THESIS

SUSTAINABILITY IN FORT COLLINS: EXPLORING THE DRIVERS OF URBAN TREE CANOPY AND HOUSEHOLD WATER CONSUMPTION IN A GROWING, SEMI-ARID CITY

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ABSTRACT

SUSTAINABILITY IN FORT COLLINS: EXPLORING THE DRIVERS OF URBAN TREE CANOPY AND HOUSEHOLD WATER CONSUMPTION IN A GROWING, SEMI-ARID CITY

Urbanization is occurring rapidly worldwide, with two-thirds of the global population expected to live in cities by 2050. As cities densify, proper provisioning of ecosystem services will be increasingly important to ensure high-quality lives for urban residents. Urban ecological research can assist cities in achieving sustainable development goals by focusing on the complex ways in which urban characteristics, such as land cover, building configuration, demographic composition, and resident lifestyles interact and drive patterns on the landscape. Such patterns can include housing trends, patterns of water and energy consumption, residents' health and lifestyle choices, or even urban wildlife distribution. Understanding the drivers of these patterns can aid in developing innovative policies that are specifically aligned to the needs of the city. We partnered with the local municipality of Fort Collins, CO to investigate the role of several urban characteristics on two variables of interest: urban tree canopy (UTC) distribution and household outdoor water consumption. Our stakeholder was interested in using our results to inform future tree planting and monitoring programs in the city, as well as raise awareness on outdoor water consumption and increase water literacy in the community. We compared our results to larger cities often studied in these contexts and found that 1) Fort Collins has undergone unique development patterns that have resulted in different UTC trends than we often expect to find in cities; 2) higher water use tends to be found in neighborhoods containing social characteristics associated with affluence; and 3) UTC may have the potential to mitigate outdoor water consumption in residential areas. These results are impactful because they provide relevant information that can support decisions for future sustainability action targeting trees and water in Fort Collins.

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CHAPTER 1: DRIVERS OF THE URBAN TREE CANOPY

1 Introduction

Urbanization is occurring rapidly worldwide, with more than half of the current global population residing in cities (Grove et al., 2014). By 2050, this is expected to increase to two-thirds (United Nations, 2018). As urban areas continue to grow, proper provisioning of ecosystem services will become increasingly important to ensure high quality lives for urban residents.

One way to attain the proper provisioning of ecosystem services is by increasing urban green space, particularly urban tree canopy (UTC), which has been associated with a multitude of benefits. In fact, several cities have undertaken progressive urban forestry campaigns due to the well-documented ecosystem services granted by trees (Grove et al., 2014). Increasing the UTC is especially important in arid and semi-arid climates because trees provide direct shade that reduces the overall surface thermal energy absorption, therefore positively impacting human health, energy use and overall carbon footprint (Gomez-Muñoz et al., 2010).

Despite the range of benefits associated with UTC, it is important to consider the potential disservices trees may also provide. Such disservices can include increased water demand, maintenance costs, allergies, and safety concerns (Schwarz et al., 2015). The matter of costs versus benefits must be framed within the context of a city's respective circumstances, which will depend on individual climate, resource vulnerability and price of water supply, sociodemographic preferences, built environment characteristics, and financial feasibility to maintain the UTC (Schwarz et al., 2015). For example, semi-arid systems must consider the trade-off between the benefit of canopy shade and the cost of increased water demand, whereas regions with ample rainfall may be more focused on the costs and benefits of planting trees in areas with poor drainage. Ultimately, the goals and priorities concerning the UTC will vary between cities based on their assessment of costs and benefits, as these are unique environments in need of site-specific intervention.

According to the literature, the primary drivers of UTC tend to be divided into three main themes: 1) Urban morphological patterns (e.g. parcel area, building density, impervious surface area); 2) Social-demographic characteristics (e.g. income, education, household size); and 3) Lifestyle preferences (e.g. individual and group behavior, motivations for conservation). Each theme contains associated individual drivers, and research has found these drivers to vary based on the city in question. Research is still needed to determine the relative influence of these overarching themes, along with their individual drivers, in a vast majority of cities.

Urban morphological characteristics refer to city composition in terms of its physical constituents and development patterns. In many cases, the physical development of the city is innately connected to the underlying social-demographic patterns (Williams et al., 2000), yet it is still treated as its own theme focusing more on physical attributes such as impervious surface cover or housing density. The morphological characteristics of the city reflect planning and policy at the time of development, and this can have an interesting effect over time as populations continuously change. Some studies incorporate historical data on social-demographic characteristics to account for these changes over time (see Bigsby et al., 2014), especially given that many trees were planted at a time when the social and built environment was drastically different.

Social-demographic characteristics can be analyzed to determine who is on the receiving end of the benefits and costs provided by trees and to what extent. Nestled within these characteristics is the widely-studied concept of social stratification, which has demonstrated its influence on both private and public UTC. For example, according to Locke & Grove (2016) private landowners with higher social and economic status are often associated with greener areas, while neighborhood power and income dynamics impact public investment in amenities such as green infrastructure.

Lifestyle preferences are a broad set of personal and group decisions and perceptions that have more recently been studied for their impact on UTC. For example, *Ecology of Prestige* is a theory stating that in addition to socioeconomic characteristics, UTC is also driven by reference group behavior at a community or neighborhood scale (Grove et al., 2014). People tend to possess a need to uphold a group identity or membership, often motivated by perceptions of social status. In this context, having more tree cover, or landscaping in general, may equate to higher social status.

A number of studies have investigated the above themes to determine the drivers of UTC, but have primarily taken place in larger, highly developed cities such as New York, Philadelphia, Baltimore, and Raleigh (Schwarz et al., 2015; Bigsby et al., 2013). Research has not addressed the drivers of UTC in smaller and mid-size cities, nor has it addressed cities with diverse climates or in earlier stages of development. This need for expanded research is heightened by the tendency for growing cities to experience some of the most significant urbanization challenges, particularly with respect to meeting infrastructure and sustainability demands. Because sustainability demands are highly dependent on the underlying ecosystem and climate variables in addition to the social and morphological composition of the city, more analyses in diverse climates is crucial. A clearer understanding of the drivers in cities of different size, age, climate, and composition will also facilitate the previously mentioned need for establishing common drivers across different cities for the purpose of comparative analysis.

By identifying UTC drivers, cities can discern which characteristics of the city are significantly impacting UTC patterns. That information can then be leveraged to explore prospective areas for future planting, since the city can identify locations that do or do not contain the driving characteristics. Previous studies have suggested planting should be based on city needs, resources and biophysical constraints, specifying the “Three P’s” framework: where planting is possible, preferable and has the most potential (see Grove et al., 2006; Locke et al., 2010). Locke et al. (2010) defines possible locations as areas where it is biophysically feasible to plant trees (e.g. biome and existing land cover); preferable as the consideration for where it is socially desirable (e.g. prioritizing environmental justice); and potential as the economic feasibility of increasing UTC (e.g. local funding and maintenance costs). Ideally, cities want to maximize the benefits of UTC and minimize any costs.

We analyzed the city of Fort Collins, CO because it is a semi-arid, medium sized city projected to undergo significant population growth. Existing literature is often focused on UTC drivers in larger, temperate cities, and we are interested in whether we can expect the same trends from understudied, rapidly changing cities like Fort Collins. Our results will inform the City of Fort Collins of current trends relating to UTC distribution. We also discuss these trends in the context of possible and preferable planting opportunities, which may facilitate sustainable urban development as the city faces major population growth. Furthermore, the City of Fort Collins is known for its commitment to managing its community with support from robust, scientific data and methods.

Our goal was to investigate the urban morphological, social-demographic, and lifestyle drivers of the Fort Collins UTC within Fort Collins neighborhoods (block groups). Considering that Fort Collins has undergone more recent urban development and has a relatively small urban population, we expect that Fort Collins UTC would be best described by morphological characteristics, rather than social-demographic or lifestyle characteristics. Our findings contribute to the existing literature on UTC because previous studies have not addressed UTC drivers in a growing, semi-arid system. The results of our analysis will also allow for future comparative analyses in cities of similar size and composition.

2 Methods

2.1 Study Location

Fort Collins, Colorado is a mid-size city with a population of roughly 165,080 according to the United States Census Bureau's July 2017 estimates (U.S. Census Bureau Quickfacts, 2018). It is located at the base of the Rocky Mountains of the northern Front Range, founded along the Cache La Poudre River. Fort Collins lies approximately 5,000 ft above sea level, primarily dominated by semi-arid grassland east of the foothills. The high elevation exposes the city to ample sunshine approximately 300 days of the year. The region is semiarid, receiving an average of 14.92 inches of precipitation per year (NOAA, 2018). Summers can be mild or hot, with persistent low humidity. This environment allows for a variety of deciduous and coniferous tree types, with major species including cottonwood, Douglas-fir, Engelmann spruce and ponderosa pine. However, the UTC primarily consists of deciduous species, such as honey locust and bur oak (City of Fort Collins, n.d.). Fort Collins prides itself on an extensive UTC, even having a "Notable Tree Tour" to educate the public on almost 30 distinguished trees throughout the city that are related to a famous or historical person, place or event (City of Fort Collins, 2008). Fort Collins also takes highly proactive tree maintenance measures (City of Fort Collins, 2017) and maintains a rigorous public tree inventory, currently with over 300 species mapped (City of Fort Collins Forestry, 2020).

We considered a variety of social-demographic, morphological and lifestyle data in our analysis of Fort Collins UTC. After removing "No data" values, we summarized all variables below to n-104 U.S. Census block groups, as block groups are the smallest unit available for social-demographic and lifestyle information. One block group consist of several census blocks within the same census tract (U.S. Census Bureau, n.d.).

2.2 Morphological and Social-Demographic Data

The U.S. Census Bureau's American Community 5-Year Survey program for 2017 contains a variety of morphological and social-demographic information. Based on previous studies, we chose predictor variables that illustrate features such as house density, building age, race and ethnicity, tenure, household size, median household income and educational attainment (Table 1.1).

Table 1.1. *Social and morphological predictors tested.*

Variable	Description	Min	Mean	Max	Variable Set
Population Density (per hectare)	Population per hectare	1.36	17.61	64.96	Social-Demographic
% White	Percent of population that is white	71.45	89.95	100.00	Social-Demographic
% African American	Percent of population that is African-American	0.00	1.28	8.12	Social-Demographic
% Hispanic	Percent of population that is Hispanic	0.00	12.52	66.12	Social-Demographic
% College Graduates	Population with at least a Bachelor's degree	6.98	35.06	60.70	Social-Demographic
% Renter	Percent of renter-occupied housing units	1.16	39.41	93.68	Social-Demographic
% Owner	Percent of owner-occupied housing units	0.00	55.93	98.84	Social-Demographic
% Single Person Households	Percentage of single-person occupied housing	3.24	23.81	64.32	Social-Demographic
% 3+ Person Households	Percentage of households with three or more people (non-family)	0.00	5.54	31.33	Social-Demographic
% Family Households	Percent of family households	9.63	59.36	88.12	Social-Demographic
% Married Households	Percent of married-couple family households	3.52	47.77	81.17	Social-Demographic
Median Household Income ($)	Median household income of the block group adjusted for 2016 inflation	18,550	65,156	130,139	Social-Demographic
House Density (per hectare)	Households per hectare	0.60	6.67	38.84	Morphological
Median Building Age (years)	Median age of buildings in block group in years	13.00	38.33	81.00	Morphological
Average Parcel Size (ft^2)	Average size for parcels in block group	7,221	47,307	364,781	Morphological

2.3 Lifestyle Data

Lifestyle predictors were obtained from ESRI's 2018 Tapestry data, a demographic dataset that provides detailed descriptions of neighborhood block group residential areas based on purchasing preferences along with socioeconomic status and demographic characteristics (Tapestry Segmentation, 2018). The dataset describes possible lifestyle behavior, such as financial decisions, favorite pastimes and preferred media platforms. This information is then used to sort block groups into various neighborhood classifications based on purchasing preferences (Table 1.2). Descriptions of each neighborhood classifications can be seen in Appendix I.

Since our lifestyle predictors were categorical, we created dummy variables to be able to include them in our linear models. We used the *dummy.data.frame* function, part of the dummies package (Brown, 2012), in R (Version 3.6.3) (R Core Team, 2018) to create the dummy variables.

Table 1.2. *Neighborhood classifications used as lifestyle predictors. Descriptions of each class are in Appendix I.*

Neighborhood Class	**Block Group Count**
Affluent Estates (AffEst)	12
Upscale Avenues (UpscaleAv)	4
Uptown Individuals (UptownInd)	1
Family Landscapes (FamLand)	9
GenXurban (GenXUrb)	18
Middle Ground (MidGround)	24
Senior Styles (SeniorStyle)	1
Rustic Outposts (RustOut)	2
Midtown Singles (MidSing)	9
Next Wave (NxtW)	1
Scholars and Patriots (ScholarsPatriots)	23

2.4 Land Cover Data

We used high resolution raster 2016 land cover classification data (1 m^2) derived from an object-oriented classification utilizing aerial imagery and LiDAR (Beck et al., 2016). We applied a custom post-processing model that uses ancillary building footprint and pavement vector data to distinguish between seven land cover classes: trees, grass and shrubs, bare soil, water, buildings, roads and railroads, and "other" paved surface cover (e.g. driveways) (Figure 1.1).We calculated the percentage of tree cover within each block group for our response variable. We also calculated the percentage of grass cover and included it in our models as a predictor variable. We integrated the buildings, roads and railroads, and other paved surface rasters to create a single predictor for the percentage of impervious cover (Table 1.3). We did not include water or bare soil in this analysis due to the minimal cover across all block groups.

