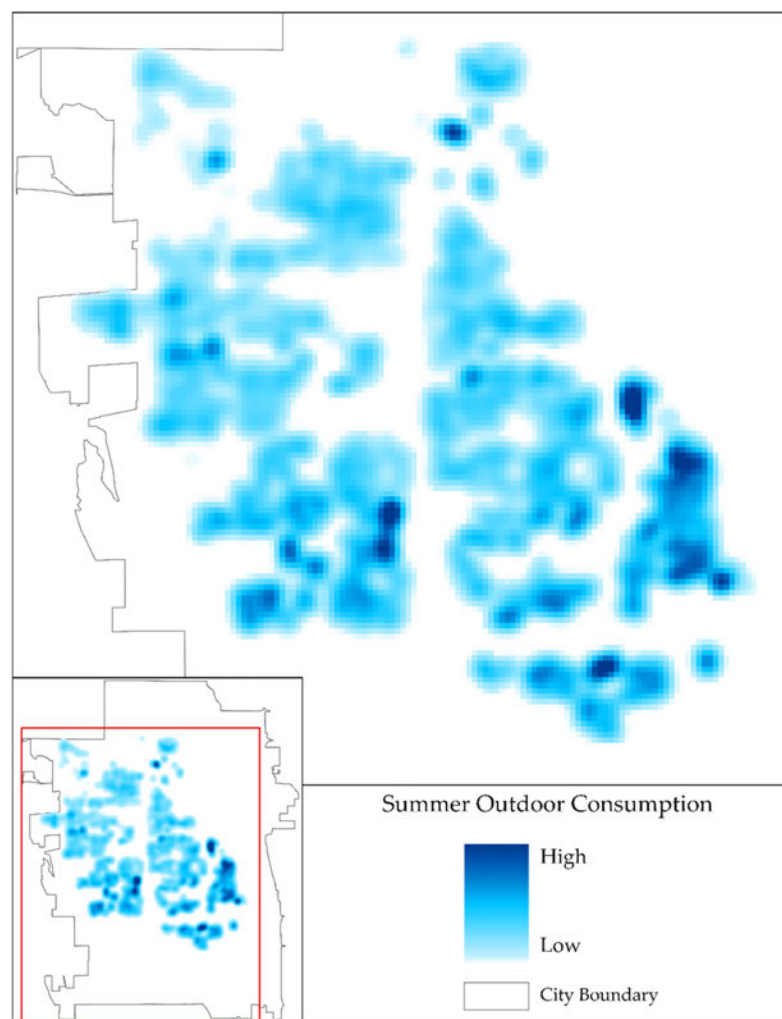


Figure 4. Kernel Density Estimation of Summer 2016 metered water consumption in the City.

2.4. Explanatory Variables

Social-demographic data, as well as house density, were provided by the US Census Bureau's American Community 5-Year Survey program [13] for 2016. Based on previous studies [11,12,14–16], we chose predictor variables that describe features such as ethnicity, tenure, household size, income and educational attainment (Table 2). These data were provided at a block group scale, which consists of several census blocks within the same census tract. Since we were unable to attain parcel-scale data, we disaggregated the broader-scale census block group data to estimate the social characteristics of each household. In doing so, we made assumptions about the social structure of each household, which does not necessarily depict its true condition.

Table 2. Descriptive statistics of continuous bio-physical, urban structural and social-demographic explanatory variables. Data obtained at the census block group scale were disaggregated, where each household was assigned the value for their respective block group.

Variable	Scale Obtained	Min	Mean	Max
Population Density per hectare (10,000 m ²)	Census block group	1.66	17.57	68.87
% White	Census block group	33.71	83.87	97.95
% Black/African American	Census block group	0.00	0.99	6.16
% Hispanic/Latino	Census block group	0.00	10.21	63.21
% Asian	Census block group	0.00	2.34	16.14
% College Graduates	Census block group	2.69	20.29	34.41
House Density per hectare (10,000 m ²)	Census block group	0.68	7.23	29.51
% Owner	Census block group	0.65	23.13	42.78
% Renter	Census block group	1.63	15.98	53.66
% Single Person Households	Census block group	1.47	9.30	38.76
% 3+ Person Households	Census block group	0.00	2.30	11.69
% Family Households	Census block group	2.21	23.13	35.52
% Married Households	Census block group	0.72	18.51	31.47
Median Household Income (\$)	Census block group	15,833	66,311	124,643
Parcel Size in ft ² (m ²)	Household	1066 (99)	9410 (874)	840,129 (78,050)
% Trees (in irrigatable space)	Household	0.00	48.66	100.00
% Herbaceous (in irrigatable space)	Household	0.00	48.25	100.00
Age of Home (years)	Household	2	40.67	152
Home Value (\$)	Household	96,100	423,365	2100,000
% Herbaceous * % Trees	Household	0	1925	2500
Vegetation/Parcel size	Household	0.02	0.61	0.99
Distance to Historic Center in mi (km)	Household	0.17 (0.27)	3.01 (4.84)	5.95 (9.58)
LST (°F)	100 m ² (resampled to 30 m ²)	80.68	92.52	101.39
NDVI	100 m ² (resampled to 30 m ²)	0.13	0.46	0.72

To estimate the effects of trees versus herbaceous vegetation within parcels, we used the land cover dataset to calculate percent cover of both vegetation types within the irrigatable space. Bare soil also comprised an extremely small proportion of irrigatable space per parcel (0–1%), but since it is not considered a land cover class that requires water, it was not included in this analysis. We created an interaction term by multiplying the percentage of trees and percentage of herbaceous cover in irrigatable space to obtain the

effects of combined vegetation cover, and a second interaction term dividing irrigatable area by the total area of the parcel to obtain a ratio of vegetation to parcel size (Table 2).

