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Structural, geographic, and social factors in urban building energy use: Analysis of aggregated account-level consumption data in a megacity

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HIGHLIGHTS

- Building energy use varies widely across metropolitan Los Angeles.
- Building age, household income, home ownership rates, and land use are all correlated with energy consumption.
- High-income areas use more energy per building, while lower-income areas use more energy per square-foot.
- Account-level energy use data can help local governments devise conservation strategies.
- Energy efficiency programs need evaluated using energy consumption data.

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ABSTRACT

Residential and commercial buildings comprise approximately forty percent of total energy consumption and carbon dioxide emissions in the U.S. Yet, while California spends $1.5 billion annually on energy efficiency programs, limited research has explored how building energy consumption varies within cities, including the social and structural factors that influence electricity and natural gas use. We present results from an analysis of aggregated account-level utility billing data for energy consumption across the over two million properties in Los Angeles County. Results show that consumption in L.A. County varies widely with geography, income, building characteristics, and climate. Several higher-income areas have greater total energy use per building even in cooler climates, while many lower-income regions rank higher for energy use per square-foot. Energy consumption also correlates with building age, which varies widely throughout the region. Our results demonstrate the many complex and interrelated factors that influence urban energy use. While billing data is critical for devising energy efficiency programs that actually realize estimated savings and promote more sustainable cities, opening access to such data presents significant challenges for protecting personal privacy. The presented approach is adaptable and scalable to cities seeking to develop data-driven policies to reduce building energy use.

1. Introduction

In the U.S., residential and commercial buildings account for over 40% of total energy consumption (US EIA, 2015a). Improving energy conservation in buildings through new technologies and efficiency measures is an important part of managing future energy demands, but the task requires more openly-available and higher-resolution data for energy consumption (DOE, 2013). Additionally, by 2010, buildings comprised forty percent of total U.S. carbon dioxide emissions (DOE, 2011). Energy efficiency in the building sector is critical for meeting long-term greenhouse gas emissions targets.

Many utilities offer individual customers access to their own detailed consumption data to inform behavioral changes and support household energy efficiency retrofits (upgrades). For instance, programs such as *Green Button*, a not-for-profit consortium of public and private organizations dedicated to openly accessible and standardized energy use data, allow customers to view, download, and disclose detailed consumption data after signing an agreement that allows a utility to share their data (Green Button Alliance, 2015a). To date, nearly one hundred utilities use *Green Button's* software and standards to provide customers with data (Green Button Alliance, 2015b).

Despite the increased availability of detailed data for customers, few sources of high-detail urban energy consumption data exist for policy-makers, researchers, and the private sector, even as such data is highly valuable for improved planning (ACEEE, 2014;

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Kolter and Johnson, 2011). Aggregated energy use data at the national or regional level, often reported by sectors, is insufficient for developing informed energy efficiency policies and programs (Pérez-Lombard et al., 2008). Yet, utilities are often reticent to share account-level or aggregated data, citing concerns of customer privacy and potential misuse. Understanding influences of behavior is important, and such data helps researchers and local governments devise better programs (Mullaly, 1998; Oikonomou et al., 2009). When available, the data can improve knowledge of energy supply and demand trends across: 1) *geographic scales*, including buildings, neighborhoods, cities, regions, and states; 2) *sectors*, such as residential, commercial, industrial, and agricultural; and 3) *time periods*, including by minute, hour, day, month, season, or year. Standardizing data formats across cities and regions can facilitate more informed energy policies (Green Button Alliance, 2015a; Pincetl et al., 2015; U.S. DOE, 2013).