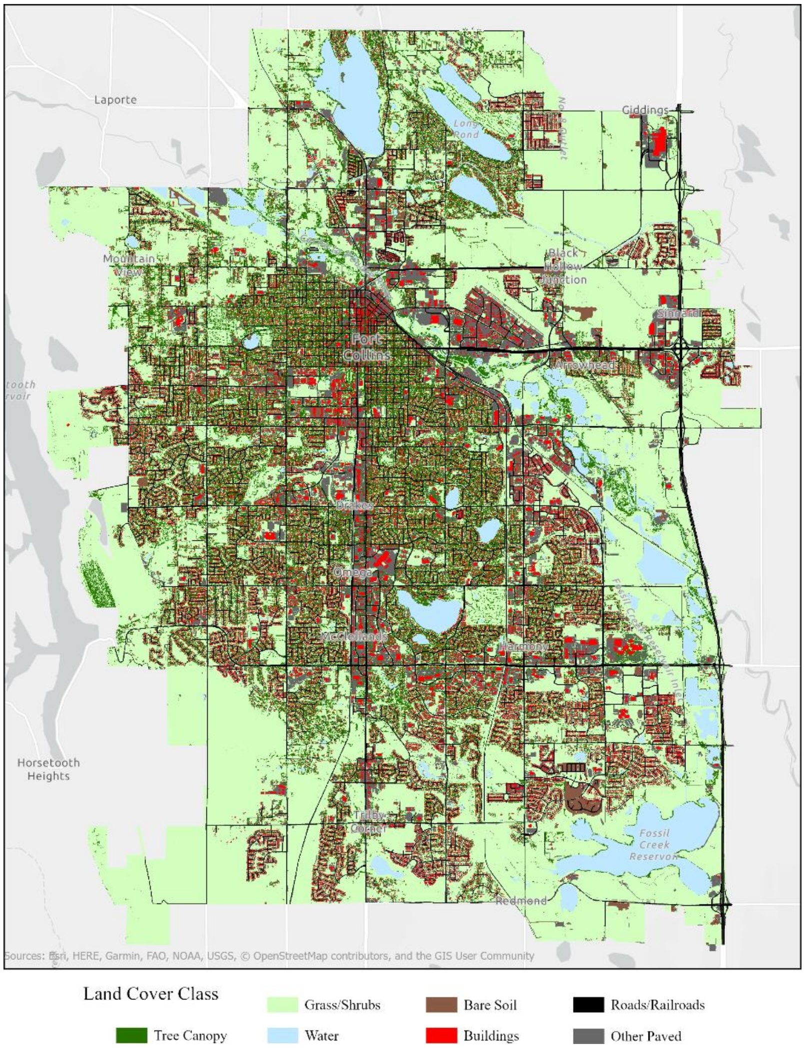

Figure 1.1. *Land cover in Fort Collins, CO.*

Table 1.3. *Descriptive statistics of land cover data across all block groups.*

Variable	**Description**	**Min**	**Mean**	**Max**
Percent Tree	Percentage of tree coverage	3.34	21.62	43.51
Percent Grass	Percentage of grass coverage	12.60	37.13	90.53
Percent Building	Percentage of building coverage	0.91	10.80	19.22
Percent Other Paved	Percentage of other paved surface coverage	1.80	15.49	40.76
Percent Road/Railroad	Percentage of road/railroad coverage	1.97	11.63	20.86
Percent Impervious Cover	Percentage of impervious cover	6.01	37.19	71.51

2.5 Correlations

Pearson's correlation coefficients were analyzed to identify the direction and strength of the relationship between each variable and tree cover. Positive correlations indicate that with an increase in the predictor, we expect an increase in tree cover. The opposite is true for negative correlations. To assess correlations to tree cover, we used the *cor.test* function from the stats package (Version 3.6.2) (R Core Team, 2018).

2.6 Ordinary Least Squares Regression Model

Only some of our variables exhibited a normal distribution, so we log-transformed several predictor variables before implementing linear models (Table 1.4). All transformations were performed using the *log1p* function, part of the SparkR package (Version 2.4.6) (Venkataraman et al., 2020) in R. The percent tree cover response variable was normally distributed and did not require any transformation.

Table 1.4. *Continuous variables along with their distribution and transformation.*

Variable	Distribution	Transformation
% Tree Cover	Symmetric	None
% Grass Cover	Positive	Log
% Impervious Cover	Symmetric	None
Population Density	Positive	Log
% White	Negative	Log
% African American	Positive	Log
% Hispanic	Positive	Log
% College Graduates	Symmetric	None
% Renter	Positive	Log
% Owner	Negative	Log
% Single Person Households	Positive	Log
% 3+ Person Households	Positive	Log
% Family Households	Symmetric	None
% Married Households	Symmetric	None
Median Household Income	Symmetric	None
Median Home Value	Symmetric	None
House Density	Positive	Log
Median Building Age	Positive	Log
Average Parcel Size	Positive	Log

We incorporated all continuous and categorical variables into an Ordinary Least Squares multiple linear regression model (OLS) to determine the most significant predictors of cover. We first tested a full model that included all our predictors and then used a stepwise selection process for model parsimony (see Locke et al., 2016). We tested a forward and a backward model to see which had a better performance. We selected the best model as that which maximized the R^2 and minimized the Akaike Information Criterion (AIC) score. In R, the *lm* function from the stats package (Version 3.6.2) (R Core Team, 2018) was used for the general linear model, while the *MASS* package provided the *stepAIC* function to run the stepwise selection process (Venables & Ripley, 2002).

We used the variance inflation factor (VIF) to test for multicollinearity in our OLS model with the lowest AIC. A VIF score of 10 is considered high correlation and would require us to adjust predictor variables. We used the *vif* function from the *car* package (Fox and Weisberg, 2019) to test the VIF in R, and we systematically removed variables until collinearity was no longer present in the OLS model.

2.7 Spatial Autoregressive Model

An important consideration when applying a general linear model to spatially explicit data is the issue of spatial autocorrelation. This phenomenon occurs when independent predictors are inherently correlated spatially, thus inflating the coefficients of the linear model. To account for spatial autocorrelation, a Moran's I analysis was run on the OLS model residuals. A spatially random configuration would yield a Moran's I estimate of approximately 0 and would not require a spatial model in place of a linear model. A clustered spatial configuration would yield closer to +1, and a dispersed spatial configuration would yield -1; in either of these latter cases, it is necessary to apply a spatial model to avoid biasing the coefficient estimates of our results.

To run the Moran's I test, we first applied the *poly2nb* function from the spdep package (Version 1.1.3) (Bivand and Wong, 2018) to create spatial neighbors. Given the irregularity in block group configuration, we chose a queen contiguity matrix with row standardized weights. Then we used the function *lm.morantest*, also part of the *spdep* package, to run the Moran's I test on the residuals of the OLS regression model. The arguments for the Moran's I test include the OLS regression model and the *poly2nb* object (as an input to the *nb2listw* function), with all other arguments left as defaults.

We then created a Spatial Autoregressive (SAR) model to test how well our explanatory variables explained tree cover after adjusting for spatial autocorrelation. We used a spatial lag model, which assumes that the spatial structure impacts the dependent variable (Schwarz et al., 2015). We applied the *lagsarlm* function from the spdep package to control for spatial effects by adopting a lagged response variable (Browning et al., 2019).

3 Results

3.1 Correlations

Analysis of the continuous variables indicated relatively strong positive relationships between tree cover and impervious cover, renters, and the percent of 3+ person households (Table 1.5). However, the strongest positive relationships were associated with house density, building age and population density.

Comparatively, relatively strong negative relationships to tree cover were associated with the percent of homeowners, family households, married households and median household income, meaning these neighborhoods were associated with less tree cover. The strongest negative relationships were associated with grass, followed by average parcel size. Less tree cover was also associated with neighborhoods consisting of more minority populations (both Hispanic and African American), however these relationships are both statistically insignificant.

Table 1.5. *Correlations between continuous variables and percent tree cover.*

Variable	Pearson's Correlation Coefficient	P Value
% Grass Cover	-0.681	< 0.001
% Impervious Cover	0.341	< 0.001
Population Density	0.579	< 0.001
% White	0.137	0.167
% African American	-0.083	0.404
% Hispanic	-0.147	0.137
% College Graduates	0.038	0.703
% Owner	-0.271	0.005
% Renter	0.282	0.003
% Single Person Households	0.195	0.048
% 3+ Person Households	0.299	0.002
% Family Households	-0.346	< 0.001
% Married Households	-0.323	< 0.001
Median Household Income	-0.261	0.007
Median Home Value	0.043	0.666
House Density	0.617	< 0.001
Building age	0.713	< 0.001
Average Parcel Size	-0.429	< 0.001

Table 1.6. *Correlations between categorical lifestyle variables and percent tree cover.*

Variable	Pearson's Correlation Coefficient	P Value
Affluent Estates	-0.252	0.009
Upscale Avenues	-0.299	0.002
Uptown Individuals	-0.035	0.721
Family Landscapes	-0.279	0.004
GenXUrban	0.139	0.160
Middle Ground	0.193	0.049
Senior Styles	-0.098	0.322
Rustic Outposts	-0.157	0.111
Midtown Singles	0.121	0.219
Next Wave	-0.095	0.337
Scholars and Patriots	0.223	0.023

The correlations between our categorical lifestyle variables and tree cover were generally not strong relationships (Table 1.6). We found relatively stronger negative relationships associated with Affluent Estates and Upscale Avenues, while a relatively stronger positive relationship was associated with Scholars and Patriots. It is likely that due to the wide range of tree cover in several classes, coupled with few observations in other classes, that these relationships are moderate to negligible (Figure 1.2).

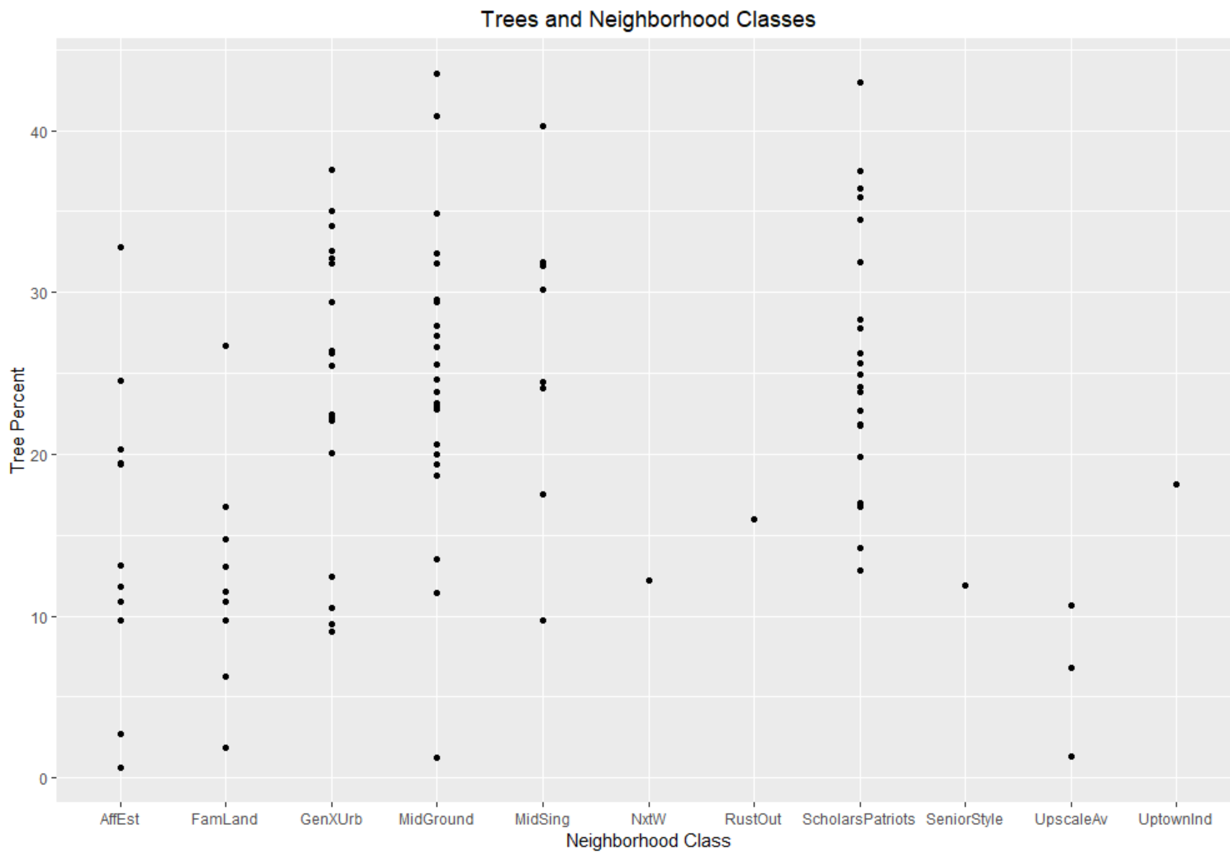

Figure 1.2. *Percent tree cover within neighborhood classes. Each point represents a neighborhood, its location corresponding to its classification on the X-axis and the percent tree cover on the Y-axis.*

3.2 Ordinary Least Squares Regression Model

Our results indicated the variables explaining the most variability in UTC were house density and building age (Table 1.7). The percent impervious cover, Hispanic population and grass cover both have a moderate effect on tree canopy. The percent white population and renters had the least effect of the top explanatory variables. None of the lifestyle variables contributed to UTC in our model.