We utilized the United States Geological Survey Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) imagery to derive variables for Land Surface Temperature (LST) and Normalized Difference Vegetation Index (NDVI). LST provided an average estimation of surface temperature over the course of the summer months, while NDVI provided a measure of “greenness”, where higher NDVI values imply greener vegetation. Using imagery for five dates in 2016 (29 May, 14 June, 16 July, 1 August, and 17 August), we derived a mean composite image to calculate LST, and a median composite image to calculate NDVI (Table 2). These data were gathered at a 100 m² spatial resolution but were resampled and provided at a 30 m² resolution. Using data that are resampled to a finer resolution inherently limits the ability to capture the true spatial variation of LST and NDVI at the household scale, as we are inferring fine-scale variation based on broad-scale information.

Lifestyle indicators were obtained from ESRI’s 2018 Tapestry LifeMode Group data [36], a demographic dataset that provides detailed descriptions of neighborhood block group residential areas based on their purchasing preferences (Table 3). These data were also disaggregated from the census block group scale. These data describe lifestyle characteristics such as financial investments, common recreational activities, preferred media platforms, and generational trends.

Table 3. Categorical explanatory variables. The lifestyle classification data were obtained from ESRI Tapestry Segmentation data. Lawn orientation for each household was calculated based on the angle of the front lawn from the nearest road.

Category	Variable	Scale Obtained	Parcel Count
Lifestyle Classification	Affluent Estates	Census block group	1367
	Upscale Avenues	Census block group	1896
	Uptown Individuals	Census block group	49
	Family Landscapes	Census block group	2319
	GenXurban	Census block group	4999
	Middle Ground	Census block group	8247
	Senior Styles	Census block group	91
	Rustic Outposts	Census block group	151
	Midtown Singles	Census block group	901
	Next Wave	Census block group	17
Lawn Orientation	Scholars and Patriots	Census block group	4134
	East	Household	3184
	Northeast	Household	2829
	North	Household	3341
	Northwest	Household	2643
	West	Household	3439
	Southwest	Household	2878
	South	Household	3293
	Southeast	Household	2564

We acquired assessor’s data on the age and value of each parcel from the local municipality [37] (Table 2). These data are unique for each parcel and exist at a finer spatial resolution than census data. We also calculated the direction of the front lawn for each parcel with the Near tool (using local roads as the “Near Feature”) in ArcGIS Pro (Version

2.5.1), assuming that households generally water their front yard more than their back yard. Cardinal and intercardinal directions were determined based on the angle of the lawn from the closest road (e.g., 30° represents a Northeast-facing lawn) (Table 3). We used visual validation to ensure these measurements were accurately representative.

Upon exploring the final dataset, we found several discrepancies. A relatively small number of parcels had negative consumption values, suggesting those households used more water during the winter than in the summer, so we removed them from the analysis ($n = 1658$). Often, students and renters leave during summer, and no one is living in these households. We also removed households that appeared to be under construction in 2016 because those parcels do not represent typical outdoor water consumption in the City ($n = 7$). Finally, we removed households that did not have any irrigatable space ($n = 4$), as well as several homes that had inaccurate or unrealistic assessor's data for their date of construction or for their value ($n = 117$). Removing observations that met these criteria left us with over 24,000 observations for analysis.

2.5. Correlation Analysis

We compared relationships between each explanatory variable and summer consumption using Spearman's correlation. By analyzing correlation coefficients, we were able to estimate the degree of increase or decrease in water consumption associated with each explanatory variable, as we were interested in the context of these relationships when assessing the regression model outputs. We used the `spearmanCI` function from the `spearmanCI` package (Version 1.0) [38] to obtain correlation coefficients.

2.6. Random Forest for Variable Selection

Random Forest (RF) [39] is a nonparametric machine learning method based on decision trees. RF does not assume normal distribution of data or independence of samples, inherently considers interactions among covariates, and often performs better on ecological data than parametric models [40].

One of the benefits of the machine learning RF algorithm is that it has several options for variable selection methods that reduce the number of explanatory variables needed in regression modeling. Ideally, the number of variables should be minimized to improve parsimony when developing regression models, and variable selection methods can identify the most important explanatory variables based on their contribution to variance explained [41]. We applied the `rf.modelSel` function in the `rfUtilities` package (Version 2.1-5) [42] for variable selection, a process that ranks all variables in order of their explanatory power. We chose to implement a RF approach for variable selection due to the complexity of the dataset, and we wanted to account for potential interactions between explanatory variables.

2.7. Regression Modeling

We incorporated all variables from the RF variable selection process in an Ordinary Least Squares (OLS) regression to determine which characteristics may explain outdoor consumption. In R, the `lm` function from the `stats` package (Version 3.6.2) [43] was used for the OLS model. We assessed the effect of each variable in the model using Cohen's F effect size statistic. Based on Sawilowsky [44], Cohen's F values generally range from 0.01 (very small effect) to 2.0 (very large effect), where a medium effect lies around 0.5.

We used the variance inflation factor (VIF) to test for multicollinearity in our OLS model. A VIF threshold of 5 is often considered a high correlation and would require us to adjust predictor variables [45]. We used the `vif` function from the `car` package (Version 3.0-9) [46] to test the VIF in R, and we systematically removed variables until collinearity was no longer present in the OLS model.

3. Results

3.1. Correlation Analysis

The correlation results revealed that homes farther from the historic center had the strongest positive relationship to water consumption overall (Figure 5). This result also reflects development patterns within the City, as much of the development has occurred outward from the historic center. Most of the households located at a greater distance from the historic center are in relatively newer neighborhoods, and these households tend to be associated with greater water consumption. Conversely, the ratio between the area of vegetation and parcel size had a strong negative relationship to water consumption. This result suggests that homes with less vegetation relative to their parcel size used more water. Parcel size itself, along with home age, also displayed a strong, negative relationship (Figure 5).

