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Influences of landscape and lifestyle on home energy consumption

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Abstract Rapid urbanization coupled with concerns about global climate change has renewed interest in energy conservation and carbon dioxide emissions reduction. Urban residential energy consumption is a valuable place to start reducing emissions, and urban tree planting programs have been both proposed and utilized as an energy conservation mechanism. Home energy savings associated with urban trees are often quantified using models because of the many complex interactions among variables that can influence home energy use. However, recent empirical analyses have found that energy savings associated with trees may be minimal relative to other important factors like building characteristics and human behaviors. We surveyed 176 residents from four neighborhoods in Raleigh, NC with varying socio-economic characteristics to assess relationships between summer energy usage, tree cover, homeowner behavior, and building characteristics. As hypothesized, we found that building characteristics, demographics, and human behaviors were all significant variables in describing the variability in summertime home energy usage. Although, total percent tree cover 18 m around the home did not affect summertime energy use, the number of trees in the NE and NW quadrants around each household did predict home energy use. These results indicate that planting trees may not be a successful strategy for reducing energy use from the residential sector in the heavily forested Southeast; rather efforts should target conservation and efficiency.

Keywords Urban tree cover · Home energy use · PRIZM · Socio-economic status · Air conditioning

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Introduction

Scientists, policy makers, and resource managers worldwide are searching for ways to reduce the anthropogenic greenhouse gas emissions responsible for global climate change (Betsill 2001; Bosch and Metz 2011). Enhancing ecosystem level carbon sequestration is debated as a potentially viable solution, along with increasing the use of renewable fuels, but it is hard to deny that one of the only guaranteed methods for attaining lower levels of greenhouse gas emissions is to directly reduce these emissions instead of searching for offsets (Bosch and Metz 2011; McGuire et al. 2001; Pataki et al. 2009; Schimel et al. 2001). The energy sector in particular is a constructive place to implement CO_2 reduction strategies, since 81 % of greenhouse gas emissions in the U.S. are carbon dioxide (CO_2) from burning of fossil fuels for energy use (EIA 2008).

Within the energy sector residential energy use is projected to increase considerably, therefore, understanding the drivers of home energy consumption should be a priority for research targeting potential energy reductions (Aune 2007). Individuals have direct control over their own home energy demands and are responsible for 21 % of total energy related emissions (EIA 2008; EIA 2005a, b). These emissions in the U.S. are primarily a function of residential space heating and cooling. In particular, urban dwellers are accountable for a majority of residential electricity use and much of this use can be attributed to summer air conditioning (EIA 2005a, b).

The urban heat island effect mitigates home energy use, and may have environmental justice implications. Urban areas can experience elevated temperatures, sometimes as much as 10 °F higher than surrounding areas, and this phenomenon exacerbates home cooling costs (Akbari et al. 1992; Santamouris et al. 2001; Souza et al. 2009). This issue is of concern to energy companies, especially when they cannot meet peak energy demands (Baxter and Calandri 1992). As future energy crises loom, it is important to understand how people live and use energy resources, as well as what are comfortable levels of resource use (Higgins and Lutzenhiser 1995). Although present policy focuses on reducing energy demands through increasing energy prices, there is little evidence that these economic considerations are actually important to homeowners, yet people's lifestyle choices associated with their conceptualization of a home play an important role in energy consumption (Aune 2007).

This further becomes an environmental justice issue as the highest vulnerability to the stresses imposed by the urban heat island effect may hit the least economically secure urban dwellers. Studies have shown that areas with the highest density of people and the least amount of vegetation tend to also experience extremes in temperature that fall outside of the human comfort zone and can be harmful to human health (Harlan et al. 2006). More importantly, these conditions are often associated with neighborhoods dominated by lower socio-economic status and minority groups (Harlan et al. 2006; Huang et al. 2011; Tomlinson et al 2011).

Trees can mitigate these impacts directly by sequestering CO_2 and indirectly by decreasing energy used for heating and cooling via modifying the microclimate, shading buildings, and blocking winter winds (Akbari 2002; Donovan and Butry 2009; Heisler 1986; McPherson and Rowntree 1993; Simpson 2002). Collectively, citywide vegetation can create an overall cooling effect for neighborhoods and cities (Akbari et al. 1992; McPherson 1992; McPherson et al. 1988; Meier 1991; Simpson and McPherson 1998). Model simulations have demonstrated tree induced reductions in cooling can range from 10–80 % depending on the climate and amount of coverage (Huang et al. 1987; McPherson and Rowntree 1993; Pandit and Laband 2010). For example, on a per tree basis, savings have ranged from 10–15 % for twelve cities throughout the U.S., but increase with more coverage (McPherson 1994; Pandit and Laband 2010). For these reasons, trees have been considered to be one method for helping achieve urban CO_2 reduction targets.

Special emphasis on how residents can manage and maintain trees for the provisioning of ecosystem services has implied, yet controversial, value in increasing the quality of life in lower socio-economic status and minority neighborhoods. Setting aside the fact that the mechanisms behind the relationship between tree cover and socio-economic status are not yet clearly understood, empirical evidence for the production of ecosystem services by trees remains uncertain (Grove et al. 2006b; McPherson 1992). Understanding how trees influence home energy use is particularly complex, because of the number of variables that can have an effect on the cooling demand associated with individual homes.

Studies on residential home energy use have shown human lifestyle choices, occupant behavior, building attributes, appliance use, and characteristics of the heating and cooling systems all play a role in energy consumption (Bin and Dowlatabadi 2005; Laverne and Lewis 1996; Pandit and Laband 2010; Schipper 1996; Schipper et al. 1989; Simpson 2002). These empirical analyses predict that energy savings from trees may be smaller than those associated with energy efficient building characteristics (e.g., insulation, window characteristics, home size). In another study, Abbott and Meentemeyer (2005) sampled modern homes and found trees had a minimal impact on energy used for summer cooling, while thermostat settings were crucial drivers of energy use.

