LIFE-CYCLE ENERGY IMPLICATIONS OF DIFFERENT RESIDENTIAL SETTINGS: RECOGNIZING BUILDINGS, TRAVEL, AND PUBLIC INFRASTRUCTURE

Brice G. Nichols
Associate Planner
Puget Sound Regional Council
bricenichols@gmail.com

Kara M. Kockelman
(Corresponding Author)
Professor and William J. Murray Jr. Fellow
Department of Civil, Architectural and Environmental Engineering
The University of Texas at Austin – 6.9 E. Cockrell Jr. Hall
Austin, TX 78712-1076
kkockelm@mail.utexas.edu
Phone: 512-471-0210 & FAX: 512-475-8744

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ABSTRACT

The built environment can be used to influence travel demand, but very few studies consider the relative energy savings of such policies in context of a complex urban system. This analysis quantifies the day-to-day and embodied energy consumption of four different neighborhoods in Austin, Texas, to examine how built environment variations influence various sources of urban energy consumption. A microsimulation combines models for petroleum use (from driving) and residential and commercial power and natural gas use with rigorously measured building stock and infrastructure materials quantities (to arrive at embodied energy). Results indicate that the more suburban neighborhoods, with mostly detached single-family homes, consume up to 320% more embodied energy, 150% more operational energy, and about 160% more total life-cycle energy (per capita) than a densely developed neighborhood with mostly low-rise-apartments and duplexes. Across all neighborhoods, operational energy use comprised 83 to 92% of total energy use, and transportation sources (including personal vehicles and transit, plus street, parking structure, and sidewalk infrastructure) made up 44 to 47% of the life-cycle energy demands tallied. Energy elasticity calculations across the neighborhoods suggest that increased population density and reduced residential unit size offer greatest life-cycle energy savings per capita, by reducing both operational demands from driving and home energy use, and from less embodied energy from construction. These results provide measurable metrics for comparing different neighborhood styles and develop a framework to anticipate energy-savings from changes in the built environment versus household energy efficiency.

KEY WORDS

Life-cycle energy use, urban systems, neighborhood design, built environment, vehicle-miles traveled, land use patterns, sustainability levers, smart growth

INTRODUCTION

As the second largest energy consumer and greenhouse gas (GHG) emitter (behind China), U.S. energy policy has large implications for global GHG emissions and the energy industry. The U.S. is seeking a (legally non-binding) GHG emissions reduction of 17% below 2005 levels by 2020 (Damassa et al. 2012), and has mentioned targets near 83% of 2005 levels by 2050 (DOE 2009). If the U.S. remains committed to these targets while accommodating growing population and urbanization, managing both transportation and the built environment will be critical focus areas. Transportation alone is responsible for about 28% of total U.S. energy consumption annually (with 60% of this share coming from personal travel [NAS 2013]), and residential and commercial buildings consume up to 41% of all the nation's energy every year (NAS 2013). Land-use policies aimed to improve energy efficiency (e.g., Smart Growth and New Urbanism) may play a critical role in reducing U.S. GHG emissions over time, while improving the nation's energy security and moderating a variety of environmental impacts.

While much research has considered built environment (BE) impacts on travel choices (see, e.g., Handy 1996a, Levine 1999, Bernick and Cervero 1997, Cervero and Kockelman 1997, Cervero et al. 2002, Khan et.al, 2013), much less research has considered impacts on buildings and infrastructure (even though buildings consume nearly 2.5 times the energy used for U.S. personal transport). Furthermore, the embodied energy of materials for constructing and maintaining buildings and other infrastructure is rarely considered alongside purported transportation energy savings from different BE designs. Thus, a more holistic energy analysis is typically overlooked, and various sectors of the urban environment (e.g., vehicles and roads, residential and commercial buildings) are too rarely compared to identify the most effective "levers" for reducing energy consumption. This analysis emphasizes a more holistic evaluation of BE variations, to better evaluate relative energy savings sources and recommend optimal focus areas.

Together, the day-to-day (operational) and embodied phases of specific materials or structures have been rather heavily researched (though much uncertainty surrounds the analyses) within the field of life-cycle analysis (LCA). LCA provides an appropriately holistic perspective on total energy (or emissions) associated with many of the urban environment's "building blocks," but very few studies have attempted to aggregate micro-scaled LCAs to a neighborhood or regional level. Many studies trace energy pathways only for distinct materials (e.g., Hammond and Jones 2008) or single structures -- like single-family homes (e.g., Keolian et al. 2001) or various commercial building types (e.g., Junnila and Horvath 2006, Fay et al. 2000). By comparing low- and high-density neighborhoods in Toronto, Norman et al. (2006) provided one of the only neighborhood-level LCA perspectives. In addition to evaluating daily transportation and household energy consumption between low- and high-density neighborhoods, they considered the impacts of embodied energy (i.e., that associated with materials manufacture, construction, and building and infrastructure maintenance). Their LCA approach provided a holistic evaluation of all energy sinks across the two neighborhoods, and showed how the low-density neighborhood could be 2 to 2.5 times more energy-intensive (per capita) than the high-density neighborhood, with the embodied energy of neighborhood materials accounting for around 10% of the life-cycle energy use, transportation accounting for 20 to 30%, and building operations from 60 to 70%. Little, if any, other work provides their level of detail and scale. Importantly, their results suggest that the embodied energy and buildings consume a significant portion of a neighborhood's energy use, and should be granted more consideration in land use-transportation analyses.

For the most part, studies of the built environment's influence on vehicle-miles traveled (VMT), building energy used, and downstream emissions have been at a microscopic level, and have included only one or two measures of land use patterns. The result is a piecemeal image of how energy consumption varies across specific settings, with little perspective on the "big picture," or how urban planning influences energy at a city level, and whether any of that really matters, at a larger scale. For instance, in a meta-analysis of travel choices vis-a-vis built environment variables, Ewing and Cervero (2010) suggest thatVMT has an average elasticity of around -0.09 with respect to land use diversity (indicating that a doubling in land use diversity tends to be associated with a nine-percent reduction in average VMT). While useful, it is not clear how a nine-percent reduction in driving really impacts a region's overall energy use. When accommodating thousands and millions of new people, it is unclear whether or not land-use diversity will impact urban energy demand to the same degree as other factors, like building design and vehicle technology.

This study expands on Norman et al.'s (2006) work by introducing a more flexible energy modeling framework, more detailed statistical modeling, and a larger sample of case studies. By quantifying holistic energy demands for residents and workers in different urban settings, this work identifies how density patterns influence aggregate energy consumption. The analysis incorporates "building blocks" from different disciplines (travel demand, building design, infrastructure energy and LCA) to construct larger neighborhoods. Energy use estimates, by source and phase, are evaluated and compared to infer the impact of the built environment on large-scale energy demands.

METHODS

This work develops a system of statistical models, energy equations, and estimates to capture "life-cycle" energy use across different neighborhoods. The approach captures not only energy used to heat and cool buildings and power personal vehicles, but also the "hidden" or "embodied" energy required to produce, manufacture, fabricate, and construct building materials and infrastructure components that support modern households. A combination of statistical models, point estimates (based on meta-analysis of literature), and GIS data were used to compare four Austin, Texas neighborhoods across different energy use sectors and life-cycle phases (i.e., embodied versus operational). Each analysis component is discussed below, separated first by phase, then by sector (e.g., residential buildings, personal transportation, and infrastructure). A diverse set of models and data sources were used to produce equations for each sector and phase, as summarized in Table 1, and described in detail in each subsection.