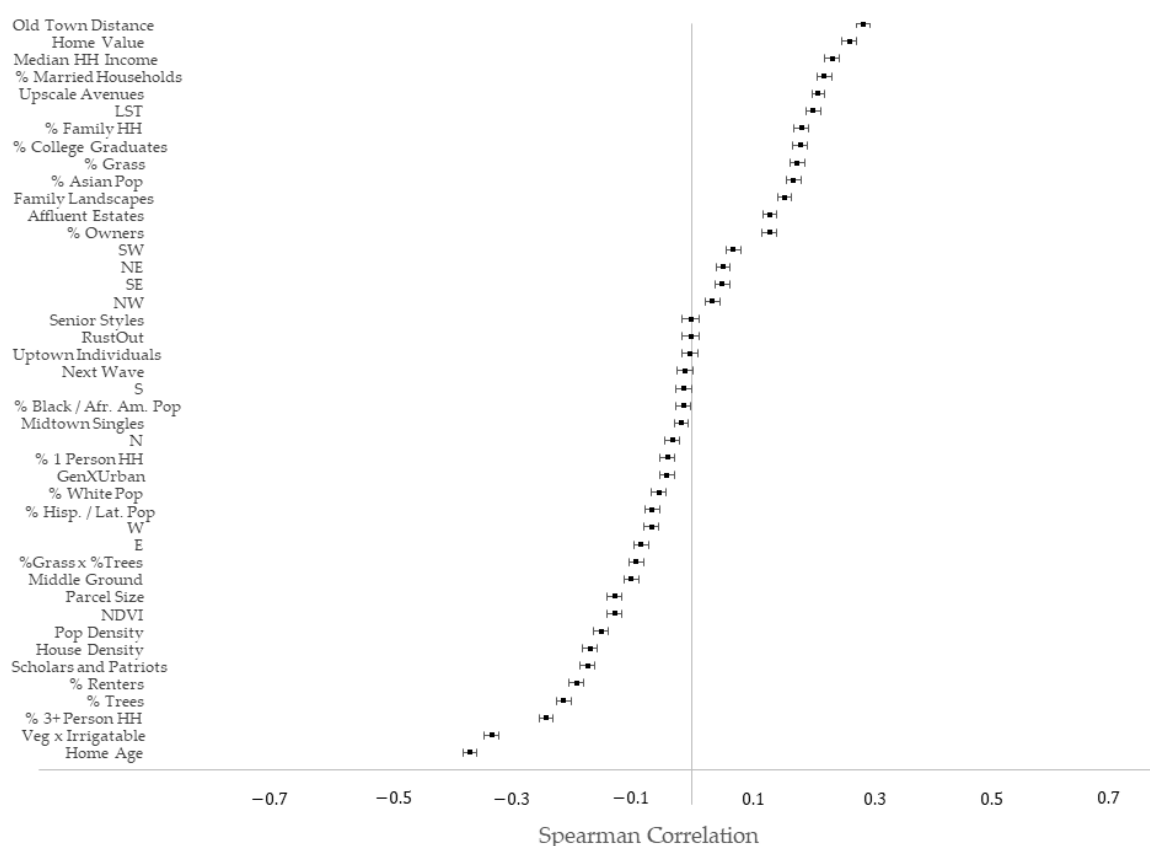


Figure 5. Spearman's correlation results. Positive coefficients suggested that increasing the variable resulted in greater water consumption, while negative coefficients suggested that increasing the variable resulted in less water consumption. For example, older homes were associated with less water consumption.

We also found that higher-income households, as well as households located in neighborhoods with more families and married couples, college graduates, and homeowners, were all significantly associated with more water use (Figure 5). Several lifestyle variables that typically indicate homes of higher socio-economic status were also displaying more water use, such as Upscale Avenues, Family Landscapes and Affluent Estates. Of all the social-demographic variables, 3+ person households had the strongest negative relationship to water consumption in the correlation analysis, followed by renters. Lifestyles that were negatively associated with water use included Scholars and Patriots, Middle Ground, and Midtown singles, which generally indicate middle to lower socio-economic status (Figure 5).

The correlation analysis revealed a significant relationship between tree canopy and water consumption and suggested that homes with greater presence of tree canopy were associated with less water use (Figure 5). Meanwhile, homes with more herbaceous cover had a relatively strong and significant positive relationship to water consumption (Figure 5).

3.2. OLS Regression

The final model consisted of a combination of 16 bio-physical, urban structural and social-demographic variables and explained roughly 20% of the variability in water consumption ($R^2 = 0.211$) (Table 4). The final variables had a very small to medium effect on water consumption in the context of the Cohen's F statistic, as indicated by values ranging from 0.006 to 0.302.

Table 4. Variables from the OLS regression. Variables are listed in order of their contribution to the OLS model, with higher Cohen's F values indicating a greater effect on the model, while the coefficient represents the magnitude of impact.