Although empirical analyses on the impacts of vegetation relative to other variables influencing home energy use are rare, research to date indicates trees may have smaller impacts on energy consumption than some models have predicted (Abbott and Meentemeyer 2005; Laverne and Lewis 1996). Furthermore, occupant behaviors (e.g., thermostat settings, amount of time home is occupied, appliance use) create considerable variation in model estimates of energy savings from trees (McPherson and Rowntree 1993). Because the CO_2 mitigating services attributed to tree planting projects have been derived from estimates of energy savings (McHale et al. 2007; McPherson 1994), we need more empirical estimates of tree impacts on home energy use.

We began addressing this need to better understand the direct effects of urban trees on energy use in Raleigh, NC, by evaluating the relationships among human lifestyle choices, tree cover, building characteristics, and household energy consumption with focus on summertime energy use. We aimed to conduct an in-depth empirical analysis on energy consumption to examine the complex and interacting variables that influence residential energy consumption. Raleigh continues to be a rapidly expanding urban center, despite the economic crisis, and has a sprawling pattern of development similar to that of younger U.S. cities (Ewing et al. 2009). More importantly, NC's capitol city is located in the southern growth zone where tree related impacts on energy usage are predicted to be among the highest due to elevated tree growth rates, high tree cover, and potentially rising summertime temperatures (McHale et al. 2007).

Our goal was to identify the drivers of summertime home energy consumption and the relative influence of trees in providing key ecosystem services associated with energy use reductions. We hypothesized that the most important variables influencing home energy use would be home size and home age, as well as, categorical indicators of lifestyle choices as defined by recent marketing analyses (The Nielsen Company PRIZM ©). Although we did not expect tree cover to be one of the most important variables influencing home energy use, we did expect that total percent tree cover 18 m around the home would have an effect on summertime home energy consumption. Specifically, we hypothesized that with increasing tree cover there would be a greater reduction in energy use. We also expected that environmental worldview might play a role in explaining some of the variation around home energy use. We hypothesized that groups with more pro-environmental beliefs would use less energy per month due to conservation and/or efficiency. Our results have important implications for understanding relationships among tree cover, energy use, and lifestyle choices, and in turn managing residential home energy use for reducing CO_2 emissions in the U.S.

Methodology

Study site

We conducted our study in Raleigh, North Carolina located at 35° 46′ 18″ N latitude and 78° 38′ 20″ W, which is in the Piedmont region and corresponds with USDA Hardiness Zone 7 (USDA-USNA 2011). This region experiences hot humid summers and mild winters, thus allowing numerous tree species to thrive (McPherson et al. 2006). Average summer daytime temperatures are in the upper 80s to low 90s °F (26.7 to 32 °C) and nighttime temperatures are in the upper 60s (15.6 °C) with an average annual precipitation of 43 inches (NOAA 2011). These climatic conditions result in a large amount of home energy use for air conditioning (Pandit and Laband 2010; Rudie and Dewers 1984).

Raleigh, NC is an expanding urban center and was the second fastest growing major metro area in the U.S. in the 2000s, despite the nationwide economic crisis (Kotkin 2010; Raleigh Demographics 2011; US Census Bureau 2010). Raleigh's population in April 2010 was 403,892 persons, an increase in about 15,000 people since 2009 (Raleigh Demographics 2011; Raleigh Department of City Planning 2010). Raleigh is representative of many forested Southeast cities, as many of these urban centers are experiencing rapid growth (USDA Forest Service 2011). Within Raleigh, housing units range from older than 200 years to recently constructed homes. The tree cover for the entire city is high, with estimates ranging from 31 % to 55 % (Bigsby et al. in prep 2011; Clayton et al. 2008), and the mix of neighborhoods provided us with the range of tree coverage conditions needed for this study.

Neighborhood selection

We chose neighborhoods that represented a range in socio-economic status, and accounted for both economic diversity and lifestyle group. Lifestyle categories were determined by the Potential Rating Index for Zipcode Markets (PRIZM). In the PRIZM classification system, urban, suburban and rural neighborhoods in the U.S. have been separated into clusters using census data. Additional data, such as point-of-purchase receipts, public opinion polls, and market research surveys, were then used to further categorize neighborhoods into three levels of aggregation: 5, 15, and 62 categories. PRIZM used six primary factors to explain neighborhood variance: social rank, household (e.g., life stage, size), mobility, ethnicity, urbanization, and housing (e.g., owner vs. renter, home values). The five-group categorization was based on urbanization; moving to 15 groups added socio-economic status, and the 62 levels disaggregated socio-economic status into a lifestyle categorization with information, such as household makeup, mobility, ethnicity, and housing characteristics (Claritas 2007, 2008; Grove et al. 2006a, b).

After we chose six lifestyle groups based on lifestyle categories, we looked at overall tree cover for 12 neighborhoods in Raleigh to see which groups had equal percent cover for the entire neighborhood and a large range in individual residential cover. For each of the 12 neighborhoods, we calculated percent tree cover using a dot-grid method in ArcGIS with 2008 leaf-on conditions (Nowak et al. 1996). We found percent tree canopy cover for the entire residential area in the PRIZM boundary, average residential percent cover per group using a sample of 30 residences, and the range in tree cover for the 12 neighborhoods.

We chose four neighborhoods based on economic diversity (2 high and 2 low income groups), sample size (at least 200 homes in the group), low residential zoning, prevalence of single-family conventional homes, large range of home ages, dominant race/ethnicity, at least 50 % tree canopy cover for the entire group, and a large range in percent canopy cover for individual residences (Table 1). The four PRIZM segments we sampled were: 12 “Brite-Lites,” “Lil-City,” 24 “Up-and-Comers,” 47 “City Startups,” and 60 “Park Bench Seniors.” According to PRIZM segment descriptions, Groups 12 and 24 represent high socio-economic status groups, and Groups 47 and 60 represent low socio-economic status groups (Claritas 2008).

