THESIS

EXPLORING SUMMER COOLING ELECTRICITY CONSUMPTION IN A MID-SIZED, SEMI-ARID CITY

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ABSTRACT

EXPLORING SUMMER COOLING ELECTRICITY CONSUMPTION IN A MID-SIZED, SEMI-ARID CITY

As climate change advances, it will threaten urban livability in the summer months through elevated temperatures and more severe heat waves. These increased temperatures, coupled with urbanization and the introduction of more impervious surfaces, will positively feed into the Urban Heat Island (UHI) effect. The combination of hotter temperatures and the inevitable population growth urban areas are going to experience will threaten sustainability through the increased demand for cooling energy resources. While there are many ways to address sustainable energy consumption in a city, one commonly cited method has been through the establishment of urban tree canopy (UTC), which has been shown to cool outdoor temperatures and decrease summer energy use through shading and microclimate regulation. Additionally, investing in research to understand local drivers of cooling energy use can help inform the development of municipal goals and programs for energy reduction. Using household electricity consumption, we aimed to understand if UTC and impervious surfaces were impacting summer cooling electricity use in single-family homes, and if so, at what distance and orientation around homes were these land covers most impactful. We then investigated drivers of summer cooling electricity use with additional urban form, building, sociodemographic, and behavioral variables to try to account for cooling consumption patterns. We found that our results showed trends that differed from previous studies and that east side UTC was the most impactful on cooling use. In addition, impervious surfaces were the most impactful when they were closer to the home. However, land cover was minimally impactful on cooling use, and additional behavioral, building, urban form, and sociodemographic characteristics explained more variability in cooling consumption patterns and highlighted the uniqueness of our study area in comparison to previous studies.

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CHAPTER 1: THE IMPACT OF LAND COVER ON SUMMER COOLING ELECTRICITY

1 Introduction

As climate change advances, it poses a risk to our society socially, economically, and environmentally through elevated temperatures as well as prolonged, more severe heat waves. These rising and extreme temperatures will threaten livability and positively feed into the Urban Heat Island (UHI) effect, where urban systems experience higher temperatures than surrounding rural areas, creating an "island" of heat (Oke, 1982). Currently, 55% of the global population lives in urban areas, which is projected to increase to 68% by 2050 (Ritchie and Roser, 2019), making maintaining livable, cool outdoor and indoor areas a priority for cities, especially during the summer months when high temperatures and heat waves are more prominent. Due to the rising utility demand that comes with urbanization, population growth, and rising temperatures, sustainable energy consumption in urban areas has become an issue of discussion. While there are many ways to address energy demand in a city, one commonly cited method has been through the establishment of urban tree canopy (UTC), which has been shown to decrease summer energy use through shading and microclimate regulation (Ko, 2018).

Different land cover types in urban areas can impact outdoor environments by altering temperatures. It is well known that urban areas can experience UHI, which is commonly associated with land modification. The introduction of paved and impervious surfaces through urban development affects moisture availability and radiative energy transfer (Mohajerani et al., 2017). The increase of impervious surfaces that comes with the growth and densification of cities is an important consideration as energy demand in cities increases by 2-4% with every 1 ºC increase in temperature (Akbari et al., 2001). One well-researched approach to address high temperatures in urban areas is by increasing UTC, as trees can alter microclimate through shading and evapotranspiration (Rahmen et al., 2020). UTC has been shown to decrease the average near-surface air temperature, improve thermal comfort, and enhance radiative cooling (Wang et al., 2018). The impact of UTC on outdoor climate has been documented in reductions in air temperatures up to 3.5 ºC during the daytime in the shade underneath *Tilia cordata,* the Littleleaf Linden *(*Rahman et al., 2017). Additional evidence of reduction in air temperatures up to 2 ºC occurred when UTC was increased from 10% to 25% in Phoenix, Arizona (Middel et al., 2015). Currently, it is estimated UTC provides up to $5.3-12.1 billion in heat-reduction services across the entire U.S. urban population, which includes the avoidance of heat-related morbidity and mortality, as well as electricity saved (McDonald et al., 2020).

Given the temperature reductions UTC can provide outdoors, many studies have tried to quantify the indoor energy savings from UTC in summer months. Studies have found that trees planted beyond 18 m of a home do not impact energy by creating shade (McPherson et al., 1988; McHale et al., 2007; Donovan & Butry, 2009; Nelson et al., 2012) and that maximum shade benefit comes from larger trees planted within 5 m of a home (Gómez-Muñoz et al., 2010; Hwang et al., 2015). Additionally, it is widely documented that azimuth can play a role in the impact trees have on energy, and that trees planted on the west, east, and south side of homes yield the most energy savings during the cooling season (Simpson & McPherson, 1996; McPherson & Simpson, 2003; Donovan & Butry, 2009; Ko & Radke, 2014; Hwang et al., 2015). For example, McPherson and Simpson (2003) used a simulated model and projected that planting 50 million shade trees to the east or west side of homes would reduce cooling energy use by 1.1% over 15 years.

Despite well-documented evidence that UTC provides energy savings in the summer months, the magnitude of those savings varies largely throughout the literature. In North America alone, over 40 peer reviewed studies have been published that provide substantial evidence to support the energy saving effects of trees; however, the range of reducing cooling energy consumption has varied from 2 - 90% (Ko, 2018). Differences in findings could be due to the dissimilar nature of simulation and empirical methods. Simulation studies inherently come with various assumptions depending on the inputs, outputs, and software used, and do not necessarily use real-world cases, but are still quite representative in the literature. Empirical approaches vary from simulated studies in the data used, variation within this methodology exists, with larger energy saving performances coming from more controlled settings, such as treatment and control (tree shade and no shade) studies (Ko, 2018). Other empirical studies use real energy consumption data, but results are heavily dependent on the resolution and quality of the data obtained (Ko, 2018). Variation in results could also be attributable differences in study locations. Many studies that have looked at the impact of UTC have taken place in warmer climates, most notably in California. However, even within the same location of Sacramento, California, the annual cooling energy saving per tree has ranged between 80 kWh to 180 kWh in simulation studies (Simpson & McPherson, 1996; Ko et al., 2015). In an entirely different climate, Nelson et al. (2012) concluded that trees did not significantly impact summertime energy savings in the heavily forested Raleigh, North Carolina. Very few studies have addressed the impact of UTC using empirical data in semi-arid, mid-sized cities, highlighting the need for such research.

Given the potential impact of impervious surfaces on summer electricity use and the high variability in the magnitude of energy savings from UTC found in previous studies, we aim to understand how land cover at various orientations around single-family homes impacts summer cooling electricity consumption using household billing data in our study area. Our goals were to 1) determine if there are summertime energy impacts from UTC and impervious surfaces in single-family homes; and 2) if effects exist, determine the most impactful location in terms of azimuth and distance from single-family homes for both tree canopy and impervious surfaces. We compared our results to other published studies in order to determine how impactful tree canopy and/or impervious surfaces are on summertime cooling electricity consumption in a mid-size, semi-arid city.

We expect that, similar to previous studies, single-family homes in the study area will experience the greatest summer cooling electricity savings with increased tree canopy on the west side of homes, but that the magnitude of this relationship will vary based on the distance from homes. Additionally, we expect that with greater impervious cover around the home, summertime cooling electricity consumption will increase, regardless of azimuth and distance from homes, due to the role impervious surfaces have in

UHI. Using a large sample of empirical data, this study will provide a significant contribution to the body of research which looks at the role of land cover, specifically tree canopy and impervious surfaces, on energy consumption. Our results will help inform future modeling efforts regarding land cover and energy use and can impact city planning and development by revealing where tree canopy and impervious surfaces are having the most impact on summertime cooling electricity consumption in single-family homes.

2 Methods

2.1 Study Location

Our study area is a mid-size, growing city of approximately 170,000 people located in northern Colorado (City of Fort Collins, 2018). It is situated on the Cache La Poudre River along the Front Range of the Rocky Mountains at approximately 5,000 feet (1,524 m) above sea level (City of Fort Collins, 2019). The city is located in a semi-arid region with average rainfall of 15 inches per year, average snowfall of 50 inches per year (NOAA, 2018) and approximately 300 days of sunshine annually (City of Fort Collins, 2019). The temperature average in the summer months is about 72 ºF but can reach a maximum average of 97 ºF during the day (NOAA, 2018). While there are a limited number of naturally occurring trees, the city has prioritized the maintenance and development of an extensive UTC (City of Fort Collins, 2017). The UTC in the study area includes a diversity of deciduous species that are adaptable to the climate, such as the Littleleaf Linden (*Tilia cordata)* and Kentucky Coffeetree (*Gymnocladus dioica*) (City of Fort Collins, n.d.). Additionally, the city maintains a mapped inventory of public trees, documenting over 300 species within the city (City of Fort Collins, 2020).

2.2 Land Cover Data

High resolution land cover data (1 m^2) was derived from WorldView-2 satellite imagery and LiDAR using object-based feature extraction techniques (Zhao & Troy, 2008; Beck et al., 2016; Rasmussen et al., 2021). A hybrid-stratified random accuracy assessment with 2400 points calculated the overall accuracy of the land cover dataset to be 95% (Congalton & Green, 2019). The land cover dataset consisted of seven cover classes: tree canopy, other vegetation (e.g., grasses, shrubs, etc.), bare soil, water, buildings, roads/railroads, and other impervious surfaces (e.g. driveways, sidewalks, etc.) (Figure 1.1; Table 1.1). For the purposes of this study, we reclassified land cover into three classes: tree canopy, impervious surfaces (roads/railroads and other impervious surfaces), and other (buildings, bare soil, water, and other vegetation).

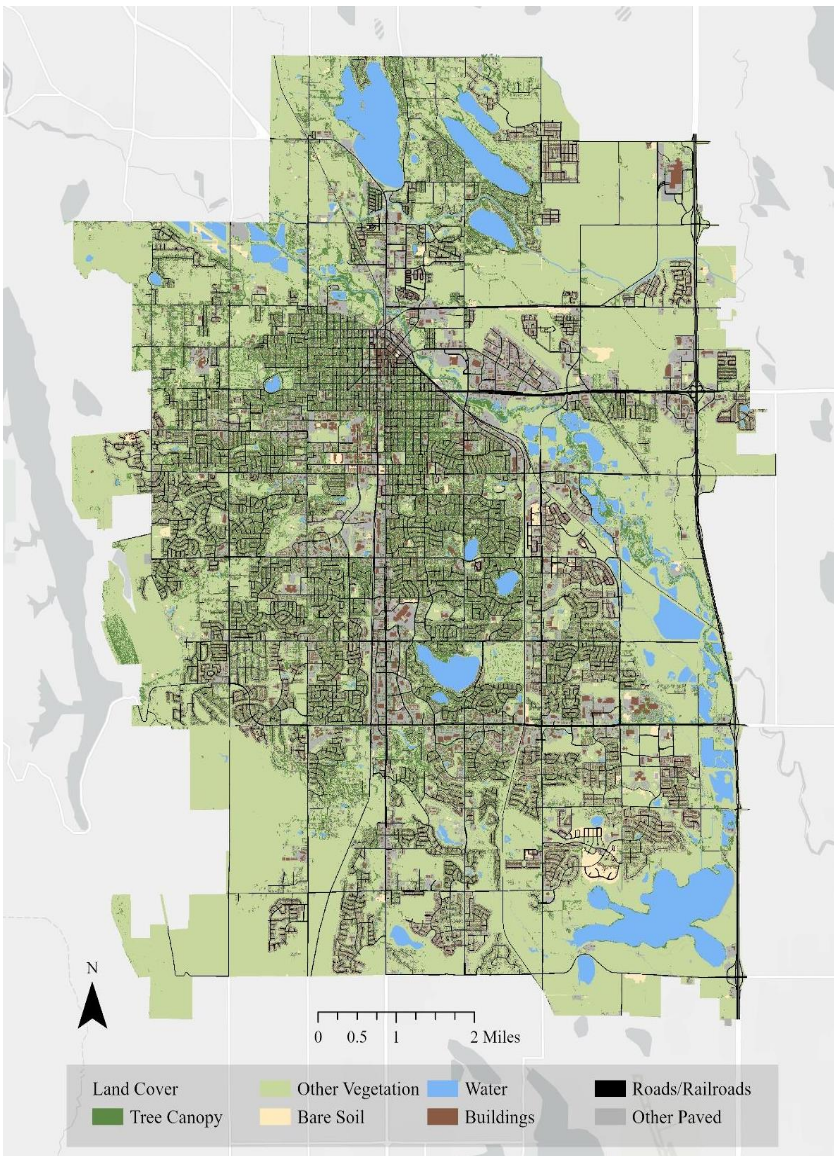

Figure 1.1 *Land cover classes of the study area (Rasmussen et al., 2021)*

Table 1.1 *Land cover distribution within the study area. The landscape is mostly dominated by other vegetation, such as shrubs and grasses, followed by tree canopy and other paved surfaces.*

Land Cover	Percentage of Landscape
Other Vegetation	52%
Tree Canopy	13%
Other Paved	13%
Roads/Railroads	8%
Buildings	7%
Water	6%
Bare Soil	1%

In order to determine the maximum cooling benefit UTC had on summer electricity consumption, as well as the impact that impervious surfaces had on summer electricity consumption, we generated four buffers of 6 m, 12 m, 18 m, and 24 m around single-family homes by using a buildings polygon layer, provided by the city. These buffers were then broken into quadrants to account for azimuth (North, South, East, and West). Creating buffers and quadrants was an important step to isolate locations of tree canopy and impervious surfaces according to their distance and direction from the home (Figure 1.2; Table 1.2).