Energy use at a neighborhood scale involves many different subsystems, including buildings (homes, apartments, offices and commercial structures), roadways, sidewalks, driveways, parking structures, water and wastewater systems, municipal lighting, and more (such as natural gas pipes and electric utility infrastructure). These subsystems' key energy requirements are estimated here via models using U.S. data sets, such as the National Household Travel Survey (NHTS) and the Residential Energy Consumption Surveys (RECS). Other sources, for the materials volumes of streets, sidewalks, and piped systems, for example, were estimated using GIS data from the City of Austin, coupled with satellite imagery and local codes and design standards. Table 1 summarizes the various data sources and modeling approaches used. Estimated energy requirements are separated by sector (buildings, transportation, and other infrastructure) and by use phase (operational/on-going or embodied/initial construction). Many of these models and energy equations, and the sector divisions, are described in following subsections, separated by operational and embodied phases. The resulting equations are computed for each neighborhood and later summed for comparison.

Operational Energy Equations

In this model, operational energy use includes residential and commercial electricity, natural gas, water, and wastewater consumption, fuel use from personal (household-owned) light-duty vehicles (LDVs), and public street lighting. When possible, these values were estimated via behavioral models (using regression equations for vehicle ownership details, driving distances, transit use, and building energy use [per ft^2 of building interior]), but the energy-related water and wastewater estimates rely on aggregate assumptions (from Austin, California, and Florida studies) and GIS-based tabulations (of actual infrastructure observed in the neighborhoods).[1]

Operational Energy Equations: Transportation

Transportation energy use was estimated for personal vehicles and transit via fuel-use models, composed of several sub-models. This approach does not employ detailed networks and regional (zone-based) travel demand models, but rather relies on household demographics and physical characteristics to estimate the number and types of vehicles owned by each household, the number of vehicle miles traveled (VMT), and owned-vehicle fuel economies, to predict each household's annual fuel use in driving, along with the annual number of transit trips and (average) transit trip lengths.

All the passenger-vehicle sub-models were estimated using the nation's 2009 NHTS data. The number of household vehicles owned (by vehicle type: passenger car, van, SUV, and pickup truck) was estimated using Poisson regression, to reflect the integer (or "count") nature of this variable. (A negative binomial model was originally specified, but a statistically insignificant dispersion parameter collapsed the model to Poisson.) Household vehicle type choice was modeled using a multinomial logit (MNL) specification, generating probabilities or shares of each of the four vehicle types for each household. These probabilities were multiplied by the estimated vehicle holdings to produce the weighted average number of each vehicle owned, by household. U.S. EPA-rated fuel economy was provided in the NHTS for each vehicle (by make, model, and production year) and these values were then estimated using ordinary least squares (OLS) regression, with indicator variables for three of the four vehicle types. Household-level VMT was also estimated using OLS (while controlling for household, neighborhood, and vehicle attributes [including fuel economy, gas cost, vehicle age and type]), with all results fed into a final OLS model for each household's annual fuel use. Separating the fuel use model into multiple components allowed separate estimates for number of vehicles by type, which allowed embodied energy calculations by vehicle type.

Transit trips were modeled using the 2005/2006 Austin Travel Survey data, which is similar to the NHTS data set, but provides more information on individuals' (monthly) transit use frequency and average trip length. Two OLS models were estimated with the NHTS data: for number of transit trips per person and transit trip distances. Explanatory variables in the first of these models included household income and size, vehicle ownership, number of workers, regional population, population and employment densities (at the block group level), distance to downtown, share of single-family homes (SFHs) in the block group, an urban location indicator, and employment status. Trip length was

[1] These categories represent the largest sources of urban energy use, both publically and privately, though other energy sources could certainly be included. For instance, life-cycle impacts of urban waste collection services have previously been evaluated (Iriarte et al. 2008), but are excluded in this analysis, due to data scarcity.

modeled as a function of fewer variables, including an employment status indicator, SFH share, employment density, household income, and the number of transit stops per mile in the neighborhood zone. (Population density was found statistically insignificant using a p-value threshold of 0.1.) Model predictions were scaled to the neighborhood zone level by multiplying the 39 individual results (for each neighborhood) by household size, and then household count, while reflecting the share of employed workers. Total annual energy from transit passenger miles was computed for each household by multiplying average bus efficiency (in megajoules per vehicle-mile) by the total transit passenger-miles traveled per household. This value was then divided by average bus occupancy to derive energy demands on a per-passenger basis. Bus efficiency is assumed to be 40 MJ/vehicle-mile, using an average city bus in 2010 (U.S. DOE 2012), and average occupancy of 10 persons, based on most recent data from Austin's transit provider (CapMetro 2013). Bus occupancy is important for determining efficiency of passenger miles traveled, and varies across cities, and across different routes in the same city. Though occupancy might increase in urban environments, overall efficiency may be reduced with increased congestion (Kockelman et al. 2008).

Operational Energy Equations: Residential and Commercial Buildings

Daily energy use in U.S. residential and commercial buildings includes electricity and natural gas consumption, as modeled by Tirumalachetty et al. (2013) using data from the 2001 Residential Energy Consumption Survey (RECS). Tirumalachetty et al. (2013) controlled for a number of climatic, demographic, and BE explanatory variables, and used such models for an integrated transportation-land use-GHG microsimulation of the Austin region (but without as much attention paid to BE impacts and no consideration of embodied-energy impacts). Building-specific variables include home age, square footage, and indicators for urban versus suburban location, and single-family versus multi-family unit type. Electricity and natural gas costs (per kWh and MMBtu, respectively) were also controlled for, and rely on state average residential rates of $0.09/kWh for electricity (EIA 2012) and $10.90/MMBtu for natural gas (EIA 2013).

Operational Energy Equations: Utilities

Street lighting, water, and wastewater require energy as well. Street lights constitute a costly portion of a municipality's expenses (The Atlantic 2012), and these were noted across the four Austin neighborhoods using Google Earth satellite and Street View imagery. Each lamp was assumed to have the standard 250-watt high-pressure sodium-vapor bulb (City of Austin 2011) and operate from sunset to sunrise, or 12 hours per day, using about 3 kWh per fixture per day. This energy demand from public lighting is, however, likely to decrease over time as LED lights (using around 40% the energy of comparable incandescent bulbs [Yun et al. 2013]) are installed more often.

Household and commercial water use requires significant energy, for treatment and distribution. Some of the consumed water is removed from the buildings and processed at a wastewater treatment plant, which requires further energy input. Detailed residential and commercial water use data are rarely collected, so aggregate estimates were assumed here. Each household was assumed to use 275 gallons of fresh water per day per household, based on City of Austin estimates (Fodor 2011). Average commercial building water use was assumed to be 0.142 gallons/ft^2/day, according to studies of Florida cities (Morales and Heaney 2010). Wastewater use (for residential and commercial buildings) was assumed at 40% of freshwater use, to include only drain flows of indoor uses (Mayer et al. 1999). The energy costs of water treatment, distribution, and wastewater treatment were assumed to be 1,200, 2,500, and 1,400 kWh per million-gallons, respectively, based on averages from several California systems (Klein et al. 2005). It would be desirable to separate these uses and estimate a model for each household, since water use (and associated energy demands) presumably varies across household demographics and settings, including as a function of various built environment factors (Wentz and Gober 2007) and pumping distances. However, early results indicated that water-related energy use was a relatively insignificant energy draw, so such efforts are expected to be insignificant at the neighborhood scale, relative to other sources.

Embodied Energy Equations

Embodied energy is estimated for buildings and infrastructure materials based on a meta-analysis of detailed life-cycle analyses. Rather than directly perform an input-output analysis or process-based LCA, this work relies on a rather large body of existing work that estimates embodied energy of different building types (in terms of energy per floor space) and various materials (energy per unit volume). The estimates here combine GIS measurements for neighborhood features like roadway and sidewalk asphalt and concrete volumes, and total square footage of residential space by home type (e.g., low-rise apartment, single family home, high-rise condominium). This work builds off existing research to avoid a tedious embodied-energy modeling process and to create an easily-repeatable approach for complex life-cycle emissions estimates.