Data collection

We implemented a stratified random sample to ensure that we had various levels of tree cover represented in each neighborhood. A total of 176 residences were sampled with 44 residences per group and four levels of tree cover. The levels of tree cover were 0–25, 25–50, 50–75, and 75–100 %. There were 11 residences in each cover category per PRIZM group. Tree cover class was initially determined in the field by estimating the cover for trees that were taller than 6 m and within 18 m of the home. After the home was sampled, we calculated actual percent cover using the aforementioned dot-grid method.

We administered a door-to-door questionnaire from May to September 2010. Residents did not receive advance notification of the study and completed the questionnaire on site. To generate random addresses within the four neighborhoods, we used Hawth’s Analysis Tools for ArcGIS, allowing for each address to have an equal chance for selection (Beyer 2004). Residences meeting the percent cover criteria were visited until a response was received or up to four visits (including an evening and weekend visit). After the fourth attempt we used the nearest proximate address, until the sample size was met. The sample size was sufficient to reflect a wide range of shade conditions, as well account for the other variables in Table 1.

Questionnaire and residence data

We asked a series of 20 questions on home energy use, building characteristics, air conditioner type and efficiency, occupant(s) behaviors, environmental beliefs, and basic sociodemographics. Each questionnaire took 20 minutes to complete.

Monthly electricity usage

The survey was administered during the summer of 2010, but we collected energy use data from the two previous years for June, July, and August. If respondents had internet access and an online account they could access their usage from 2008, 2009, and 2010. Alternatively, if they did not have an online account, they called customer service to get usage from 2008 and 2009. In some instances the resident did not live at their recent address in 2008 and therefore we could not access energy information for those months. All of the households sampled provided data for 2009, and 61 % of households included data for 2008. We calculated an average monthly energy use in kilowatt-hours (kWh) for each residence as well as standardized monthly energy use by home size (kWh/ sq. ft. / month) for comparison purposes.

Table 1 Characteristics of final four neighborhoods sampled

	PRIZM GROUP			
Variable	Brite Lites, Li'l City (12)	Up-and-Comers (24)	City Startups (47)	Park Bench Seniors (60)
Median household income reported by PRIZM	$75,255	$52,258	$24,355	$24,958
Zoning/Density	Low and Medium	Medium	Low and Medium	Medium
Number of homes	458	289	902	324
Average housing age	52 years	80 years	42 years	63 years
Housing type	Single-family	Single-family	Single-family	Single-family
Percent canopy cover PRIZM boundary	65 %	56 %	56 %	57 %
Percent canopy cover entire residential	65 %	72 %	70 %	61 %
Average residential percent canopy cover and standard deviation	54 %; 25 % std. dev.	55 %; 28 % std. dev.	56 %; 28 % std. dev.	52 %; 27 % std. dev.
Range of canopy cover for sample of 30 homes	8–100 %	0–100 %	0–100 %	8–100 %
Race within sample group	100 % White	100 % White	76 % White; 24 % Black/Other	9 % White; 91 % Black/Other
Median income from sample	$217,838	$125,000	$35,063	$28,857

Building and air conditioner attributes

Each resident described the size of their home in square feet, the age of their home in years, and listed any appliances that used natural gas. We collected information on the number of air conditioning units, the type of unit(s) (central, window, wall, or other), and the age of the unit(s).

After we began to synthesize our data, we realized the potential importance of historic building characteristics in our study. One neighborhood in particular was considered historic. In the 18th century, buildings were constructed to deal with regional climate; in warm humid climates, porches, awnings, and high ceilings reduced the impact of the sun. Elevated living floors, shutters, and large windows helped to circulate air in the home (Park 1991). After questionnaires were administered, we drove through each neighborhood and sampled 30 of the previously sampled homes for the following traits: high ceilings (greater than 8 ft.), awnings, large front porches (take up entire front porch), and shutters. Then, we calculated the percent of homes in each neighborhood that had these characteristics, and the percent of homes that had all of these characteristics.

Occupant behaviors

Residents indicated whether or not they programmed their air conditioners for a specific temperature, and if so they described the temperatures for: Monday through Friday 9 am–5 pm, Monday through Friday nighttime, weekend 9 am–5 pm, and weekend nighttime. These values were used to calculate a weighted inside temperature (Appendix A). Also, they were asked whether they turned their thermostat to a warmer temperature when the house was unoccupied and if someone was home more than 18 h a day during the summer. Lastly, we asked the surveyor to rate how comfortable he/she was in the residence during the summer using a scale of 1–5, with 1 being ‘very uncomfortable’ and 5 being ‘very comfortable.’

Environmental attitudes

Using an instrument called the New Ecological Paradigm (NEP) scale, we measured people’s environmental attitudes. This 15 item scale has been widely used as an indicator of pro-environmental attitudes. A high score on the scale represents a pro-ecological orientation, and should lead to pro-environmental beliefs and attitudes (Dunlap et al. 2000).

In addition, we asked the respondent to rate (1) how important it is for him/her to reduce energy usage in their home using a scale of 1–5, with 1 being ‘not important at all’ and 5 being ‘very important’; (2) how likely he/she would be to make energy efficiency improvements to his/her home if they knew it would lower their energy bill using a scale of 1–5, with 1 being ‘very unlikely’ and 5 being ‘very likely.’

Sociodemographics

We asked questions regarding gender, race/ethnicity, age, education level, household income, and number of people living in the residence. Other energy studies that documented lifestyles, behaviors, and demographics have found some of the above variables to be influential (Druckman and Jackson 2008; Schipper 1996; Schipper et al. 1989; Souza et al. 2009; Wei et al. 2007).

Tree cover and weather data

Initially in the field, we estimated tree cover and grouped each residential unit into one of the four tree cover categories: 0–25, 25–50, 50–75, or 75–100 %. Also, the number of trees taller than 6 m and within 18 m of the home was documented for each quadrant (northwest, northeast, southwest, southeast). After we implemented the questionnaire at each home, we measured the actual percent cover using the dot-grid method (Nowak et al. 1996) for all trees within 18 m of the home to confirm the initial classification. We measured trees within 18 m of the home due to previous findings that trees beyond that range do not affect energy use directly through shading (Donovan and Butry 2009; McHale et al. 2007; McPherson et al. 1988).