In recent decades, energy efficiency improvements in buildings have resulted in measurable energy savings (Geller et al., 2006). Building owners in many U. S. states can obtain monetary rebates for energy audits, though information gaps suppress participation, often among lower-income with fewer resources and access to information (Palmer et al., 2013). California has incentivized energy efficiency improvements for decades through multiple programs that target various users and building sectors, which together spent over $2 billion from 2013 to 2015 (CPUC, 2016a). Multiple programs incentivize more energy efficient buildings, including the *Home Energy Efficiency Rebate* program and the *Home Upgrade* program for residential buildings through *Energy Upgrade California*, which are overseen by the California Public Utilities Commission and implemented by state utilities. Yet, while long-term savings from improvements often exceed costs to building owners, motivating homeowners to spend money upfront on energy efficiency is difficult. Many voluntary rebate programs, especially for residences, do not tie rebates with achieved energy savings (Greening et al., 2000; Morrissey and Horne, 2011; Sadineni et al., 2011). Moreover, actual energy savings from home retrofits is often less than modeling estimates, though utilities report estimates as part of assessing home retrofit program impacts (Brown, 2012; CPUC, 2016b). Thus, limited information exists to broadly evaluate energy efficiency programs, especially in residential buildings, and connect program data with socio-demographic and building characteristics. Thus, many questions remain in developing energy conservation programs. Should limited funds be spent retrofitting old apartment buildings, incentivizing homeowners to replace appliances, supporting commercial building improvements, or promoting better attic insulation in all buildings? Building owners with multiple accounts, too, often have limited access to total consumption data that can inform smarter investments (ACEEE, 2014).

In the absence of available account-level consumption data, researchers use models, sampling, statistical inferences, and advanced computing to estimate energy consumption from limited data. Models often use *top-down* or *bottom-up* approaches (Swan and Ugursal, 2009). *Top-down models* predict energy consumption in a sector (i.e. residential or commercial) based on income, demographics, economic activity, and other factors, while *bottom-up models* simulate building energy consumption and demand profiles by summing appliance consumption and calibrating model results to real data using parameters from existing literature, statistical analysis, and modeling (EIA, 2005; Paatero and Lund, 2006; Richardson et al., 2010). Surveys, correlated with utility data, are another common method. For instance, the U.S. Energy Information Administration (EIA) surveys residential and commercial buildings to report average consumption of end-uses such as lighting and heating (EIA, 2013; US EIA, 2015b).

Many factors can limit the accuracy of modeled energy use predictions. To model *direct use* (actual consumption) in buildings, models must characterize climate, building construction and design, household demographics, inhabitant behavior, device profiles, and energy prices (Reiss and White, 2005; Ritchie et al., 1981). Such considerations also do not account for *indirect use* of energy for manufacturing construction materials and consumer goods in buildings (Moll et al., 2008; Reyna and Chester, 2015).

Emerging statistical techniques augment available data by disaggregating energy consumption data from households into individual appliance loads using device signatures within account-level data (Kolter et al., 2010; Kolter and Johnson, 2011; Neenan and Robinson, 2009). Yet, such methods typically assume available account-level data. If delivered to customers by utilities, disaggregated household data can support increased awareness of effective conservation habits, but privacy concerns remain in making such data available to policy-makers and researchers hoping to devise more informed energy efficiency and investment programs.

Another computing challenge results from managing increasingly large amounts of data. Examining energy consumption and demand trends over time critically supports energy policy development (Brown and Koomey, 2003), but tracking account-level energy consumption over both *time* and *space* requires management of "big data" sets (Widén et al., 2009). High-resolution data is critical for meeting peak energy demands. For metropolitan areas, the spatial distribution of energy consumption, along with associated greenhouse gas emissions is of particular interest. In California, the 2006 Global Warming Solutions Act (Assembly Bill 32) requires localities to develop *Climate Action Plans* that describe their strategies for reducing Greenhouse Gas emissions by 15% (CARB, 2016). Appropriate strategies differ by locality and are closely related to the mix of industrial, commercial, and residential buildings in each district. Actual consumption data is critical for developing thoughtful plans to reduce emissions beyond measures such as updating municipal transit fleets, but localities often have limited access to detailed electricity and natural gas consumption in their jurisdictions. Moreover, many localities looking to assess new renewable supply sources such as rooftop solar potential can use consumption data to link supply and conservation planning (Callahan et al., 2014; LA County, 2015). Thus, readily available detailed building energy consumption data across a locality can assist with numerous aspects of implementing, facilitating, and promoting energy efficiency.