Building, vehicles', and materials' lifespans are a key assumption for embodied energy analysis. Here, all energy demands are annualized, and longer life-span assumptions reduce the relative impact of the embodied energy phase. When possible, well-documented lifespans were selected (as described below) and kept constant across neighborhoods for consistency. However, such numbers can vary, changing the relative roles of different neighborhood features. The following sections describe the approaches used to quantify the embodied energy requirements of buildings, other infrastructure, and structures, along with data sources used.

Embodied Energy Equations: Transportation and Water Infrastructure

Streets, roads, driveways, and parking lots, cover a large share of a city's surface, requiring much concrete, asphalt, and base materials for construction and maintenance. Street characteristics vary by their functional classification in terms of width, paving material, depth, curb and gutter, lane marking, and signage. This analysis considered neighborhoods with a range of roadway types, but mostly involved local streets and minor arterials (though some neighborhoods included sections of major arterials and highways). City of Austin GIS files provided road centerlines and classifications, and road widths were assumed to follow existing City design standards, by classification. By inspection, all roads were assumed to be asphalt topped, with depths based on anticipated average daily traffic (for each class) using AASHTO (1998) guidelines, and an optimistic lifespan of 20 years.[2]

Sidewalk material volumes were estimated similarly for each neighborhood, using Austin GIS centerlines, and city design standards for materials, depth, and width (City of Austin 2013). Sidewalk data files also included information on driveway entrances crossing sidewalks, which was used to extrapolate total driveway volumes, assuming an average depth and length for each neighborhood. Sidewalks were assumed to have a lifespan of 35 years (City of Dover 2006) and driveways a lifespan of 20 years (Seiders et al. 2007).

In addition to streets and sidewalks, parking lots and garages consume a great deal of land (Chester et al. 2010). Parking infrastructure energy was estimated from City of Austin land-use GIS data. Parking

[2] Chester et al. (2010) used an asphalt lifespan of 10 years for parking surfaces,

structure floor area was estimated from building footprint data, multiplied by the number of floors for each structure (through visual inspection). An embodied energy range of 79 to 215 MJ/ft^2 (depending on construction materials and technique) was applied to total floor space, based on detailed life-cycle analyses from Griffin et al. (2010) and Chester et al. (2010). Embodied energy for surface lots was calculated as for roadways, using GIS land-use data and City of Austin design parking space design standards. In some cases, GIS data excluded some private parking spaces, mostly for apartment and townhome buildings. These additional spaces were estimated using City parking requirements (one parking space required for single-bedroom units, and 0.5 spaces required for each additional bedroom per unit).

Finally, water and wastewater pipe materials were estimated with Austin GIS data for locations, materials, and diameters. Pipe materials' lifespans are based on estimates by Seiders et al. (2007), and their embodied energy estimates come from Hammond and Jones (2010).

Embodied Energy Equations: Residential Buildings

Life-cycle analyses include a great deal of uncertainty, even when analyzing just one material or structure. Since this paper's LCA approach evaluates multiple materials and building types (each with unique construction techniques and input sources), it becomes very difficult to ensure accuracy and precision (Lloyd and Ries 2008). However, general estimates of average energy consumption still provide a useful metric when held constant across several different neighborhood types. Therefore, this analysis assumes an average rate of embodied energy per square foot, by building type. Building type and base footprint were collected for each of the four neighborhoods using Google Earth data, and total built area (per building) came from visual inspection of the number of stories per building, using Google's StreetView imagery. Embodied energy was assumed to be 0.5 GJ/ft^2 for single-family homes and 0.6 GJ/ft^2 for multi-family homes, based on an analysis by Hammond and Jones (2010). The final components considered for embodied infrastructure impacts are water and wastewater pipes. Their locations, materials, and diameters are available through the City of Austin[3], and were tabulated for each neighborhood. Pipe material lifespan are based on estimates by Seiders et al. (2007).

Case Study Applications

The above models and equations were used to estimate energy demands for four Austin neighborhoods, selected to represent a range of neighborhood styles. All come from the Austin area, in order to provide some focus and comparability, but they are general enough to have come from most U.S. urban areas.[4] As detailed in Table 2, these neighborhoods range from a proto-typical U.S. suburban subdivision, with curvilinear roads and cul-de-sacs (Anderson Mill [neighborhood #2]), to a very dense, low-rise multi-family apartment area (Riverside [#4]). Hyde Park (#3) offers a rather high density mix of single-family and multi-family homes, on a gridded street pattern, very near Austin's central business district (CBD). The Westlake neighborhood (#1) represents a sprawling, wealthy neighborhood, with semi-rural character mixed in. It varies significantly from Anderson Mill (#2), in its large lots and home sizes, but greater proximity to downtown. Table 2 characterizes these four neighborhoods while also reporting several model outputs. Neighborhoods are numbered from 1 to 4, based on density, beginning with the least dense. Each neighborhood's geographical size reflects a

[3] The City of Austin provides a large amount of GIS data at ftp://ftp.ci.austin.tx.us/GIS-Data/Regional/coa_gis.html. Water and wastewater data was made available upon email request.
[4] Embodied energy estimates are most easily transferred to new locations, but regression-based model inputs should be changed to account for possible climate variations that impact building energy demands.

census tract, or a combination of two census tracts in the case of #4 – Riverside, to include relatively similar populations, ranging from around 3,300 to 7,700 total residents. The Riverside neighborhood consists of two census tracts to ensure an equal overlap with Austin's travel analysis zone (TAZ) data, which was used to derive employment data.

Table 2's summary and Figure 1 illuminate these residential neighborhoods' clear diversity, even within a single urban area. The settings vary dramatically, and some land-use patterns clearly demand greater travel, infrastructure provision, and energy expenditure. For instance, the number of street centerline-miles per capita is much higher for the mostly-SFH neighborhoods, especially in suburban neighborhoods 2 and 4. Water and wastewater pipe infrastructure demands (per capita) are also much greater for the lower-density developments (neighborhoods 1, 2, and 4).

Case Study Applications: Population Synthesis

To ensure comparability in energy expenditures, the same cross-section of residential and worker population was assumed in all neighborhoods. In this way, one controls for demographic variation and is able to evaluate energy differences based solely on each neighborhood's physical and regional location characteristics. Thirty-nine different household types were considered, and distributed across 2010 Austin metropolitan area demographics, based on household size (1 to 4+ persons), number of workers (0 to 3+ per household), and (annual) income level (low [<$15,000 per household per year], medium [$15,000 – $50,000] and high [>$50,000]). Using a Census Public Use Microdata Sample seed for Austin and marginal distributions on each of the 3 attributes, household shares were distributed across the 39 classes using an iterative proportional fitting procedure (see, e.g., Feinberg [1970] and Norman [1999]). For instance, results indicate that only about 2% of the area households have a combination of 4-or-more members, 3-or-more workers, and a medium income level, while 10% of area households are classified as having only one member, who is employed, and at the low-income stratification. This approach provides an approximation of the Austin area population with sufficient resolution to allow for variation across the models, without creating an unwieldy cross-section sample. The number of classes derives from an original grid of 3 income levels, 4 levels of household workers (0, 1, 2, 3+), and 4 levels of household size (1, 2, 3, 4+). Together, these provide 48 possible household variations, but 3 within each income class are nonsensical, (i.e., number of workers must be less than or equal to household size) thus reducing the possible household types to 39.

While the mix or shares of household types is constant across the distinctive neighborhoods studied, neighborhood population and number of dwelling units vary, so all results are normalized by population (which is extracted from Census [2010] data). All dwelling units are considered 100% filled, which may be unrealistic, but represents the best case scenario when considering per-capita impacts. Additionally, average vacancy rates for rented and owned units are considerably different,[5] potentially skewing differences across neighborhoods. It should also be noted that the units chosen to normalize results may be important to interpreting final results across different neighborhoods in some contexts. Norman et al. (2006) for instance, found that a low-density neighborhood used around 2 to 2.5 times more energy than a high-density neighborhood on a per capita basis, but only 1 to 1.5 as much energy on a per "unit of living space" basis. For this analysis, however, no large difference between the two metrics was found, so only the population metric is used in results and discussion here.