We obtained weather information from NOAA for 2008 and 2009 summer seasons, and assumed weather conditions for Raleigh were representative of our neighborhoods in central Raleigh. The station was located on Centennial Campus of North Carolina State University, and was in the center of the sampled neighborhoods. The temperature outside individual homes may have had discrepancies due to microclimate effects, but we were unable to control for this high heterogeneity in our sampling design. However, our sample design was meant to account for this issue in that the neighborhoods sampled had similar overall tree cover, and we targeted homes with varying levels of tree cover in each group.

We documented the monthly maximum, minimum, and average temperatures for June, July, and August. This information was later used to calculate an average monthly temperature differential for each summer, which was the difference between outside and inside temperature (Appendix A).

Data analysis

Model and analysis

We used SAS 9.2 (SAS ®9.2 Software) for all analysis. Before analyzing the data, some variables were collapsed based on sample size (Appendix A). For the ANOVA and regression analyses, the following assumptions were met: (1) the observations were independent; (2) the errors were normally distributed; (3) all groups had equal response variances; (4) no variables expressed collinearity.

Equation 1 was representative of the two-way ANOVA model (α=0.05) for analyzing the means for standardized energy usage, NEP score, and inside temperature for the effect of PRIZM and percent cover. The parameters P corresponded to the effects of the four PRIZM groups; the parameters C corresponded to the effects of the four levels of percent cover with a nested PRIZM parameter. Tukey's LS means test was conducted for energy usage and NEP score to determine which groups were significantly different from each other.

$$Y_{ijk} = \mu + P_i + C(P)_{ij} + e_{ijk,} \tag{1}$$

for i=12, 24, 47, 60, j=1,2,3,4, and k=1

where, Y = energy use per square foot, NEP score, or inside temperature

We regressed monthly energy usage (Υ_i) against all variables with the iterative stepwise method using Mallows' Cp for model selection. Mallow's Cp was used to guard against the issue of over-fitting a model with the most possible variables. This model uses criteria that address issues of sample size and potential collinearity (Mallows 2000). This was done for total monthly energy consumption and monthly energy consumption standardized to the square footage of the home.

Results

We modeled total energy and standardized energy use per month. There was a large amount of variation among the explanatory variables for the 176 homes in the sample (Tables 2, 3 and 4). Mean energy usage across the entire sample was 1522 kWh/month and 0.89 kWh/sq. ft. /month (Table 4).

Total energy use

Our general model to estimate total monthly energy use (kWh) per residence during the summer season with α=0.10 is represented by Eq. 2.

$$\begin{aligned} \mathrm{Yi} = {} & 761.1630 + 0.0019\,\alpha + 0.3709\,\gamma - 5.8218\,\delta + 28.9042\,\eta - 52.9746\,\theta \\ & + 60.2393\kappa + 207.2473\,\lambda + 515.6439\,\nu + 268.6094\,\rho - 222.6203\,\sigma \\ & - 196.2911\,\tau + \varepsilon_{\mathrm{i}} \end{aligned} \tag{2}$$

where,

α household income in 2009 before taxes
γ square footage of residence
δ age of home in years
η differential for cooling in summer of 2009
θ number of trees in NW quadrant that were taller than 6 m and within 18 m of home
κ number of trees in NE quadrant that were taller than 6 m and within 18 m of home
λ number of air conditioning unit(s)
ν type of air conditioning unit, (0) other-window, wall, or combination (1) central only
ρ whether someone is home more than 18 h/day
σ indoor comfort level in the summer, (0) uncomfortable or neutral (1) comfortable
τ education level of survey taker, (1) no high school, high school, or vocational (2) some college or associates degree (3) bachelors (4) masters, doctoral, or professional
φ weighted mean inside temperature during summer
ω race of person taking survey, (1) white (2) black or other
i sample households (i=1 to 176)
ε normally distributed error term

Stepwise regression (α=0.10) results showed that building size had the largest effect on total monthly home energy use (R^2=37.7 %) (Table 5). Although the PRIZM lifestyle category was not significant in our model, other demographic variables, including income (R^2=4.9 %) and education level (R^2=4.5 %) were significant. Also, air conditioning characteristics played a more important role than we expected.

Specifically, for every 100 square feet (9.29 m^2) above the mean home size, energy use per month increased 37.1 kWh (2.4 %) (Table 5). While temperature differential (the difference between thermostat setting and outside temperature) and home age were both

Table 2 Summary statistics for time-invariant attributes across all samples

Attributes	Mean	Std. Dev.	Min.	Max.
Home size (ft^2)	1921.61	1099.64	500	8011
Age of home (yr)	59.52	27.70	1	102
Age of ac unit (yr)	9	6.21	.42	30
# air conditioners	1.44	0.68	1	4
NEP score	55.24	9.23	23	74
Household income[a]	$107,919	$111,644	$7,500	$337,500
# trees NW[b]	2.46	2.31	0	12
# trees NE[b]	2.47	2.62	0	20
# trees SW[b]	2.45	2.20	0	11
# trees SE[b]	2.38	2.38	0	15
% cover 18m[c]	52.94	23.06	12	96

[a]Yearly household income before taxes for 2009
[b]Number of trees in each quadrant taller than 6 m and within 18 m of the home
[c]Actual percent cover for all trees within 18 m of the home for all homes sampled

significant in the model, they had minimal effects on energy use. Each degree of difference between mean outside temperature and homeowner's mean thermostat temperature raised electricity use by 28.9 kWh/month (1.9 %), while energy use decreased by 5.8 kWh (0.4 %) for every additional year of the home above the mean age of 59.5 years.