Table 1.7. *Summary of variables explaining Fort Collins UTC.*

Variable	Coefficient	Std. Error	*P* value	Cohen's F
Intercept	50.896	31.824	0.113	-
House Density	7.832	0.964	<0.001	1.395
% Renter	-2.029	0.725	0.006	0.124
% Hispanic	-0.705	0.607	0.248	0.342
% White	-7.393	6.451	0.254	0.270
Median Building Age	12.296	1.741	<0.001	1.303
% Grass Cover	-10.518	2.119	<0.001	0.316
% Impervious Cover	-0.256	0.066	<0.001	0.397

3.3. Spatial Autoregressive Model

The residuals of our OLS model were indicative of spatial autocorrelation and had statistically significant P values for Moran's I (0.14, P value = 0.009). UTC also demonstrated statistically significant Moran's I (0.56, P value < 0.001). We proceeded to address spatial autocorrelation by applying a SAR model using the spatial lag technique.

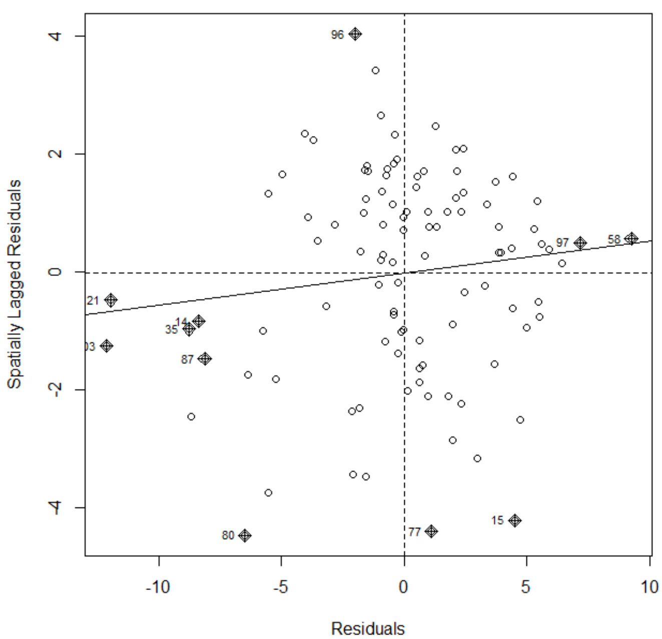

Figure 1.3. *Plotted residuals from the spatial lag model.*

We again tested the residuals of our SAR model using Moran's I and found it removed spatial autocorrelation (0.05, P value = 0.113). The relationships between each explanatory variable and UTC did not change when we applied the SAR model. We compared the OLS and SAR results based on their AIC score, and we found the AIC score improved by applying the SAR model (Table 1.8).

Table 1.8. *Comparing OLS and SAR regression models.*

Model	AIC
OLS Model	616.9
SAR Model	601.5

4 Discussion

4.1 Drivers of Tree Cover

Our regression results indicate that the variables explaining the most tree cover in Fort Collins, CO are a combination of morphological and social characteristics, with the two main variables being morphological (house density and building age). These results support our hypothesis that morphology may play a major role in Fort Collins UTC.

We found that the older buildings in Fort Collins are associated with high tree cover. Opposite results were found in several studies such as Bigsby et al. (2014), which analyzed both Baltimore, Maryland and Raleigh, North Carolina and found that newer buildings were associated with more tree canopy. Conway (2009) analyzed vegetation in Toronto, Canada and found that older homes had less overall vegetation than newer homes. These contrasting results may be explained by the biome of Fort Collins; this is a semi-arid region where few natural tree species thrive, resulting in a heavily-managed UTC. Much of the vibrant UTC has long been planted and maintained throughout the oldest parts of the city, whereas the UTC in newer developments has been planted more recently as the city has undergone rapid population growth.

We also found that more tree cover is associated with high house density, while other studies have found that areas with higher house density contain less tree cover. These effects were seen in a study by Iverson and Cook (2000) that took place in Chicago, Illinois, where the authors found tree cover to be strongly and inversely related to house density. This opposite finding for Fort Collins could also be explained by the morphological development of the city, because higher house density is also found in the oldest parts of the city where the UTC has been created and maintained the longest.

We saw an important relationship between UTC and impervious cover, but again this relationship does not follow the trends found in previous studies. Higher impervious cover is located in central Fort Collins (see Figure 1.1); although contradictory to the notion that impervious cover constrains the amount of area available for tree planting (Nowak and Greenfield, 2012; Coseo et al. 2019), Fort Collins has actively planted much of the UTC in this intensely developed portion of the city.

Our results indicated that grass cover had a significant negative relationship to tree cover, and this is something we might expect given the location of the city. Nowak et al. (1996) assessed the distribution of UTC in 58 U.S. cities and found UTC to be lower in cities situated in grasslands, which also tend to have more agricultural land. Nowak and Greenfield (2020) stated that in drier grasslands, unmanaged land will also not naturally regenerate with trees and will have lower UTC unless tree planting and watering programs are established. These findings may explain the inverse relationship we see between grass and tree cover. Because Fort Collins is still in the process of urbanizing, areas in the outskirts of the city have yet to be transformed from grassland and agricultural land to a more urbanized landscape that can accommodate a larger population, and it may take years before trees are fully established (Figure 1.4).

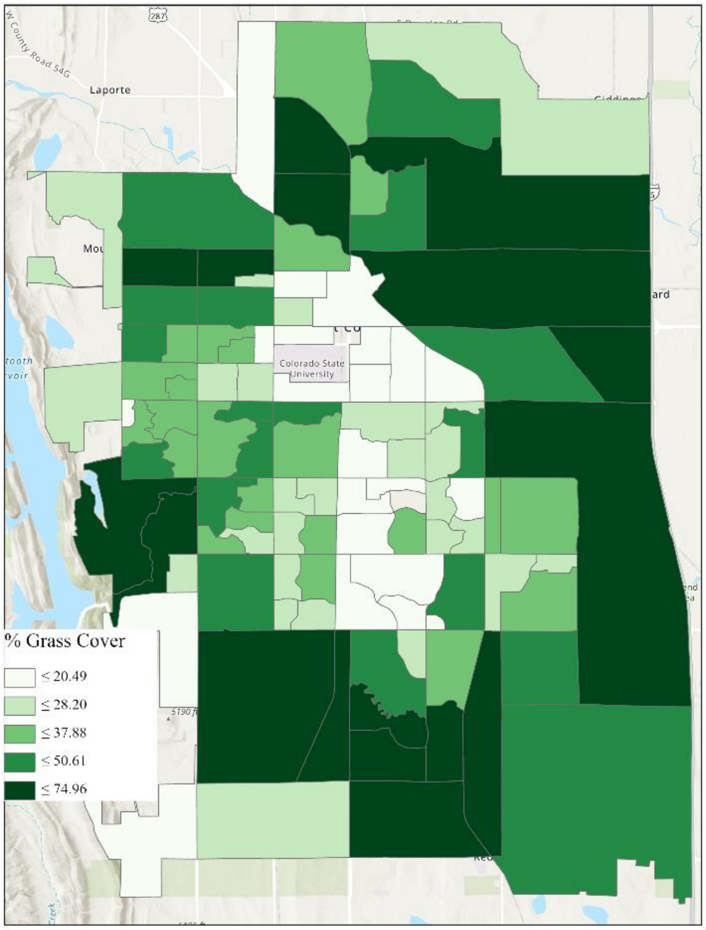

Figure 1.4. *Percent grass cover per block group.*

When we analyzed the effects of social characteristics on tree cover in Fort Collins, we observed some trends that were in alignment with previous studies, while other trends were opposite of what we would expect. Often in large cities, we see higher UTC in areas with more homeowners, more white population, and higher income, while we tend to see lower UTC in areas with more renters, minority populations and lower income (see Grove et al., 2014; Schwarz et al., 2015; Heynen, 2003).

The regression results revealed the social predictors contributing the most to UTC were the percent Hispanic population, percent white population and percent renters. The percent Hispanic population was associated with lower tree canopy in our correlation analyses, while the percent white population was associated with higher tree canopy. These results are similar to what several studies have found relating to the distribution of tree cover and race and ethnicity; previous studies have suggested that some disparities in UTC have reflected racial segregation (see Flocks et al., 2011, Schwarz et al., 2015, Riley and Gardiner, 2020), and this segregation represents one type of environmental injustice. Fort Collins currently has little racial and ethnic diversity (see Table 1.1), yet based on our results, we still see potential environmental injustices that may be developing within the city.

Previous work has also suggested less UTC exists in areas with more disadvantaged populations, such as renters or areas with lower income (see Riley and Gardiner, 2020). However, in the correlation analysis we found that more renters are associated with higher UTC in Fort Collins. This could be due to the location of Colorado State University, one of the oldest establishments in the city, being close to Old Town which contains a large amount of UTC.

4.2. Possibility and Potential for Tree Planting and Maintenance

Studies on the distribution of UTC can have the power to inform future management decisions, establishing areas where we may want to prioritize tree planting and maintenance. We discuss planting and maintenance in the context of the "Three P's" framework introduced by Grove et al. (2006). This framework can assist in maximizing the benefits of UTC while minimizing the potential disservices, as it considers areas for *Possible*, *Preferable* and *Potential* UTC. We only focus on the first two "P's" *(Possible and Preferable)* to highlight areas where it is biophysically feasible to plant and maintain trees in Fort Collins, and areas where it may be socially desirable to plant and maintain trees (Locke et al., 2010).

Possible UTC includes areas where it is biophysically feasible to create and maintain UTC, which is shaped by the type of existing land cover (e.g. impervious vs. pervious cover). In Fort Collins, most of the current UTC is already located in areas with high impervious cover. As the city continues to develop, more trees should be planted in areas dominated by grass, as these areas are currently associated with less UTC and pervious cover is the most biophysically feasible land cover for tree planting. Conversely, impervious cover limits space for additional planting (see Nowak and Greenfield, 2012; Coseo et al., 2019), and also limits the natural regeneration of trees (Nowak and Greenfield, 2020); therefore, maintenance will be preferred to ensure there is adequate UTC in areas with high impervious cover. Maintenance will be especially important in impervious areas because tree shade can help decrease the negative impacts associated with the Urban Heat Island (UHI) effect, a phenomenon that leads to higher temperatures in areas with more impervious cover (Zhou et al., 2011; Wang and Akbari, 2016). Proper maintenance of UTC in impervious areas may be critical to keep Fort Collins residents physiologically comfortable during the warmer months (see Gomez-Muñoz, 2010; Coseo et al., 2019).

Extending beyond planting possibility, cities then should consider preferable UTC to reduce the number of communities that may be vulnerable to environmental injustices, such as social, physical and economic inequities relating to UTC (Flocks et al., 2011). In Fort Collins, our results indicate that less tree canopy is associated with minority communities, homeowners, family and married households, and households with higher income (see Table 1.5). We recommend these areas are a priority for planting to ensure distributional equity. We want to ensure that families, particularly children and the elderly, are able to experience the benefits of UTC as it has been shown to positively impact their mental and physical health (see Sivarajah et al., 2018; Browning et al., 2019),

Many of the residents living in the areas with higher tree canopy tend to be low-income, renters and 3+ person households (non-family). If UTC is not adequately maintained, these communities may be vulnerable to future tree collapse from old age, or removal for pests and disease. For example, Fort Collins recently detected Emerald Ash Borer (EAB), an invasive pest that has decimated ash tree populations in other regions of the world (Herms and McCullough, 2014), and it is expected that many public trees will be removed to help contain EAB spread. Once those trees are removed, these communities will be underserved by the UTC, exposing them to distributional inequity.

There are many different contexts as to why distributional inequities appears in our cities. We acknowledge that complex interactions take place between the social-demographic preferences of urban residents and the morphological development, as well as the unique biomes of cities, that can influence

UTC distribution. The results of our study can provide relevant information that can be used in future planning and development in numerous ways, such as establishing zoning codes that require planting trees in new developments, targeting planting in areas that are currently underserved by the UTC, and maintaining UTC in areas that will be susceptible to EAB.

4.3. Caveats and Future Research

We also acknowledge that with a block group scale, it is difficult to identify larger-scale trends that may contribute to UTC distribution, and we cannot accurately identify specific locations for planting and maintenance.

Our future work will expand on UTC relationships by comparing various spatiotemporal scales, as we expect different patterns to emerge under differing spatial and temporal conditions (see Locke et al., 2016). Our work would greatly benefit by gathering unique household level information on social information, which may require a more qualitative study using survey methods. We can otherwise perform the same analysis for disaggregated Census block group social statistics.

In Fort Collins, it will be especially valuable to consider legacy effects (see Troy et al. 2006; Bigsby et al., 2014), since the city has experienced rapid morphological and social change in a relatively short amount of time. Our work is a steppingstone to understanding the function and distribution of UTC in young, semi-arid urban systems, and will serve as a basis for future sustainability planning in Fort Collins. We will also consider controlling for age in future analyses so we can isolate additional trends that may be temporally dependent.

Our next step will be to separate public from private tree canopy to see if different patterns emerge based on zoning and development. This information can then be used as leverage when developing policies to support homeowners as they deal with EAB in Fort Collins, as it is a matter that will need strategic coordination between both public and private landowners.

5 Conclusion

Our study has revealed that UTC in Fort Collins, a mid-size semi-arid city expected to undergo significant population growth, may currently be more impacted by urban morphological patterns than the social or lifestyle characteristics of its residents. We also note the importance of the grassland biome that does not naturally support many tree species, resulting in a UTC that has been heavily managed in areas where people have long been present.