Previous studies have estimated spatial distributions of urban energy consumption by scaling data from representative buildings with known usage to larger geographic scales (Brownsword et al., 2005; Heiple and Sailor, 2008; Yamaguchi et al., 2007). One geographically comprehensive study modeled building energy consumption, including heating, cooling, and other end-uses, across the boroughs of New York City (Howard et al., 2012). The authors estimated electricity and fuel consumption using regression to determine contributing factors of zip code-level energy consumption, which was mapped to zip codes in New York City. While robust, the analysis necessarily contained assumptions to compensate for the lack of available account-level data. Pincetl et al. (2015) described the limitations of estimating energy consumption without account-level data and demonstrated a method of reporting higher-resolution billing data for the City of Los Angeles within the context of urban metabolism (Pincetl et al., 2012). In L. A. City, residential energy consumption varies in relation to building type, building size, and income.

Analysis of account-level billing data at the metropolitan scale thus has significant value for research, energy efficiency policy development, and smarter investments. This paper presents a novel analysis of aggregated, account-level energy consumption data across the Los Angeles metropolis area that spans 88 cities and additional unincorporated areas. The procedure analyzes and aggregates data for account-level monthly energy use (2006–2010), as well as parcel-level characteristics for building square-footage and age, land use classifications, and socio-demographics, to demonstrate a robust, empirical methodology that identifies contributing factors of energy consumption within cities. It expands the scope, geography, procedures, and policy relevance of previous research (Pincetl et al., 2015). We demonstrate the usefulness of aggregated account-level data, correlated with socio-demographic and building characteristics, to reveal trends in urban energy use across a large geographic region.

The analysis has several key goals: 1) validate the feasibility and usefulness of obtaining and responsibly reporting account-level energy use data from electric and fuel utilities; 2) describe a methodology for analyzing high-resolution energy consumption data that incorporates procedures to protect personal identifying information of customers; 3) report research findings of energy use data, aggregated over time and space; and 4) demonstrate the value of collaboration between public researchers and utilities in developing strategies to reduce urban energy use and greenhouse gas emissions. We describe below relevant findings from the analysis. Additional results, including analysis of institutional buildings, trends over higher resolution time periods, and across many geographic scales will be reported elsewhere. In total, the analysis illustrates a novel and scalable empirical methodology to analyze energy use in cities. We conclude with a summary of insights and policy implications for applying data-driven strategies to improve energy efficiency programs, along with next steps for extending the research.

2. Methods

The *LA Energy Atlas* was developed to improve data availability to analyze spatial and temporal trends in urban energy consumption across L. A. County (Pincetl and LA Energy Atlas Development Team, 2015). The tool contains: 1) a relational database of account-level energy use, building characteristics, and socio-demographic data; 2) software that aggregates parcel-level information to meet privacy requirements for wider reporting of consumption data; 3) an *Application Programming Interface (API)* to query aggregated data; 4) and a web-based user interface featuring interactive maps, charts, tables, data visualization tools, and documentation.

The core of the L. *A. Energy Atlas* is the relational database that contains 500 million records depicting service addresses, energy consumption, greenhouse gas emissions, and demographic characteristics for over 2.3 million parcels throughout the county for a five-year period (2006–2010). This object-relational database, developed in *PostgreSQL*, is spatially enabled and contains parcel-level energy consumption data obtained from utilities and building characteristics derived from the 2008 Los Angeles County Assessor's property dataset (LA County Office of the Assessor, 2008). Parcels delineate land ownership or public spaces and may contain multiple buildings, landscapes, and residents. The Assessor maintains tax-related information for each property, including vintage, land use code, square footage, and building design type, though the accuracy of parcel-level data varies by building type and land use code. For instance, building area is often inaccurate for institutional buildings such as schools primarily because the county does not assess taxes on schools or much institutional property.

We obtained consumption data for electricity (in kWh) and natural gas (in therms) for the entire region by working directly with regional Municipally-Owned Utilities (MOUs) or through agreement with the California Public Utilities Commission (CPUC). Municipal utilities that provided data include the Los Angeles Department of Water and Power (LADWP), which serves the City of Los Angeles, Burbank Water and Power (BWP), Glendale Water and Power (GWP), and Long Beach Gas and Oil (LBGO), which provides natural gas to the City of Long Beach. Remaining geographic areas of the county are served by Investor-Owned Utilities (IOUs), which report to the CPUC. Two IOUs serve Los Angeles: Southern California Edison (SCE) for electricity and Southern California Gas (SCG) for natural gas.