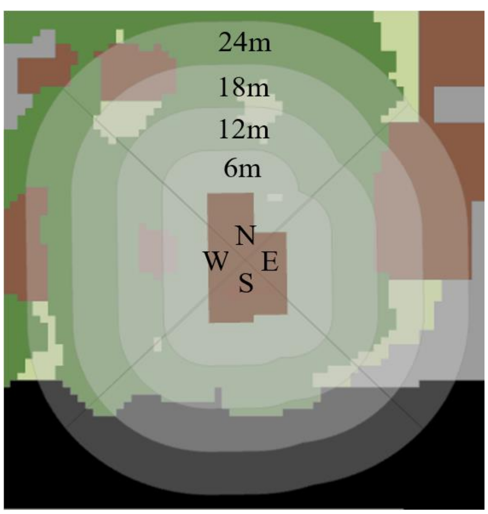

Figure 1.2 *Buffers broken into quadrants. 6 m, 12 m, 18 m, and 24 m buffers were broken down by azimuth (North, South, East, and West) resulting in 32 separate quadrants.*

Table 1.2 *Descriptive statistics of quadrant sizes (m^2). Area of quadrants was calculated for every azimuth within each buffer distance (6 m, 12 m, 18 m, 24 m). Note that 6 m buffer contains the area over the home up to 6 m away, while 12 m buffer is the area 6 – 12 m, the 18 m buffer is the area 12 – 18 m, and the 24 m buffer is the area 18 – 24 m.*

	6m			**12m**			**18m**			**24m**		
	Min	**Mean**	**Max**	**Min**	**Mean**	**Max**	**Min**	**Mean**	**Max**	**Min**	**Mean**	**Max**
North	60	174	768	115	174	370	171	230	420	228	287	473
East	63	172	648	116	174	359	173	230	397	229	286	446
South	60	174	768	115	174	370	171	230	420	228	287	473
West	63	172	648	116	174	359	173	230	397	229	286	446

We summarized tree canopy and impervious surfaces by percent cover within each quadrant for every household to incorporate it into our statistical analysis, resulting in 32 explanatory variables (Table 1.3). The 6 m quadrants consisted of the area over the home up to 6 m away, the 12 m quadrants were the area 6 – 12 m from the home, the 18 m quadrants were the area 12 – 18 m from the home, and the 24 m quadrants were the area 18 – 24 m from the home. The distribution of all land cover variables was positively skewed, but included a spread across all percentage values, negating the need for any type of transformation.

Table 1.3 *Descriptive statistics of tree canopy and impervious surfaces (%) in quadrants.* [b] *where two values appear in a cell, the first includes all households, and the second includes only households where that variable > 0*

	6m			**12m**			**18m**			**24m**		
	Min	**Mean**	**Max**	**Min**	**Mean**	**Max**	**Min**	**Mean**	**Max**	**Min**	**Mean**	**Max**
	TREE CANOPY											
North	0	22/27	100	0	29/33	100	0	23/27	100	0	22/25	100
East	0	21/26	100	0	28/32	100	0	22/26	100	0	22/25	100
South	0	25/31	100	0	28/32	100	0	22/26	100	0	22/25	100
West	0	27/33	100	0	27/32	100	0	22/25	100	0	22/24	100
	IMPERVIOUS SURFACES											
North	0	20/24	85	0	26/29	100	0	38/42	100	0	39/42	100
East	0	22/25	85	0	24/27	100	0	36/39	100	0	38/41	100
South	0	19/23	87	0	26/30	100	0	38/42	100	0	39/42	100
West	0	20/24	89	0	24/28	100	0	36/40	100	0	39/41	100

2.3 Electricity Data

Unlike many other localities, the city is unique because they own their electricity utility, allowing us to obtain parcel-level electricity consumption data for the year 2016. For the purpose of our study, we wanted to isolate the analysis to single-family detached houses in an effort to reduce the variability in consumption patterns that might arise by including commercial and multi-unit properties. Due to limitations on electric heating information as well as seasonal variation, we focused on summer, defined as June 1st – August 31st, cooling electricity consumption. Annual electricity consumption is known for having an "M" type distribution curve, with peaks occurring in summer and winter, making it important to analyze the data seasonally to prevent any trends or patterns from being averaged out (Figure 1.3).

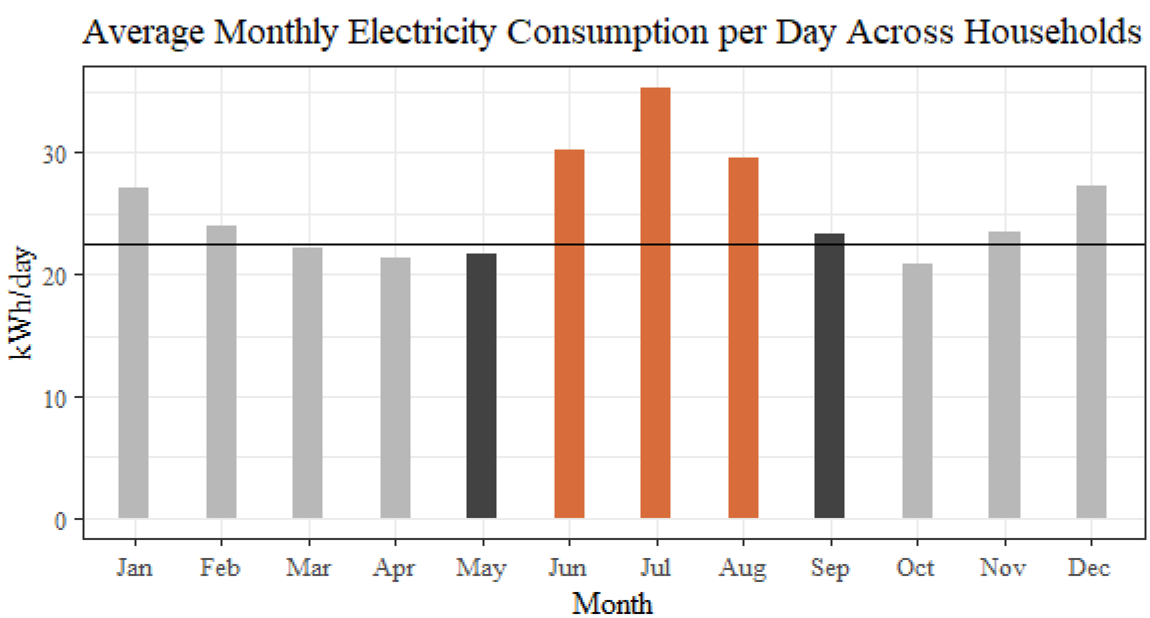

Figure 1.3 *Average monthly kWh/day across single-family households in the study area. Two peaks are observable in the winter and summer months. Months in dark gray are shoulder months, and months in orange are peak summer months. The horizontal line represents the average consumption in shoulder months. Cooling electricity consumption would be what falls above the line during the months of June, July, and August.*

To prepare the data for analysis, we isolated single-family residential households using parcel information from the city, as well as the county accessor's office (Larimer County Assessor's Office, 2019). We joined unique premise codes of household electricity consumption data to single-family residential parcel polygons and removed parcels that had duplicate information (i.e. multiple premise codes per parcel or multiple parcel numbers per premise), incomplete consumption readings, or a change in residency during the year, resulting in 24,346 single-family residential parcels.

To determine average consumption for each household, we used billing information to prorate electricity consumption based on read dates and days of service to calculate the average use for each calendar month. We then averaged each household's use for the months June – August and divided by the number of days from June 1st – August 31st (92) to get a unique average summer kilowatt hours per day (kWh / day) for each household.

To get cooling electricity use, we used the shoulder months of May and September when electricity is less likely to be used for cooling or heating due to milder temperatures. We averaged the kWh / day for May and September together and subtracted that from summer kWh / day to get cooling kWh / day (Fig. 1.3). We normalized the electricity consumption data by the square footage of the home, documented by the assessor's office, to calculate our response variable as kilowatt hours per day per square foot (kWh / day / ft^2) (Table 1.4). Our analysis response variable was performed using English units due to the preferences of the local utility, however metric conversions are documented in parenthesis.

Table 1.4 *Descriptive statistics of house size and electricity consumption in our study sample. Values in parenthesis represent metric conversions (m^2).*

Variable	Min	Mean	Max
House size (ft^2)	381 (35.4)	1918 (178.1)	7241 (672.7)
Cooling electricity use (kWh / day)	0.0006	9.21	63.71
Cooling electricity use (kWh / day / ft^2)	0.0000005 (.000005)	0.005 (.05)	0.013 (.15)

From our initial 24,346 households, we removed 2,866 households that had negative consumption patterns, meaning they used more electricity in the shoulder months than in the summer months. This could be due to a variety of reasons, such as summer being a common time for vacationing in the city. Additionally, we found 432 households to be outliers by removing those with consumption values 1.5

times the interquartile range beyond the third quartile and less than the first quartile. Outliers were not due to a skewed distribution, but rather individual circumstances due to extremely high average cooling electricity consumption, small household square footage, or a combination of both. Once outliers were removed, the distribution for the response variable met normality assumptions for analysis (n = 21,048).

2.4 Correlations

We calculated Pearson's correlation coefficients for both tree canopy variables (n = 16) and impervious surface variables (n = 16), as well as between all land cover variables and summer cooling electricity consumption. Correlations between land cover variables and electricity consumption were used to identify the direction and magnitude of an existing relationship. Positive correlations indicated that with an increase in the land cover variable, there was an increase in cooling electricity consumption, while the opposite was true for negative correlations.

2.5 Linear Regression Models

We performed three Ordinary Least Squares multiple linear regression models (OLS); one with just tree canopy variables, one with just impervious surface variables, and a combined model with tree canopy and impervious surface variables. Our goal in applying a regression model was not necessarily to determine the best model for predicting energy consumption, but rather, to explore the relationship land cover variables had with summer cooling electricity consumption and further isolate the most impactful location for UTC and impervious surfaces. As such, we did not apply a variable selection process in this analysis. Similar to correlations, positive coefficients in these models indicated that an increase in the land cover variable coincided with an increase in cooling electricity consumption, while the opposite was true for negative coefficients.

3 Results

3.1 Correlations

Results from the correlation analysis among tree canopy variables showed relatively strong, positive relationships among all quadrants (6 m, 12 m, 18 m, 24 m) in the same cardinal orientation (Figure 1.4). We found a similar pattern in impervious surface variables, excluding the 6m quadrants. Meaning, impervious surface quadrants at 12 m, 18 m, and 24 m had strong, positive relationships in the same cardinal direction (Figure 1.5).