Variable	Coefficient	Std. Error	p Value	Cohen's F
Intercept	−4.506e-01	2.543e-01	0.0764	-
Vegetation/Parcel size	−1.573e+00	5.310e-02	<2e-16	0.302
Parcel Size	−1.329e-05	4.423e-07	<2e-16	0.229
Distance to Historic Center	7.718e-02	7.674e-03	<2e-16	0.227
Home Value	1.386e-06	5.656e-08	<2e-16	0.214
Home Age	−5.240e-03	4.213e-04	<2e-16	0.098
% Trees	−3.807e-03	3.201e-04	<2e-16	0.075
% 3+ Person HH	−2.551e-02	3.226e-03	2.73e-15	0.062
% College Graduates	1.025e-02	1.422e-03	5.74e-13	0.043
% Family HH	4.992e-03	1.990e-03	0.0121	0.040
LST	1.271e-02	2.463e-03	2.48e-07	0.038
% Owner	−4.830e-03	1.446e-03	0.0008	0.035
% Black/Afr. Am. Pop	−2.678e-02	4.996e-03	7.06e-08	0.035
% Asian Pop	7.134e-03	2.377e-03	0.0027	0.018
House Density	6.026e-03	2.189e-03	0.0059	0.014
NDVI	7.944e-01	9.624e-02	<2e-16	0.009
% Hispanic/Latino Pop	3.748e-03	9.922e-04	0.0002	0.006

Based on our model results, the ratio between the area of vegetation and parcel size (Cohen's F = 0.302), as well as parcel size itself (Cohen's F = 0.229), and the distance to the historic center (Cohen's F = 0.227) had the greatest effects on the model, all of which were significant (Table 4). The model indicated that higher ratios between vegetation and parcel size exhibited lower water use. Although parcel size had a relatively important effect on the model itself, its magnitude of impact was small, decreasing water consumption by less than 1% for every additional 1000 ft² (93 m²) in size. The distance to the historic center had a large magnitude of impact in the model, increasing water consumption by ~7% for every additional mile (1.6 km) from the historic center.

Home age (Cohen's F = 0.098) and the percent of tree cover (Cohen's F = 0.075) also had relatively important effects on the model; both also had a relatively large magnitude of impact, where water consumption decreased by ~5% for every 10 years of age, and ~4% for every additional 10% of canopy cover. With the exception of home value (Cohen's F = 0.214), most of the social-demographic variables, as well as house density, LST and NDVI, had less of an effect on the model, as indicated by small Cohen's F values.

Home value had the greatest effect of all the social-demographic variables and was associated with significantly more water use in the model (Cohen's $F = 0.214$), although its magnitude of the impact was small (Table 4). Households located in neighborhoods with more college graduates were also associated with significantly more water use, but had less of an effect than home value (Cohen's $F = 0.043$). On the contrary, the percentage of 3+ person households had a small but relatively important effect on the model (Cohen's $F = 0.062$), and significantly reduced water consumption (Table 4). Similarly, the percent of tree canopy had a small but relatively important effect (Cohen's $F = 0.075$) and was associated with significantly less water consumption (Table 4).

4. Discussion

4.1. Bio-Physical Composition and Urban Structure Greatly Affected Water Use

Of all the variables we tested, the regression model suggested that a combination of bio-physical (e.g., landcover, vegetation type), urban structural (e.g., parcel size, distance to historic center) and social-demographic (e.g., home value) variables explained most of the variance of water consumption in the City. The final model included most of the bio-physical and urban structural variables that were a part of the correlation analyses, notably excluding lawn orientation. In other words, 44% of the bio-physical/urban structural variables, and 32% of the social-demographic/lifestyle variables, we initially tested were included in the final model. The three most impactful variables included the ratio between vegetation and parcel size, parcel size, and distance to the historic town center.

Our results showed that smaller yards, or smaller irrigatable areas relative to total parcel size, and smaller parcels used more water. This result was contrary to what is often discussed in the literature [14–16], where large parcels are generally expected to have greater water requirements. Our findings may be due to the fact that larger yards have greater maintenance requirements in semi-arid ecosystems than in temperate ecosystems, and therefore residents with larger yards in semi-arid cities may steer away from landscapes that require a lot of water. Alternatively, it requires less effort to create and maintain a green landscape on small properties, particularly on smaller yards. Furthermore, since small properties are often positioned closer to their neighbors, these households may be more influenced by social norms [47] or have Homeowners Associations (HOAs) enforcing highly maintained green landscapes [48]. Over time, social norms can result in landscape conformity, and may play an important role in whether people choose to have a green landscape [21]. The desire to conform to neighborhood aesthetics may prompt households to maintain green lawns in a space where, due to its smaller size, it is already more viable to irrigate compared to a larger parcel.

Parcels located farther from the historic center were associated with higher water use, possibly because these newer areas are still being transformed from the natural, semi-arid grassland and agricultural land to a more irrigated, green landscape. Conversely, older parts of the city already contain denser, more mature tree cover and established green space compared to the outskirts of the city. These older areas were generally associated with less water use, suggesting that maintaining this established urban green space generally requires less water than developing the urban green space in newer neighborhoods.

4.2. Higher Socio-Economic Status Was Associated with More Water Use

Home value was the most important social-demographic variable, with higher-valued homes using more water. This finding is consistent with previous studies, where households of higher socio-economic status tend to use more water [11]. We reviewed correlation results of other variables indicative of higher socio-economic status, including income, the percentage of college graduates, Upscale Avenues, Family Landscapes and Affluent Estates lifestyles, and found they were also associated with greater water consumption. House-Peters et al. [7] yielded similar results for Portland, Oregon, where newer, larger homes with higher property values and more affluent and educated residents used the most outdoor water. These results

indicate that, like the larger cities previously studied, socio-economic status may be an influential factor on outdoor water consumption in this City.

4.3. Trees Were Associated with Less Water Consumption

One of our goals was to compare the percentage of tree versus herbaceous cover in residential parcels to understand the relative influence of vegetation types on outdoor water consumption. It is well established that trees provide benefits in urban regions, particularly in arid and semi-arid climates where shade trees can create a significantly more comfortable urban environment [49], yet many studies have suggested trees are disservices in these regions because they are associated with increased water costs [11,50,51]. Therefore, many cities prone to drought must consider tradeoffs between maintaining a vegetated landscape and preserving critical water resources.

We found that herbaceous cover is the only vegetation variable that was associated with higher water consumption. More tree cover, however, was associated with lower water consumption. The interaction term, combining the percent tree cover and percent herbaceous cover, was also correlated with lower water consumption.