[5] In the first quarter of 2013, average U.S. rental vacancy rates (typically associated with multi-family units) were 8.6%, while average homeowner (typically single-family) vacancy was 2.1% (Census 2013).

Travel Demand's Energy Elasticities

Accounting for energy consumption sources across neighborhoods offers insight into the relative impacts of different sectors across land-use styles, but does not necessarily identify how specific land-use and behavioral changes can impact total energy use. Elasticity estimates allow analysts to appreciate the relative roles of model inputs, such as the effects that population density and dwelling unit type have on a neighborhood's annual energy use.

Elasticities were computed here to estimate energy consumption response to changes in the built environment or user behavior. Elasticity values have often been computed identify impacts of BE changes on travel demand, but such analyses rarely extend to include holistic energy impacts. For instance, Ewing and Cervero (2010) reviewed nearly 200 studies to compute weighted-average elasticities forVMT, non-motorized (walking and biking) trip-making, and transit ridership response to changes in built-environment characteristics. While these results are useful to understand how behaviors might be influenced by neighborhood design, such analysis rarely predicts energy use. Especially important here is the phase under which impacts might occur (operational or embodied). For instance, increasing density may reduce VMT and therefore reduce operational demands, but will also decrease per-capita embodied energy demands. Understanding the individual sources and aggregate impacts of life-cycle energy savings becomes an informative extension of elasticity analysis.

Wherever possible, new "energy elasticities" were computed here, by changing urban design variables used directly in the neighborhood energy equations, such as population and jobs density, SFH shares, residential unit size, building age, gasoline price, and bus occupancy. The effects of some other important metrics (not directly computed for each neighborhood), such as land-use mix and regional accessibility, were also considered here, by simply pivoting off VMT percentage changes (using Ewing and Cervero estimates [2010]), after assuming a base/reference (accessibility or mix) value for each neighborhood.

Overall, separate elasticities ($\eta_{i,x}$) were computed for each energy "phase" i (operational, embodied, or total life-cycle energy), for several urban design variables (x), via the following equation:

$$\eta_{i,x} = \left|\frac{\Delta E_i}{\Delta x} \times \frac{x}{E_i}\right|$$

where E_i is the energy use for phase i. This is a typical form of elasticity calculation, and the resulting energy elasticities provide context for how much transportation, land use, and home efficiency policies and programs fare, across neighborhoods. They allow one to extend earlier, context-specific evaluations (e.g., of a neighborhood's physical attributes on its residents' total miles driven) to larger-scale energy analyses.

RESULTS

Combining all sub-models together yields total life-cycle energy for each neighborhood. Table 3 presents overall energy consumption estimates, per capita, for operation versus embodied energy phases, segmented also by transport, building, and infrastructure sectors. Results are presented in terms of GJ energy consumed per year, per capita.

The total shares of life-cycle energy phases appear more clearly in Figure 2, which shows how operational demands comprise the majority (83 to 92%) of annual energy requirements across all case-study neighborhoods. The bars in Figure 2 also show how the more suburban neighborhoods (Westlake and Anderson Mill, #1 and #2) require the most energy per capita, in terms of individual operational and embodied demands, and overall life-cycle uses. In the most extreme cast, the densest neighborhood (4 – RS) consumes only 60% of the life-cycle energy per capita consumed by the least dense, and largest energy consumer, Westlake (1 – WL).

Separating total impacts by source (Figure 3) illuminates the relative magnitude of transportation sources, versus buildings and other infrastructure (namely water, wastewater and municipal lighting). Figure 3 shows that annual fuel use for personal transport, along with embodied energy required to build and maintain streets, sidewalks, driveways, surface parking, and parking structures, can comprise from 40 to 46% of total life-cycle energy across these neighborhoods. Building energy use, for heating, cooling, appliances, electronics, and other uses, along with embodied energy for building materials and construction and maintenance, comprise nearly "all" the remaining portion of life-cycle energy use by these settings' residents: roughly 53 to 55% of the totals computed here, across all four neighborhood cases. The remaining uses (water usage, water and wastewater pipes, and lighting) may represent a significant municipal cost, but appear insignificant in these residential contexts.

Finally, Table 4 reports the resulting energy elasticities for variables considered directly in the behavioral sub-models, along with some other important BE metrics (like regional accessibility and land use mix). The first set of elasticity values corresponds to model-integrated variables that can impact vehicle ownership, VMT, home energy use, and/or the amount of residential structures and infrastructure (for embodied energy calculations). The latter set relies on VMT- specific elasticities from Ewing and Cervero (2010).

Sensitivity Analysis

While elasticities illustrate the relative sensitivity of specific variables, such effects can often be examined more directly via a sensitivity analysis for specific parameters. As noted above, driving and home use of electricity and natural gas emerge as primary energy-consuming sinks, yet these choices can vary greatly across households within a single neighborhood. For example, some families may own a very-fuel efficient hybrid vehicle (or even a plug-in electric vehicle), while others own large SUVs. Among these households, some vehicle owners may seldom drive while others drive many times the norm, based on unobserved factors. Such variation is important to consider in a more comprehensively comparison of neighborhoods.[6] Figure 4 considers LDV energy use with VMT increases and reductions ranging from 75% less than modeled average to 75% more.

This result suggests that the more suburban neighborhoods are subject to greater variation in per-capita energy consumption, and that, even with significant VMT reductions (50 to 75%), these neighborhoods are still associated with more LDV energy per capita than the other neighborhoods. Even with significant driving increases assumed, the other neighborhoods do not reach the averages seen in the two suburban neighborhoods.

A similar result is observed by adjusting the average household fuel economy assumptions (while holding all other variables constant), as shown in Figure 5.   This result closely resembles that of Figure 5, but does suggest that larger, more suburban neighborhoods (R1-WL and R2-AM) amy reduce

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[6] These sensitivity analyses are based on actual neighborhood demographics results (see Section 3.2.1) to capture more realistic behavioral variations.

their overall demands to those of neighborhoods R3-HP and R4-RS by turning to relatively fuel-efficient vehicles, averaging 30 to 40 miles per gallon. This result is rather encouraging, since U.S. Corporate Average Fuel Economy (CAFE) standards are poised to rise substantially, to 54.5 mpg by 2025. Of course, this shift will likely impact all neighborhoods' drivers over time, maintaining the imbalance across neighborhoods, unless VMT changes significantly.

In addition to LDV use, another key source of variation across neighborhoods is home electricity and natural gas usage. Figure 6 shows how this energy-use sector depends on average household size, within each neighborhood, to capture building structure diversity. This result suggests that average home sizes are quite different across neighborhoods, and that even with rather sizeable changes in living space, household is more a function of demographics than neighborhood design. Though some neighborhoods have the opportunity to reduce their LDV energy demands (via increased fuel economy) to compete with other more dense neighborhoods, energy use by suburban households will usually be more intense than those of more urban neighborhoods.

DISCUSSION

Transportation and household energy use calculations illustrate how neighborhood attributes significantly influence (expected) vehicle purchases, driving choices, transit use, and heating and cooling demands. Results suggest that a neighborhood's physical characteristics and setting have important impacts on household energy use, after household demographics (such as income and household size) are controlled for. Though such a result is expected, this work provides a novel method of accounting for energy differences between neighborhoods in a way that considers most major energy-consuming sectors, like personal travel, home energy use, and the embodied energy of supporting infrastructure.