Demographics also influenced the energy used in the home. Income was positively related with energy use; each $10,000 increase in yearly income raised energy use by 20 kWh/month (1.3 %). Also, for each unit increase in education level, energy use decreased by 196 kWh/month (13 %). When the home was occupied more than 18 h a day, energy use increased by 269 kWh/month (18 %). Furthermore, those that reported being comfortable indoors during the summer used 223 kWh/month (15 %) less energy than those that reported being uncomfortable.

Table 3 Summary statistics for categorical variables by utility or structural types across all samples

Variables	Utility/structural type	# of sample households
Air conditioner	Central	154
	Other[a]	22
Gas appliances (any)	Yes	143
	No	33
Home 18 h[b]	Yes	86
	No	90
Comfort level[c]	Comfortable	131
	Uncomfortable	45
Race	White	124
	Black/Other	52
Education	High school	32
	Associates degree	31
	Bachelors	56
	Masters or higher	57

[a]Window, wall, or combination of window, wall, and central units
[b]Home occupied by someone more than 18 h/day
[c]Indoor comfort level during the summer

Table 4 Summary statistics for time-variant attributes across all samples

Attributes	Mean	Std. Dev.	Min.	Max.
Mean kWh/month/sq. ft.[a]	0.89	0.48	0.10	2.79
Mean kWh/month	1522	984.25	257	7959
Mean inside temp. °F[b]	76.13	4.49	65	95/off
Mean outside temp. 2008[c]	79.40	–	–	–
Mean outside temp. 2009[c]	79.37	–	–	–
Mean differential 2008[d]	3.68	3.11	0	14.35
Mean differential 2009[d]	1.55	2.28	0	11.10

[a] Calculated using kWh from June, July, and August of 2008 and 2009 and standardized to size of home

[b] Weighted average temperature based on thermostat settings—See Appendix A

[c] Average monthly value for that summer–Calculated using monthly maximum and minimum outside temperatures as reported by NOAA

[d] Average differential per month–See Appendix A for more detailed calculations

Standardized energy use

Equation 3 represents the model we used to estimate monthly energy use (kWh) standardized by home size (residence size in square feet) (α=0.10).

$$\begin{aligned} \text{Yi} = {} & 2.6480 - 0.0238\,\phi - 0.0002\,\gamma - 0.0025\,\delta - 0.0309\,\theta + 0.1470\,\lambda + 0.4168\,\nu \\ & + 0.1570\,\rho - 0.1378\,\sigma + 0.1529\,\omega - 0.0653\,\tau + \varepsilon \end{aligned} \tag{3}$$

where, variables are in the same list as Eq. 2.

Table 5 Stepwise regression results for total monthly energy use in order of increasing R-square value (α=0.10). Dependent variable = kWh/month. This model explains 57.92 % of the total variation. Percent tree cover within 18 m of the home was not significant in the model

Explanatory variables	Coefficient	S.E.[a]	R-square	p-value
Intercept	761.163	301.083	–	0.0124
Home size	0.371	0.068	0.3771	<.0001
Education level	−196.291	58.325	0.4224	0.0003
Income	0.002	0.0007	0.4713	<0.0001
Home age	−5.822	1.860	0.5001	0.0020
Differential 2009	28.904	11.687	0.5185	0.0116
Home 18+ hours	268.609	108.856	0.5312	0.0340
Comfort level	−222.620	116.527	0.5392	0.0907
Number trees NE[b]	60.239	22.471	0.5490	0.0585
Number trees NW[b]	−52.975	26.399	0.5593	0.0505
Type AC unit	515.644	190.251	0.5691	0.0545
Number AC units	207.247	104.031	0.5792	0.0480
Percent cover 18 m	–	–	–	>0.1500
Model R-square 0.5792				

[a]S.E. = Standard Error

[b]Trees taller than 6 m and within 18 m of the home

Table 6 Stepwise regression results for standardized energy use (energy use per square foot) in order of increasing R-square value (α=0.10). Dependent variable = kWh/month/sq. ft. This model explains 42.25 % of the total variation. Percent tree cover within 18 m of the home was not significant in the model

Explanatory variables	Coefficient	S.E.[a]	R-square	p-value
Intercept	2.648	0.585	–	<0.0001
Education level	−0.065	0.037	0.1608	<0.0001
Inside temperature	−0.024	0.007	0.2162	0.0006
Home size	−0.0002	0.00004	0.2843	<.0001
Type AC unit	0.417	0.106	0.3054	0.0238
Number AC units	0.147	0.058	0.3433	0.0020
Home age	−0.003	0.001	0.3596	0.0400
Home 18+ hours	0.157	0.062	0.3741	0.0499
Race	0.153	0.090	0.3870	0.0624
Comfort level	−0.138	0.067	0.4011	0.0500
Number trees NW[b]	−0.031	0.015	0.4284	0.0834
Percent cover 18 m	–	–	–	>0.1500
Model R-square 0.4225				

[a]S.E. = Standard Error

[b]Trees taller than 6 m and within 18 m of the home

We modeled standardized energy use using α=0.10 (Table 6), and the model was similar to that produced for total energy use, except the income and temperature differential were no longer significant, and thermostat setting and race were significant. The variables that explained the highest amount of variability in the data were: education level, home size, inside temperature, number of air conditioners, type of air conditioner, and home age. For every degree increase in thermostat setting above 76 °F, but below 95 °F, 0.024 kWh/sq. ft. /month (2.7 %) less energy was used. In relation to demographics, predominately white households used 0.153 kWh/month (17 %) less energy per square foot than those dominated by blacks and other minority groups.

Tree cover and energy use

Total percent tree cover around the home did not significantly influence energy use (Tables 5 and 6). The ANOVA and regression analyses for total monthly and standardized energy use showed that total percent tree cover 18 m around the home was not an explanatory variable of home energy use across the entire sample or within PRIZM groups. However, the number of trees taller than 6 m and within 18 m of the home for certain azimuth categories was significant in the total energy use model. The mean number of trees in all quadrants (NE, NW, SE, SW) was 2.4 to 2.5 trees (Table 2), but each additional tree in the NW quadrant decreased total energy use by 53 kWh/month (3.5 %), while each additional tree in the NE quadrant increased total energy use by 60 kWh/month (3.9 %).