The central part of the City, near the historic center, contains a large amount of green space, including tree canopy and many irrigated lawns. Urban trees in this region are typically large and aged, and they provide critical shade that aids in controlling the microclimate. It is possible this shade prevents a large portion of the water used for irrigation from evapotranspiring [52,53]. Since evapotranspiration is a function of solar radiation [25], tree canopy shade may be blocking direct radiation, thus slowing the rate at which lawns dry out and decreasing the need for frequent irrigation to maintain them. It is important to note that this result is dependent on the assumption that the land cover underneath trees is mostly dedicated to lawn cover. Future studies in this City, and many others, need to quantify the landcover underneath trees.

Furthermore, households farther from the historic urban center were associated with more water use, and they also tend to have lower tree canopy. It is unclear if these residences were using more water for lawn irrigation, or for planting trees, or both. Regardless of the type of vegetation, the initial phases of landscape establishment require large amounts of water [54].

In conclusion, our results showed that mature trees may decrease the need for metered outdoor water use, and/or that people do not water mature trees. This does not mean that trees do not need or use water. Studies have shown that although trees have water requirements, once trees are established, they tend to pull water from underground reserves (e.g., runoff, groundwater), potentially lowering irrigation requirements [55]. It is also important to note, that even though people may not be watering their trees with metered water, it does not mean that trees are not receiving water subsidies from nearby landscapes that are being watered. For instance, in California, there is preliminary evidence that when homeowners remove lawns and replace them with water-wise landscapes, that nearby trees, and especially mature trees in the right-of-way, begin to decline [56]. Furthermore, some species of trees need more water than others, and in particular, trees native to semi-arid ecosystems may require more water than non-native trees due to their stomatal adaptations [18,57,58]. Nonetheless, based on our results, we expect that once trees are established, they may help mitigate outdoor irrigation on single-family parcels.

4.4. Policy Implications

Our results suggest that cities in semi-arid ecosystems may want to incentivize the establishment of landscapes that can reduce outdoor water-use over the long-term. Although, many water-limited cities have established regulations to reduce water consumption during droughts, or have provided incentives for water-wise landscaping, it is possible that mature tree canopy will also be needed to support water conservation policies that mitigate the impacts of climate change and the urban heat island effect. Further, our results suggest

these policies may be most valuable when targeting newer neighborhoods where people are in the process of designing and establishing their landscapes.

Since higher socio-economic status households were associated with greater water consumption, it may also be important to promote the benefits of, or perhaps set requirements for, smart irrigation technology or xeriscaping in neighborhoods where households have more access to such environmental amenities. Introducing building codes that require smart irrigation technology, or a percentage of the property to be xerophytic vegetation in place of grass, are some practical examples. Understanding the role of HOAs in water-use patterns is also a valuable next step. If HOA's guidelines are indeed leading to more outdoor water use in this city, and others, it will be essential to work closely with these groups on developing water conservation policies and neighborhood norms.

Although mandatory regulations have historically been used in the state, the local utility uses them as a conservation tools when the City is under severe water stress but does not recommend them as standard practice for water efficiency in the community. For instance, a study by Olmstead and Stavins [59] showed that a combination of conservation approaches (e.g., landscape education programs and watering regulations) resulted in small but significant reductions in total water use, as opposed to mandatory regulations which had mixed results. Therefore, programs that emphasize water and landscape literacy may continue to be an important strategy for local utilities. Interactive classes or certifications, incentives and rebates, and quantified savings may help motivate people to approach water conservation from a voluntary standpoint. Voluntary programs target lifestyle change [9], which is typically more long-term and sustainable. Lifestyle changes would also ease the community's transition to water-efficient practices for when droughts become more prevalent. Moreover, the impacts of these incentives and voluntary water conservation programs can be evaluated and should be a priority for future research in this city and others.

4.5. Misalignment in Spatial Scales Hinders Our Understanding of Social and Lifestyle Effects

Other than home value, all of the social-demographic and lifestyle data were provided at a coarser resolution than the bio-physical data. The coarser-scale variables were disaggregated from a larger block group scale; therefore, houses within the same block group were assigned the same generalized social-demographic and lifestyle information, rather than a unique value for that household, and may not accurately depict the unique situation of each household. Unique, parcel-level, social and lifestyle data may show trends associated with human behaviors and decision-making that were undetectable in this analysis due to coarse spatial resolution. In the future, in-depth interviews or household level surveys would allow us to discern mechanistic relationships between people's values and perceptions and water conservation behaviors.

4.6. Future Directions

Although our analysis included a large range of potential predictors of outdoor water consumption, there are additional explanatory variables that could be explored in the future. For instance, the presence of outdoor water features, like swimming pools and hot tubs, has been shown to impact water consumption and there is reason to believe that more households are adding these features to their properties, especially with social distancing guidelines presented during our most recent covid-19 pandemic. Landscape configuration (e.g., spatial arrangement of buildings or vegetation) plays an important role on urban structure and microclimate and has been shown to impact water consumption patterns [17,60]. Furthermore, landscape metrics such as vegetation patch size and tree density can provide additional insight on irrigation trends, particularly under changing climate and precipitation patterns. We also did not have data for irrigated versus non-irrigated herbaceous cover and have not yet quantified the type of land cover beneath tree canopy. Finally, attaining information on vegetation species, or which households have

undergone a xerophytic transition, will help us understand the impact of xeriscaping on water use.

5. Conclusions

It is generally understood that a wide array of urban characteristics within cities can have important impacts on outdoor water consumption patterns; however, the main driving characteristics and their degree of influence is debated and inconsistent in the literature. These characteristics may include bio-physical composition (e.g., vegetation type), urban structure (e.g., parcel size), social-demographic patterns (e.g., income), or lifestyle behavior (e.g., conservation motivation).