Fort Collins has already experienced rapid population growth, prompting the need to accommodate more residents. As the city continues to be subjected to population growth, the newly developed outskirts of the city will need to plant trees in order to gain UTC benefits in the natural grassland and agricultural system, but it takes time for trees to become established. Those living in these the outskirts are currently not receiving the benefits of UTC, and it will be a priority for Fort Collins to begin planting trees if it has not yet taken place.

Individuals currently receiving UTC benefits in central Fort Collins will be vulnerable to disservices if trees need to be removed, whether it be from intentional tree removal or collapse. Many are not going to be able to plant and care for new trees themselves because they are often low-income and renter communities. To ensure an equitable distribution of UTC, they may need to closely monitor the areas with high UTC.

We found several unexpected relationships to UTC that suggest cities of different size, composition and climate, such as Fort Collins, may exhibit UTC trends unlike those concluded in previous studies. We provide valuable information that can add to the sphere of research surrounding UTC, and our results can facilitate urban planning and development to maximize the benefits provided by the UTC and to minimize environmental injustices experienced by urban residents.

CHAPTER 2: FORT COLLINS WATER CONSUMPTION

1 Introduction

By the turn of the 20th century, Colorado began to experience a significantly warmer and drier climate compared to the early 20th century (Colorado Climate Plan, 2015). Climate change models project temperatures to increase 4°F by 2050, relative to the 1950 – 1999 baseline; these greater temperatures are expected to increase the severity of droughts and exacerbate their impacts throughout the state (Ray and Hoerling, 2008). Precipitation patterns remain relatively uncertain, while a reduction in snowpack and earlier snowmelt and runoff are already evident (Lukas et al., 2014). 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 (Colorado Water Conservation Board, 2015). The pressures of climate change and urbanization demand innovative and sustainable water management solutions for Colorado cities.

One way to sustainably manage urban water supply is by reducing or limiting outdoor water consumption (Hanak and Browne, 2006; Tinker et al., 2005). The 2002 drought crisis in Colorado demonstrated the effectiveness of this strategy by imposing temporary, mandatory water restrictions that curbed overall water consumption by 13 – 53% across several different municipalities (Kenney et al., 2004). However, many local water managers are now focusing on long-term strategies to reduce water consumption that can more readily respond to climate change (House-Peters et al., 2010). Responsive and adaptive conservation efforts will need to include programs and policies for water efficiency that can become a regular part of residents' lives (Balling Jr. et al., 2008). To help estimate the effects of policy changes on residential consumption patterns, it is imperative that cities have a firm understanding of the local drivers of urban water consumption (Wentz and Gober, 2007).

Urban characteristics, including morphology (e.g. house density, lawn orientation), biophysical environment (e.g. lawns, trees and shrubs), social composition (e.g. income, tenure) and lifestyles (e.g.

conservation perceptions and motivations), play a significant role on outdoor water consumption patterns (see Harlan et al., 2009; Ghavidelfar et al., 2017). However, many studies have found disparities in the relative importance of these urban characteristics in predicting water consumption.

Some studies have shown that the most important predictors of water consumption are morphological characteristics. 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 (Stoker and Rothfeder, 2014; Jansen and Schulz, 2006; Chang et al., 2010). For example, Stoker and Rothfeder (2014) found newer homes use more water in Salt Lake City, Utah, while Chang et al. (2010) found that older homes use more water in Portland, Oregon. Sanchez et al. (2018) tested several landscape metrics that describe spatial configuration of buildings, along with various biophysical and social characteristics, to determine the drivers of domestic water use in North and South Carolina. Their most important finding was that spatial patterns of morphological development drives water consumption, but they also suggested that biophysical characteristics were important.

Biophysical characteristics of cities have been widely studied in the context of urban water consumption, primarily concerning the presence of urban tree canopy (UTC) and residential landscaping preferences. 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 landscapes where water is already scarce (Dwyer et al., 1992). If trees are associated with more water consumption in arid and semi-arid urban landscapes, cities will need to consider promoting alternative, water-efficient residential landscapes. Several studies have shown that residential landscaping can potentially impact outdoor water consumption; Olmost and Loge (2013) 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 (2007) found that xeric landscaping in Phoenix, Arizona was not as important for residential water consumption patterns as they expected, but they noted that this was more because residents were not adjusting their water practices to coincide with different seasonal water requirements.

Wentz and Gober's (2007) findings exemplify the complex interplay between urban characteristics and the resulting effect it can have on water consumption. Despite testing for the effect of biophysical variables, they found social watering practices to significantly impact 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 affluent households tend to use water for maintaining lawns and gardens, and for amenities such as swimming pools, fountains, whirlpools, hot tubs, spas and misters (Harlan et al., 2009). Ghavidelfar et al. (2015) and Jorgensen et al. (2009) both found that households with higher income use more outdoor water. Jorgensen et al. (2009) also found tenure to be important, with homeowners using more water than renters. Age of household members and overall household size can also influence water consumption because families with young children or teenagers may be more likely to install swimming pools (Corbella and Pujol, 2009).

Another important factor to consider when addressing water consumption and conservation efforts is the consumer's lifestyle, or the characterization of their behavior. Lifestyles are a more complex facet of social characteristics, encompassing attitudes, opinion, values, feelings, intentions and habits (Newton and Meyer, 2013). According to Jorgensen et al. (2009), consumption behavior is influenced by the individual's awareness and perception of water conservation, along with their personal motivation for it. Jorgensen et al. were able to reaffirm the idea, initially presented in Berk et al.'s (1993) study, that people with higher income, more education, and a higher job status were more likely to engage in water-saving practices. They also 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., (2018) 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 water consumption patterns.

It is indisputable that a wide range of variables influence water consumption patterns, as identified by previous studies. The complex nature of these studies suggests that trends in water consumption will be dependent on the study region as well as the unique morphological, biophysical, social 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 (Yang and Wang, 2015) and Los Angeles, California (Renwick and Green, 1999). Few studies have investigated water consumption drivers in growing, semi-arid cities where we expect increased population to exert substantial stress on local water supplies (see Ahmad, 2016). To better understand the drivers of water consumption and compare across cities, we must identify the unique characteristics that result from the urbanization process within more cities of different size and development stages.

Our study will add to this expanding body of literature by investigating the relationships between single-family households and outdoor water consumption patterns in the growing, semi-arid city of Fort Collins, CO. The objectives of this study are to 1) determine which morphological, biophysical, social and lifestyle variables may be driving outdoor water consumption and compare their importance; and 2) discern relationships between vegetative patterns (trees vs. grass) and outdoor water consumption at a single-family residential parcel scale. We expect water consumption to be predominantly driven by biophysical characteristics, and that the presence of trees may increase overall outdoor consumption. This research will inform the Fort Collins and its residents of outdoor water consumption patterns, providing data that can be used to implement sustainable urban planning as well as further educate the community on efficient outdoor water practices.

2 Methods

2.1. Study Location

Fort Collins, Colorado is a healthy, vibrant community transitioning from a large, suburban town to a small urban city (City of Fort Collins, 2014). The city has been showered with various honors and awards, including the best American city for cycling, third best place for business and career, and the fourth happiest city in America (City of Fort Collins Visitor Awards, n.d.). Historic Old Town, as the name suggests, is one of the oldest areas in the city. Being a popular urban center filled with nature, tourist, cooking, retail and novelty and confectionery shops, it regularly attracts many residents and tourists alike. With over 84 restaurants, seasonal events and festivals, tours and a rich energy, Old Town is a unique and enriching Fort Collins experience (Visit Fort Collins, n.d.) and serves as an important place for community in the city.

Fort Collins also prioritizes the well-being of the community through proactive and informed urban planning. For decades, the local municipality has led the way in innovative and sustainable water policies, promoting conservation and efficiency. Fort Collins recognizes the significant population growth and 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 (City of Fort Collins, 2014). Despite these efforts, residents are still relatively unaware of opportunities for sustainable living at the personal and community level; therefore, community education and programs are needed to foster this development. Consequently, Fort Collins hopes to leverage metered water use data to better communicate and increase awareness of consumption and to promote water literacy in the community.

2.2. Water Consumption Data

Water consumption data was provided by Fort Collins through metered information within single-family residential parcels (households). Each parcel included combined indoor and outdoor water use for the year 2016 (n = 28,773). Water use was calculated by the total gallons of water usage divided by the number of days of service (a range of 20 – 40 days within each billing cycle). Every parcel record contained a rate of use for the consumer's billing cycle, but each parcel had a different billing date that did not align with the calendar month, requiring us to recalculate an accurate daily rate of use for each month. To identify seasonal trends and develop our response variable, we converted our corrected rate of use (gal/day) to monthly total gallons (Table 2.1, Figure 2.1), and then those values were averaged for the entire season.

Table 2.1. *Average monthly consumption across all parcels in total gallons and gallons / day.*

Time Period	Total Gallons	Gallons / Day
January	3,988.38	128.66
February	3,735.87	128.83
March	4,092.59	132.02
April	4,316.85	143.90
May	6,978.32	225.11
June	13,253.98	441.80
July	16,078.95	518.68
August	14,205.85	458.25
September	11,282.76	376.09
October	7,141.87	230.38
November	4,472.85	149.10
December	4,177.59	134.76

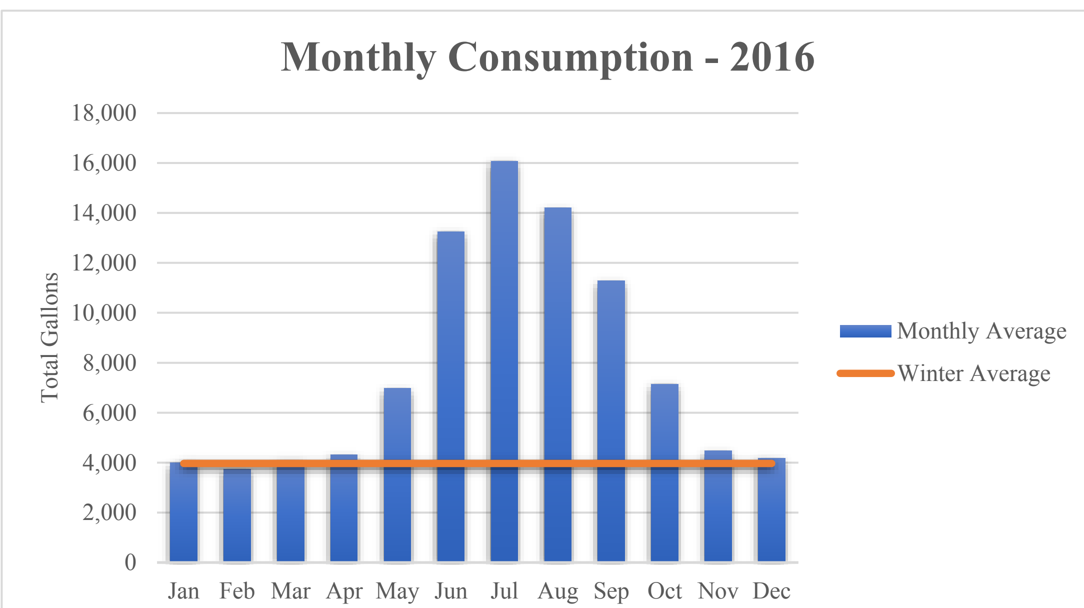

Figure 2.1. *Average monthly consumption trends (gallons) across all parcels in comparison to the winter season average.*

To distinguish between indoor and outdoor consumption, we took the summation of each household's water use (total gallons) during the 2016 winter season (Dec – Feb) and subtracted it from their summer use (June – August), which was our timeframe of interest. The local municipality of Fort Collins recommended this method with the assumption that households are not irrigating outdoors during the winter months, leaving us with a proxy for outdoor water consumption. This approach was a critical step in developing our response variable.

We were interested in the amount of water being used on irrigatable space, or pervious area within the parcel boundary. We used high resolution raster land cover classification data (1 m^2) derived from an object-oriented classification utilizing aerial imagery and LiDAR (Beck et al., 2016) to distinguish irrigatable space from non-irrigatable space. This land cover dataset provided data for trees, grass and shrubs, bare soil, water, buildings, roads and railroads, and "other" paved surface cover (e.g. driveways). We used the ArcGIS Pro (Version 2.5.1) *Erase* tool to remove buildings and other paved surface cover (e.g. driveways) from each parcel, leaving only the area for irrigatable space (ft^2).

2.3. Response Variable

We took the summation of water consumption (total gallons) for the summer season and divided it by the amount of irrigatable space (ft^2) on each parcel to obtain our response: summer outdoor consumption, ranging from approximately 0 - 390 gallons / ft^2. For privacy reasons, we were unable to share water consumption data for every parcel, so we created a Kernel Density map of summer outdoor water consumption (Figure 2.2).