Socio-economic status, environmental attitudes, and energy use

Initially, we predicted that although the higher socio-economic status groups would use the most energy per month, neighborhoods with different lifestyle categories (PRIZM categories) would have significantly different environmental attitudes than one another

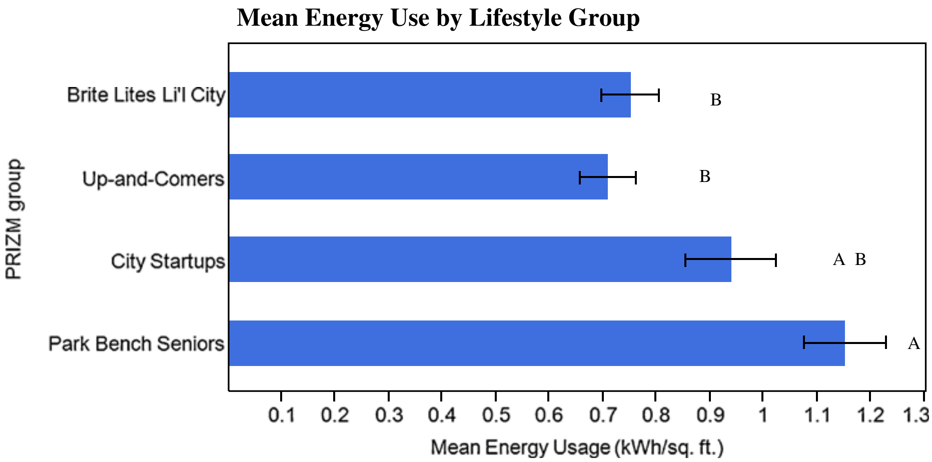

Fig. 1 Standardized mean energy use (kWh/ sq. ft. /month) per lifestyle group. The lowest energy users were Up-and-Comers (Group 24) and they were a high socio-economic status group. The highest energy users were Park Bench Seniors (Group 60) and they were a low socio-economic status group. Levels not connected by the same letters were significantly different

(NEP scores), and the groups with higher NEP scores would use less energy. Contrary to what we expected, the lowest socio-economic status group used the most energy per square foot (Fig. 1). Also, mean energy use was statistically different between “Bright Lights Li’l City” (Group 12) and “Park Bench Seniors” (Group 60) ($p=0.0002$) and “Up and Comers” (Group 24) and “Park Bench Seniors” (Group 60) ($p<0.0001$), even though thermostat settings were not significantly different per PRIZM group. Although environmental attitudes were not significantly different among most groups (Fig. 2), environmental attitudes may be influencing energy use as hypothesized. We found that Group 24 had the highest NEP score ($p<0.0001$), and they used the least amount of energy per square foot (Figs. 1 and 2).

Historic building characteristics

“Up-and-Comers” (Group 24) was a state designated historic neighborhood with historic building qualities; 67 % of the homes had design features that improve comfort in warm climates: high ceilings (67 %), awnings (93 %), and large front porches (93 %). The other three groups were not state designated historic areas. For “Brite Lites Li’l City” (Group 12), 33 % of the homes had high ceilings, 47 % had awnings, and 3 % had large front porches. “City Startups” (Group 47) had no high ceilings, no awnings, and no large front porches. The last group, “Park Bench Seniors” (Group 60), had no high ceilings, 10 % with awnings, and 7 % with large porches.

Discussion

Research suggests tree cover around homes has a small effect on energy use relative to building characteristics, such as window area, insulation levels, and surface to volume ratios

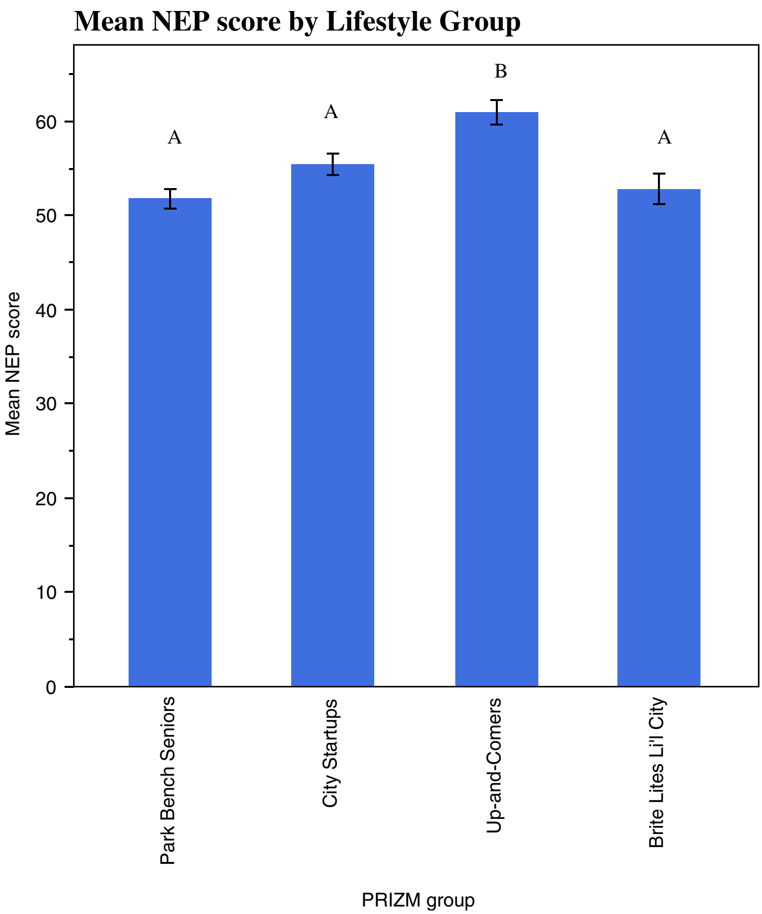

Fig. 2 NEP score per lifestyle group. Up-and-Comers had the highest NEP score. Levels not connected by the same letters were significantly different