Similar to other studies on outdoor metered water consumption, we found that indicators of higher socio-economic status, in our case study housing prices, were associated with more water use. We were also not surprised that parcels with more area dedicated to herbaceous cover like lawns were significantly correlated to high outdoor water use.

In this semi-arid city along the Colorado Front Range, there were some important deviations from the norms that have been established in larger temperate cities. Although at first, the most important characteristics for explaining outdoor residential water (ratio between parcel size and vegetation cover, parcel size itself, and the distance to the historic urban center) might not seem all that surprising, it is the directionality of these relationships that were somewhat unexpected. For instance, smaller parcels, and parcels with a small yard (e.g., irrigatable space) relative to the parcel size were associated with greater water consumption. We suspect in a semi-arid city, where water is limited and urban vegetation requires maintenance and subsidies, that people are unlikely to choose landscapes that require a lot of irrigation. Further, households with smaller parcels may be more likely to conform to neighborhood social norms or feel pressure from groups like HOAs to keep their small grassy areas as green as possible.

There has been extensive research focused on the ecosystem services provided by trees, but water-limited cities tend to worry about the tradeoffs between tree planting and maintenance programs, and water and native biodiversity conservation. Our results showed that people may not be actively watering their trees, especially when tree canopy is established and mature, like in the older neighborhoods that have up to 70 percent tree cover. Higher tree cover could also be providing critical shade, keeping the region cooler, and also reducing the evapotranspiration of lawns, and therefore their demand for precious water resources. Cities can incentivize voluntary landscape solutions that reduce irrigated herbaceous cover and also increase mature tree cover over time. These creative solutions will become even more important to semi-arid cities into the future, as temperatures continue to increase and precipitation decreases with global climate change, and as persistent urbanization continues to put pressure on local water resources.

Author Contributions: All authors contributed to the study conception and design. Conceptualization, M.M. and A.N.; methodology, M.M., S.R., A.N.; software, A.N., S.R., E.G.; validation, J.O.-D.; formal analysis, S.R.; investigation, M.M.; resources, M.M., A.N., J.O.-D.; data curation, S.R., J.O.-D., A.N., E.G.; writing—original draft preparation, S.R.; writing—review and editing, S.R., M.M., T.W., A.N.; visualization, S.R., J.O.-D.; supervision, M.M., T.W., A.N.; project administration, M.M.; funding acquisition, M.M. All authors have read and agreed to the published version of the manuscript.

Funding: Funding was provided by McHale's start-up from Colorado State University.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Restrictions apply to the availability of these data. Data was obtained from the local water utilities and are available from the authors with the permission of the City.