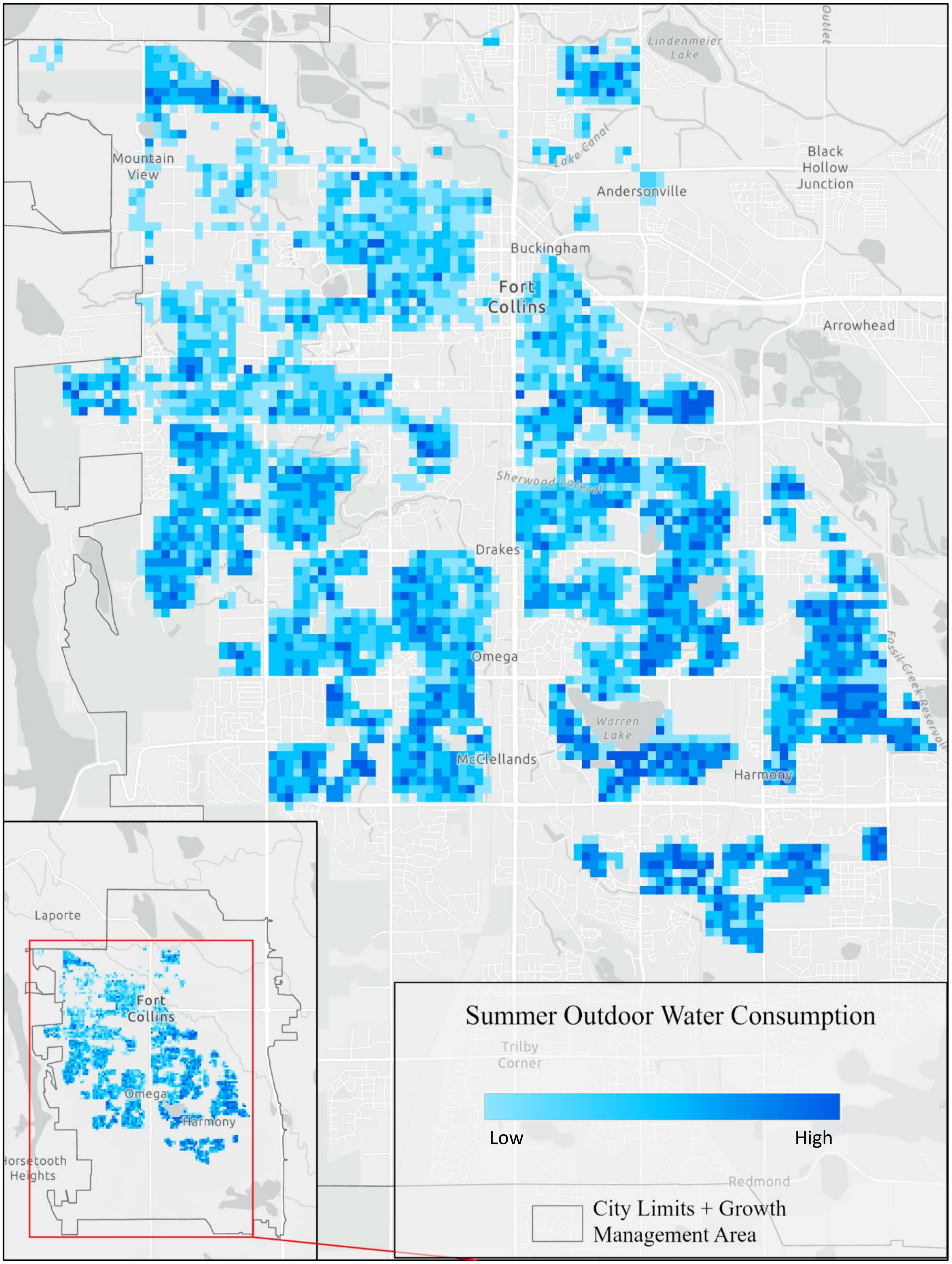

Figure 2.2. *Summer 2016 water consumption in Fort Collins.*

2.4. Explanatory Variables

Most of our social and morphological data were provided by the US Census Bureau's American Community 5-Year Survey program for 2017. Based on previous studies (Harlan et al., 2009; Ghavidelfar et al., 2017; Stoker and Rothfeder, 2014; Jansen and Schulz, 2006; Chang et al., 2010), we chose predictor variables that illustrate features such as ethnicity, tenure, household size, income and educational attainment (Table 2.2). These data were provided at a block group scale, which consists of several census blocks within the same census tract. We were unable to attain parcel-scale social data for most of our social variables. Therefore, we disaggregated broader-scale Census block group data to represent the social characteristics of the household. In doing so, we made assumptions about the social structure of each household, which does not necessarily depict its true condition.

Additional lifestyle predictors were obtained from ESRI's Tapestry Segmentation data (Tapestry Segmentation, 2018), a demographic dataset that provides detailed descriptions of neighborhood block group residential areas based on socioeconomic and demographic composition (Table 2.3). These data are also disaggregated from the Census block group scale, making assumptions about lifestyles in each household. Descriptions of neighborhood class predictors can be viewed in Appendix I. These data are the first set of categorical variables in our model, so we created dummy variables in the R statistical environment using the *dummy.data.frame* function, part of the dummies package **(**Brown, 2012), to be able to employ them in our models.

We used the land cover dataset to distinguish between vegetation type on each parcel. We calculated the percent cover of grass / shrub and trees within the remaining irrigatable space. Bare soil 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 then created an interaction term by multiplying the percentage of grass / shrubs and percentage of trees in irrigatable space to obtain combined vegetation cover, and a second interaction term multiplying overall vegetation cover with the area of irrigatable space (Table 2.2).

We acquired assessor's data on the age and value of each parcel from the City of Fort Collins (Authier, 2019) (Table 2.2). 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 roads) in ArcGIS Pro. Cardinal directions were determined as follows: an angle of 0° indicates East, 90° indicates North, -180° and 180° indicates West, and -90° indicates South. We allowed for 5° of angular freedom around each Cardinal direction (e.g. 3° or -3° still indicates East). We also calculated intercardinal directions of NE, NW, SE and SW as being any value that falls in between the cardinal directions (e.g. 22° indicates NE) (Table 2.4). We used visual validation to ensure these measurements were accurately representative. Direction of the front lawn comprised the second set of categorical variables in our dataset, therefore we created dummy variables using the same *dummy.data.frame* function in R (Brown, 2012) to account for lawn direction in our models.

We utilized 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) for six dates in 2016 (May 29, June 14, July 16, August 1, August 17 and September 18) (Table 2.2). In R, we created a cloud mask for May 29 and July 16. We then derived a mean composite image to calculate average LST, and a median composite image to calculate NDVI, both at a 30 m × 30 m spatial resolution. Both LST and NDVI were calculated in ArcGIS Pro using the *Raster Calculator* and the *NDVI Raster Function,* respectively. Both LST and NDVI were resampled to 10 m × 10 m rasters so the *Zonal Statistics as Table* tool in ArcGIS Pro could capture as much information as possible when applying the data to the smaller scale parcels.

Table 2.2. *Descriptive statistics of continuous social, morphological and biophysical explanatory variables.*

Variable	Min	Q1	Mean	Q3	Max
Population Density (per hectare)	1.36	13.50	17.06	21.34	64.96
% White	71.45	88.57	90.42	93.74	100.00
% African American	0.00	0.00	1.19	1.95	8.12
% Hispanic	0.00	4.79	10.57	12.71	66.12
% College Graduates	6.98	28.91	35.06	40.67	60.70
House Density (per hectare)	0.60	4.87	7.04	8.96	28.95
% Owner	3.62	48.02	62.16	79.73	98.34
% Renter	1.16	20.27	34.69	45.74	93.68
% Single Person Households	6.91	15.26	21.51	27.62	64.32
% 3+ Person Households	0.00	0.00	5.50	7.62	31.33
% Family Households	9.63	48.45	59.36	70.58	88.12
% Married Households	3.52	37.38	47.77	58.25	81.17
Median Household Income ($)	18,550	52,159	71,264	89,167	130,139
Parcel Size (ft^2)	1,066	6,917	9,515	9,766	840,118
% Trees in Irrigatable Space	0.25	35.10	50.24	65.95	100.00
% Grass in Irrigatable Space	0.39	34.29	50.26	64.93	100.00
Age of Home	0.00	25.00	37.72	44.00	139
Home Value ($)	153,600	363,275	433,041	480,125	1,974,200
Grass x Trees	24.88	1,859.96	2,078.60	2,441.54	7,399.49
Vegetation x Irrigatable Area	105,231	7,746,447	11,958,690	14,363,504	450,050,219
LST (°F)	82.57	90.50	92.22	94.04	98.86
NDVI	0.02	0.26	0.30	0.34	0.51
Distance to Old Town (mi)	0.29	2.40	3.19	4.11	5.92

Table 2.3. *Categorical lifestyle explanatory variables.*

Neighborhood Class	Parcel Count
Affluent Estates	1,834
Upscale Avenues	1,870
Uptown Individuals	49
Family Landscapes	2,239
GenXurban	5,006
Middle Ground	8,125
Senior Styles	88
Rustic Outposts	8
Midtown Singles	900
Next Wave	18
Scholars and Patriots	4,151

Table 2.4. *Categorical lawn orientation explanatory variables.*

Direction of Lawn	Parcel Count
East	3,171
Northeast	2,887
North	3,374
Northwest	2,686
West	3,403
Southwest	2,929
South	3,334
Southeast	2,594

2.5. Bivariate Analyses

We compared relationships between each explanatory variable and summer consumption using a simple linear regression model. By analyzing bivariate relationships, we were able to estimate the degree of increase or decrease in water consumption associated with each explanatory variable. We were interested in the context of these relationships when assessing the prediction model outputs. While some variables may be considered more important for predicting water consumption, we still need to consider the degree of influence they have on water consumption. We used the *lm* function from the stats package (Version 3.6.2) (R Core Team, 2018) to create the linear models.

2.6. Random Forest

Random Forest (RF) (Breiman, 2001) is a nonparametric machine learning method used to develop regressive models through a series of regression 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 (Severson et al., 2017). Despite RF being insensitive to collinearity, variable importance, and overall variance explained, the regression models can still be deflated in the presence of collinearity and variable selection processes are recommended (Murphy et al., 2010).

2.7. Variable Selection

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 (Speiser et al., 2019).

We applied the *rf.modelSel* function in the *rfUtilities* package (Murphy et al., 2010) for variable selection. This process ranks all variables in order of their explanatory power. We then created a correlation matrix of the top-ranking variables and removed those which yielded a Pearson's correlation coefficient > | 0.75 |.

2.8. Regression Modeling

We implemented RF using the *randomForest* package (version 4.6-12**)** in R **(**Breiman, 2001**)**. The two parameters we adjusted were: 1) *mtry*, which determines the number of input explanatory variables randomly chosen at each split; and 2) *ntrees*, which dictates the number of decision trees used (Genuer & Tuleau-Malot, 2010). We employed several iterations of the RF model with *mtry* ranging from 3 – 5 and *ntrees* ranging from 500 – 700. Although our models did not improve after approximately 300 decision trees, we tested our models with the *ntrees* parameter at or above the default value of 500 to achieve a more reliable output. We used the percentage of variance explained and the Root Mean Squared Error (RMSE) statistic to report the accuracy of our RF prediction models.

We tested several different combinations of variables in the RF models. One of our goals was to compare which predictors best described water consumption, so we created five combinations of explanatory variables and compared their accuracy in explaining water consumption variance: 1) a model comprised of the top variables from the RF variable selection process; 2) a model comprised of only morphological variables; 3) a model comprised of only biophysical variables; 4) a model comprised of only social variables; 5) a final model comprised of variables that are unique data for each parcel, as opposed to data disaggregated from the larger block groups. The five models were tested with an *mtry = 4* and *ntrees = 500*, as they all performed the best under these parameters.

3 Results

3.1 Bivariate Analyses

The strongest bivariate relationships in terms of the coefficient and R^2 include percent white population, percent college graduates, percent 3+ person households, percent owners and renters, percent family and married households, LST, NDVI, percent grass and percent trees, and the age of the home (Table 2.5). Of these variables, large increases in water consumption were associated with percent college graduates, percent family and married households, and LST. Affluent Estates and Upscale Avenues neighborhoods had the greatest increase in consumption (Table 2.6). The lawn orientation variables had marginal effects on water consumption.

Many variables were associated with significant decreases in water consumption, but the greatest magnitude occurred with percent white population, percent trees and NDVI (Table 2.5). None of the categorical variables resulted in large decreases for water consumption (Table 2.6). We expect this to be due to the spatial scale of the lifestyle variables coupled with the relatively few classes residents could be categorized in. However, Upscale Avenues did have a stronger relationship to water use when compared to the rest of the lifestyle variables (Table 2.6).

Table 2.5. *Bivariate relationships for summer consumption and continuous variables.*

Variable	Log Transform	Coefficient	R^2	*P* value
Population Density	Yes	-0.209	0.013	< 0.001
% White	Yes	-0.859	0.004	< 0.001
% African American	Yes	-0.014	-3.872e-05	0.813
% Hispanic	Yes	-0.001	-4.075e-05	0.934
% College Graduates	No	1.177	0.028	< 0.001
House Density	Yes	-0.273	0.030	< 0.001
% Owner	No	0.603	0.029	< 0.001

% Renter	No	-0.644	0.031	< 0.001
% Single-Person Households	Yes	0.003	-3.891e-05	0.821
% 3+ Person Households	Yes	-0.149	0.046	< 0.001
% Family Households	No	0.918	0.043	< 0.001
% Married Households	No	0.964	0.047	< 0.001
Median Household Income	No	0.001	0.047	< 0.001
Parcel Size	Yes	-0.409	0.051	< 0.001
% Trees in Irrigatable Space	No	-0.968	0.038	< 0.001
% Grass in Irrigatable Space	No	0.794	0.057	< 0.001
Age of Home	Yes	-0.570	0.159	< 0.001
Home Value	No	0.0001	0.042	< 0.001
Grass x Trees	No	-0.019	0.025	< 0.001
Vegetation x Irrigatable Area	Yes	-0.088	0.094	< 0.001
LST	Yes	5.497	0.042	< 0.001
NDVI	Yes	-2.298	0.019	< 0.001
Distance to Old Town	No	0.493	0.055	0.267

Table 2.6. *Bivariate relationships for summer consumption and categorical variables.*

Variable	**Coefficient**	**R^2**	***P* value**
Neighborhood Class:			
Affluent Estates	0.319	0.013	< 0.001
Upscale Avenues	0.707	0.065	< 0.001
Uptown Individuals	0.036	-3.609e-05	0.728
Family Landscapes	0.332	0.018	< 0.001
GenXUrban	-0.083	0.002	< 0.001
Middle Ground	-0.158	0.010	< 0.001
Senior Styles	-0.042	-2.953e-05	0.593
Rustic Outposts	-0.467	9.077e-05	0.073
Midtown Singles	-0.077	0.0003	0.002
Next Wave	-0.357	0.0001	0.039
Scholars and Patriots	-0.347	0.031	< 0.001
Lawn Orientation:			
East	-0.195	0.007	< 0.001
Northeast	0.148	0.004	< 0.001
North	-0.071	0.0002	0.009
Northwest	0.074	0.0009	< 0.001
West	-0.144	0.004	< 0.001
Southwest	0.179	0.006	< 0.001
South	-0.038	0.0002	0.005
Southeast	0.113	0.002	< 0.001

3.2. Variable Selection

We included a total of 41 variables to the *rf.modelSel* function, of which 11 were considered most important for regression modeling. The variable with the most explanatory power was parcel size, followed by the distance to Old Town. Home value, LST, percent 3+ person households and the grass and tree interaction term followed. Percent tree and college graduates were the next most important. The percent of owners, single-person households and white population ranked the lowest of the top explanatory variables (Figure 2.3).