Model results (some of which were shown previously in Table 2) suggest average households from the two suburban neighborhoods (1 – WL and 2 – AM) are expected to drive more miles, own more vehicles, and purchase more SUVs or CUVs, trucks, and vans, than passenger cars. Average fuel economy is relatively constant across neighborhoods due to a lack of BE-sensitive variables in the fuel economy OLS model.[7] The households' LDV energy use levels come directly from a fuel-use model (total gallons, based on household VMT and fuel economy in the NHTS data set), which, as expected, predicts the largest per-household gasoline consumption for Westlake (1 – WL), followed closely by Anderson Mill (2 – AM). Essentially, fewer miles driven, fewer vehicles owned in general, and a lower concentration of lower-fuel-economy vehicles (vans, SUVs, and trucks) are associated with the higher density neighborhood (4 – RS) and the neighborhood with more mixed SFH/MFH units (3 – HP).

The behaviorally-based regression models for transit use suggest that the suburban neighborhoods of Anderson Mill (2 – AM) and Westlake (1 – WL) will generate nearly the same number of transit-trip-miles as Riverside (4 – RS) – and more than those in Hyde Park (3 – HP). In general, transit miles used per household were quite low in all four neighborhoods, which is generally consistent with Austinites' existing travel patterns. Due to the greater distances, suburban travelers with fewer stop options per square mile, end up experiencing longer transit trips (according to the NHTS data sets, ceteris paribus), when they do take transit. Thus, despite a lower *number* of transit trips per household or per capita in these suburban areas (neighborhoods 1 and 2), their longer trip lengths largely equalize the total number of passenger miles traveled by transit. In reality, Austin' Capital Metro transit coverage does

[7] BE variables from NHTS data (e.g., population, housing, and employment density, urban setting, rented vs. owned home shares) were found to be insignificant well beyond p-values of 0.1.

not actually include the Anderson Mill (2 – AM) neighborhood (so transit miles there are zero) and is very sparse in the Westlake (1 – WL) area, and actual ridership will be even lower for residents of these neighborhoods.

When considering energy use across different sectors, this analysis ignores households' energy demands while at work, school, the gym, and other settings; while traveling by air or boat; and when consuming clothing, food, and other goods, for example. But these other expenditures are expected to be quite comparable across these same households. Additionally, this analysis does exclude other urban energy use from commercial, office, and government and or educational buildings, along with commercial and industrial shipping and other energy demands. The share of these buildings types varies across neighborhoods surveyed here, so they were excluded to maintain consistency. However, jobs-housing mix does impact travel behavior (Cervero 1989, Kockelman 1997) and therefore transportation energy, so some of these effects are not captured.

While it is informative to quantify and compare the sources of life-cycle energy use across existing neighborhoods, it is perhaps even more critical to understand which energy-saving strategies be implemented most effectively. For instance, reducing passenger vehicle fuel use and home energy consumption may be logical targets, but it is often unclear which strategies are most effective in reducing energy demand (and/or emissions, for instance). This work facilitates such analyses, by exploring (model-predicted) energy use changes, following changes in various BE characteristics (via the energy elasticities described earlier).

Energy elasticity values (Table 4) are useful for identifying which design and policy parameters have greatest influence over energy use, by neighborhood type, and across operational or embodied sources. It seems that embodied energy is greatly affected by population density, resulting in very sizable overall life-cycle energy impacts. Similarly, average living space increases day-to-day energy consumption, but it is this variable's embodied energy impacts (associated with more building materials) that have the greatest impact on total energy expenditures. Together, these two variables, Population Density and Residential Unit Size, are estimated to have the greatest practical impacts on energy use, in terms of average elasticities, across a wide variety of residential settings. While this finding is not necessarily new (e.g., see Wilson and Boehland [2008] on home size and Newman and Kenworthy [1989] on density), this study does provide a measurable estimate of how changes in these parameters can affect energy use, and the importance of those changes relative to other residential energy uses.

It may not be surprising that the most direct energy-saving variables are politically contentious. Municipal plans encouraging higher density and multi-family housing units face criticism from some citizens and political groups concerned about property right losses and excessive controls over local communities (Kaufman and Zernike 2012). Such built environment changes are some of the most extreme approaches to energy efficiency, however, and a suite of other solutions can reduce demands. Here, sensitivity analysis results suggest that improving vehicles' fuel economies can dramatically reduce the more energy-intensive neighborhoods' impacts, while VMT reduction and home energy efficiency improvements can also help. Policies like the U.S. fuel economy standards (54.5 mpg average by year 2025 [NHTSA 2011]) and various home energy-efficiency tax credits (e.g., Energy Star tax credit [EPA 2013]) tend to be more politically palatable and may produce more immediate success in a community's quest to improve its energy efficiency.

CONCLUSIONS

This analysis provides a holistic approach for evaluating the long-term energy impacts of different neighborhood types, and creates some metrics that help evaluate how land-use and transportation designs and policies may impact energy use at the neighborhood level, and even higher (larger) spatial scales. By evaluating a diverse set of real-world neighborhoods, this work quantifies energy savings from different land-use patterns. While some of the results developed here may best apply to only the four Austin neighborhoods evaluated, it is likely that most (if not all) of the general trends uncovered here can be extrapolated to other cities and settings. Certainly, the methods, model framework, and metrics used here can be employed elsewhere. This work's major achievement lies in disentangling a complex set of urban subsystems and compiling energy estimates via interconnected models and careful visual and GIS analysis. This work provides a framework for evaluating new and existing neighborhoods – of any kind, making extensions a natural possibility.

Most energy-reduction policies focus on reducing VMT or improving building efficiencies, but this analysis shows that between 8 and 17% of life-cycle energy can be attributed to the BE's embodied energy impacts in the four residential neighborhoods examined here. These more compact, higher-density developments provide opportunities to reduce *both* VMT (and thus transportation's energy demands) *and* embodied energy. In the most extreme case, the traditional suburban neighborhood examined here (Anderson Mill, AM – 2) required up to 3.2 times the embodied energy (per capita) of the densest neighborhood (Riverside, RS – 4) and 1.6 times its total (life-cycle) energy. Even if Neighborhood 2's operational energy demands were to remain constant, changing its physical characteristics to match those of Neighborhood 4 (R2 – 4), could reduce annual total energy use by nearly 5%, simply by reducing embodied energy demands. Such energy savings are not easy to estimate, and this analysis offers a more holistic view of how neighborhood design can impact energy consumption.

Energy elasticity calculations suggest that changes in two important built-environment variables, population density and residential unit size, can trigger the greatest per capita energy savings. Though perhaps political contentious, these critical neighborhood characteristics can be used to drive energy efficiency in future developments by way of astute planning and zoning policy, and municipal infrastructure investments that align with density and sizing goals. In many ways, this work supports "Smart Growth" planning strategies, which rely on substantial literature regarding successful urban design (e.g., Ewing 1999, Duany et al. 2010, Benfield et al. 2001,) and policy implementation (Porter 2002, Bengston et al. 2004, O'Connell 2009).

This evaluation also illuminates out how most improvements in energy efficiency must come through reduced fuel consumption and less energy-intensive transportation infrastructure, including parking facilities and roadways. Altogether, fuel use and transportation infrastructure comprised around 45% of life-cycle energy demands across the distinctive residential neighborhoods examined here (both real and simulated/extrapolated [for elasticity computations]). Since per-capita VMT in the U.S. has been falling recently and vehicle fuel economies are improving (thanks to rising Corporate Average Fuel Economy standards), such a statistic is rather encouraging, since it indicates reachable goals of energy reductions in the near future.

In summary, there are many opportunities to improve urban energy efficiency, and thoughtful BE planning and transport policy can improve aggregate energy efficiency and reduce associated environmental, societal, and economic impacts. Taking a life-cycle perspective on energy analysis provides more context on how density and residential building styles impact total energy use. While operational energy from driving and electricity and natural gas use are the major consumption sources in neighborhoods, their estimated rates varied significantly across neighborhood types in Austin, with the least efficient neighborhood consuming nearly twice the total energy per-capita as its most efficient counterpart. Combined with the fact that embodied energy estimates comprise between 8 and 17% of total life cycle energy, this study suggests that development patterns can have a significant impact on energy consumption rates.