(Abbott and Meentemeyer 2005; Laverne and Lewis 1996). As discovered in previous studies, we found building attributes explained more variance in energy usage than tree cover (Abbott and Meentemeyer 2005; Laverne and Lewis 1996). Building characteristics associated with increased energy efficiency are typically associated with newer homes, leading to the result that modern houses are more energy efficient (Simpson and McPherson 1998). For instance, in Ann Arbor, MI, and Atlanta, GA newer homes used significantly less energy than older homes (Abbott and Meentemeyer 2005; Laverne ad Lewis 1996). However, in our analysis, we found the exact opposite; older homes used less energy per square foot than the newer homes. We may have seen these results in our region because many older homes have been retrofitted for increased energy efficiency. It could have also been due to the fact that many of these older homes were designed for making homes more comfortable in the hot southeastern U.S. before the widespread use of air conditioning.

To evaluate the likelihood of the latter hypothesis associated with building design, we determined the presence or absence of large awnings, high ceilings, large porches, and shutters in each of the four neighborhoods in the study. As suspected, homes older than the median age were three times more likely to have large awnings and porches than newer homes. This result is important because many models assume that trees will play a larger role in reducing energy around older homes due to inefficiency. In much of the southern U.S. where older homes were designed for use without air conditioners (e.g., large awnings, high ceilings, large porches) this may be a faulty assumption. Southern cities with historic districts, particularly those that experience revitalization, may also exhibit the negative relationship between energy usage and home age.

In addition to building characteristics, occupant demographics and behaviors, turned out to be an essential part of our model. Education level influenced both the total energy and standardized energy used. This may be because those with higher education spent more of their time and money on energy efficient modifications. In the total energy model, income was a significant variable, however, in the standardized model race/ethnicity influenced energy use. These results may indicate potential inequities in the distribution of housing quality among different ethnic groups, with minorities living in homes that are less energy efficient.

It is interesting to note that the individuals that reported being less comfortable in the summer months also lived in houses that used more energy per square foot. Again this relationship seems like it could be associated with the efficiency of the home or appliances used. Although, we documented air conditioner type and age, we did not actually check on the type of insulation in each home. Insulation is typically assumed to vary with home age because it is very difficult to acquire accurate information about insulation type from residents. Future studies that describe the relationship between insulation and comfort are needed and would add value to these results.

Not surprisingly, when a person was home during the day, energy use increased. Since the rise of an economic crisis in the U.S., there has been an increase in unemployment which may result in a greater number of residents spending more time at home, and therefore increasing home energy use. Moreover, many cities, businesses, and institutions have implemented plans where employees work from home a few days a week to avoid commuting, and some of the positive effects associated with reductions in travel may be offset by increased home energy use.

PRIZM lifestyle categories were not an important explanatory variable in our models. This may be explained in part by the fact that income and education are factors used to develop PRIZM groups, but individually might be more important drivers of energy use than the PRIZM groups themselves. However, we only looked at four different PRIZM categories in detail, which may not reflect dynamics among all 66 groups. In the future, analyzing residents from more PRIZM groups may improve estimates of lifestyle impacts on energy use.

As lifestyle categories have been shown to describe tree cover across cities like Baltimore and Raleigh (Grove et al. 2006a; Bigsby et al. in prep 2012), we were further interested in whether different neighborhoods identified by PRIZM categories had significantly different environmental attitudes (NEP score), as well as mean standardized energy use. We compared NEP scores among the PRIZM lifestyle groups and found that Up and Comers (Group 24) used the least amount of energy and had significantly higher NEP scores than the other three lifestyle categories we sampled (Figs. 1 and 2). These results suggest an expanded analysis of more PRIZM groups may provide evidence that lifestyle, environmental attitudes, and energy may be related.

The lowest socio-economic status group, the Bench Park Seniors (Group 60), used the most amount of energy per square foot (Fig. 1). As the thermostat settings varied little among these groups, this analysis further suggests people living in the least efficient homes used the most energy, and perhaps more importantly, the people who are least likely to afford higher energy bills were using the most energy per square foot. This brings up a series of interesting questions relating to environmental justice: (1) Did they not have control over their home efficiency choices (i.e., they are renters or could not afford to retrofit their homes), or (2) Were they not able to access information about how to make their homes more efficient? Although, lack of awareness associated with potential energy retrofits may be a bigger issue for energy efficiency than the renter/homeowner dynamics (Granade et al. 2009), we did not specifically include home ownership in our study and therefore cannot determine the role of this potential explanatory variable. We did see evidence that income and education played a role in home energy use, however, which may support the idea that retrofits are more likely to occur when people know of, and have the resources to implement, these modifications. Future research in the area should include a more nuanced analysis of the mechanisms underlying these explanatory variables.

Our results suggest tree location, not overall tree cover, around the home influenced home energy usage in Raleigh, NC. Most home energy use models predict increasing tree cover around the home creates significant reductions in energy used for cooling (Akbari 2002; Heisler 1986; McPherson and Rowntree 1993; Simpson 2002). We analyzed total percent tree cover 18 m around the home, and found that it was not significant in our analysis, even for older homes. Our analyses on the number of trees in various azimuths show that trees in certain locations may actually increase energy use, therefore offsetting some positive shading effects associated with trees elsewhere around the home. Many of the previous studies on the energy effects of trees are based on models that do not allow for the possibility of increased summertime energy use with increased tree cover, and therefore may be overestimating the amount of electricity savings associated with trees around homes. As proponents of planting trees to offset carbon dioxide emissions assume that the energy savings benefits significantly outweigh the direct benefits of carbon sequestration, our results further question the efficacy of tree planting strategies for offsetting CO_2 emissions.