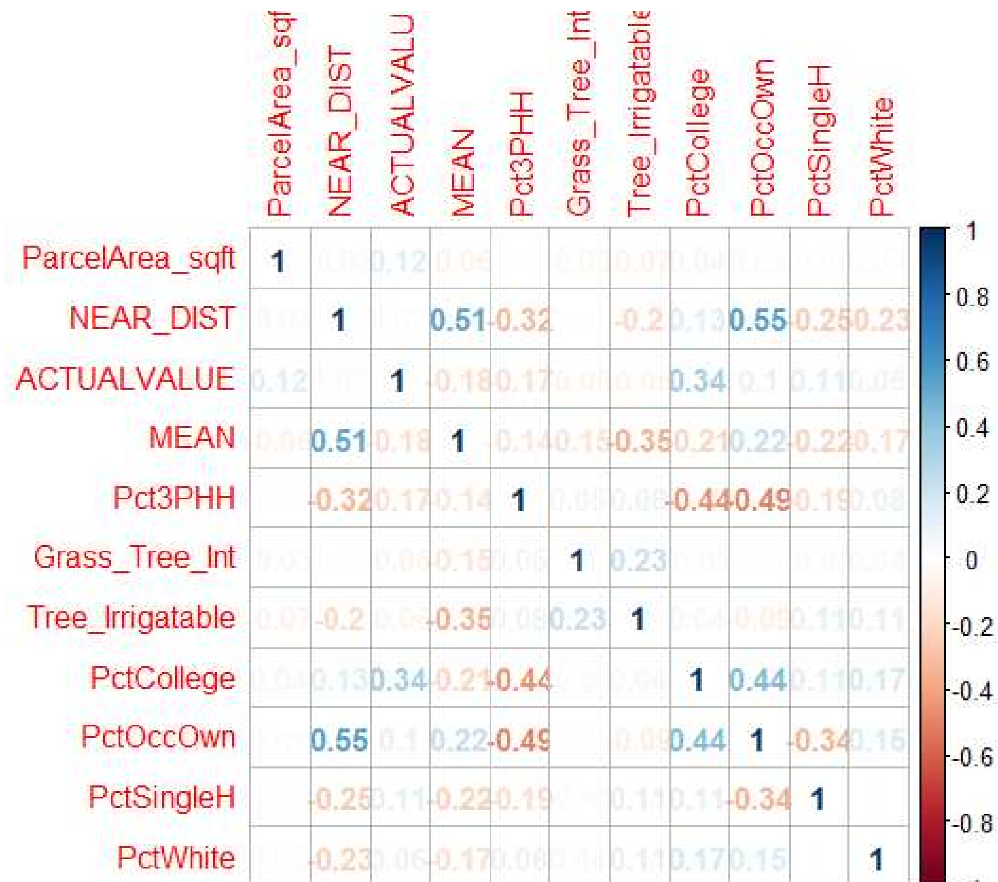

Figure 2.3. *Correlation matrix of the top variables ranked from most to least important in the variable selection process. Parcel size was the most important predictor and the percent white population was the least important.*

3.3. Regression Modeling

We created five models, each containing a different combination of explanatory variables. Model 1 included the top variables listed in variable selection process; Model 2 included only morphological variables; Model 3 included only biophysical variables; Model 4 included only social and lifestyle variables; and Model 5 included only variables unique to each parcel, rather than those disaggregated from block group data. The best model explained approximately 34% variance, while the poorest model explained approximately 15% variance. Model summaries are displayed in Table 2.7, with their variance and RMSE specified.

Table 2.7. *Regression model summaries for summer water consumption.*

Model	Variance Explained	RMSE
1. Variable Selection	34.33 %	7.81
2. Morphological	32.61 %	7.92
3. Biophysical	22.24 %	8.50
4. Social	15.43 %	9.69
5. Unique	34.69 %	7.79

Model 1 included morphological, biophysical and social variables (Table 2.8). No lifestyle variables were included. Parcel size was the most important variables, while the distance to Old Town and home value followed and were similar in importance. Percent 3+ person households and percent owners were similar in importance. LST was slightly more important than percent trees. Single-person households, college graduates, the percent white population were ranked less important, and the grass and trees interaction term was the least important of all. Model 1 explained 34.33% variance with an RMSE of 7.81 (Table 2.7) (Figure 2.4).

Table 2.8. *Variable importance for Model 1 – Variable selection model.*

Rank	Variable	% Increase in MSE
1	Parcel Size	24.57
2	Distance to Old Town	23.60
3	Home Value	21.37
4	Percent 3+ Person Households	14.40
5	Percent Owner	14.20
6	LST	13.82
7	Percent Tree	13.14
8	Percent Single-Person Households	12.52
9	Percent College Graduates	11.25
10	Percent White Population	10.32
11	Percent Grass x Percent Tree	7.92

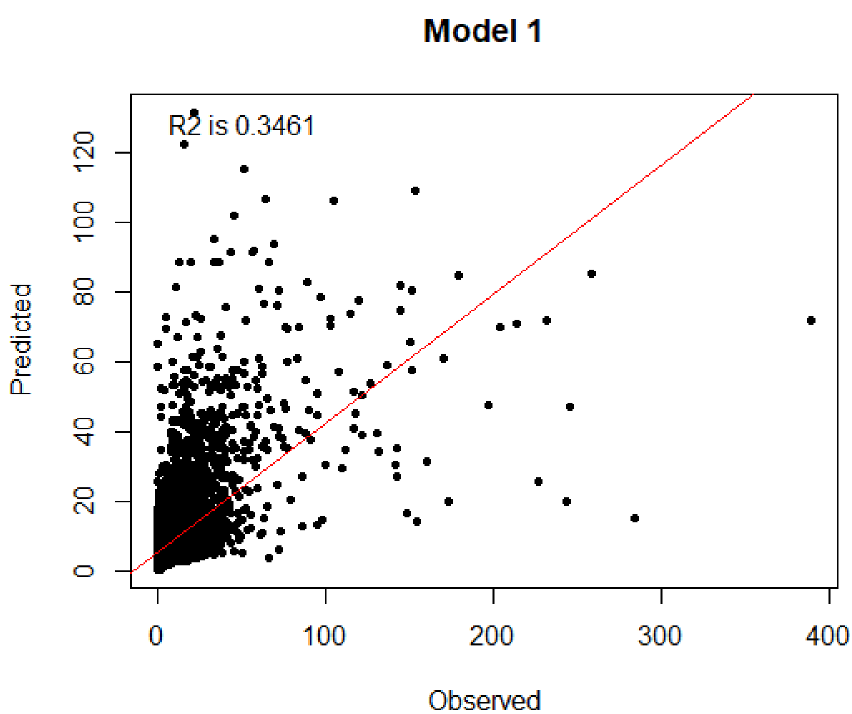

Figure 2.4. *Predicted versus observed plot for Model 1 - Variable selection model.*

Model 2 included only morphological variables (Table 2.9). The most important variables were parcel size, age of the home, and distance to Old Town. House density was also a top variable. All the lawn orientation variables contributed less to overall variance explained. Model 2 explained 32.61% variance with an RMSE of 7.92 (Table 2.7) (Figure 2.5).

Table 2.9. *Variable importance for Model 2 – Morphological model.*

Rank	Variable	% Increase in MSE
1	Parcel Size	32.16
2	Age of Home	31.87
3	Distance to Old Town	30.52
4	House Density	26.16
5	Direction: NE	11.45
6	Direction: E	9.79
7	Direction: NW	9.44
8	Direction: W	8.10
9	Direction: SE	7.43
10	Direction: S	7.08
11	Direction: N	3.76
12	Direction: SW	1.36

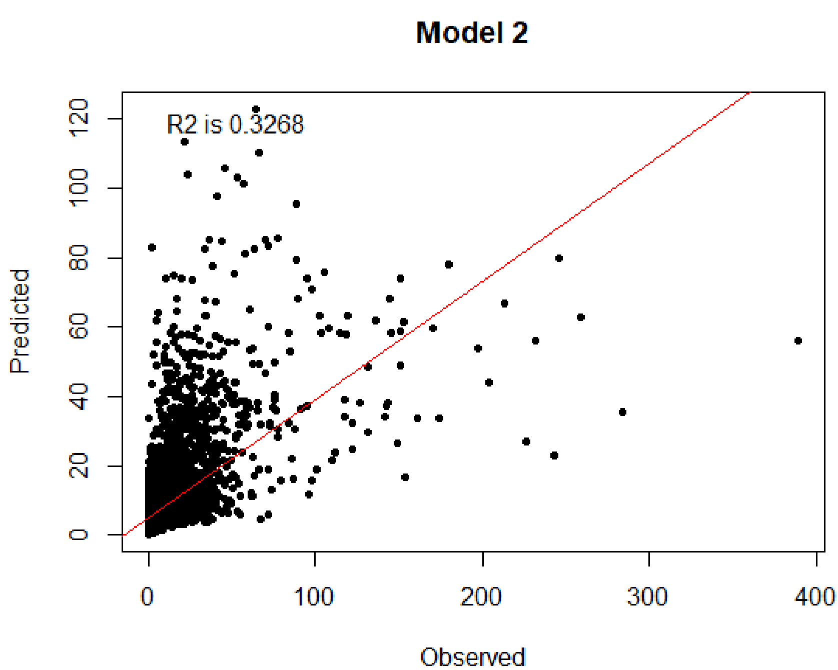

Figure 2.5. *Predicted versus observed plot for Model 2 – Morphological model.*

Model 3 included only biophysical variables (Table 2.10). The biophysical model did not perform as strong as our previous variable selection and morphological models. The vegetation and irrigatable area interaction term, along with LST, were the two most important variables. Trees and grass in combination was more important than trees or grass on their own, and trees explained more than grass overall. The least important biophysical variable was NDVI, and it was the only variable with a negative percent increase in MSE, suggesting a random variable would perform better. Model 3 explained 22.24% variance with an RMSE of 8.50 (Table 2.7) (Figure 2.6).

Table 2.10. *Variable importance for Model 3 – Biophysical model.*

Rank	Variable	% Increase in MSE
1	Vegetation x Irrigatable Area	27.34
2	LST	25.02
3	Percent Grass x Percent Tree	20.01
4	Percent Tree	9.54
5	Percent Grass	7.98
6	NDVI	-6.61

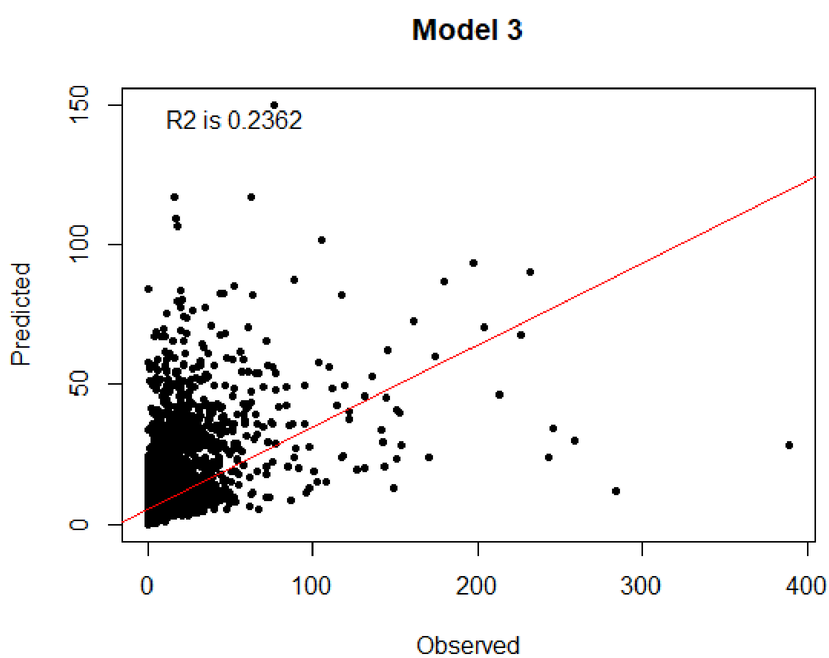

Figure 2.6. *Predicted versus observed plot for Model 3 – Biophysical model.*

Model 4 included only social variables and explained the least variance at 15.43% with an RMSE of 9.69 (Table 2.7). The most important variables were home value, percent white population, and percent 3+ person households. The only lifestyle class ranked highly in importance was Upscale Avenues. All other variables steadily decreased in importance, with all other lifestyle classes being consistently the least important.