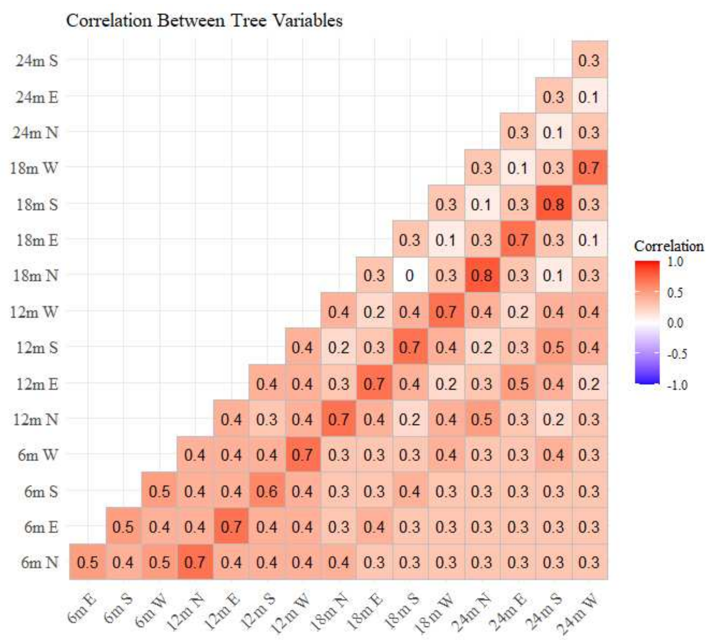

Figure 1.4 *Pearson's correlation coefficients among tree canopy variables (%). The strongest correlations occurred in quadrants located in the same cardinal direction, for example 6 m north and 12 m north.*

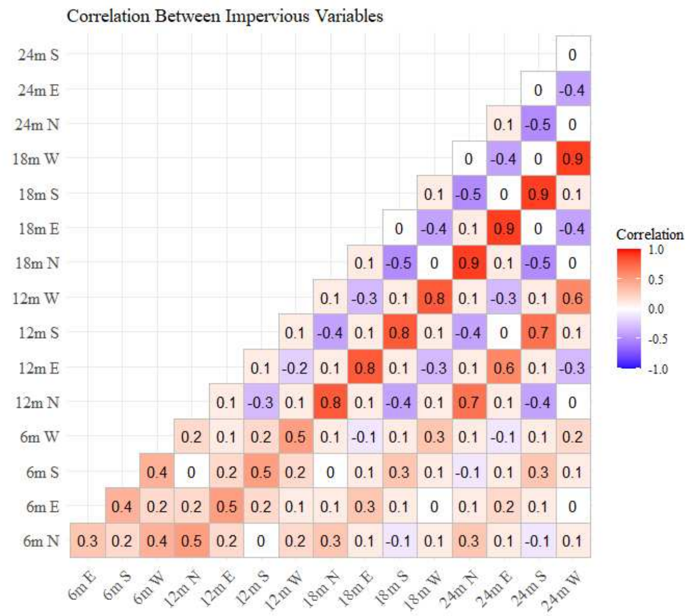

Figure 1.5 *Pearson's correlation coefficients among impervious surface variables (%). The strongest correlations occurred in quadrants located in the same cardinal direction beyond 6 m, for example 12 m north and 18 m north.*

The correlations between our tree canopy variables and cooling electricity consumption showed small, statistically significant negative correlations for most quadrants and orientations (Figure 1.6). The 6 m and 12 m quadrants in the east and west orientations had relatively stronger correlations than those at 18 m and 24 m west, 12 m north, and 24 m south. Contrastingly, the correlations between our impervious surface variables and cooling electricity consumption displayed small, but statistically insignificant positive correlations across all quadrants and orientations (Figure 1.6). Correlations were relatively strongest within the 6 m quadrants at all orientations.

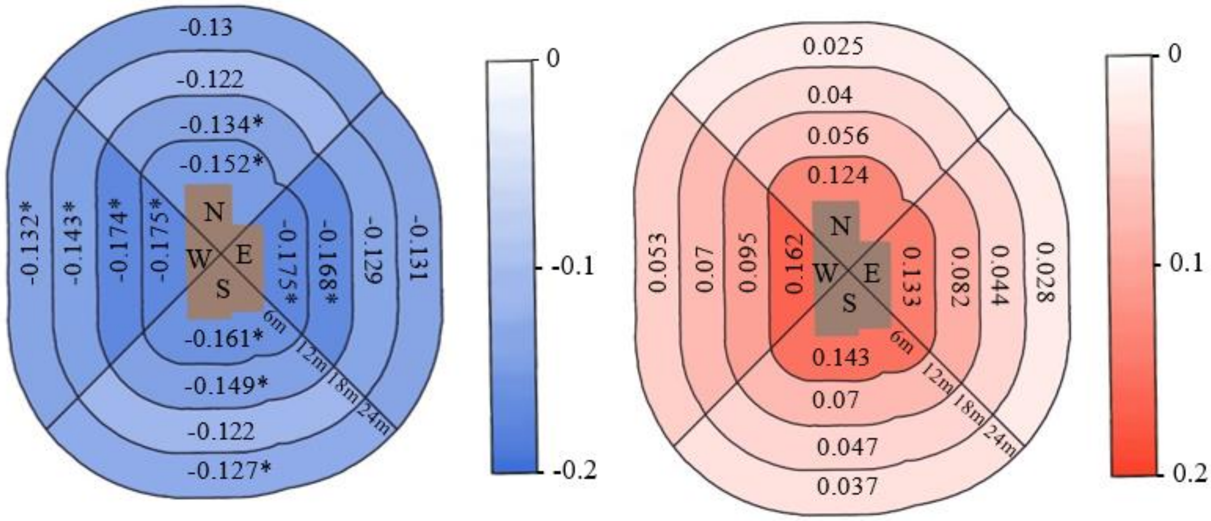

Figure 1.6 *Pearson's correlation coefficients between tree canopy (left) and impervious surface variables (right) and cooling electricity consumption (kWh/day/ft^2). All tree canopy variables had a negative relationship with cooling electricity consumption, and all impervious surface variables had a positive relationship with cooling electricity consumption. Values with * notes statistical significance < .05*

3.2 Linear Regression Models

We fit three models to determine, in relationship to one another, what were the most impactful orientations for tree canopy and impervious surfaces on cooling electricity consumption. In the tree model, many variables had a negative relationship with cooling electricity consumption, with tree canopy in the 6 m and 24 m buffers at all orientations, and in the east and west of the 12 m buffer all showing statistical significance (Table 1.5). Variables in the tree model that were both significant and had the largest impact on cooling electricity use was tree canopy on the eastern side of the home in the 6 m buffer, the 12 m buffer and the 24 m buffer (Table 1.5). Negative coefficients indicated that as the percentage of tree canopy increased, cooling kWh / day / ft^2 consumption decreased. In context, the average sized single-family home (1918 ft^2 (178.1 m^2); Table 1.4) with the average percent of tree canopy within 6 m east of the home (21%; Table 1.3), would decrease cooling electricity consumption over the course of peak summer about 26 kWh, compared to a home with no tree cover withing 6 m east of the home, holding all other tree canopy variables constant.

Table 1.5 *OLS regression model results using tree canopy variables. Variables are sorted by the magnitude of the coefficient and statistical significance, with percent tree canopy at 6 m east having the largest, statistically significant coefficient.*

	Model 1 - Tree Canopy	
Predictors	*Estimates*	*CI*
(Intercept)	0.00586384 ***	0.00578747 – 0.00594021
6m E	-0.00000702 ***	-0.00000980 – -0.00000424
24m E	-0.00000684 ***	-0.00000976 – -0.00000391
12m E	-0.00000529 ***	-0.00000810 – -0.00000247
12m W	-0.00000466 **	-0.00000747 – -0.00000185
6m W	-0.00000455 ***	-0.00000686 – -0.00000224
24m W	-0.00000414 **	-0.00000710 – -0.00000117
24m N	-0.00000360 *	-0.00000654 – -0.00000066
24m S	-0.00000328 *	-0.00000624 – -0.00000032
6m S	-0.00000325 **	-0.00000566 – -0.00000085
6m N	-0.00000324 *	-0.00000596 – -0.00000052
12m N	0.000002510	-0.00000030 – 0.00000532
18m E	0.000002250	-0.00000103 – 0.00000553
18m S	0.000001650	-0.00000167 – 0.00000498
18m N	-0.000001510	-0.00000475 – 0.00000173
18m W	-0.000002250	-0.00000561 – 0.00000110
12m S	-0.000002590	-0.00000537 – 0.00000019
Observations	21048	
R^2	0.056	

* *p<0.05* ** *p<0.01* *** *p<0.001*

Results from the impervious surfaces model showed a consistent pattern where impervious surfaces in the 6 m buffer at all orientations around the home had the most impactful, positive coefficients of all our impervious surface variables (Table 1.6). Positive coefficients for impervious surface variables indicated that as the percentage of impervious surface increased, cooling kWh / day / ft^2 consumption increased as well. In context, the average sized single-family home (1918 ft^2 (178.1 m^2); Table 1.4) with the average percent impervious surface within 6 m west of the home (20%; Table 1.3), would increase cooling electricity consumption over the course of peak summer about 54 kWh, compared to a home with no impervious surfaces within 6 m west of the home, holding all other impervious surface variables constant.

Table 1.6 *OLS regression model results using impervious surface variables. Variables are sorted by the magnitude of the coefficient and statistical significance, with percent impervious surfaces at 6 m west of the home having the largest, statistically significant coefficient.*

	Model 2 - Impervious Surfaces	
Predictors	*Estimates*	*CI*
(Intercept)	0.00353010 ***	0.00339263 – 0.00366757
6m W	0.00001529 ***	0.00001231 – 0.00001826
6m S	0.00001175 ***	0.00000864 – 0.00001486
6m E	0.00001028 ***	0.00000731 – 0.00001324
6m N	0.00000791 ***	0.00000480 – 0.00001102
18m N	0.00000653 ***	0.00000312 – 0.00000994
12m N	-0.00000544 ***	-0.00000863 – -0.00000224
18m W	0.00000516 **	0.00000179 – 0.00000852
18m S	0.00000356 *	0.00000011 – 0.00000700
12m S	-0.00000325 *	-0.00000641 – -0.00000009
24m N	-0.00000320 *	-0.00000605 – -0.00000035
18m E	0.00000337	-0.00000000 – 0.00000674
12m E	0.00000287	-0.00000027 – 0.00000601
12m W	-0.00000012	-0.00000318 – 0.00000294
24m W	-0.00000022	-0.00000304 – 0.00000260
24m E	-0.00000065	-0.00000343 – 0.00000213
24m S	-0.00000104	-0.00000392 – 0.00000183
Observations	21048	
R^2	0.044	

* *p<0.05* ** *p<0.01* *** *p<0.001*

Our third model which included both tree canopy and impervious surface variables, showed somewhat similar results to both our tree canopy and impervious surfaces models (Table 1.7). Again, tree canopy located either in the 6 m buffer, 12 m buffer, or 24 m buffer on the east side of the home, as well as the 12 m buffer on the west side and 24 m buffer on the north side, had the largest, significant negative coefficients, with tree canopy in the 12 m buffer on the east and west side, 24 m buffer on the south side, and 6 m on the west side also showing statistical significance. Impervious surfaces in the 6 m buffer on the west and south orientations were statistically significant and showed a strong positive relationship with cooling consumption. Impervious surfaces in the 18 m buffer on the west side and 6m buffer on the north side also had a statistically significant positive relationship. In context, the averaged sized single-family home (1918 ft^2 (178.1 m^2); Table 1.4) with the average percent tree canopy in the 24 m buffer on the east side (22%; Table 1.3) and average percent impervious surface in the 6 m buffer on the west side (20%; Table 1.3) of the home would result in the same magnitude of impact, a 27 kWh decrease and 27 kWh increase in cooling consumption over the course of peak summer, respectively, compared to a home with no tree canopy or impervious surfaces in these quadrants, when all other land cover variables are held constant. Our combined model also showed a slightly higher R^2 when compared to the separate tree canopy and impervious surface models.

Table 1.7 *OLS regression model results using tree canopy (TC) and impervious surface (IS) variables. For clarity, impervious surface (IS) variables are shaded in gray in the table. Variables are sorted by the magnitude of the coefficient and statistical significance, with percent impervious surfaces at 6 m west, and percent tree canopy at 24 m east having the largest, statistically significant coefficients.*

Model 3 - Tree Canopy & Impervious Surfaces		
Predictors	*Estimates*	*CI*
(Intercept)	0.00541441 ***	0.00516648 – 0.00566233
IS 6m W	0.00000763 ***	0.00000437 – 0.00001090
TC 24m E	-0.00000703 ***	-0.00001032 – -0.00000374
TC 24m N	-0.00000609 ***	-0.00000940 – -0.00000278
IS 6m S	0.00000600 ***	0.00000260 – 0.00000940
TC 6m E	-0.00000559 ***	-0.00000859 – -0.00000258
IS 12m N	-0.00000499 **	-0.00000835 – -0.00000162
IS 24m N	-0.00000498 **	-0.00000813 – -0.00000183
IS 12m S	-0.00000494 **	-0.00000828 – -0.00000161
TC 12m W	-0.00000491 **	-0.00000792 – -0.00000191
TC 12m E	-0.00000477 **	-0.00000774 – -0.00000181
IS 18m W	0.00000412 *	0.00000051 – 0.00000773

TC 24m S	-0.00000401 *	-0.00000734 – -0.00000068
IS 6m N	0.00000387 *	0.00000051 – 0.00000723
TC 6m W	-0.00000276 *	-0.00000523 – -0.00000029
IS 18m N	0.00000363	-0.00000008 – 0.00000733
IS 18m E	0.00000357	-0.00000003 – 0.00000717
IS 6m E	0.00000313	-0.00000011 – 0.00000638
TC 12m N	0.00000255	-0.00000045 – 0.00000555
TC 18m S	0.00000214	-0.00000152 – 0.00000580
IS 18m S	0.00000201	-0.00000171 – 0.00000573
TC 18m E	0.0000016	-0.00000199 – 0.00000520
IS 24m W	0.00000063	-0.00000247 – 0.00000373
IS 12m E	0.0000001	-0.00000318 – 0.00000337
TC 18m W	-0.0000005	-0.00000418 – 0.00000318
TC 18m N	-0.00000082	-0.00000445 – 0.00000280
TC 24m W	-0.00000151	-0.00000484 – 0.00000182
TC 6m S	-0.00000183	-0.00000442 – 0.00000076
TC 6m N	-0.00000188	-0.00000477 – 0.00000102
IS 24m S	-0.000002	-0.00000518 – 0.00000118
IS 12m W	-0.00000209	-0.00000530 – 0.00000112
TC 12m S	-0.0000023	-0.00000527 – 0.00000068
IS 24m E	-0.00000251	-0.00000558 – 0.00000056
Observations	21048	
R^2	0.061	

* *p<0.05* ** *p<0.01* *** *p<0.001*

4 Discussion

4.1 Impact of Tree Canopy and Impervious Surfaces

Our correlation and regression results indicated that both tree canopy and impervious surfaces had an impact on summer cooling electricity consumption in the city. Pearson correlation coefficients between land cover variables and cooling electricity consumption, as well as results from all three regression models, indicated that increased UTC was generally associated with less energy consumption, in contrast to increased impervious surfaces which was associated with more energy consumption. This is in line with previous studies that indicate tree canopy can mitigate energy consumption through shading and evapotranspiration (Ko, 2018). It is also suggestive of impervious surfaces increasing electricity consumption, possibly due to their role in increasing land surface temperatures in urban environments (Chithra et al., 2015).