We received data in multiple formats, including comma-separated value (csv) and data files for the statistical software SAS (SAS Institute, Inc, 2015). All files were uploaded to the database as csv files and data files from SAS were converted using open-source *Python* software sas7bdat.py (Hobbs, 2015; Python Software Foundation, 2001). We used the electricity and natural gas consumption values to then calculate total account-level energy consumption (in British Thermal Units, or BTUs) and greenhouse gas emissions (in Tons of Carbon Dioxide).

Statistics and analysis in the *LA Energy Atlas* are reported at four, increasingly large, geographic scales across L. A. County: neighborhoods, cities, Councils of Governments (COGs), and the entire county. Reported results in this analysis focus on the neighborhood and city levels. City and county boundaries were obtained from the Los Angeles County GIS Data Portal (LACDPW, 2012). The source data for cities includes 88 municipalities and nearly 200 unnamed unincorporated areas in the county. Unincorporated areas were combined into 11 entities based on location within the county's 2012 Service Planning Areas (SPAs), which are used by several county departments to plan and manage service delivery. Data for SPAs are also available from the County GIS Data Portal. Neighborhoods were defined using shape files originating from the *Los Angeles Times* delineation of 272 neighborhoods in L. A. County (LA Times, 2015).

To protect the privacy of individual account holders in reported data, the *LA Energy Atlas* uses custom software to mask potential Personal Identifying Information (PII) by aggregating account-level data according to guidelines from CPUC regarding the number of accounts and percent of individual users comprising published consumption data (CPUC, 2015). The relational database with account-level data was aggregated into new tables of annual energy (electricity and natural gas) at each geographic scale, which support the mapping and download capabilities. Aggregation procedures differ by land use type. Aggregated data reports only median values to provide additional privacy protection.

2.1. Use codes and building types

A primary unit of analysis is the *megaparcel*, a parcel layer dissolved on geometry that maintains reference to parcel polygons that comprise each *megaparcel* polygon. Each megaparcel is assigned a building type according to its use and construction design. The building type categories were developed by Arizona State University researchers (Reyna and Chester, 2015) and include building shell materials by vintage (year built) and use codes as assigned by the LA County Assessor. Across 17 possible building classifications, the majority of buildings (64%) in the county are classified as single-family residences (Table A1).

2.2. Geocoding

Geocoding links account addresses with geographic locations and associated characteristics of surrounding cities, neighborhoods, census blocks, and parcels. Geocoding is an iterative process and the success (match) rate varies based on the geocoding method and level of accuracy. In the *LA Energy Atlas*, accounts are assigned spatial information in the following priority:

1. *Parcel centroids* use a custom locator provided by LA County to match addresses to the parcel in which they are located. This is the most accurate method of geocoding but also the one with the comparatively lowest match rate (90% of accounts). This method allows for analyzing consumption in comparison to parcel-level characteristics such as built square footage or building vintage.
2. *Utility-provided locations* are available for most areas. LADWP provided street-level coordinates for 99.9% of residential accounts and 99.1% of non-residential, while CPUC data included coordinates for 69.4% of non-residential SCE accounts.
3. *Street centerlines* use a street level locator, designed by UCLA's Institute for Digital Research and Education, to place addresses on the street in which they exist. This information is used for aggregating to block groups, cities and neighborhoods, and has a match rate of 95%.
4. *ZIP code centroids* were used for addresses that could not be located using any of the previous methods. This location information is the most complete with a 99.9% match rate, though it is less precise than other methods.

Customized *Python* scripts and *ArcGIS* tools processed geocoding of addresses (ESRI, 2012; Python Software Foundation, 2001). This software converted heterogeneous addresses and accounts into a standardized record format suitable for geocoding and uploading to the database. Service address points geocoded to the street or ZIP Code level contain coordinate information sufficient to match accounts to block group demographics and administrative layers. To match electricity and natural gas accounts with associated parcel and building information, we geocoded the standardized addresses to more precise parcel centroids when possible, using a custom locator provided by L.A. County. Service addresses unable to be matched at this level of precision were checked for street level coordinates. If none existed then they were geocoded to street centerlines or ZIP Codes. Additionally, due to inconsistencies in the data and limitations of the County locator, significant sections of data were geocoded manually. Documentation on the *LA Energy Atlas* website reports the validity of geocoding procedures.