Table 2.11. *Variable importance for Model 4 – Social / Lifestyle model.*

Rank	Variable	% Increase in MSE
1	Home Value	22.99
2	Percent White Population	22.77
3	Percent 3+ Person Households	21.87
4	Neighborhood Class: Upscale Avenues	20.34
5	Percent Hispanic Population	16.69
6	Percent African American Population	16.57
7	Income	15.84
8	Percent Single-Person Households	15.77
9	Percent Owner	14.99
10	Percent College Graduates	14.46
11	Neighborhood Class: Scholars & Patriots	12.54
12	Neighborhood Class: Affluent Estates	10.78
13	Neighborhood Class: Middle Ground	10.36
14	Neighborhood Class: GenXUrban	10.14
15	Neighborhood Class: Family Landscapes	7.23
16	Neighborhood Class: Midtown Singles	5.86
17	Neighborhood Class: Senior Styles	4.26
18	Neighborhood Class: Next Wave	2.55
19	Neighborhood Class: Uptown Individuals	0.62
20	Neighborhood Class: Rustic Outposts	-1.97

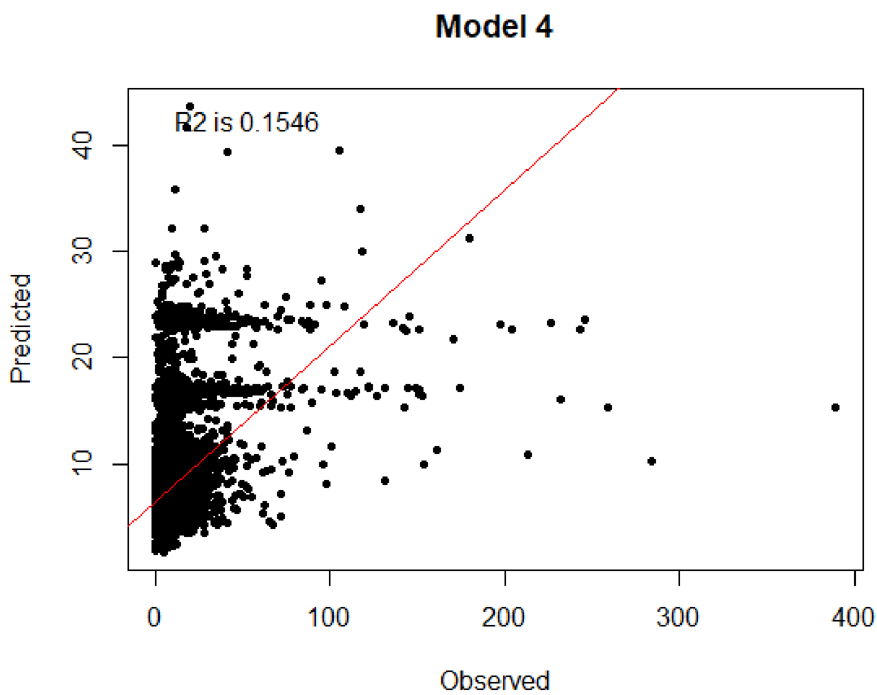

Figure 2.7. *Predicted versus observed plot for Model 4 – Social / Lifestyle model.*

Model 5 explained the most variance at 34.69% with an RMSE of 7.79. (Table 2.7). It included only variables that had unique data for every parcel, rather than disaggregated data from block groups; therefore, the only social variable that was included was home value. The distance to Old Town was the most important variable, followed by parcel area, LST and home value. We noticed that the distance to Old Town became more important than parcel size, unlike our other models. The biophysical variables followed, and the lowest ranked variables were the age of the home, orientation of the lawn, and NDVI.

Table 2.12. *Variable importance for Model 5 – Unique model.*

Rank	Variable	% Increase in MSE
1	Distance to Old Town	18.98
2	Parcel Size	17.18
3	LST	10.96
4	Home Value	10.22
5	Vegetation x Irrigatable Area	9.32

6	Percent Grass x Percent Tree	8.88
7	Percent Grass	7.08
8	Percent Tree	6.40
9	Age of Home	5.49
10	Direction: NE	3.34
11	NDVI	3.16
12	Direction: SE	2.50
13	Direction: E	1.75
14	Direction: W	1.59
15	Direction: NW	0.66
16	Direction: N	0.55
17	Direction: S	0.50

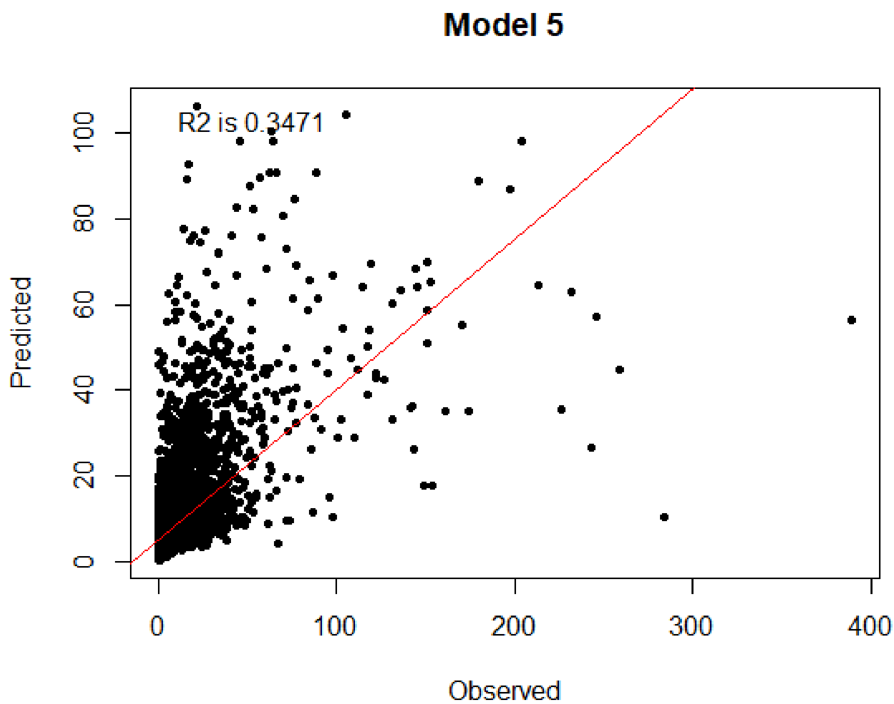

Figure 2.8. *Predicted versus observed plot for Model 5 – Unique model.*

4 Discussion

4.1 Important Variables for Water Consumption

Both the variable selection and unique models performed the best and contained a combination of morphological, biophysical and social predictors, suggesting there are likely interaction effects between different categories of urban characteristics that are important for explaining water consumption. Both of these models were comprised of several morphological variables, but differed the most in the number of social and biophysical variables.

Of all the variables we tested, our RF models suggest urban morphology explains most of the variance of water consumption in Fort Collins. The top variables in both the variable selection model and the unique model were morphological (parcel size, distance to Old Town), and the morphological model performed almost as well as the variable selection and unique models (Table 2.7). The bivariate model shows that larger parcels are associated with less water use, which is often the opposite of what is found in the literature (Stoker and Rothfeder, 2014; Jansen and Schulz, 2006; Chang et al., 2010). Increased water use in parcels of smaller size may be partially driven by social conformity (see Burkhardt and Chan, 2018) among close, neighboring homeowners. 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. Jorgensen et al. (2009) stated that conservation motivations may be dictated by social norms, and we may be witnessing some social and landscaping conformity in Fort Collins where people have long strived to create a lush, green landscape in an ecosystem that is naturally semi-arid.

The biophysical model indicated that biophysical characteristics alone were not as important for explaining water consumption (Table 2.7). LST was consistently a top biophysical variable, exemplifying the importance of temperature on water consumption (Tables 2.8, 2.10 and 2.13).

Parcels located farther from Old Town are associated with higher water use; some of these newer areas are generally still being transformed from the natural, semi-arid grassland and agricultural land to a more irrigated, green landscape, which may explain their higher water use. Conversely, central Fort Collins contains higher UTC and established green space compared to the outskirts of the city, and is generally associated with less water use.

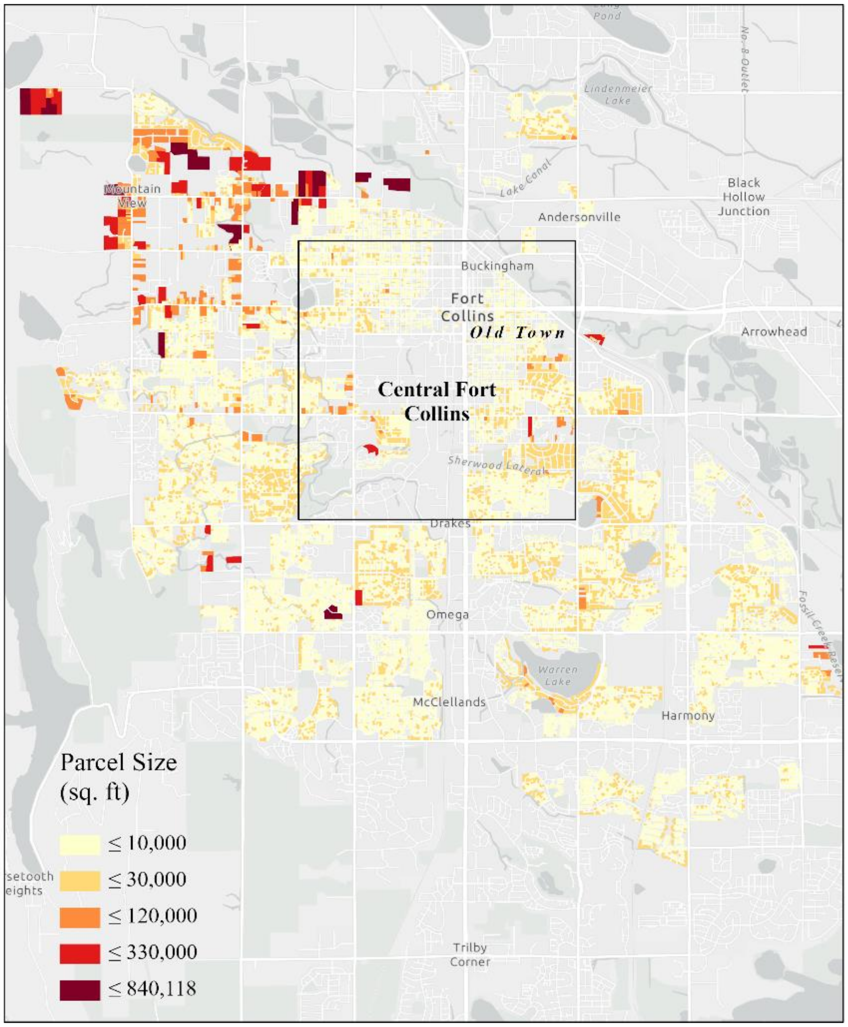

Figure 2.9. *Parcel sizes in Fort Collins. Parcel size was consistently one of the top variables explaining water consumption, with smaller parcels using more water.*

Social and lifestyle characteristics explained little variance on their own, but they were important in the variable selection model. The top social variables in the variable selection model were home value, the percent of 3+ person households and percent owners. The bivariate models indicated that owners, college graduates, and households with higher home value and income tend to use more water. In both the social and the bivariate models, neighborhoods classified as Upscale Avenues were relatively more important and were associated with more water use than any of the other neighborhoods (Tables 2.6 and 2.11). Many of these social variables, along with the Upscale Avenues lifestyle, are associated with higher socioeconomic status, which is often uses more water in the literature (see Harlan et al., 2009). Despite the social RF model's poor performance relative to our other RF models, our results indicate that Fort Collins may be experiencing the same water consumption trends relating to higher socioeconomic status that are often seen in the larger cities previously studied.

We note that home value was consistently the most important social variable and it is the only social variable that is unique to every parcel. In the unique model, it demonstrated more importance than all the biophysical variables. This finding raised an important caveat in our study: the misalignment in the spatial scale of social and lifestyle variables. Other than home value, all the social and lifestyle variables were disaggregated from a larger block group scale and they do not accurately depict the unique situation on the ground. This inflates our models with duplicate social and lifestyle values for every home located within the same block group. If we were able to attain accurate parcel-level social and lifestyle data, we might be able to isolate more trends that are currently undetectable due to coarse spatial resolution, and ideally be able to explain more of the interactions between morphological, biophysical and social characteristics.