4.2 Most Impactful Orientations

The most impactful orientations for both tree canopy and impervious surfaces did not align with our expectations and showed different patterns when compared to previous studies. A well-established body of literature on the impact of tree canopy on cooling electricity savings has consistently shown that tree canopy on the west sides homes produces the largest savings, followed by the east and south sides (Simpson & McPherson, 1996; Donovan & Butry, 2009; Ko & Radke, 2014; Hwang et al., 2015). Additionally, it is stated that trees planted beyond 18m of a home do not impact electricity use directly through shading (McPherson et al., 1988; McHale et al., 2007; Donovan & Butry, 2009; Nelson et al., 2012). However, our results challenge this in both the tree canopy model and combined model, where the most impactful variables were the 6 m buffer on the east, followed by the 24 m and 12 m buffer east in our tree model, and the 24 m east, followed by 24 m north and 6 m east in our combined model.

The impact of impervious surfaces around homes and cooling electricity consumption is not well-documented in the literature, but the role of impervious surfaces in urban environments is, specifically when it comes to the heat island effect (Chithra et al, 2015; Estoque et al., 2017). Because of this, we expected impervious surfaces to impact cooling electricity consumption regardless of orientation. However, our results showed a clear pattern that impervious surfaces within 6 m of the home at all orientations were the most impactful in our impervious surfaces model. The combined model showed slightly more variation, but impervious surfaces within 6 m of the home on the west and south sides still showed high impact and significance. All significant impervious surface variables with a positive relationship were within 18m of the home in both the impervious surfaces model and combined model. Since increases in impervious surfaces in cities can result in higher ambient temperatures (Weng, 2001), it is possible that impervious surfaces closer to the home would have a more significant, immediate impact on the microclimate than those located at a further distance.

4.3 Comparison to Other Studies

While previous studies on the impact of orientation of impervious surfaces around homes on cooling electricity are scarce, there is plenty of evidence that urban heat island increases ambient temperature, which can then impact electricity consumption. However, there is high variation in this impact, with the increase in electricity demand per increase in degree of temperature falling between 0.5% and 8.5% (Santamouris et al., 2015). More specifically in Colorado, data showed that daily electricity demand in the Colorado Spring utility district increased 4,000 kW, or about 1%, for every 1 ^{o}F increase in (Akbari et al., 1992). Because our analysis did not have access to ambient air temperature around homes, we cannot directly compare our results to those that have studied temperature changes and electricity demand. However, our results do support the notion that impervious surfaces around homes have a positive relationship with cooling electricity consumption.

The study of the impact of tree canopy on energy use has taken many forms in the literature and can be broken down into two broad categories of simulation or empirical studies (Ko, 2018). Within these studies there is much variation among sample size, residential building type, location, explanatory and response variables, and the method of analysis. For example, in simulation studies, annual cooling has been found to be up to 160 kWh / tree on the high end (Simpson & McPherson, 1998) and 80 kWh / tree on the lower end (Ko et al., 2015). This lower end of 80kWh / tree is comparable to empirical results found by Donovan and Butry (2009). However, some empirical studies have also found little to no impact of tree canopy on summer energy savings (Abbott & Meentemeyer, 2005; Nelson et al., 2012).

This variation and subsequent spread in the magnitude of results, as well as how results were reported, makes it difficult to draw direct comparisons between our results and other studies. However, even compared to the low end of savings found in both simulation and empirical studies, our results show a much smaller impact. Our most impactful tree canopy variable common to our tree model and combined model was positioned 18 – 24 m east of the home. The average tree canopy in this quadrant was 22%, which would be equivalent to about 63 m^2, based on the average quadrant size. This area roughly translates to a tree with a 30-foot crown, which would be a common size for a large, deciduous tree in the city, such as a Green Ash. Using these calculations, we estimated savings of 27 kWh / tree in our combined model and 26 kWh / tree in our tree canopy model over the course of peak summer while holding all other variables constant, which is considerably less than the low end of savings, 80 kWh / tree annually (Donovan & Butry, 2009; Ko et al., 2015).

It is likely that the study location and methodology employed are playing a role in how different our findings are compared to previous studies. Our methodology included a large sample size at 21,048 single-family households, giving us an extensive pool of data to work with. Additionally, our explanatory variables were calculated using high resolution spatial data which did not discriminate between individual trees, their heights, or their species. These differences in methodology and assumptions are important to consider, as they could be contributing to differences in results.

Our study area is a semi-arid city where most trees are not naturally occurring. Central air conditioning in the city has historically been less common due to cooler temperatures and low humidity, which contrasts to study locations in warmer climates, like Sacramento. In addition to being semi-arid, the study area is located close to the Rocky Mountains, which could have climatic impacts altering the relative importance of UTC on summer cooling electricity. In contrast to somewhat older, larger, and more established cities, our study area is a relatively young, mid-size city. This age and size difference could be reflected in the age of homes, how they were developed, or the overall design of homes in the study area, ultimately impacting the overall role UTC plays on cooling electricity consumption.

Based on our study, which used a large amount of high-resolution data for both the explanatory and response variables, the impact of tree canopy on summer cooling electricity is comparatively less than studies that are often referenced for energy savings provided by trees. For context, running a 10W LED lightbulb instead of a 60W incandescent lightbulb for 5 hours / day over the course of the summer would save you about 23 kWh, just shy of the 26 kWh / tree savings in our study area. Despite low cooling energy savings, it is important to note that UTC provides other ecosystem services such as removing particulate matter from the air, sequestering carbon, reducing noise, improving water quality, and reducing outdoor water use, enhancing its overall value to urban ecosystems (Herrington, 1974; Dwyer et al., 1992; Scholz, Hof, & Schmitt, 2018; Rasmussen et al., 2021).

4.4 Caveats and Future Research

A component that our analysis omits is tree species, which can impact the cooling effectiveness of trees. Tree growth rates, Leaf Area Index (LAI) and crown size have all been found to impact cooling effects in urban areas (Rahman et al., 2015; Armson et al., 2013; Speak et al., 2020). This type of analysis would be especially helpful in the study area, where most trees are not naturally occurring, and it takes good planning and care to ensure the health and sustainability of the UTC.

Looking at electricity data seasonally is important to prevent averaging out of trends, however, it leaves out the impact that trees or impervious surfaces have on winter energy use. Our data set is solely for electricity use, so applying a similar analysis to winter would not account for homes that may use natural gas for heating. There is evidence that trees, especially those planted on the south side, can hinder passive solar warming during the heating season and increase energy use (Heisler, 1986; Hwang et al., 2015). This is an important consideration to consider for future analysis to fully understand the role that land cover can play in energy use in single family homes.

While the purpose of this study was solely to see if tree canopy and impervious surfaces are impacting summer cooling electricity use in the city, the lack of explanation of variance in our models, as indicated by low R^2 values, suggests that there is much more to investigate. Our future work will expand on drivers of summer cooling electricity consumption in the city by bringing in more explanatory variables such as urban form, building, sociodemographic, and behavioral characteristics. This could help identify major contributors to cooling electricity use which could be targeted for policy or program intervention.

5 Conclusion

Energy consumption is an aspect of urban ecosystems that is the result of a variety of drivers. Urban form, such as land cover, has been found to impact energy consumption in urban environments. Specifically, impervious surfaces can impact ambient temperatures in cities, but the impact around homes is not well-documented. Tree canopy can reduce outdoor temperatures through shading and evapotranspiration which can impact nearby homes resulting in cooling energy savings; however, the magnitude of these savings varies greatly in the literature.

In our study area, we found that impervious surfaces had the strongest impact on single-family electricity consumption within 6 m of the home. Additionally, these relationships were consistently positive, indicating that increasing impervious surfaces close to homes resulted in an increase in cooling electricity consumption.

In regard to tree canopy, we found our results contrasted to previous studies both in the most impactful orientation and in the magnitude of savings. Our most impactful tree canopy variables were positioned within 6 m and between 18 – 24 m on the east side of the home, as well as between 6 – 12 m on the west side. These results contrast with results of previous studies that have found the most significant cooling energy savings occur when trees are planted on the west side of homes. Additionally, our findings oppose other findings that trees do not directly impact energy consumption beyond 18 m of the home. Lastly, the impact on cooling electricity from tree canopy we found was significantly less than low-end estimates found in other studies.

While our study has contrasting conclusions to those of previous studies, it is difficult to provide direct comparisons due to the variation in methodology, study location, and reporting of results. However, our results do indicate that tree canopy and impervious surfaces are having a negative and positive impact on electricity consumption, respectively, and significant orientations result in different magnitude of savings.

CHAPTER 2: DRIVERS OF COOLING ELECTRICITY CONSUMPTION

1 Introduction

As global population grows and shifts to urban living, household energy consumption, without changes to utility resources, will result in higher carbon dioxide emissions and increasingly impact climate change. Globally, urban consumption accounts for between 71-76% of energy-related CO_2 emissions (Seto et al., 2014). In the United States, about 81% of the population currently lives in urban areas and residential energy consumption accounts for about 20% of energy related CO_2 emissions (US Census Bureau, 2010; EIA, 2019). As climate change advances, it poses a risk to our society through impacts such as increased energy demand to maintain comfortable spaces in elevated temperatures, reduced air quality, and unequitable distribution of resources to help with climate change mitigation. Given the imminent need to address climate change though societal transformations, growing cities have the capacity to explore sustainable solutions for reductions in energy consumption. In order to address energy efficiency in sustainability goals and programs, it's important to understand what underlies patterns of energy use in our cities.

Many studies have embarked on determining drivers of energy consumption with a general consensus that urban form, building characteristics, and sociodemographics can all play significant roles. Urban form consists of a variety of structures within an urban landscape, for example, land cover composition, street orientation, and house and population density. Land cover composition, such as tree canopy or nearby greenspace, has been shown to impact energy consumption in multiple studies. Tree canopy can reduce energy consumption anywhere from 2-90% in cooling and 1-20% in heating through shading effects in the summer and wind-break effects in the winter (Ko, 2018). Additionally, nearby and higher densities of green space, such as parks, have been found to influence energy demand (Silva et al., 2017). Higher green space density has statistically significant effects on reducing summer cooling consumption (Ko & Radke, 2014), and the presence of greenery can impact energy consumption by reducing outdoor air temperatures up to 2 ºC (Wong et al., 2011). Other land cover, such as dark, impervious surfaces can impact consumption as well by altering urban thermal efficiency and contributing to the Urban Heat Island (UHI) effect (Ko, 2013).

Aside from land cover, community layout and street orientation are other urban form variables that have been found to have a significant impact on energy consumption. Community layout, especially the position of the building, can impact the amount of sunlight exposure a building receives. North facing buildings receive the least sun in northern latitudes, while east or west facing buildings receive the most, resulting in more direct heat in the morning or afternoon (Ko, 2013). Street orientation is another way of looking at community and building layouts. Ko & Radke found that north-south, northwest-southeast, and northeast-southwest, when compared to east-west street configurations, tended to have a higher cooling electricity use (2014). This is likely because east-west oriented streets mean buildings are north-south oriented, which result in less direct sun exposure. Li et al. corroborated Ko and Radke's findings that street configuration had a significant impact on summer electricity use, and also found street orientation to be significant for annual and winter electricity use (2018).