Other empirical studies, ranging from Pennsylvania to California, have used detailed measurement buffers, and found that trees in the south and west regions of the home decreased summertime electricity use (Heisler 1986; McPherson 1994), while those on the north end within 6.1 m tended to increase electricity use (Donovan and Butry 2009). While our findings of increased energy associated with trees in the NE area of the home provide evidence that trees in the northern region can have negative effects on energy use, our results that trees within 18 m of the NW area of the home decreased energy use are inconsistent to previous findings. The negative effects of trees on energy use could be because trees can add more moisture to the air, trap in heat, and reduce wind speed which can actually increase air conditioning demands (Donovan and Butry 2009; Huang et al. 1987; Souch and Souch 1993).

We expected to see that trees in Raleigh would have a larger influence on energy use, especially because models predict the southern states are where people receive the greatest energy related benefits. It is possible that at 55 % cover (Bigsby et al. in prep 2012) versus the average urban tree cover of 28 % in the U.S. (McPherson 1994), the climate and evaporative cooling effects of trees in Raleigh could make shading effects at the household scale less important. Specifically, previous research has found overall evapotranspiration to account for most of the cooling savings (Akbari et al. 1992; Huang et al. 1987; Jo and McPherson 2001; McPherson 1994; McPherson and Rowntree 1993). Also, models assume that past a certain number of trees, there are diminishing marginal returns on energy savings (McHale et al. 2007; Simpson and McPherson 1996, 1998). Raleigh's urban tree canopy may be acting like a rural forest, where the individual effects of shade trees are less important than the overall climate effects of the forest. To tease out the effects of shade trees on home energy use, microclimate data and detailed buffer measurements will have to be incorporated in future studies.

Conclusion

Tree planting projects in heavily forested urban areas may not be a substantial way to achieve further carbon emission offsets. Modeling analyses on tree planting projects that aim to offset carbon emissions have concluded that the majority of the CO_2 offset is from the reduction in energy used for cooling buildings, not from the direct sequestration of carbon (McPherson and Rowntree 1993; Pataki et al. 2009). However, our study suggests energy reductions achieved through tree planting in southern cities with high tree cover may be small even if trees are planted strategically. This could be because the overall climate and evaporative cooling effects of the urban forest effectively reduced additional direct shading effects. Alternatively, benefits provided by trees in one location may be offset by energy costs associated with trees in another location. These results enhance our general understanding of the complexities associated with tree placement and its potential effects on home energy use.

Furthermore, our results suggest built, natural, and social environments influence summer energy usage in the Southeast U.S. The social (e.g., behavior, neighborhood history, perceived comfort) and built environment (e.g., house size, AC efficiency) had more impact than the natural environment (e.g., tree cover and position). The inclusion of the social environment in empirical models of energy use represents a novel addition to studies traditionally focusing on connections between building characteristics and vegetation (Abbott and Meentemeyer 2005; Laverne and Lewis 1996; Pandit and Laband 2010). Studies that have focused solely on building and vegetation characteristics cite occupant behavior as additional necessary data for future studies (Laverne and Lewis 1996; Pandit and Laband 2010). By looking at the social, built, and natural environments together, we obtained a more comprehensive model of home energy use. Accordingly, efforts to target home energy reduction should continue to focus on building attributes, but with a renewed emphasis on human behavior. Given the importance of thermostat settings, education level, and length of time the home is occupied, these efforts should focus on changing behaviors by taking an approach that makes efficiency more convenient, increases motivation, and provides more actionable and pertinent information (Carrico et al. 2011). Therefore, an effective reduction in energy use and emissions will come from building efficiency, energy conservation actions based on human behaviors, and conservation education.

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APPENDIX A

Descriptive statistics

A. Weighted inside temperature:

- Daytime (9 am–5 pm) thermostat settings and nighttime (5 pm–8 am) thermostat settings were reported for weekdays and weekends
- Calculated average daily and nightly thermostat setting

– Avg. day or night temperature=((5*temp weekday)+(2* temp weekend))/7
- Weighted inside temp=(day avg. *0.33)+(night avg. * 0.67)
- If air conditioner was OFF, a value of 95 °F was used

B. Differentials:

- Differential = outside temperature-inside temperature
- Differential calculated for daytime and nighttime for each month using average low outside temperature, average high outside temperature, and weighted average for inside temperature based on thermostat settings. Then, calculated one differential per month from averaging day and night differential.

C. Manipulating/Collapsing variables:

- Use average age of all air conditioner units if more than one unit.
- Air conditioner types are 'Central' and 'Other' based on sample sizes. Other is any type or combination of units other than central. (Central = 154, central and window = 4, central and wall = 3, window = 14, and wall = 2).
- Income: use midpoint of range for each residence. Highest income category calculations: divide other incomes (midpoints) in half and add to the high value of $150,000 or more.
- Missing income data: use mean from data for each group (12: $217,838) (24: $145,313) (47: $40,125) (60: $28,857)

Table 7 2008 and 2009 outside temperatures as report by NOAA

Month/Year	Average low °F	Average high °F	Monthly average °F
June 2008	68.3	93	80.7
July 2008	68.4	89.5	79.0
August 2008	67.6	89.3	78.5
June 2009	67.6	89.1	78.3
July 2009	68.6	90.5	79.5
August 2009	70.4	90.3	80.3

- Interpolate temperatures for air conditioners with settings (high, medium, low) by graphing kWh/ sq. ft. vs. mean inside temperature for known values. High setting = 3rd quartile 73 °F, Medium setting = median 75.57 °F, and Low setting = 1st quartile 78 °F.
- Made *comfort level* into two categories based on sample sizes. Uncomfortable = 'Very Uncomfortable,' 'Uncomfortable,' or 'Neutral.' Comfortable = 'Very Comfortable' or 'Comfortable.'
- Made *race* into two categories based on sample sizes: 'White' and 'Black/Other' based on White=124, Black=49 and Other=3.
- *Education level*: (1) 'No high school,' 'High school,' and 'Vocational' combined into one category; (2) 'Some college and associates degree' into one category; (3) 'Bachelors'; (4) 'Master's,' 'Doctoral,' and 'Professional' into one category.

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