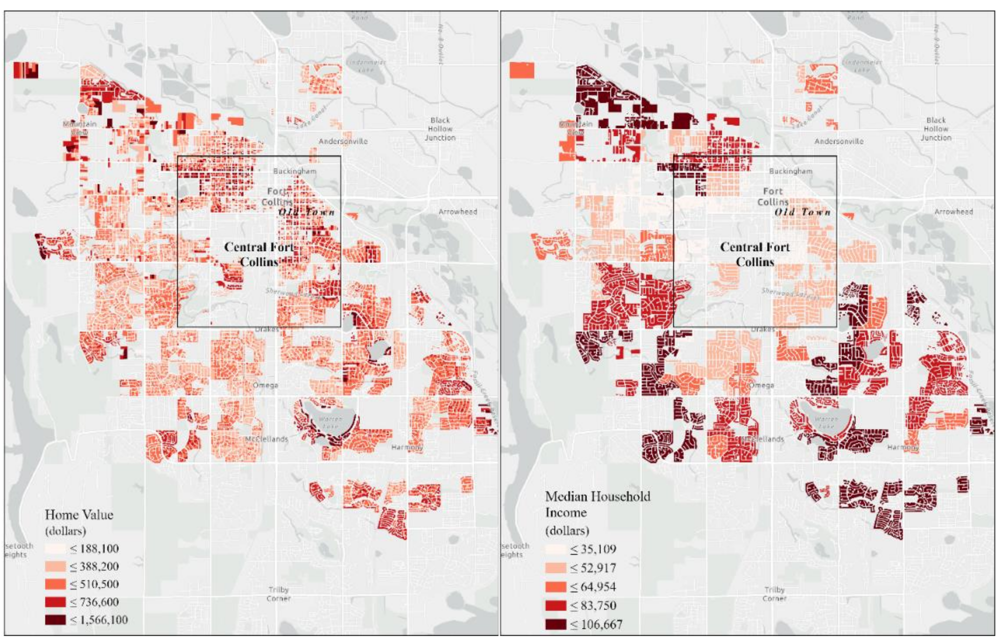

Figure 2.10. *Home value and median household income. Home value the only social variable with unique values for every household. In comparison, median household income is disaggregated from a larger block group scale and demonstrates the coarser spatial resolution.*

4.2 Vegetation

We wanted to compare between grass and trees in residential parcels to understand the relative influence of vegetation types on outdoor water consumption in Fort Collins. It is well established that trees provide benefits in urban regions, particularly in arid and semi-arid climates due to shade trees creating a significantly more comfortable urban environment (see Wang et al., 2016), yet many studies have suggested trees are disservices in these regions because they are associated with higher water consumption costs (see McPherson & Dougherty, 1989; Harlan et al., 2009; Cariños et al., 2017). Irrigated grass is also associated with more comfortable urban environments because its high rate of evapotranspiration can aid in microclimate regulation (Wang et al., 2016). Therefore, many cities prone to drought must consider tradeoffs between maintaining a vegetated landscape and preserving critical water resources.

We found that grass is the only vegetation variable that was associated with higher water consumption. Trees, however, were associated with a decrease in water consumption (Table 2.5). This is a crucial finding, and it is reinforced when we compare linear models between each interaction term and water consumption. Both interaction terms (vegetation and irrigatable space, trees and grass), contain a combination of grass and trees, and both were associated with a decrease in water consumption. These results suggest trees are associated with less water consumption in Fort Collins. However, areas with low UTC outside central Fort Collins also tend to use more water, and it is unclear if this water is being used for lawn irrigation, planting trees or both. In the initial planting stages, trees do require large amounts of water. However, once tree roots are established, the frequency of watering decreases, and the total water requirement may be offset by the additional benefits an established tree can provide. Based on these our results, we expect that once trees are established, they may help mitigate outdoor irrigation.

Central Fort Collins contains most of the green space, including UTC 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 may impact lawn irrigation by delaying evapotranspiration of grass. A study conducted by Qaiser et al., (2011) found that a large portion of water used for outdoor lawn irrigation evapotranspires, and evapotranspiration is a function of solar radiation (Yang and Wang, 2015). During the summer, tree shade may be blocking direct radiation and slowing the rate at which lawns dry out, decreasing the need for frequent irrigation to maintain them.

Based on our bivariate analysis, we estimate that by increasing the UTC on parcels, households could save water used for outdoor irrigation during the summer. For every 1% increase in tree cover, we would expect a 0.968% decrease in water consumption (gal/ft^2), a nearly one-to-one relationship. As an example, we applied this relationship to a household with about 80% grass cover and 20% tree cover that dramatically increased water consumption during the summer months. During the winter, this household used approximately 8,500 gallons of water (~ 3,000 gallons / month); during the summer, they skyrocketed to approximately 226,000 gallons of water (~ 75,000 gallons / month). With irrigatable space at 4,448 ft^2, they were using about 48 gal / ft^2 from June - August. If we were to increase tree cover on this parcel by 50%, from 20% to 30% cover, we would expect a decrease in water consumption by 48.4%, reducing their usage to 24.77 gal / ft^2 during the summer. If we take this same example and increase grass cover by only 10%, from 80% to 88%, we would expect an increase of 7.94% in water consumption, resulting in 51.76 gal / ft^2 during the summer.

This example demonstrates the importance of vegetation type within irrigatable space in Fort Collins households. However, biophysical variables were not the most important predictors in our RF models, and we have not accounted for additional morphological and social interactions that are likely contributing to water consumption patterns in this example.

4.3. Policy Implications

As we previously mentioned, the 2002 drought in Colorado resulted in mandatory regulations on outdoor water use by strictly controlling the amount of water that can be used for outdoor irrigation, and it was found to be one of the most effective methods for water conservation (Kenney et al., 2004).

However, a study by Olmstead and Stavins (2009) found mixed results on the effectiveness of mandatory restrictions, and instead suggested that a combination of conservation approaches (landscape education programs and watering restrictions) had small but significant reductions in total water use. This suggests that, in addition to regulatory action, outreach can invoke behavioral change. Therefore, it may be valuable for Fort Collins to consider more programs to induce voluntary forms of water conservation, as they target lifestyle change (Balling Jr. et al., 2008). Lifestyle changes are typically more long-term and require less transition should droughts become more prevalent. Examples of conservation programs might include greater incentives for lawn management, and continued xeriscaping and tree planting programs.

A xeriscaping program already exists in Fort Collins and it may be beneficial to increase awareness of it. Fort Collins may consider expanding or increasing incentives to xeriscape along with establishing partnerships with landscapists to make water reduction approaches more appealing and easier for residents. Currently, residents need to invest a fair amount of time and creativity in designing their own property, and this may deter people from participating.

We recognize the importance of lawns in sustaining personal well-being through their ability to provide a space for individual activities and social gatherings, so we suggest ensuring there is enough access to public open spaces to fulfill these personal and group needs. Areas for prospective infill development, underused parking lots, or vacant properties could be leveraged to expand open spaces. Fort Collins could begin developing community-empowered programs to decrease pavement and increase public greenspace, therefore reducing the amount of irrigation needed on private land and allotting it for public use.

4.4. Caveats and Future Work

We have acknowledged several caveats in our study. One of the most important caveats is that our values for outdoor water consumption are only representative, as we do not have separate water meters for indoor and outdoor consumption. However, our approach of subtracting winter use from summer use to obtain outdoor consumption is the standard method recommended by the City of Fort Collins Utilities.

There are additional explanatory variables that are important but were not considered, including the presence of swimming pools, precipitation, and landscape metrics such as patch size and density, connectivity, and spatial aggregation. In developing our variables for the direction of the front lawn, we assumed people would be watering their front lawn more than their back lawn, which may not accurately reflect outdoor irrigation practices in households. We also have coarse-resolution lifestyle characteristics, and more unique information for every household would also help us understand household values, perceptions and motivations for water conservation. Incorporating these variables could give more meaningful insight to water consumption patterns and should be considered in future studies.

We performed a RF analysis because our variables are not linear, and we expect there are inherent interactions occurring between our morphological, biophysical, social and lifestyle variables. There may be spatially-dependent interactions occurring as well, and we did not consider any spatial modeling in this study. Future studies should consider the spatial configuration of the landscape because several studies have found it to have important implications for outdoor water consumption (see Ghavidedelfar et al., 2017; Wentz and Gober, 2007; House-Peters et al., 2010; Balling et al., 2008; Sanchez et al., 2018; Chang et al., 2010; Hwang et al., 2015).

We recommend that a further analysis to confirm the relationship between shade and grass on private residences in Fort Collins should also be conducted to see if this relationship is as important for water consumption as we expect. If residences that irrigate are consistently exposed to more direct solar radiation, they could be using considerably more water to maintain a green lawn. This further analysis could also give additional insight into the relative importance of morphological and biophysical characteristics in the household because shade is produced by both trees and by tall building structures. We could compare the height and spatial configuration of buildings and vegetation to determine if tree shade or building shade has a greater impact on water consumption.

5 Conclusion

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 morphological patterns, biophysical patterns, social patterns, or lifestyle behavior.

In the semi-arid city of Fort Collins, CO, we found the most important characteristics for explaining 2016 summer outdoor residential water use were morphological variables, including parcel size and the distance to Old Town. Biophysical characteristics were also important, but we found them to be more important when combined with other urban characteristics in our RF predictive models. Social and lifestyle characteristics explained the least amount of water consumption trends, however most of these characteristics were limited by a coarser spatial resolution and may not contain an accurate depiction of social composition in the city.

Older parts of Fort Collins have long been managed to sustain a green landscape, despite the natural ecosystem not being suitable for UTC and lawns. Semi-arid ecosystems need intensive human management in order to achieve the level of green space that exists in these older parts of Fort Collins. More research will be needed with unique, parcel-scale social data to explore the importance of human management of urban green space and its relationship to water consumption.

There may be also social conformity effects, where neighboring households tend to uphold a community aesthetic of green space, prompting more water use in the relatively newer, developing outskirts of Fort Collins. We cannot tell if more irrigation on the outskirts of the city are due to tree planting or lawn irrigation. High UTC was associated with decreased water consumption, possibly because UTC provides critical shade that keeps the region cooler and delays evapotranspiration of lawns. The additional microclimate regulation by trees will become especially important as temperatures continue to increase in the region, as many climate models project by mid-century.

These findings can assist city officials in conservation endeavors by providing results that can be implemented in designing water-efficient landscapes, and provides supporting information that can be leveraged by programs to increase awareness for water conservation.

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APPENDIX

Appendix I: Neighborhood classifications derived from Tapestry Segmentation (2018).

Variable	**Description**
Affluent Estates	• Established wealth-educated, well-traveled married couples • Homeowners with mortgages • Expect quality; invest in time-saving services • Participate actively in communities • Active in sports and travel
Upscale Avenues	• Prosperous married couples living in older suburban enclaves • Ambitious and hard-working • More diverse population with many older children • Homeowners prefer denser, urban settings with older homes • Serious shoppers that appreciate quality and bargains • Active in fitness pursuits and premium movie channel subscriptions
Uptown Individuals	• Young, successful singles in the city • Intelligent (best-educated market), hard-working and averse to traditional commitments of marriage and home ownership • Prefer credit cards over debit cards, while paying down student loans • Green and generous to environmental, cultural and political organizations • Internet dependent and adventurous
Family Landscapes	• Successful young families in their first home • Non-diverse, prosperous married-couple families, residing in suburban or semirural areas with low vacancy rate • Homeowners with mortgages living in single-family homes with median home value slightly higher than the U.S. • Do-it-yourselfers, who work on home improvement projects • Sports enthusiasts, owning newer sedans or SUVs, dogs, and savings accounts/plans, comfortable with latest technology Eat out frequently at fast food or restaurants to accommodate busy lifestyle
GenXurban	• Gen X in middle age; families with fewer kids and a mortgage • About a fifth of residents are 65 or older; about a fourth have retirement income • Own older single-family homes in urban areas with 1 or 2 vehicles • Live and work in the same county, creating shorter commute times • Invest wisely, well-insured, comfortable banking online or in person • News junkies • Enjoy reading, renting movies, playing board games and cards crossword puzzles, museums and rock concerts, dining out
Middle Ground	• Lifestyles of thirtysomethings • Millennials in the middle: single/married, renters/homeowners, middle class/working class • Majority attended college or attained a college degree • Households have ditched their landlines for cell phones • Online all the time: use Internet for entertainment, social media, and to search for employment Leisure include night life, some travel and hiking
Senior Styles	• Households are commonly married empty nesters or singles living alone; homes are single-family, retirement communities, or high-rise apartments • More affluent seniors travel and relocate to warmer climates; less affluent settled seniors are still working toward retirement • Cell phones popular, but so are landlines

	• Many prefer print to digital media: avid newspaper readers • Subscribe to cable TV Prefer vitamins to increase mileage and a regular exercise regiment
Rustic Outposts	• Country life with older families in older homes • Depend on manufacturing, retail and healthcare, with pockets of mining and agricultural jobs • Low labor force participation in skilled and service occupations • Own affordable, older single-family or mobile homes • Live within their means, shop at discount stores and maintain their own vehicles (purchased used) and homes • Outdoor enthusiasts who grow their own vegetables, love their pets and enjoy hunting and fishing • Technology is cost prohibitive and complicated. Pay bills in person, use the yellow pages, read newspapers, magazines, and mail-order
Midtown Singles	• Millennials on the move- single, diverse, urban • Seeking affordable rents in apartment buildings • Work in service and unskilled positions, usually close to home or public transportation • Single parents depend on their paycheck to buy supplies for their very young children • Embrace the Internet for social networking and downloading content • From music and movies to soaps and sports, radio and television fill their lives • Brand savvy shoppers select budget friendly stores
Next Wave	• Urban denizens, young, diverse, hard-working families • Extremely diverse with a Hispanic majority • Large share are foreign born and speak only their native language • Most are renters in older multi-unit structures built in 1960s or earlier • Hard-working with long commutes to jobs, often utilizing public transit to commute • Spending reflects youth of these consumers, focus on children and personal appearance • Partial to soccer and basketball
Scholars and Patriots	• College and military populations that share many traits due to transitional nature of this group • Highly mobile, recently moved to attend school or serve in the military • Youngest market group with majority in the 15 to 24-year-old range • Renters with roommates in nonfamily households • For many, no vehicle is necessary as they live close to campus, military base or jobs • Millennials are tethered to their phones and electronic devices, typically spending over 5 hours online everyday tweeting, blogging, and consuming media • Purchases aimed at fitness, fashion, technology, and necessities of moving • Highly social, free time is spent enjoying music, out with friends, seeing movies • Try to eat healthy but often succumb to fast food