2.3. Incorporating socio-demographic variables

The *LA Energy Atlas* database includes demographic and income characteristics taken from the American Community Survey (ACS, 2006–2010) at the block group level (US Census, 2011). ACS data supplied statistics for population density, median household income (MHI), and home ownership rates, which were geographically aggregated to neighborhoods and cities for analysis in relation to aggregated energy consumption. For income, in particular, the analysis reported below considered if energy use differs in lower- and higher-income areas, both neighborhoods and cities. We considered a broad definition of "lower-income" as areas with a MHI in the lower half of all neighborhoods/cities. This included neighborhoods with MHI below $62,217 and cities with MHI below $62,250.

2.4. Analysis procedure

The *LA Energy Atlas* reports median consumption of electricity, natural gas, or total energy, including both total consumption and consumption per square-foot (energy use intensity) in geographic regions. The median value of consumption in a selected geographic region (cities, neighborhoods, or census tracts) was calculated by determining the median energy consumption in a given time period (a temporal median) for each parcel, then determining the median value of energy consumption for all parcels in the selected geographic region (a spatial median).

The analysis reported below mapped electricity, natural gas, total energy consumption, and greenhouse gas emissions across L. A. County by building type. We developed raster maps of consumption using a raster interpolation algorithm (*inverse distance to power*) in QGIS 2.6 based on spatially distinct centroids for each polygon in the neighborhood shape file (QGIS Development Team, 2014). These maps focused on consumption data from 2010. We also graphed median energy consumption over time (2006–2010) in areas (neighborhoods or cities) and analyzed trends by demographic and building characteristics, including percentage of renters vs. owners, building age, and median household income. Results below present overall energy use by sectors and then focus on consumption in residential (single- and multi-family buildings) and commercial properties. Finally, while local climates across metropolitan L.A. likely affect differences in urban energy consumption, the current version of the *LA Energy Atlas* does not incorporate climate data, a recognizable limitation in interpreting results.

Table 1.
Median annual energy consumption (BTUs/sq-ft) across all parcels by building type.

Parcel Type	Min	Max	Range
Residential:	11,361	55,057	43,696
Single-Family:	0	56,691	56,691
Multi-Family:	0	53,962	53,962
Condominium:	0	51,957	51,957
Commercial:	14,849	83,416	68,567
Industrial:	0	110,859	110,859
Institutional:	4973	2,943,912	2,938,939
All building types:	***11,872***	***133,445***	***121,573***

3. Results

Energy consumption varies widely in L.A. County. Results presented below summarize and compare: 1) energy consumption by sector, 2) consumption trends for total energy use and energy use per square-foot (energy use intensity), 3) energy consumption and median household income, 4) energy consumption and building age, 5) energy consumption and population density, and 5) energy consumption and home ownership rates.

3.1. Summary trends

Across cities in L.A. County, median annual consumption per square-foot varies by building type, with residential properties in a city consuming between approximately 11,000 and 55,000 BTUs/sq-ft, commercial properties annually consuming between 15,000 and 83,000 BTUs/sq-ft, and industrial properties annually consuming up to 110,859 BTUs/sq-ft (all reported as medians), as shown in Table 1 below. Institutional buildings had the highest maximum value as well as the largest range, which likely results from the number of different building types (government buildings, schools, universities, and others), inaccuracies in the LA County Assessor's records of square-footage in such buildings, and the presence of many buildings on a given parcel. Annual per capita residential consumption in cities, calculated as the median consumption in a city divided by its population, ranged from approximately 5.2 million to 9.5 million BTUs.