One of the most important urban form characteristics studied in energy consumption dynamics has to do with density. Density can be defined in two main ways: density of the built environment or density of people living in a given area (Silva et al., 2017). Density impacts overall urban energy demand by altering transportation times, but also by influencing UHI through the distribution of urban surfaces (Silva et al., 2017). Stone and Rodgers are often cited when discussing density, as they found that lower density development patterns contributed more radiant heat to UHI formation than higher density patterns (2001). In addition to UHI, sprawling counties have been found more likely to have residents that lived in larger single-family detached houses when compared to more compact counties, leading to higher energy use (Ewing & Rong, 2008). Multiple studies have gone on to affirm the findings that higher density, both housing and population, generally results in less energy consumption (Wilson, 2013; Ko and Radke, 2014; Güneralp et al., 2017; Osario et al., 2017; Chen et al., 2018; Li et al., 2018).

Building characteristics have also been shown to play a large role in electricity consumption. Larger home size has been one of the more important building characteristics, which is linked to higher energy consumption, and in some cases has been one of the most important factors in explaining the variability in energy consumption (Nelson et al., 2012; Huebner et al, 2016). In addition to the size of the home, the number of rooms or bedrooms has often been used as a proxy for conditioned spaced when precise information about the size of the home is limited. The impact of room number has varied and has ranged from having no impact to having a significant positive influence on energy use (Wiesmann et al., 2011; McLoughlin et al., 2012; Wilson, 2013). A similar sentiment has been used regarding the number of floors, or stories of a home, with the idea that increased number of floors typically means increased amount of area to be conditioned. Again, the impact of the number of floors has varied, and has been found to be insignificant in some cases but contributed to higher electricity use in other cases (Wilson, 2013; Huang, 2015; Jones & Lomas, 2015).

Aside from variables describing the size of a building, the age of the building has also commonly been used in studies looking to understand drivers of energy consumption. However, the impact of structure age has often been more important on heating energy, having little to no effect on cooling (Kaza, 2010; Huebner et al., 2016). The housing type, such as single-family detached homes or multi-family attached units, also significantly impacts energy use, with single-family detached homes typically using more energy than all other dwelling types, possibly due to size, number of occupants, or other structural factors (Yohanis et al., 2008; Kaza 2010; McLoughlin et al., 2012).

The number of appliances present, as well as their relative efficiency can be considered both characteristics of a particular home and be associated with behavioral tendencies which can impact electricity use. For example, Iwafuna and Yagita found that the use of appliances, such as a water server, portable humidifiers, and air purifiers had positive impacts on cooling use, suggesting that households that can afford extra appliances prefer heavy AC use (2016). More evidence available that occupant behaviors can impact electricity consumption has been found with increased use being associated with individuals that reported being less comfortable in the summer and individuals that were home during the day (Nelson et al., 2012).

Sociodemographic characteristics such as the number of occupants or household size, tenure, income, and age of occupants have all been found to be significant predictors of energy consumption (Weismann et al., 2011; Nelson et al., 2012; Wyatt, 2013; Xu et al., 2020). In multiple studies, older adults have been found to use less energy when compared to younger inhabitants (Weismann et al., 2011; Chen et al., 2018). Additionally, it is well documented that larger household sizes or increased number of occupants are associated with increased in energy demand. (Weismann et al., 2011; Wilson 2013; Wyatt, 2013; Iwafune & Yagita, 2016). Household income has had a varying relationship with energy use but has generally been associated with increased consumption (Yohanis et al., 2008; Wilson, 2013). Ownership of the property is another characteristic that has had a varying relationship, with some results showing owners have increased energy use compared to those who rent but other results indicating that renters use more (Kaza 2010; Weismann et al., 2011; Valenzuela et al., 2014).

Our study investigated the drivers of summer cooling electricity consumption using household electricity data from single-family homes in a mid-sized, semi-arid city in Colorado. Our goal was to determine which urban form, building, sociodemographic and behavioral characteristics were driving summer cooling electricity, and compare their relative importance for explaining cooling consumption variability. We expected that a combination of urban form, except for land cover, building, sociodemographic, and behavioral characteristics would explain cooling consumption due to our previous analysis showing land cover having a minimal impact, as well as the overall prevalence of all these variables in the body of literature that explores drivers of electricity consumption. However, we anticipated that the relative importance of these characteristics would vary given the unique qualities of our study area.

2 Methods

2.1 Study Location

Our study area is a mid-size city of approximately 170,000 people located in northern Colorado (City of Fort Collins, 2018). However, in the coming years it is expected to experience significant population growth and urban development. The study area is situated near the base of the Rocky Mountains along the Front Range, at approximately 5,000 feet (1,524 m) above sea level (City of Fort Collins, 2019a). Located near the Cache La Poudre River, the city is in a semi-arid region with nearly 300 days of sunshine annually, and average rainfall and snowfall of 15 and 50 inches per year, respectfully (NOAA, 2018). On average, the temperature in the summer months is about 72 ºF but can reach a daytime maximum average of 97 ºF (NOAA, 2018). While there are a limited number of naturally occurring trees in the area, the city has prioritized the maintenance and development of an extensive urban forest (City of Fort Collins, 2017).

The local municipality has been working to prioritize environmental impact within the community, with goals to have 100% renewable electricity by 2030 and to be carbon neutral by 2050 (City of Fort Collins, 2020b). To reach these goals, addressing energy use is of upmost importance, as energy emissions make up more than 70% of the community's total greenhouse gas emissions (City of Fort Collins, 2019b). Currently, most of the electricity for the community is generated through the use of coal and hydropower, but an increasing amount of wind and solar resources are being added to the portfolio (City of Fort Collins, 2019b). In addition, numerous initiatives exist for residents to engage in more energy efficient measures, such as investing into community shared solar and solar rebate programs (City of Fort Collins, 2019b).

2.2 Electricity Data

Unlike many other localities, the city owns their electricity utility, allowing us to obtain parcel-level electricity consumption data for the year 2016. For the purpose of our study, we wanted to isolate the analysis to single-family detached houses in an effort to reduce the variability in consumption patterns that might arise by including commercial and multi-unit properties. Due to limitations on electric heating information as well as seasonal variation, we focused on summer, defined as June 1st – August 31st, cooling electricity consumption. Annual electricity consumption is known for having an "M" type distribution curve, with peaks occurring in summer and winter, making it important to analyze the data seasonally to prevent any trends or patterns from being averaged out (Figure 2.1).

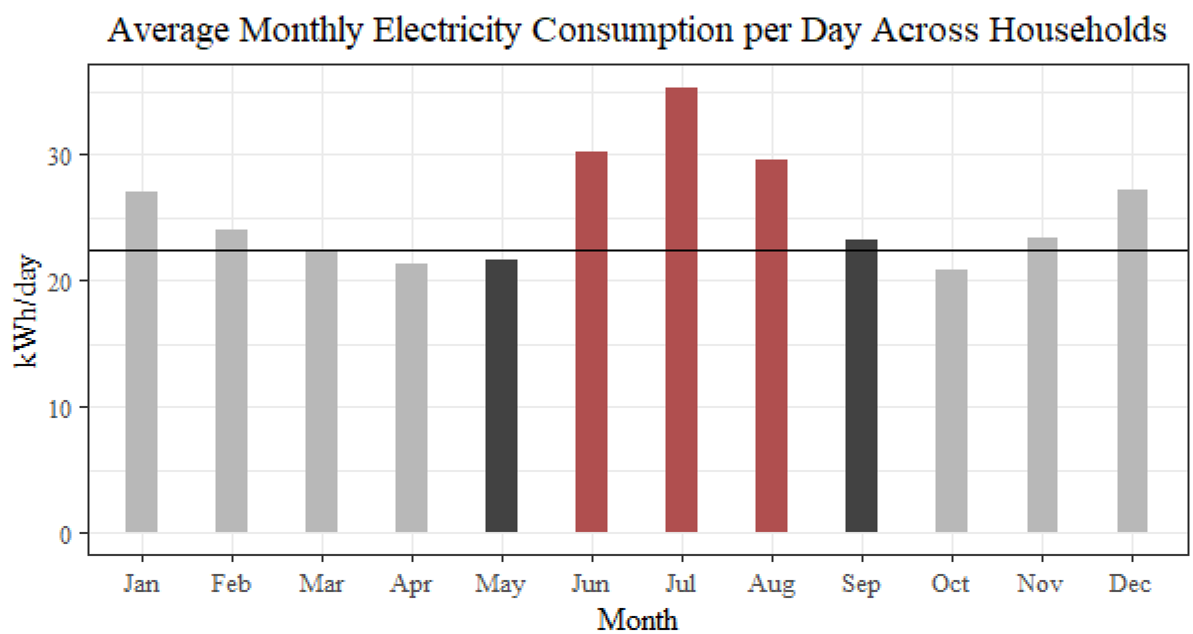

Figure 2.1 *Average monthly kWh/day across single-family households in the study area. Two peaks are observable in the winter and summer months. Months in dark gray are shoulder months, and months in orange are peak summer months. The line represents the average consumption in shoulder months. Cooling electricity consumption would be what falls above the line during the months of June, July, and August.*

To prepare the data for analysis, we isolated single-family residential households using parcel information from the city, as well as the county accessor's office (Larimer County Assessor's Office, 2019). We joined unique premise codes of household electricity consumption data to single-family residential parcel polygons and removed parcels that had duplicate information (i.e. multiple premise codes per parcel or multiple parcel numbers per premise), incomplete consumption readings, or a change in residency during the year, resulting in 24,346 single-family residential parcels.

To determine average consumption for each household, we used billing information to prorate electricity consumption based on read dates and days of service to calculate the average use for each calendar month. We then averaged each household's use for the months June – August and divided by the number of days from June 1^{st} – August 31^{st} (92) to get a unique average summer kilowatt hours per day (kWh / day) for each household.

To get cooling electricity use, we used the shoulder months of May and September when electricity is less likely to be used for cooling or heating due to milder temperatures. We averaged the kWh / day for May and September together and subtracted that from summer kWh / day to get cooling kWh /day (Fig. 2.1). We normalized the cooling consumption data by the square footage of the home, documented by the county assessor's office, to calculate our response variable as kilowatt hours per day per square foot (kWh / day / ft^2) (Table 2.1). Our analysis response variable was performed using English units due the preferences of the local utility, however metric conversions are documented in parenthesis.

Table 2.1 *Descriptive statistics of summer cooling electricity consumption and house size in our study sample. Values in parenthesis represent metric conversions (m^2).*

Variable	Min	Mean	Max
Cooling electricity use (kWh / day)	0.0006	9.24	63.71
Cooling electricity use (kWh / day /ft^{t2})	0.0000005 (.000005)	0.005 (.05)	0.013 (.15)
House Size (ft^{t2})	381(35)	1917 (178)	7241 (673)

From our initial 24,346 households, we removed 2,866 households that had negative consumption patterns, meaning they used more electricity in the shoulder months than in the summer months. This could be due to a variety of reasons, such summer being a common time for vacationing in the city. We also removed 421 households due to incomplete or errored assessor's data for our explanatory variables of interest. Additionally, we found 432 households to be outliers by removing those with consumption values 1.5 times the interquartile range beyond the third quartile and less than the first quartile. Outliers were not due to a skewed distribution, but rather individual circumstances resulting from extremely high average cooling electricity consumption, small household square footage, or a combination of both. Once outliers were removed, the distribution for the response variable met normality assumptions for analysis (n = 20,627).

2.3 Urban Form

Land cover data (1 m^2) was derived using WorldView-2 satellite imagery and LiDAR with object-based feature extraction techniques (Zhao & Troy, 2008; Beck et al., 2016; Rasmussen et al., 2021). The overall accuracy of the land cover dataset was found to be 95% using a hybrid-stratified random accuracy assessment with 2400 points (Congalton & Green, 2019). The land cover dataset consisted of seven cover classes: tree canopy, other vegetation (e.g., grasses, shrubs, etc.), bare soil, water, buildings, roads/railroads, and other impervious surfaces (e.g. driveways, sidewalks, etc.) For the purposes of this study, we reclassified land cover into three classes: tree canopy, impervious surfaces (roads/railroads and other impervious surfaces), and other (buildings, bare soil, water, and other vegetation).