LIMITATIONS AND FUTURE WORK

Though this study provides a novel method to estimate and compare holistic energy use across neighborhoods, it is based on many assumptions that can be bolstered via future research. Life-cycle frameworks introduce significant uncertainty, and resulting point estimates may neglect important yet subtle variations occurring within any given neighborhood. This work sought to reflect operational energy demand variations by using a single/constant cross-section of household types, and embodied energy estimates were based on reasonable point estimates from a literature survey. Readers should be cautious when using such results and remember how much uncertainty is involved in these initial estimates. The brief sensitivity analysis performed here illustrates the importance of variability across households, and should be expanded to consider more built environment variables (such as household material types and energy-efficient appliances) and household behaviors.

In addition, to better reflect the marginal impacts of these VMT-focused neighborhood features, a study that quantifies local accessibility, mix, and other attributes, and then controls for these in one or more of the LCA sub-models, is also needed. Such studies may find greater (marginal) impacts (holding all other variables constant). It also is quite possible that the variables of population (and jobs) density, single-family home shares, and residential unit size are partly proxying for facets of these other features, so their estimated impacts (and elasticities) may somewhat diminish once more urban design attributes are controlled for, in the behavioral sub-models.

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Table 1. Microsimulation Models and Data Sources.

Sector	*Consumption Source(s)*	*Operational Energy*	*Embodied Energy*	*Model(s)*	*Data Source(s)*
Buildings	Electricity Use	☑		OLS	RECS & CBECS
Buildings	Natural Gas Use	☑		OLS	RECS & CBECS
Buildings	Building Materials		☑	GIS	City of Austin
Transportation	Personal Vehicles' Fuel Use	☑		OLS, Poisson, MNL	NHTS
Transportation	Transit Fuel Use	☑		OLS	Austin Travel
Transportation	Streets		☑	GIS	City of Austin
Transportation	Sidewalks		☑	GIS	City of Austin
Infrastructure	Water & Wastewater		☑	GIS	City of Austin
Infrastructure	Water & Wastewater Use	☑		GIS	City of Austin
Infrastructure	Street Lighting	☑		GIS	Google Earth

Note: OLS refers to ordinary least squares regression, MNL to multinoial logit model, GIS to geographic information systems measurements, RECS to Residential Energy Consumption Survey, CBECS to Commercial Building Energy Consumption Survey, and NHTS to National Household Travel Survey.

Table 2. Austin Neighborhood Characteristics and Summary Statistics (from GIS Analysis and Model Applications).

		1 – Westlake	***2 – Anderson Mill***	***3 – Hyde Park***	***4 – Riverside***
		Large-lot SFH	Newer, small SFH	Mixed SFH, MFH	Low-rise MFH
Site Attributes & Behavioral Estimates					
Total Population (Census 2010)		4,865	3,394	4,939	7,728
Total Area (mi^2)		5.06	0.64	0.86	0.50
Population Density (residents/mi^2)		962	5,277	5,713	15,401
Employment Density (employees/mi^2)		94	530	2,317	1788
% Detached SFH		93%	92%	65%	8%
Miles from Centroid to Austin CBD		4.5	13.4	2.5	2.3
Streets (centerline miles/capita)		20.5	16.9	12.1	3.6
(Directional) Sidewalks (miles/capita)		4.3	24.7	9.0	3.3
Transit Stops per mi^2		0	0	27	18
Water & Wastewater Pipes (mi/capita)		15.6	10.9	12.2	3.5
Avg. LDV VMT per HH per year		8,200	7,984	7,077	7,096
Behavioral Estimates/Outputs					
Avg. Vehicles per HH		1.69	1.68	1.27	1.04
Vehicle-Type Shares	Passenger Car	64%	63%	68%	68%
	Van	12%	12%	11%	12%
	SUV & CUV	18%	19%	17%	17%
	Pickup Truck	6%	6%	3%	4%
Avg. LDV Fuel Economy (mi/gal)		23.2	23.3	23.5	23.7
Avg. LDV Fuel Use (gal/year/HH)		849	832	584	473
Annual Transit Miles per HH		346	271	167	300
Avg. HH Electricity Use (GJ/year)		97.9	91.6	74.9	66.9
Avg. HH NG Use (GJ/year)		26.9	24.8	21.8	22.0

Note: SFH and MFH stand for single- and multi-family housing, LDV is for light-duty vehicle (cars and trucks), HH signifies household, and NG is natural gas. Miles from Centroid is Euclidean distance from centroid to downtown Austin, set at the intersection of 6th St. and Congress Ave.

Table 3.Life-Cycle Energy Estimates for Four Austin Neighborhoods (GJ/year/capita)

		Operational Energy				***Embodied Energy***				***Total Life-Cycle Energy***			
		1 -WL	***2 -AM***	***3 -HP***	***4 -RS***	***1 -WL***	***2 -AM***	***3 -HP***	***4 -RS***	***1 -WL***	***2 -AM***	***3 -HP***	***4 -RS***
Transport Sources	LDV Fuel Use	45.85	40.17	31.55	25.59	--	--	--	--	45.85	40.17	31.55	25.59
	Transit Fuel Use	0.34	0.41	0.25	0.29	--	--	--	--	0.34	0.41	0.25	0.29
	Parking Garages	--	--	--	--	0.00	0.00	0.07	0.00	0.00	0.00	0.07	0.00
	Surface Parking	--	--	--	--	0.00	0.00	0.44	1.17	0.00	0.00	0.44	1.17
	Sidewalks	--	--	--	--	0.04	0.30	0.10	.03	0.04	0.30	0.10	0.03
	Streets and Roads	--	--	--	--	6.32	9.18	5.91	2.20	6.32	9.18	5.91	2.20
Building Sources	Res. – SFH	51.24	47.79	39.73	34.89	10.19	8.17	3.80	0.22	61.43	55.96	43.53	35.11
	Res. – Duplex					0.03	0.00	0.18	0.04	0.03	0.00	0.18	0.04
	Res. – Apt.					0.51	0.78	0.97	1.54	0.51	0.78	0.97	1.54
	Office/Commercial	0.00	1.59	9.23	3.04	0.00	1.61	3.59	2.85	0.00	3.2	12.82	5.89
Infrastructure Sources	Freshwater	0.15	0.15	0.15	0.15	0.25	0.21	0.19	0.22	0.4	0.36	0.34	0.37
	Wastewater	0.21	0.21	0.21	0.21	0.10	0.10	0.14	0.02	0.31	0.31	0.35	0.23
	Lighting	0.12	0.09	0.03	0.02	--	--	--	--	0.12	0.09	0.03	0.02
Transport	Sub-Total	46.19	40.58	31.8	25.88	6.36	9.48	6.52	3.4	52.55	50.06	38.32	29.28
Buildings	Sub-Total	51.24	47.79	39.73	34.89	10.73	8.95	4.95	1.8	61.97	56.74	44.68	36.69
Infrastructure	Sub-Total	0.48	2.04	9.62	3.42	0.35	1.92	3.92	3.09	0.83	0.76	0.72	0.62
Grand Total		97.91	90.41	81.15	64.19	17.44	20.35	15.39	8.29	115.35	110.76	96.54	72.48

Note: WL stands for Westlake, AM for Anderson Mill, HP stands for the Hyde Park neighborhood, and RS for Riverside.

Table 4. Energy Elasticity Calculations for Four Austin Neighborhoods.