Energy consumption also varied by building type, size, and age (Table 2). For instance, the range of median annual consumption in multi-family residential buildings up to 40,000 square-feet was relatively consistent, with a maximum value of 54,000–57,000 BTUs. For non-residential buildings, however, values varied widely,

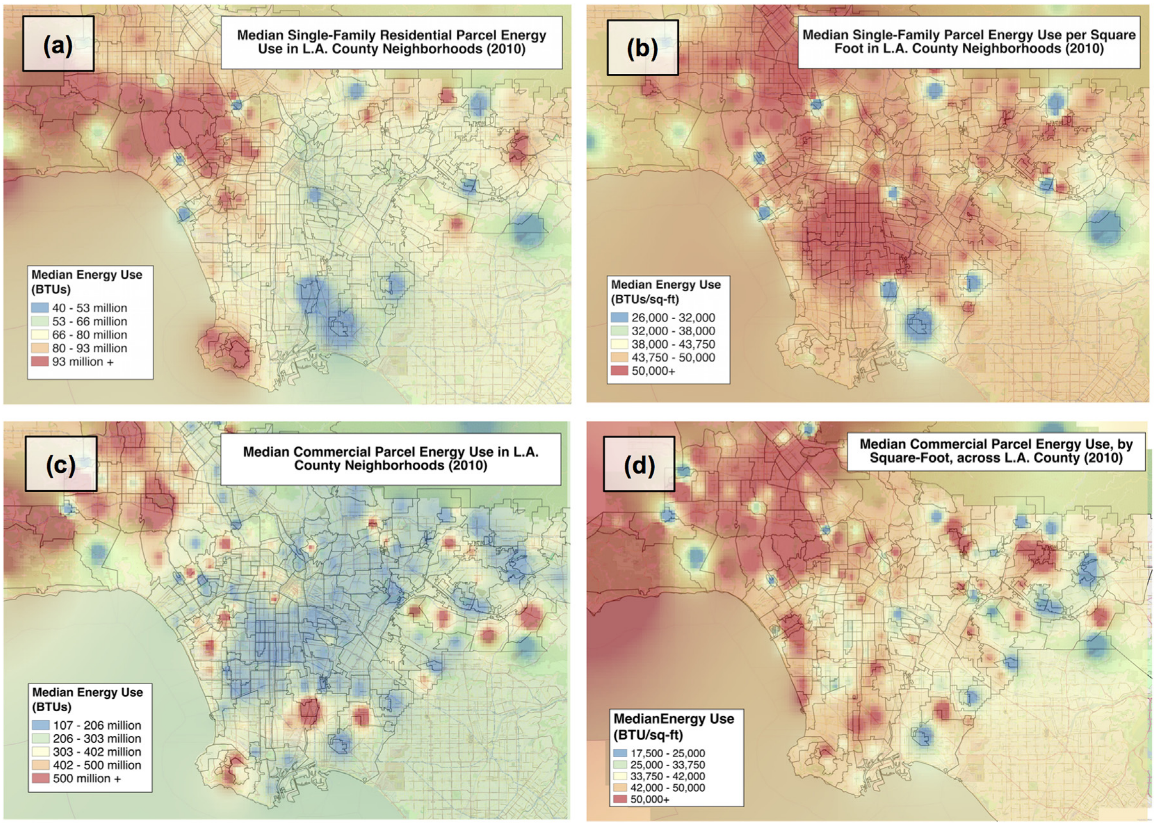

Fig. 1. Median energy consumption in 2010 across neighborhoods in LA County for: single-family homes, total (a) and per square-foot (b); and commercial buildings, total (c) and per square-foot (d). For residential consumption, while coastal areas in the northwestern areas of LA County have higher total consumption, denser areas in central LA and much of the San Fernando Valley (north) have greater intensity of use in buildings.