In order to isolate the possible impact of land cover on cooling electricity consumption, we created four buffers of 6 m, 12 m, 18 m, and 24 m around single-family homes by using a buildings polygon layer provided by the city. The 6 m buffer consisted of the area over the home up to 6 m away, the 12 m buffer was the area 6 – 12 m from the home, the 18 m buffer was the area 12 – 18 m from the home, and the 24 m buffer was the area 18 – 24 m from the home. These buffers were then broken into quadrants to account for azimuth (North, South, East, and West) (Figure 2.2). We summarized tree canopy and impervious surfaces by percent cover within each quadrant for every household, resulting in 32 explanatory variables (Table 2.2).

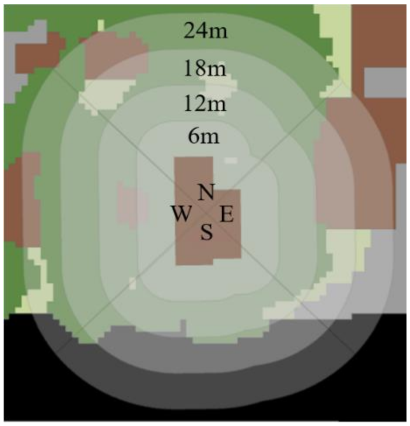

Figure 2.2 *Buffers broken into quadrants. 6 m, 12 m, 18 m, and 24 m buffers were broken down by azimuth (North, South, East, and West) resulting in 32 separate quadrants.*

Table 2.2 *Descriptive statistics of land cover variables represented as a percent (%). Percentages were calculated as % land cover (tree canopy or impervious surfaces) of the entire quadrant area.*

	6m			**12m**			**18m**			**24m**		
	Min	**Mean**	**Max**	**Min**	**Mean**	**Max**	**Min**	**Mean**	**Max**	**Min**	**Mean**	**Max**
	TREE CANOPY											
North	0	22/26	100	0	29/33	100	0	23/27	100	0	22/24	100
East	0	21/26	100	0	28/32	100	0	22/26	100	0	22/25	100
South	0	25/30	100	0	28/32	100	0	22/26	100	0	22/25	100
West	0	27/33	100	0	27/32	100	0	21/25	100	0	22/24	100
	IMPERVIOUS SURFACES											
North	0	20/24	85.4	0	26/29	100	0	38/42	100	0	39/42	100
East	0	22/25	85.2	0	24/27	100	0	36/39	100	0	38/41	100
South	0	19/23	86.6	0	26/30	100	0	38/42	100	0	39/42	100
West	0	20/25	88.6	0	24/28	100	0	37/40	100	0	39/41	100

Average land surface temperature (LST) was provided by Rasmussen et al. (2021). It was derived using imagery for five dates in 2016 (May 29, June 14, July 16, August 1, and August 17) from United States Geological Survey Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) to create a mean composite image of surface temperature, resampled from a 100 m² spatial resolution to a 30 m² resolution (Rasmussen et al., 2021). Using the centroids from the building shapefile provided by the city, the values of LST were extracted to the points to get a unique LST for each household (Table 2.3).

Table 2.3 *Descriptive statistics of continuous numerical explanatory variables. Variables came at varying resolutions depending on the dataset they were obtained from. Census block group data was disaggregated to apply to each household within that block group. Metric conversions are in parenthesis where applicable (gallons to liters; ft^2 to m^2)*

Variable	Resolution	Min	Mean	Max
Age of Home (years)	Household	1	30	131
Average Water Use (gallons/month)	Household	383 (1450)	8451 (31,991)	54,475 (207,232)
Average Annual Electricity Use (kWh/day/ft^2)	Household	0.001 (0.01)	0.014 (0.15)	0.212 (2.28)
Bedroom Count	Household	1	4	8
House Footprint (m^2)	Household	28	210	1087
House Perimeter (m)	Household	22	64	204
Distance from Foothills (m)	Household	2556	8365	15,458
Distance from street (m)	Household	6	24	108
Room Count	Household	1	7	19
House Size (ft^2)	Household	381(35)	1917 (178)	7241 (673)
% 3+ Person Household	Census Block Group	0.00	1.51	11.69
% College Graduates	Census Block Group	2.70	20.95	34.41
% Family Households	Census Block Group	2.21	24.79	35.52
% Married Household	Census Block Group	2.18	20.40	31.47
% Renter	Census Block Group	1.27	11.44	53.66
% Single Person Household	Census Block Group	1.47	7.69	38.76
Housing density per hectare (10,000 m^2)	Census Block Group	0.44	5.19	29.13
Median Household Income ($)	Census Block Group	15,833	78,187	132,361
Population Density per hectare (10,000 m^2)	Census Block Group	1.01	13.02	68.00
LST (°F)	100 m^2 (resampled to 30 m^2)	80	93	101

House density and population density were calculated at a census block group resolution using the 2016 American Community Survey 5-year Estimates for the city (U.S. Census Bureau, 2016). Both variables were calculated by dividing the population value or housing unit number of the census block group by the area of the census block group in hectares (Table 2.3).

Distance from foothills and distance from the street were both calculated using the Near tool in ArcGIS Pro 2.7 using the building centroids derived from the building polygons provided by the city. For distance from the foothills, a 6000 ft (1828.8 m) contour was created from a 30 m^2 resolution Ground Surface Elevation dataset (USGS, 2013) and used as the near feature for the building centroids (Table 2.3). This elevation was chosen because it lies well within what is considered the foothills ecosystem in Colorado (CNHP, 2010). Distance from the street was determined by using street centerlines provided by the city as the near feature for the building centroids (Table 2.3).

Street orientation was determined in a similar fashion to distance from the street. Using the Near tool in ArcGIS Pro 2.7, street centerlines were used as the near features for the building polygons, and the angle ranging continuously from -180 degrees to 180 degrees was documented rather than the distance. This angle was reclassified into four categories of street orientation (East-West, North-South, Northeast-Southwest, Northwest-Southeast) (Table 2.4).

Table 2.4 *Descriptive statistics of categorical variables. Categorical variables were recategorized based on distribution and similar categories. Actual building values was converted to a categorical variable to account for skewed distribution and easier interpretation. All categorical variables were at a household resolution.*

Category	**Variable**	**Resolution**	**Household Count (%)**
Actual Building Value ($)	< 350,000	Household	3858 (19)
	350,000 - 450,000	Household	8777 (43)
	450,001 - 550,000	Household	4785 (23)
	> 550,000	Household	3207 (16)
HVAC Type	Central Air to Air	Household	13679 (66)
	Forced Air	Household	6186 (25)
	Electric Baseboard	Household	270 (1)
	Other	Household	492 (2)
Roof Type	Gable	Household	18051 (88)
	Hip	Household	1636 (8)
	Other	Household	940 (5)
Roof Cover	Composition	Household	17643 (86)
	Wood	Household	2769 (13)
	Other	Household	215 (1)

House Type	2 story	Household	10248 (50)
	Ranch	Household	6542 (32)
	Split Level	Household	2848 (14)
	Other	Household	989 (5)
Street Orientation	East-West	Household	5373 (26)
	North-South	Household	4584 (22)
	Northeast-Southwest	Household	5085 (25)
	Northwest-Southeast	Household	5585 (27)
Building Stories	1	Household	6549 (32)
	2	Household	14078 (68)

2.3 Building Characteristics

Building footprint and building perimeter were based off of the building polygon layer provided by the city (Table 2.3). The rest of the building characteristics were obtained from county assessor's data. Numerical variables from the assessor's data included room count, bedroom count, square footage, and building age (Table 2.3). Building value was initially a numerical continuous variable but was categorized into four categories due to skew in its distribution (Table 2.4). House type, HVAC type, roof type, roof cover and building stories were additional categorical variables included from the assessor's data and were recategorized based on category counts and category similarities (Table 2.4). The Other category for house type contained modular and bi level 2 story types. The Other category for HVAC type contained homes with air exchange, electric radiant, floor/wall furnace, heat pump, hot water baseboard, or none. The Other category for roof type contained flat, gambrel, hip/gable combo, irregular, or shed types. The Other category for roof cover contained clay tile, built up rock, concrete tile, formed seam metal, preformed metal, and slate types. Composition roof cover contained composition shingle, composition shingle heavy and composition roll. Wood roof cover contained wood shake and wood shingle.

2.4 Sociodemographic and behavioral characteristics

Sociodemographic characteristics were obtained from the American Community 5-year Survey for the year 2016 at a block group scale and disaggregated to apply to each household (U.S. Census

Bureau, 2016). These included median household income, percent renter, percent college graduate, percent single person household, percent 3+ person household, percent married households, and percent family households (Table 2.3).

Both average yearly electricity consumption (kWh /day / ft^2) and average monthly water consumption (gallons / month) were used as a proxy for behavioral characteristics (Table 2.3). Average yearly electricity consumption was calculated from the same dataset as our response variable, pulling from the entire year of complete data for each household. Average monthly water consumption (gallons / month) was provided by the local water utility and prepared by Rasmussen et al. (2021). Only a subset of water data was available for the homes in our analysis (n = 13,492)

2.6 Bivariate Models

We analyzed the relationship between every explanatory variable and summer cooling electricity consumption using a simple bivariate linear regression. By investigating individual relationships, we could better understand the association each explanatory variable had with cooling consumption without bringing in the complexity of multiple variables. In these bivariate models, positive coefficients in our continuous variables indicated that an increase in the variable coincided with an increase in cooling electricity consumption and for categorical variables indicated an increase when compared to the reference category, while the opposite was true for negative coefficients. These bivariate models also ensured relationships were present before including explanatory variables into a multivariate model, and overall gave us more context when interpreting our multivariate model.

2.7 Linear Regression Model

We performed an Ordinary Least Squares multiple linear regression model (OLS) with all of our variables we looked at in our bivariate models, with the exception of water use. Water use was omitted due to its limited sample size in comparison to our electricity data. The remaining variables were chosen due to their prevalence in previous studies showing impact on electricity consumption, so we had no need to go through a variable selection process. Our goal in applying a regression model was to determine how much of summer cooling electricity use can be described by urban form, building, sociodemographic, and behavioral characteristics. We used Cohen's f^2 to understand each variable's effect size within the context of the model. An $f^2 \geq 0.02$ represents small effect size, $f^2 \geq 0.15$ represents moderate effect size, and $f^2 \geq 0.35$ represents large effect sizes (Cohen, 2013). Similar to our bivariate models, positive coefficients in our continuous variables indicated that an increase in the variable coincided with an increase in cooling electricity consumption and for categorical variables indicated an increase when compared to the reference category, while the opposite was true for negative coefficients.

3 Results

3.1 Bivariate Models

Results from our bivariate analysis showed that all of our land cover variables had a significant relationship with summer cooling electricity consumption, but with low R^2 (Table 2.5). All tree canopy variables showed a negative relationship with summer cooling electricity, and impervious surfaces showed a positive relationship, determined by the sign of the coefficient. The tree canopy variables with the highest R^2 were those located in 6 m and 12 m east and west. Impervious surface variables with the highest R^2 were in 6 m south and west and had lower R^2 than the highest tree canopy variables.

Table 2.5 *Bivariate results from land cover variables. TC stands for tree canopy and IS stands for Impervious surfaces. Negative coefficients in blue and imply a relationship that an increase in the variable results in a decrease in summer cooling electricity. The opposite relationship is true for positive relationships in red.*

Variable	Coefficient	CI	R^2	*p* value
TC 6m N	-0.0000208	-0.00002260 – -0.00001890	0.023	<0.001
TC 6m E	-0.0000244	-0.00002631 – -0.00002252	0.030	<0.001
TC 6m S	-0.0000193	-0.00002090 – -0.00001762	0.025	<0.001
TC 6m W	-0.0000195	-0.00002096 – -0.00001795	0.030	<0.001
IS 6m N	0.0000220	0.00000470 – 0.00000778	0.016	<0.001
IS 6m E	0.0000233	0.00002094 – 0.00002575	0.017	<0.001
IS 6m S	0.0000250	0.00002264 – 0.00002741	0.020	<0.001
IS 6m W	0.0000270	0.00002474 – 0.00002926	0.026	<0.001
TC 12m N	-0.0000158	-0.00001736 – -0.00001415	0.018	<0.001
TC 12m E	-0.0000195	-0.00002107 – -0.00001794	0.028	<0.001
TC 12m S	-0.0000171	-0.00001868 – -0.00001552	0.021	<0.001

TC 12m W	-0.0000203	-0.00002182 – -0.00001869	0.030	<0.001
IS 12m N	0.0000062	0.00000470 – 0.00000778	0.003	<0.001
IS 12m E	0.0000100	0.00000828 – 0.00001162	0.007	<0.001
IS 12m S	0.0000077	0.00000620 – 0.00000924	0.005	<0.001
IS 12m W	0.0000115	0.00000981 – 0.00001312	0.009	<0.001
TC 18m N	-0.0000149	-0.00001660 – -0.00001323	0.014	<0.001
TC 18m E	-0.0000162	-0.00001797 – -0.00001451	0.016	<0.001
TC 18m S	-0.0000151	-0.00001677 – -0.00001336	0.014	<0.001
TC 18m W	-0.0000186	-0.00002033 – -0.00001680	0.020	<0.001
IS 18m N	0.0000033	0.00000213 – 0.00000445	0.002	<0.001
IS 18m E	0.0000040	0.00000274 – 0.00000525	0.002	<0.001
IS 18m S	0.0000040	0.00000281 – 0.00000512	0.002	<0.001
IS 18m W	0.0000063	0.00000508 – 0.00000756	0.005	<0.001
TC 24m N	-0.0000175	-0.00001938 – -0.00001562	0.016	<0.001
TC 24m E	-0.0000182	-0.00002014 – -0.00001632	0.017	<0.001
TC 24m S	-0.0000175	-0.00001934 – -0.00001557	0.016	<0.001
TC 24m W	-0.0000175	-0.00002073 – -0.00001687	0.016	<0.001
IS 24m N	0.0000022	0.00000095 – 0.00000355	0.001	<0.001
IS 24m E	0.0000027	0.00000130 – 0.00000401	0.001	<0.001
IS 24m S	0.0000034	0.00000214 – 0.00000472	0.001	<0.001
IS 24m W	0.0000053	0.00000392 – 0.00000663	0.003	<0.001

Most of our numerical variables resulted in significant bivariate models as well (Table 2.6). Variables that were not statistically significant included house footprint, house perimeter, and distance from the street. Among significant bivariate models, our behavioral variable of average annual electricity use had the highest R^2 at 0.112 and positive relationship with cooling electricity, followed by LST with an R^2 of .0397, which also had positive relationship with cooling electricity. Our subset of samples with water consumption data showed an R^2 of 0.028, as well as a positive relationship with cooling electricity use.