	Operational Energy				***Embodied Energy***				***Total Life-Cycle Energy***				***VMT Elasticity***
	1-WL	***2-AM***	***3-HP***	***4-RS***	***1-WL***	***2-AM***	***3-HP***	***4-RS***	***1-WL***	***2-AM***	***3-HP***	***4-RS***	
Directly Modeled Variables													
Population Density	-0.01	-0.03	**-0.19**	**-0.09**	**-0.91**	**-0.77**	**-0.58**	**-0.60**	**-0.24**	**-0.14**	**-0.25**	**-0.21**	--
Housing Unit Density	-0.00	-0.03	**-0.06**	**-0.14**	+0.01	+0.03	+0.03	**+0.09**	0.00	-0.02	-0.04	**-0.09**	--
Employment Density	-0.02	-0.01	-0.03	-0.02	0.00	0.00	0.00	0.00	-0.01	0.00	-0.01	-0.02	--
% Residential SFH	-0.01	-0.01	-0.02	0.00	**+0.62**	**+0.49**	**+0.29**	+0.03	**+0.29**	**+0.08**	+0.04	0.00	--
Resid. Building Age	**+0.05**	**+0.05**	**+0.05**	+0.04	0.00	0.00	0.00	0.00	+0.03	+0.04	+0.03	+0.03	--
Resid. Unit Size	**+0.12**	**+0.08**	**+0.05**	**+0.06**	**+0.56**	**+0.53**	**+0.40**	**+0.47**	**+0.29**	**+0.25**	**+0.21**	**+0.18**	--
Gasoline Price	-0.04	-0.04	-0.04	**-0.06**	0.00	0.00	0.00	0.00	-0.02	-0.04	-0.03	**-0.05**	--
Avg. Bus Occupancy	0.00	-0.01	-0.01	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	--
Other BE Variables													
Land Use Mix	-0.02	-0.02	-0.02	-0.02	0.00	0.00	0.00	0.00	-0.01	-0.01	-0.01	-0.02	-0.09
% 4-way Intersections	-0.03	-0.03	-0.02	-0.03	0.00	0.00	0.00	0.00	-0.02	-0.02	-0.01	-0.02	-0.12
Job Accessibility (via auto)	-0.05	-0.05	-0.04	-0.05	0.00	0.00	0.00	0.00	-0.03	-0.03	-0.02	-0.04	-0.20
Job Accessibility (transit)	-0.01	-0.01	-0.01	-0.01	0.00	0.00	0.00	0.00	-0.01	-0.01	-0.01	-0.01	-0.05
Distance to CBD	-0.05	-0.06	-0.04	-0.06	0.00	0.00	0.00	0.00	-0.03	-0.04	-0.02	-0.04	-0.22
Transit Stop Accessibility	-0.01	-0.01	-0.01	-0.01	0.00	0.00	0.00	0.00	-0.01	-0.01	0.00	-0.01	-0.05

Note: Elasticities of greatest practical significance (exceeding +/- 0.05) are bolded, and their corresponding variable names italicized.

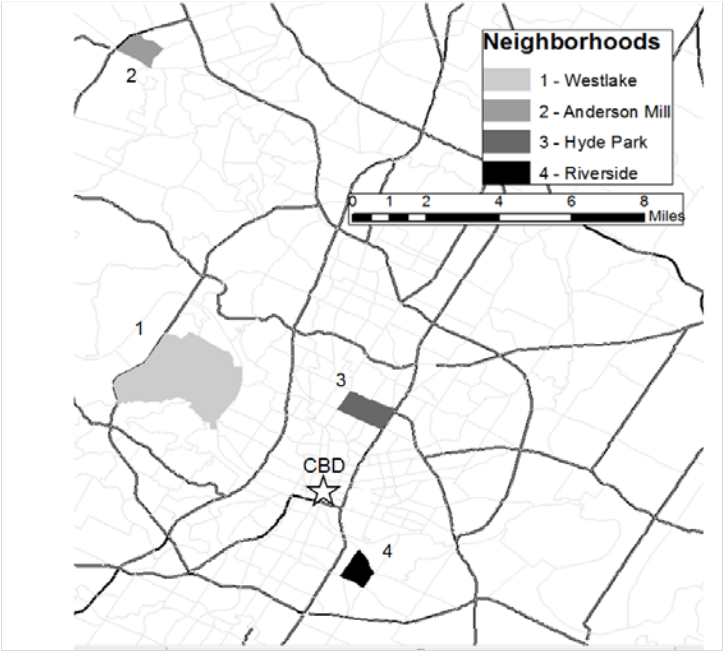

Figure 1. Map of Selected Austin, Texas Neighborhoods.

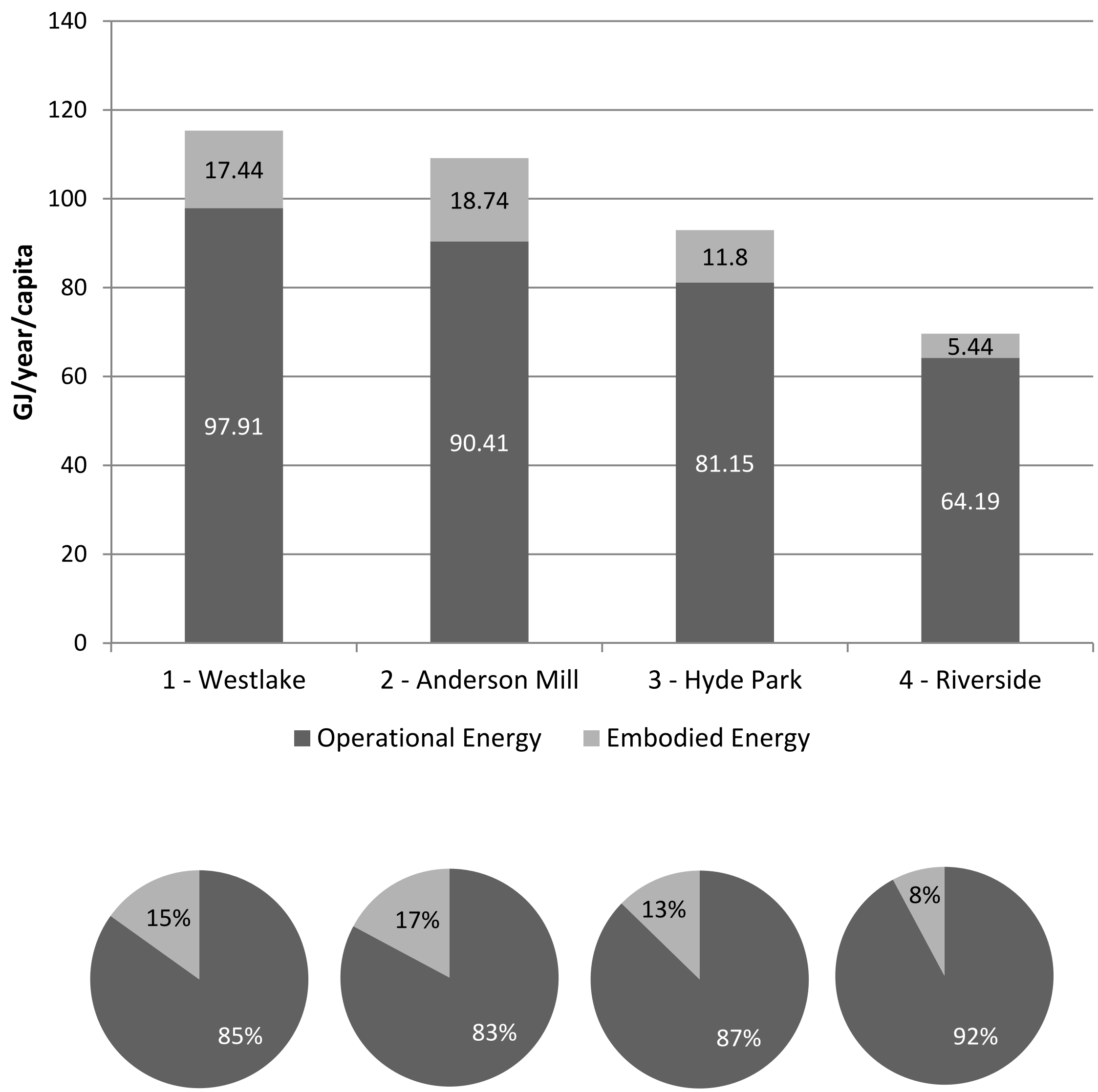

Figure 2. Comparing Energy-Use Stages Across Neighborhoods.