Acknowledgments: The City provided GIS and Lidar data that allowed us to complete the land cover classification and our analyses. Jesse Burkhardt helped solidify the data agreement between the City and the University. Liesel Hans and Lauren Abram provided feedback on methodology and data analysis. Wade Tinkham and Melinda Laituri were valuable committee members and provided feedback on exploratory data analysis and interpretation of results. We also acknowledge the use of imagery from the NASA Worldview application, part of the NASA Earth Observing System Data and Information System (EOSDIS). Finally, we'd like to thank Edward Gage for his assistance in data processing and visualization.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Colorado Climate Plan 2015 Regional Assessment | USDA Climate Hubs. Available online: <https://www.climatehubs.usda.gov/hubs/northern-plains/topic/colorado-climate-plan-2015-regional-assessment> (accessed on 18 November 2020).
2. Lukas, J.; Barsugli, J.; Doesken, N.; Rangwala, I.; Wolter, K. *Climate Change in Colorado: A Synthesis to Support Water Resources Management and Adaptation*; University of Colorado Boulder: Boulder, CO, USA, 2014; p. 2.
3. Colorado Water Conservation Board. *Colorado's Water Plan*; Colorado Water Conservation Board: Denver, CO, USA, 2015.
4. Hanak, E.; Browne, M.K. Linking Housing Growth to Water Supply: New Planning Frontiers in the American West. *J. Am. Plan. Assoc.* **2006**, *72*, 154–166. [\[CrossRef\]](#)
5. Tinker, A.; Bame, S.; Burt, R.; Speed, M. Impact of “Non-Behavioral Fixed Effects” on Water Use: Weather and Economic Construction Differences on Residential Water Use in Austin, Texas. *Electron. Green J.* **2005**, *1*. [\[CrossRef\]](#)
6. Kenney, D.S.; Klein, R.A.; Clark, M.P. Use and Effectiveness of Municipal Water Restrictions During Drought in Colorado. *JAWRA J. Am. Water Resour. Assoc.* **2004**, *40*, 77–87. [\[CrossRef\]](#)
7. House-Peters, L.; Pratt, B.; Chang, H. Effects of Urban Spatial Structure, Sociodemographics, and Climate on Residential Water Consumption in Hillsboro, Oregon. *JAWRA J. Am. Water Resour. Assoc.* **2010**, *46*, 461–472. [\[CrossRef\]](#)
8. Pincetl, S.; Porse, E.; Mika, K.B.; Litvak, E.; Manago, K.F.; Hogue, T.S.; Gillespie, T.; Pataki, D.E.; Gold, M. Adapting Urban Water Systems to Manage Scarcity in the 21st Century: The Case of Los Angeles. *Environ. Manag.* **2019**, *63*, 293–308. [\[CrossRef\]](#) [\[PubMed\]](#)
9. Balling, R.C.; Gober, P.; Jones, N. Sensitivity of residential water consumption to variations in climate: An intraurban analysis of Phoenix, Arizona. *Water Resour. Res.* **2008**, *44*. [\[CrossRef\]](#)
10. Wentz, E.A.; Gober, P. Determinants of Small-Area Water Consumption for the City of Phoenix, Arizona. *Water Resour. Manag.* **2007**, *21*, 1849–1863. [\[CrossRef\]](#)
11. Harlan, S.L.; Yabiku, S.T.; Larsen, L.; Brazel, A.J. Household Water Consumption in an Arid City: Affluence, Affordance, and Attitudes. *Soc. Nat. Resour.* **2009**, *22*, 691–709. [\[CrossRef\]](#)
12. Ghavidelfar, S.; Shamseldin, A.Y.; Melville, B.W. A Multi-Scale Analysis of Single-Unit Housing Water Demand Through Integration of Water Consumption, Land Use and Demographic Data. *Water Resour. Manag.* **2017**, *31*, 2173–2186. [\[CrossRef\]](#)
13. US Census Bureau. Glossary. Available online: <https://www.census.gov/programs-surveys/geography/about/glossary.html> (accessed on 15 February 2021).
14. Stoker, P.; Rothfeder, R. Drivers of urban water use. *Sustain. Cities Soc.* **2014**, *12*, 1–8. [\[CrossRef\]](#)
15. Jansen, A.; Schulz, C. Water Demand and the Urban Poor: A Study of the Factors Influencing Water Consumption Among Households in Cape Town, South Africa. *S. Afr. J. Econ.* **2006**, *74*, 593–609. [\[CrossRef\]](#)
16. Chang, H.; Parandvash, G.H.; Shandas, V. Spatial Variations of Single-Family Residential Water Consumption in Portland, Oregon. *Urban Geogr.* **2010**, *31*, 953–972. [\[CrossRef\]](#)
17. Sanchez, G.M.; Smith, J.W.; Terando, A.; Sun, G.; Meentemeyer, R.K. Spatial Patterns of Development Drive Water Use. *Water Resour. Res.* **2018**, *54*, 1633–1649. [\[CrossRef\]](#)
18. McCarthy, H.R.; Pataki, D.E. Drivers of Variability in Water Use of Native and Non-Native Urban Trees in the Greater Los Angeles Area. *Urban Ecosyst.* **2010**, *13*, 393–414. [\[CrossRef\]](#)
19. Dwyer, J.F.; McPherson, E.G.; Schroeder, H.W.; Rowntree, R.A. Assessing the Benefits and Costs of the Urban Forest. *J. Arboric.* **1992**, *18*, 227–234.
20. Olmos, K.C.; Loge, F.J. Offsetting water conservation costs to achieve net-zero water use. *J. AWWA* **2013**, *105*, E62–E72. [\[CrossRef\]](#)
21. Jorgensen, B.; Graymore, M.; O'Toole, K. Household water use behavior: An integrated model. *J. Environ. Manag.* **2009**, *91*, 227–236. [\[CrossRef\]](#) [\[PubMed\]](#)
22. Corbella, H.M.; Pujol, D.S.I. What lies behind domestic water use? A review essay on the drivers of domestic water consumption. *Boletín Asoc. Geógrafos Españoles* **2009**, *50*, 297–314.
23. Newton, P.; Meyer, D. Exploring the Attitudes-Action Gap in Household Resource Consumption: Does “Environmental Lifestyle” Segmentation Align with Consumer Behaviour? *Sustainability* **2013**, *5*, 1211–1233. [\[CrossRef\]](#)
24. Bollinger, B.; Burkhardt, J.; Gillingham, K. *Peer Effects in Water Conservation: Evidence from Consumer Migration*; National Bureau of Economic Research: Cambridge, MA, USA, 2018.