Table 2.6 *Bivariate results from numerical variables. Negative coefficients are in blue and imply a relationship that an increase in the variable results in a decrease in summer cooling electricity. The opposite relationship is true for positive relationships in red.*

Variable	**Coefficient**	**CI**	**R^2**	***p* value**
Age of Home (years)	-0.00004349	-0.00004602 – -0.00004096	0.052	< 0.001
Average Water Use (gallons/month)	0.00000013	0.00000011 – 0.00000014	0.028	< 0.001
Average Annual Electricity Use (kWh/day/ft^2)	0.12880000	0.12385770 – 0.13376982	0.112	< 0.001

Bedroom Count	0.00025920	0.00021115 – 0.00030717	0.005	< 0.001
House Footprint (m^2)	-0.00000018	-0.00000082 – 0.00000046	0.000	1.000
House Perimeter (m)	-0.00000090	-0.00000430 – 0.00000249	0.000	1.000
Distance from Foothills (m)	0.00000017	0.00000015 – 0.00000018	0.026	< 0.001
Distance from street (m)	-0.00000797	-0.00001616 – 0.00000021	0.000	< 0.1
Room Count	0.00018970	0.00016782 – 0.00021164	0.014	< 0.001
House Size (ft^2)	0.00000016	0.00000010 – 0.00000023	0.001	< 0.001
% 3+ Person Household	-0.00022110	-0.00024025 – -0.00020205	0.024	< 0.001
% College Graduates	0.00002936	0.00002154 – 0.00003718	0.003	< 0.001
% Family Households	0.00005133	0.00004256 – 0.00006010	0.006	< 0.001
% Married Household	0.00005069	0.00004298 – 0.00005841	0.008	< 0.001
% Renter	-0.00005105	-0.00005609 – -0.00004600	0.019	< 0.001
% Single Person Household	-0.00005913	-0.00006926 – -0.00004901	0.006	< 0.001
Housing density per hectare (10,000 m^2)	-0.00012510	-0.00013628 – -0.00011388	0.023	< 0.001
Median Household Income	0.00000002	0.00000002 – 0.00000002	0.019	< 0.001
Population Density per hectare (10,000 m^2)	-0.00005064	-0.00005542 – -0.00004586	0.020	< 0.001
LST (°F)	0.00022610	0.00021090 – 0.00024125	0.040	< 0.001

Other variables of note included distance from the foothills, median household income, and room count, all of which had significant, positive relationships with cooling electricity. In addition, percent 3+ person household, housing density, population density, and percent renter all had significant, negative relationships with summer cooling electricity consumption.

All categorical bivariate models were significant, and were interpreted based on the reference category, listed as the first category in each variable which lacks a coefficient (Table 2.7). HVAC type had the highest R^2 out of all the categorical variables at .0397, on par with other variables such as LST. For HVAC, the reference category was central air, and all other categories used less summer cooling electricity comparatively, as noted by negative coefficients.

House types had the second highest R^2 of categorical variables, with all categories of homes using less summer electricity consumption when compared to 2 story homes. A similar finding occurred with house stories, where homes with 2 stories used more cooling electricity than single story homes. The remaining categorical variables had significant relationships, but relatively low R^2. Homes with higher assessed value used more cooling electricity than homes valued less than $350,000. When it comes to roofs, homes with wood or other types of roof cover used less cooling electricity than homes with composition roof cover, and homes with hip roof types used less cooling electricity than homes with gable. Lastly, homes on streets oriented north-south used less electricity than homes on streets oriented east-west, and homes that were oriented on streets northeast-southwest and northwest-southeast used more compared to homes on streets oriented east-west.

Table 2.7 *Bivariate results from categorical variables. Negative coefficients are in blue and imply a relationship that an increase in the variable results in a decrease in summer cooling electricity. The opposite relationship is true for positive relationships in red.*

Variable	Category	Coefficient	CI
Actual Building Value ($)	< 350,000		
R^2: 0.0007	350,000 - 450,000	0.00005064	-0.00006435 – 0.00016563
p value: <.01	450,001 - 550,000	0.00005064	-0.00001015 – 0.00024746
	> 550,000	0.00024860	0.00010636 – 0.00039086
HVAC Type	Central Air to Air		
R^2: 0.0396	Forced Air	-0.00110600	-0.00119531 – -0.00101648
p value: <.001	Electric Baseboard	-0.00210000	-0.00245828 – -0.00174100
	Other	-0.00214200	-0.00241016 – -0.00187459
Roof Type	Gable		
R^2: 0.003	Hip	-0.00036490	-0.00051837 – -0.00021133
p value: <.001	Other	0.00061470	0.00041579 – 0.00081363
Roof Cover	Composition		
R^2: 0.006	Wood	-0.00069350	-0.00081482 – -0.00057214
p value: <.001	Other	-0.00043800	-0.00084532 – -0.00003069
House Type	2 story		
R^2: 0.024	Ranch	-0.00055820	-0.00065134 – -0.00046513
p value: <.001	Split Level	-0.00097700	-0.00110166 – -0.00085240
	Other	-0.00174500	-0.00194091 – -0.00154911
Street Orientation	East-West		
R^2: 0.0009	North-South	-0.00010460	-0.00022433 – 0.00001502
p value: <.001	Northeast-Southwest	0.00016030	0.00004389 – 0.00027679
	Northwest-Southeast	0.00004129	-0.00007245 – 0.00015504
House Stories	1		
R^2: .0014	2	0.00024011	.00015111 – 0.00032912
p value: <.001			

3.2 Linear Regression Model

Our multiple linear regression OLS model had 38 urban form variables, 12 building variables, and 7 sociodemographic and behavioral variables and explained about 24% of the variability in summer cooling consumption ($R^2 = 0.24$) (Table 2.8). The variables had a range of no effect to medium effect size on summer cooling electricity consumption as indicated by their Cohen's f^2 values, ranging from 0 to 0.17.

Table 2.8 *Results from the OLS multiple linear regression model ordered from variables with the highest Cohen's f^2 to variables with the lowest Cohen's f^2. Categorical variables are grouped together and have one Cohen's f^2 value. An $f^2 \geq 0.02$ represents small effect size, $f^2 \geq 0.15$ represents moderate effect size, and $f^2 \geq 0.35$ represents large effect sizes. Negative coefficients are in blue and imply a relationship that an increase in the variable results in a decrease in summer cooling electricity. The opposite relationship is true for positive relationships in red. The overall model had an R^2 of 0.240.*

Variable	Coefficient	CI	Cohen's f^2
(Intercept)	-0.00519126 *	-0.00928812 – -0.00109439	
Average Annual Electricity Use (kWh/day/ft)	0.14636337 ***	0.14145492 – 0.15127182	0.1668
Age of Home	-0.00000665 **	-0.00001087 – -0.00000243	0.0628
Room Count	0.00008704 ***	0.00005534 – 0.00011874	0.0210
HVAC [Electric Baseboard]	-0.00370835 ***	-0.00404369 – -0.00337302	0.0181
HVAC [Forced Air]	-0.00066804 ***	-0.00075395 – -0.00058213	
HVAC [Other]	-0.00101499 ***	-0.00126717 – -0.00076282	
Distance from Foothills	0.00000009 ***	0.00000007 – 0.00000010	0.0109
% 3+ Person Household	-0.00008782 ***	-0.00011479 – -0.00006085	0.0079
LST	0.00005334 ***	0.00003341 – 0.00007327	0.0054
House Type [Other]	-0.00048887 ***	-0.00067972 – -0.00029803	0.0045
House Type [Split Level]	-0.00033136 ***	-0.00046012 – -0.00020259	
House Type [Ranch]	0.00071604	-0.00103420 – 0.00246627	
TC 6m E	-0.00000519 ***	-0.00000795 – -0.00000244	0.0033
Roof Cover [Wood]	-0.00020689 ***	-0.00032915 – -0.00008463	0.0017
Roof Cover [Other]	0.00023359	-0.00013117 – 0.00059835	
% Family Households	-0.00001667	-0.00003442 – 0.00000108	0.0014
House Size	-0.00000019 *	-0.00000035 – -0.00000003	0.0014
TC 6m N	-0.00000044	-0.00000311 – 0.00000222	0.0013
TC 6m W	-0.0000021	-0.00000436 – 0.00000016	0.0012
IS 18m N	-0.00000471 **	-0.00000779 – -0.00000162	0.0009
% College Graduates	0.00002537 ***	0.00001621 – 0.00003452	0.0009
House Footprint	-0.00000461 ***	-0.00000670 – -0.00000251	0.0007
IS 6m W	-0.00000283 *	-0.00000559 – -0.00000008	0.0006
TC 6m S	-0.00000188	-0.00000425 – 0.00000049	0.0006

Street [North-South]	-0.00004857	-0.00018550 – 0.00008836	0.0005
Street [Northeast-Southwest]	0.00011569 *	0.00000289 – 0.00022848	
Street [Northwest-Southeast]	0.00001919	-0.00009066 – 0.00012904	
TC 18m W	0.00000370 *	0.00000069 – 0.00000671	0.0005
Population Density	-0.00001255	-0.00003814 – 0.00001304	0.0004
TC 24m W	0.00000139	-0.00000199 – 0.00000477	0.0003
IS 18m W	0.00000064	-0.00000231 – 0.00000360	0.0003
IS 12m E	-0.00000321 *	-0.00000624 – -0.00000017	0.0002
TC 24m E	0.00000450 **	0.00000115 – 0.00000785	0.0002
IS 18m S	-0.00000264	-0.00000569 – 0.00000042	0.0002
Roof Type [Hip]	-0.00001488	-0.00015699 – 0.00012724	0.0002
Roof Type [Other]	0.00004634	-0.00013616 – 0.00022884	
TC 12m W	-0.00000041	-0.00000378 – 0.00000296	0.0001
IS 6m E	-0.00000320 *	-0.00000592 – -0.00000047	0.0001
Distance from Street	0.00001070 *	0.00000150 – 0.00001991	0.0001
House Stories	0.00105902	-0.00069112 – 0.00280917	0.0001
IS 12m W	0.00000016	-0.00000291 – 0.00000324	0.0001
IS 24m W	0.00000189	-0.00000095 – 0.00000474	0.0001
IS 18m E	-0.00000034	-0.00000334 – 0.00000266	0.0001
IS 24m E	-0.00000173	-0.00000454 – 0.00000108	0.0001
IS 24m N	-0.00000183	-0.00000472 – 0.00000106	0.0001
TC 18m N	0.00000308	-0.00000000 – 0.00000617	0.0001
Bedroom Count	0.00000592	-0.00005384 – 0.00006568	0.0001
IS 6m N	0.00000148	-0.00000127 – 0.00000423	0.0001
% Married Household	0.00001144	-0.00000540 – 0.00002827	0.0001
TC 12m S	0.00000255	-0.00000081 – 0.00000590	0.0000
TC 24m N	0.00000059	-0.00000286 – 0.00000405	0.0000
% Single Person Household	-0.00002578 **	-0.00004174 – -0.00000981	0.0000
TC 12m E	0.00000299	-0.00000030 – 0.00000628	0.0000
Value [350,000 - 450,000]	-0.00004474	-0.00015771 – 0.00006823	0.0000
Value [450,001 - 550,000]	-0.00010983	-0.00026694 – 0.00004728	
Value [> 550,000]	-0.00010392	-0.00032369 – 0.00011586	
% Renter	0.0000023	-0.00000650 – 0.00001110	0.0000
TC 18m E	0.00000109	-0.00000189 – 0.00000407	0.0000
House Density	0.00004395	-0.00001935 – 0.00010726	0.0000
IS 12m N	-0.00000045	-0.00000351 – 0.00000261	0.0000
IS 6m S	-0.00000072	-0.00000346 – 0.00000201	0.0000
IS 12m S	-0.00000059	-0.00000368 – 0.00000249	0.0000
TC 24m S	0.00000005	-0.00000343 – 0.00000354	0.0000
TC 12m N	-0.00000083	-0.00000415 – 0.00000249	0.0000
TC 18m S	0.00000001	-0.00000313 – 0.00000315	0.0000
IS 24m S	0.00000005	-0.00000288 – 0.00000298	0.0000
House Perimeter	0.00002078 ***	0.00001129 – 0.00003028	0.0000
Observations		20627	
R^2 / R^2 adjusted		0.240 / 0.237	

* $p<0.05$ ** $p<0.01$ *** $p<0.001$

Based on the full model, average annual electricity use (Cohen's $f^2 = 0.16$) had the greatest effect size, although still only moderate, on the model and showed statistical significance. Age of the home and number of rooms showed small effect sizes greater than or equal to .02 but were statistically significant variables. Higher annual electricity consumption and increased number of rooms were both associated with higher cooling electricity use, whereas increased age of the home was associated with less cooling electricity use.