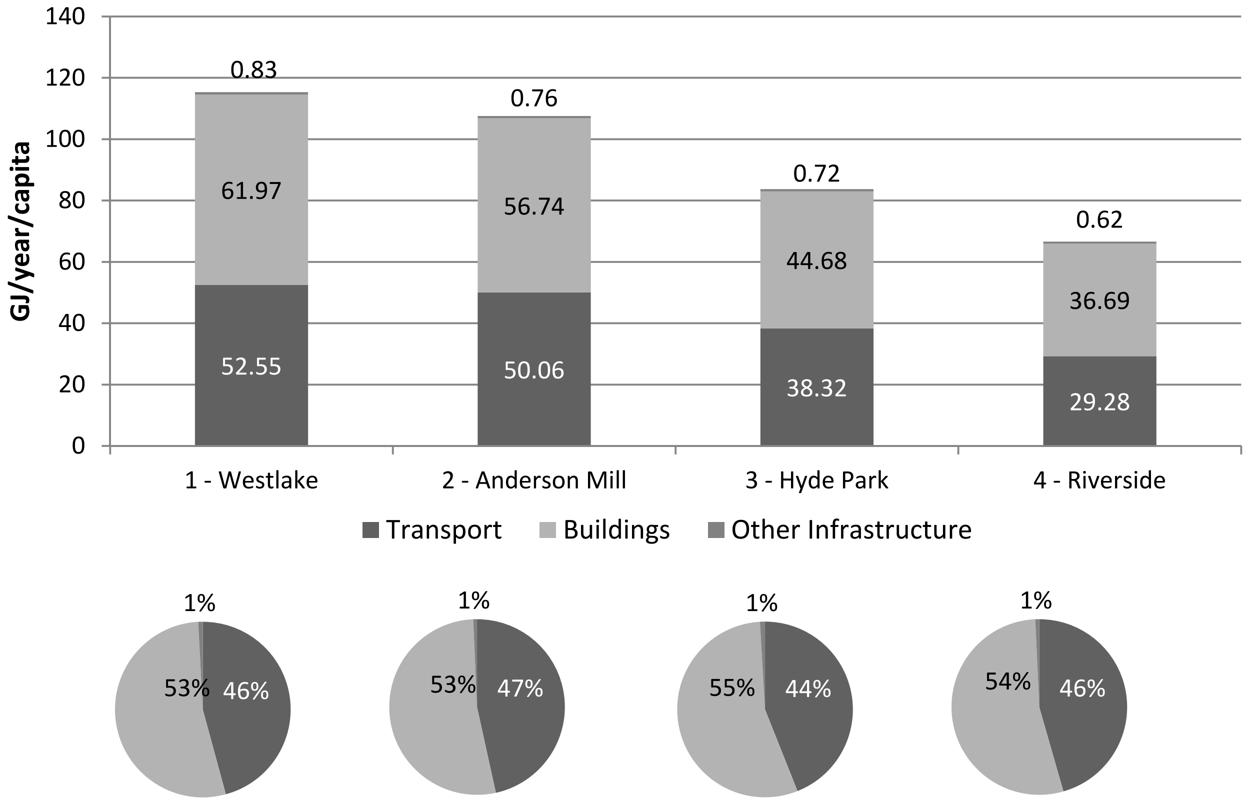

Figure 3. Life-Cycle Energy Use by Sector

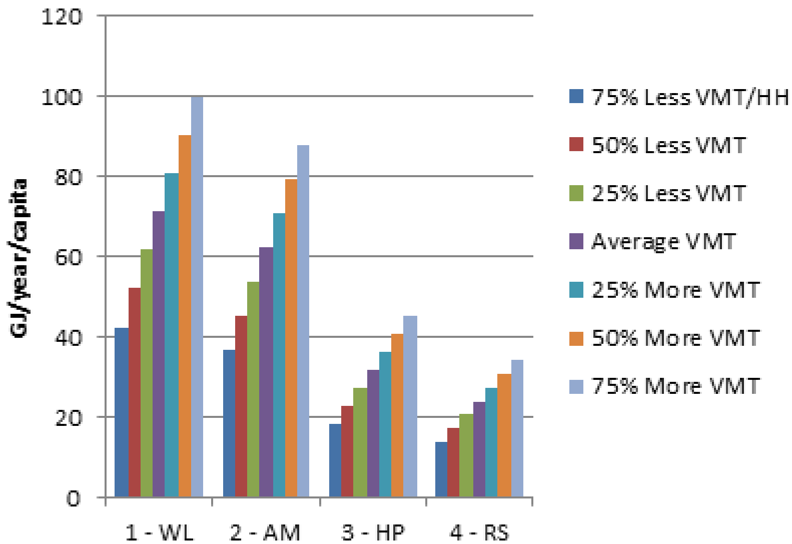

Figure 4: Annual LDV Per-Capita Energy Use with VMT Ranges

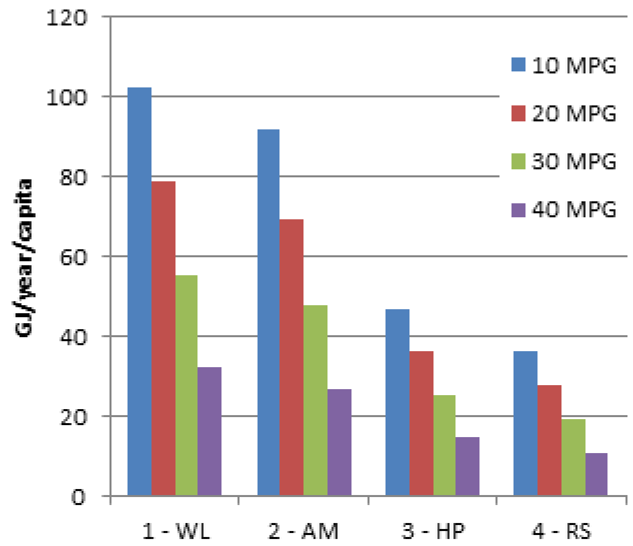

Figure 5: Annual LDV Per-Capita Energy Use with Fuel Economy Ranges

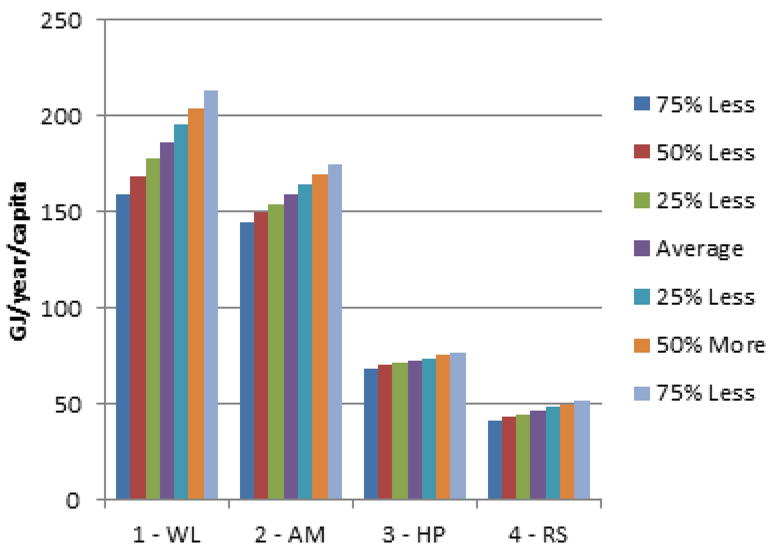

Figure 6: Annual Electricity & Natural Gas Per-Capita Energy Use with Residential Unit Size Ranges