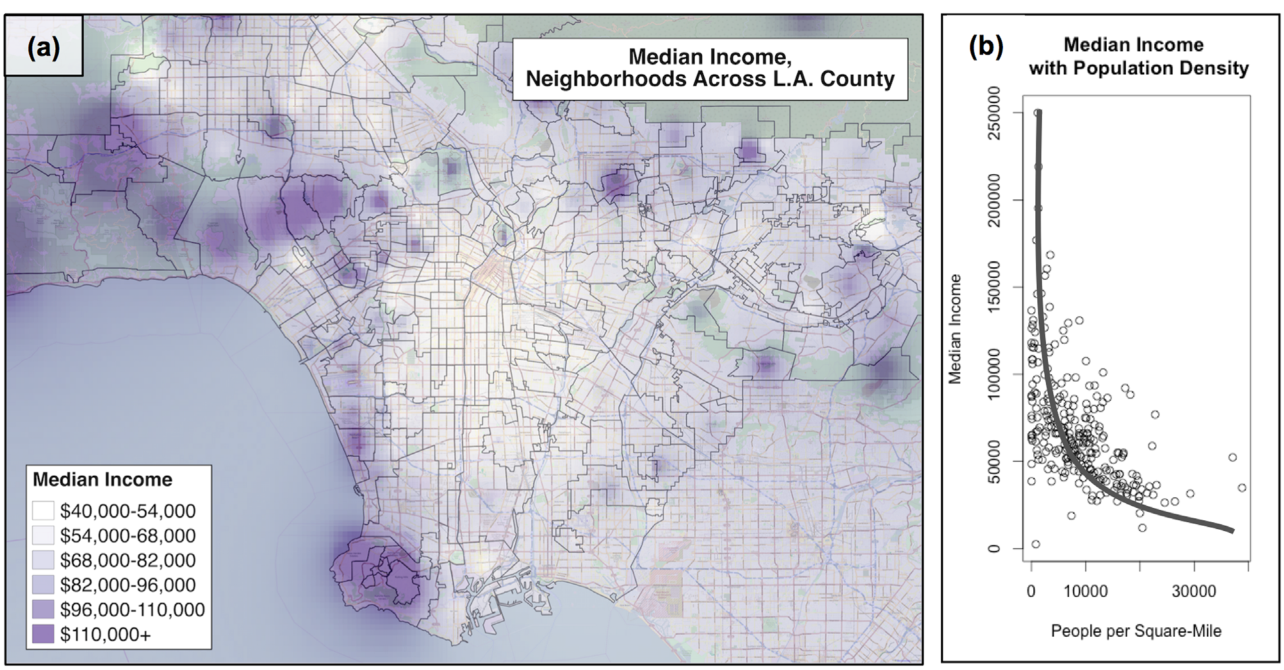

Fig. 2. Median household income (a) mapped across LA County using an interpolation algorithm and (b) compared to population density in neighborhoods, plotted with linear axes (right) (Source: ACS 2011).

revealing both wide building uses and noted inaccuracies in the L. A. County Assessor's database. For instance, non-residential buildings with no reported area (in sq-ft) had a range of energy consumption between 23,000 and 3,000,000 BTUs. Across all building types, age and consumption are noticeably related (Table 2). For instance, buildings built before 1950 have the highest median annual consumption (per square-foot), while those built after 1990 have the lowest. Buildings built between 1950 and 1978 have a slightly lower median annual consumption than those built between 1978 and 1990.

Table 2.
Energy use ranges (BTUs/sq-ft) for all parcels in L. A. County, assessed by *building size* for multi-family and non-residential buildings, as well as *building vintage* for all buildings.

Building Size (in sq-ft)			
Multifamily Buildings	**Min**	**Max**	**Range**
0–10k:	0	54,251	54,251
10–20k:	0	55,701	55,701
20–30k:	0	57,961	57,961
30–40k:	0	57,185	57,185
40–50k:	0	149,333	149,333
Over 50k:	0	174,690	174,690
Non-Residential Buildings			
0	23,662	3,329,622	3,305,960
0–10k:	0	233,198	233,198
10–20k:	0	246,780	246,780
20–30k:	0	72,089	72,089
30–40k:	0	1,129,185	1,129,185
40–50k:	0	439,577	439,577
Over 50k:	0	2,728,479	2,728,479
Building Vintage			
Age Range			
Pre-1950:	0	66,947	66,947
1950–1978:	0	58,766	58,766
1978–1990:	0	64,361	64,361
Post-1990:	0	44,495	44,495

3.2. Spatial Variability in Energy Consumption: Total vs. per Square-Foot

Geographic variation in median parcel energy consumption (2010) appears when examining both consumption by total (BTUs) or unit (BTUs/sq-ft) for a parcel (Fig. 1). For both single-family (Fig. 1(a),(b)) and multi-family homes, many coastal areas in northwestern L.A. have higher median values of total residential parcel energy use, while neighborhoods in Central L.A. have generally higher median values of energy use per sq-ft. South L.A. also has several neighborhoods with higher energy consumption per square-foot but lower total energy consumption, including East and West Compton, and Watts. For median neighborhood energy consumption in single-family buildings, ninety percent of buildings comprise an equivalent amount of total consumption, while only four percent of neighborhoods account for over eight percent of total consumption (see Appendix).