25. Yang, J.; Wang, Z.-H. Optimizing urban irrigation schemes for the trade-off between energy and water consumption. *Energy Build.* **2015**, *107*, 335–344. [CrossRef]
26. Renwick, M.E.; Green, R.D. Do residential water demand side management policies measure up? An analysis of eight California water agencies. *J. Environ. Econ. Manag.* **2000**, *40*, 37–55. [CrossRef]
27. Ahmad, S. Managing Water Demands for a Rapidly Growing City in Semi-Arid Environment: Study of Las Vegas, Nevada. *Int. J. Water Resour. Arid Environ.* **2016**, *5*, 35–42.
28. 2020 Strategic Plan—Create Our Five-Year Road Map 2020. Available online: https://ourcity.fcgov.com/2020strategicplan?tool=quick_poll (accessed on 2 November 2020).
29. Demographic Information | Comprehensive Planning. Available online: <https://www.fcgov.com/planning/trends.php> (accessed on 18 November 2020).
30. National Oceanic and Atmospheric Administration. National Weather Service Climate. Available online: <https://w2.weather.gov/climate/xmacis.php?wfo=bou> (accessed on 18 November 2020).
31. About Fort Collins | Visit Fort Collins. Available online: <https://www.visitftcollins.com/maps-info/about-fort-collins/> (accessed on 5 October 2020).
32. Water Efficiency Plan | 2015. Utilities. Available online: <https://www.fcgov.com/utilities/residential/conserve/water-efficiency/water-efficiency-plan> (accessed on 2 November 2020).
33. Zhou, W.; Troy, A. An object-oriented approach for analyzing and characterizing urban landscape at the parcel level. *Int. J. Remote Sens.* **2008**, *29*, 3119–3135. [CrossRef]
34. Beck, S.M.; McHale, M.R.; Hess, G.R. Beyond Impervious: Urban Land-Cover Pattern Variation and Implications for Watershed Management. *Environ. Manag.* **2016**, *58*, 15–30. [CrossRef] [PubMed]
35. Congalton, R.G.; Green, K. *Assessing the Accuracy of Remotely Sensed Data: Principles and Practices*, 3rd ed.; CRC Press: Boca Raton, FL, USA, 2019; ISBN 978-0-429-62935-8.
36. Tapestry Segmentation—Esri Demographics | Documentation. Available online: <https://doc.arcgis.com/en/esri-demographics/data/tapestry-segmentation.htm> (accessed on 3 November 2020).
37. Larimer County Assessor's Office. Available online: <https://www.larimer.org/assessor> (accessed on 5 December 2019).
38. De Carvalho, M.; Marques, F.J. spearmanCI: Jackknife Euclidean / Empirical Likelihood Inference for Spearman Rho. *N. Am. Actuar. J.* **2012**, *16*, 487–492. [CrossRef]
39. Breiman, L. Random forests. *Mach. Learn.* **2001**, *45*, 5–32. [CrossRef]
40. Severson, J.P.; Hagen, C.A.; Maestas, J.D.; Naugle, D.E.; Forbes, J.T.; Reese, K.P. Effects of conifer expansion on greater sage-grouse nesting habitat selection. *J. Wildl. Manag.* **2017**, *81*, 86–95. [CrossRef]
41. Speiser, J.L.; Miller, M.E.; Tooze, J.; Ip, E. A comparison of random forest variable selection methods for classification prediction modeling. *Expert Syst. Appl.* **2019**, *134*, 93–101. [CrossRef]
42. Murphy, M.A.; Evans, J.S.; Storfer, A. Quantifying Bufo boreas connectivity in Yellowstone National Park with landscape genetics. *Ecology* **2010**, *91*, 252–261. [CrossRef] [PubMed]
43. R Core Team. *R: A Language and Environment for Statistical Computing*; R Foundation for Statistical Computing: Vienna, Austria, 2018; Available online: <https://www.R-project.org/> (accessed on 12 December 2019).
44. Sawilowsky, S.S. New Effect Size Rules of Thumb. *J. Mod. Appl. Stat. Methods* **2009**, *8*, 597–599. [CrossRef]
45. James, G.; Witten, D.; Hastie, T.; Tibshirani, R. *An Introduction to Statistical Learning: With Applications in R*, 1st ed.; Springer: New York, NY, USA, 2013.
46. Fox, J.; Weisberg, S. *An {R} Companion to Applied Regression*, 3rd ed.; Sage: Thousand Oaks, CA, USA, 2019; Available online: <https://socialsciences.mcmaster.ca/jfox/Books/Companion/> (accessed on 12 April 2020).
47. Burkhardt, J.; Chan, N.W. What is the value of conformity? Evidence from home landscaping and water conservation. *Am. J. Agric. Econ.* **2021**, under review.
48. Ozan, L.A.; Alsharif, K.A. The Effectiveness of Water Irrigation Policies for Residential Turfgrass. *Land Use Policy* **2013**, *31*, 378–384. [CrossRef]
49. Wang, Y.; Akbari, H. The effects of street tree planting on Urban Heat Island mitigation in Montreal. *Sustain. Cities Soc.* **2016**, *27*, 122–128. [CrossRef]
50. McPherson, E.G.; Dougherty, E. Selecting Trees for Shade in the Southwest. *J. Arboric.* **1989**, *9*, 35–43.
51. Cariñanos, P.; Calaza-Martínez, P.; O'Brien, L.; Calfapietra, C. The Cost of Greening: Disservices of Urban Trees. In *The Urban Forest: Cultivating Green Infrastructure for People and the Environment*; Pearlmutter, D., Calfapietra, C., Samson, R., O'Brien, L., Krajter Ostoić, S., Sanesi, G., del Amo, R.A., Eds.; Future City; Springer International Publishing: Cham, Switzerland, 2017; pp. 79–87, ISBN 978-3-319-50280-9.
52. Litvak, E.; Pataki, D.E. Evapotranspiration of urban lawns in a semi-arid environment: An in situ evaluation of microclimatic conditions and watering recommendations. *J. Arid Environ.* **2016**, *134*, 87–96. [CrossRef]
53. Qaiser, K.; Ahmad, S.; Johnson, W.; Batista, J. Evaluating the impact of water conservation on fate of outdoor water use: A study in an arid region. *J. Environ. Manag.* **2011**, *92*, 2061–2068. [CrossRef] [PubMed]
54. Watering Newly Planted Trees and Shrubs. Available online: <https://extension.umn.edu/planting-and-growing-guides/watering-newly-planted-trees-and-shrubs> (accessed on 15 February 2021).

-
55. Litvak, E.; Bijoor, N.S.; Pataki, D.E. Adding Trees to Irrigated Turfgrass Lawns May Be a Water-Saving Measure in Semi-Arid Environments. *Ecohydrology* **2014**, *7*, 1314–1330. [[CrossRef](#)]
 56. Cadenasso, M.L.; (University of California, Davis, Davis, CA, USA). Personal communication, 2020.
 57. Pataki, D.E.; (University of California, Davis, Davis, CA, USA). Personal communication, 2020.
 58. Bush, S.E.; Pataki, D.E.; Hultine, K.R.; West, A.G.; Sperry, J.S.; Ehleringer, J.R. Wood Anatomy Constrains Stomatal Responses to Atmospheric Vapor Pressure Deficit in Irrigated, Urban Trees. *Oecologia* **2008**, *156*, 13–20. [[CrossRef](#)]
 59. Olmstead, S.M.; Stavins, R.N. Comparing price and nonprice approaches to urban water conservation. *Water Resour. Res.* **2009**, *45*. [[CrossRef](#)]
 60. Connors, J.P.; Galletti, C.S.; Chow, W.T.L. Landscape configuration and urban heat island effects: Assessing the relationship between landscape characteristics and land surface temperature in Phoenix, Arizona. *Landsc. Ecol.* **2013**, *28*, 271–283. [[CrossRef](#)]