Additional urban form, building, and sociodemographic variables were also statistically significant but had small to no effect size on the model, indicated by small to zero Cohen's f^2 values. (Table 2.8). Urban form variables that were significant and had a positive relationship with summer cooling electricity consumption included distance from the foothills, distance from the street, street orientation of northeast-southwest compared to those with east-west street orientation, and LST. Tree canopy was significant at 6 m east, 18 m west, and 24 m east with a varying relationship where 6 m east had a negative relationship, but 18 m west and 24 m east had a positive relationship. Impervious surfaces at 18 m north, 6 m east and west, and 12 m east all had a negative relationship with summer cooling electivity (Table 2.8).

Building characteristics aside from room count and age of the home that were significant in the OLS model included HVAC type, house type, roof cover, house size, house footprint, and house perimeter. All HVAC types were associated with less summer electricity consumption when compared to homes with central air, and split level and other types of homes also were associated with less summer electricity consumption, when compared to 2 story homes. Wood roof cover had a negative relationship to summer cooling electricity use when compared to homes with composition roof cover. House size and house footprint both had a negative relationship with cooling electricity, whereas house perimeter had a positive relationship (Table 2.8).

Significant sociodemographic characteristics included percent 3+ person household, percent college graduates, and percent single person households, where an increase in percent college graduates were associated with more cooling electricity use, and an increase in percent single person households, as well as percent 3+ person household were associated with less cooling electricity use (Table 2.8).

4 Discussion

4.1 Urban form

Our bivariate models using urban form variables showed similar findings to other studies, where both population density and housing density decreased electricity use (Wilson, 2013; Ko and Radke, 2014; Güneralp et al., 2017; Osario et al., 2017; Chen et al., 2018; Li et al., 2018). In addition, all tree canopy variables were associated with less summer cooling electricity use, where the opposite was true for impervious surfaces. Street orientation, where studies have found that east-west streets use less than all other orientations, was somewhat corroborated by our findings (Ko & Radke, 2014; Li et al., 2018). In our bivariate model, homes on east-west oriented streets used less summer cooling electricity when compared to other home orientations, with the exception of north-south.

In the full model, the function of urban form complicated some, but many variables held the same relationship as they did in the bivariate models, such as distance from the foothills and LST. LST had the greatest effect size of the urban form variables, as indicated by its higher Cohen's f^2 value. This is not surprising and indicates that temperature is highly correlated summer cooling electricity use, a finding that has been documented in other studies (Beccali et al., 2008; Psiloglou et al., 2009; Kavousian et al., 2013).

Other urban form variables became insignificant in the full model or their relationship with summer cooling electricity switched. Northeast-southwest street oriented homes were the only homes that used significantly more electricity than those on east-west streets. Population density and housing density became statistically insignificant, which contrasts with other findings that have found a significant relationship showing that denser urban development lends to less energy use (Wilson, 2013; Ko and Radke, 2014; Güneralp et al., 2017; Osario et al., 2017; Chen et al., 2018; Li et al., 2018).

The relationship that land cover variables had with cooling use varied and showed significant impervious surfaces variables reducing electricity use and some tree canopy variables increasing use, opposite of what was found in bivariate models. However, the most significant tree canopy variable, 6 m east, in the OLS also had the highest R^2 value in its bivariate model but had a low overall effect size. This finding is similar to our previous study which solely looked at land cover variables and summer cooling electricity consumption and found tree canopy on the east side to be significant, although minimally impactful (Chapter 1). This contrasts with other findings, which have found that trees located on west side of homes result in the most cooling electricity savings (Donovan & Butry, 2009; Ko & Radke, 2014).

Our results with tree canopy and street orientation, two commonly cited variables that have an impact on summer cooling electricity use, differ from previous findings. This difference could be a function of the unique location of our study area just east of the foothills of the Rocky Mountains. Distance from the foothills was significant in both the bivariate and multivariate models, where it was found that as distance increased, cooling use increased as well. This finding suggests there could be factors impacting climate, such as cooler temperatures due surrounding areas, prevailing winds, or western afternoon shading occurring from the foothills.

4.2 Building Characteristics

Aside from house footprint and house perimeter, all building characteristics were significant in the bivariate models. The building characteristic variable in the OLS model that had the greatest effect size was home age. This was surprising considering previous studies found home age little to no impact on cooling electricity use (Kaza, 2010; Huebner et al., 2016). However, the pattern we found of increased age being associated with a decrease summer cooling electricity use has been documented previously (Chong, 2012). This could be attributed to older homes often lacking central air or having less appliances for cooling space conditioning. Central Air was associated with using more summer cooling electricity when compared to all other HVAC types in both the bivariate and full model, which is to be expected, and could also suggest why older homes tend to use less cooling electricity.

Increased room count had the second highest effect size of the building characteristics in the full model and was associated with increased summer cooling electricity, consistent with previous findings that room count generally means increased space to condition (McLoughlin et al., 2012; Wilson, 2013), The relationship house size had with cooling electricity use not only changed between the bivariate and full model, but also had very low explanatory power and effect size. Because of this, room count may be a more reliable indicator of cooling electricity use, regardless of the size of the home. A more partitioned home may require a more extensive HVAC system to maintain conditioning throughout, or more AC appliances to circulate cooling air into all living spaces.

House type maintained statistical significance from its bivariate models to the full model. The type of single-family homes and the relationship to energy consumption has not been well-documented in the literature, and most house type research has compared single-family attached, detached, or multifamily units, rather than the actual architecture of the home (Kaza, 2010; Li et al., 2018). Split level homes used less cooling electricity than 2 story homes. Split level homes usually have one level partially underground, whereas 2 story homes are completely above ground level. This could be impacting summer cooling electricity use as having walls partially in the ground results in a higher level of moisture, which can induce evaporative cooling, a mechanism that can help maintain cooler temperatures in drier climates.

The roof cover is another building characteristic that maintained statistical significance in both the bivariate and full model . Although roof cover showed relatively low effect size in the full model, the results pointed to wood roofs using less summer cooling use when compared to composition roofs, which are commonly made from materials such as fiberglass and asphalt. Looking into roof assemblies, Winandy et al. found that the temperature of fiberglass shingles was up to 20 °C hotter than wood shingles in the summer months (2004). That much of a temperature difference could be impacting the indoor environment of homes with composition roofs, requiring them to use more cooling electricity to maintain the same indoor temperatures as homes with wood roofs.

4.3 Sociodemographics and Behavior

Percent 3+ person households had a negative relationship with cooling electricity use in both the bivariate and full model and had the highest effect size in the OLS model of all the sociodemographic variables. Generally, studies have found that increased household sizes and occupants increases consumption (Wilson, 2013; Huang, 2015; Iwafune & Yagita, 2016;). 3+ person households in this case refers to unrelated inhabitants occupying the same housing unit, which is not necessarily the same metric used in previous findings. However, increased percent single person households used less cooling electricity, which is more in line with previous findings of increased occupancy increasing use. Increased percent college graduates was associated with more cooling electricity use but had very low R^2 in the bivariate model and relatively low effect size in the full model. This result contrasts with findings that increased education is associated with less energy because they may be more aware of energy-saving opportunities or generally more environmentally conscious (Leahy and Lyons, 2010; Nelson et al., 2012; Xu et al., 2020)

Overall, the variable with the largest R^2 of the bivariate models and the largest effect size in the full model is average annual electricity use, used as a behavioral proxy. Households that use more electricity throughout the year are associated with increased summer cooling electricity use. Another behavioral characteristic, average water use, had the same relationship where households who used more water also were associated with more summer cooling electricity use. Our results coincide with previous findings that behavioral characteristics are fundamental to understanding energy consumption. Studies that have examined the role of behavior in driving energy use have included variables such as daytime occupancy, selection of energy efficient appliances, environmental attitudes, energy conservation habits, and thermostat settings (Nelson et al., 2012; Sanquist et al., 2012; Wilson, 2013; Ko & Radke, 2014; Xu et al., 2020). Ko and Radke used a similar metric to our annual electricity use for a behavior proxy, and found that it also had the dominant impact on summer cooling electricity use (2014).

4.4 Caveats and Future Research

It is important to point out that the resolution of some of our explanatory variables makes the impact and interpretation of their role in summer cooling electricity use more complex. The resolution of our sociodemographic variables, as well as population and housing density, were coarser than all other variables, including our response. This results in duplicate values for every home located within the same block group, and do not accurately represent each household's unique situation. In the future, obtaining more accurate parcel-level sociodemographic information, may increase the overall explanation of the variance in our response variable.

Additional high resolution household behavioral characteristics were not available for our study but would be a future direction to undertake which would likely yield a more nuanced understanding of what is driving cooling electricity use and overall consumption patterns. This is especially important considering the nature of the study area, where during the summer months renter turnover is high and it is common to vacation.

Aside from the addition of higher resolution sociodemographic and behavioral variables, future directions should consider a quantile regression, which has been applied before to understand the determinants of household electricity consumption (Kaza, 2010; Valenzula et al., 2014; Huang, 2015). This type of analysis would be able to sort out the effects of variables across the spectrum of consumption and could better isolate what variables are important to different consumers. Results from a quantile regression could reveal possible opportunities for reductions in consumption in high energy consuming households.

5 Conclusion

Electricity consumption is a function of multiple drivers including urban form, building characteristics, sociodemographic attributes, and behavioral tendencies. Electricity demand can peak in the summer, raising the need to look at drivers seasonally to understand what underlies existing patterns of energy use in our cities. While there is a general consensus among the drivers of electricity use, the relationship these drivers have can vary in the significance, effect size, and relationship they have with electricity use.

In our study area, we found that behavioral, building, and urban form characteristics were vital to explaining variation in summer electricity cooling consumption. Our behavioral proxy of overall annual electricity had the strongest explanatory power among our variables. After behavior, select building characteristics were important to the model: home age, room count, and HVAC type. Most land cover had little explanatory power and were insignificant in the full model, however, distance from the foothills, a variable describing urban form, suggested that homes further from the foothills consumed more summer cooling electricity. This points to the uniqueness of the study area, as this type of variable has not been included in previous studies. LST was also important as a driver of cooling electricity use and is an important consideration as climate change advances and increases temperatures and urban heat islands.

Our results are in line with previous studies that have found multiple variables to be important in the explanation of energy consumption. However, the overall impact of these variables has varied throughout the literature, possibly due to differences in study location, response variable, or resolution of data. This highlights the need to continue to study individual localities rather than looking to previous studies to determine what the most important variables are for understanding patterns of electricity use.

Further research needs to be done to unveil more patterns in summer cooling electricity use. The addition of more behavioral variables and higher resolution sociodemographic variables may increase the understanding of what is driving summer cooling electricity. Additionally, a quantile regression could reveal what variables are important for the spectrum of cooling electricity. These findings could then help inform local sustainability policy and programs targeted at energy efficiency and energy conservation measures.

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