For commercial properties, areas near Beverly Hills and some coastal areas have high total median consumption (Fig. 1(c)), while when measured per square-foot, the San Fernando Valley and areas of the San Gabriel Valley rank highly (Fig. 1(d)). Areas of Central L. A. do not rank highly for consumption per square-foot. Much of the San Fernando Valley ranks highly across all the maps.

3.3. Energy use, household incomes, and building types

Some aspects of energy use correlate with incomes. Median household income (MHI) varies widely for neighborhoods throughout L. A. County, ranging from $250,001 (Hidden Hills) to $11,868 (University Park). Fig. 2(a) maps the distribution using a raster interpolation algorithm (*inverse distance to power*) of median income values based on spatially distinct centroids for each polygon in the neighborhood shape file. Plotting density and median household income (Fig. 2(b)) shows a moderate relationship ($R^2=0.34$). Neighborhoods with higher population densities tend to have lower median incomes.

Some lower-income cities/neighborhoods (those with MHI in the bottom half of all cities/neighborhoods) rank highly among all areas across the county for consumption per square-foot. Table 3 compares median parcel energy consumption (BTUs/sq-ft) among the top-five lower-income cities with the top-five cities overall across building types. Several cities, such as Compton and West Hollywood, appear on both lists for a building type.

Quantifying variability in energy consumption for each building type in lower-income areas reveals widely variability across building types (Fig. 3). Residential and commercial buildings have the highest overall consumption (per square-foot), while institutional buildings have the highest variability, represented by the error bars in Fig. 3.

Unit consumption of natural gas and electricity differs by building type, but the differences are relatively consistent across income (Fig. 4). Commercial buildings tend to use the most electricity per square-foot, followed by institutional and single-family

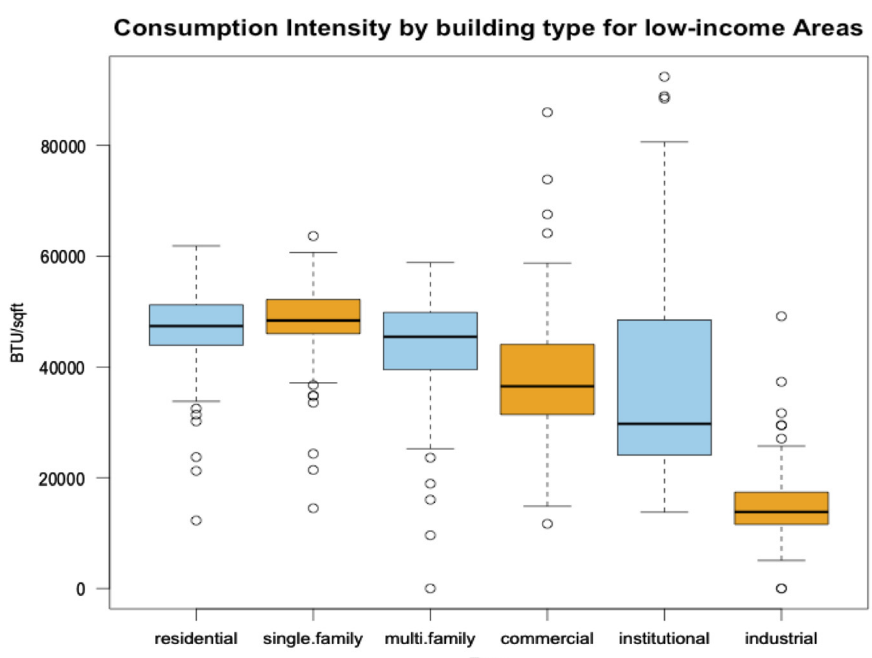

Fig. 3. Median energy consumption (per sq-ft) for lower-income cities in 2010, including quartiles and outliers.

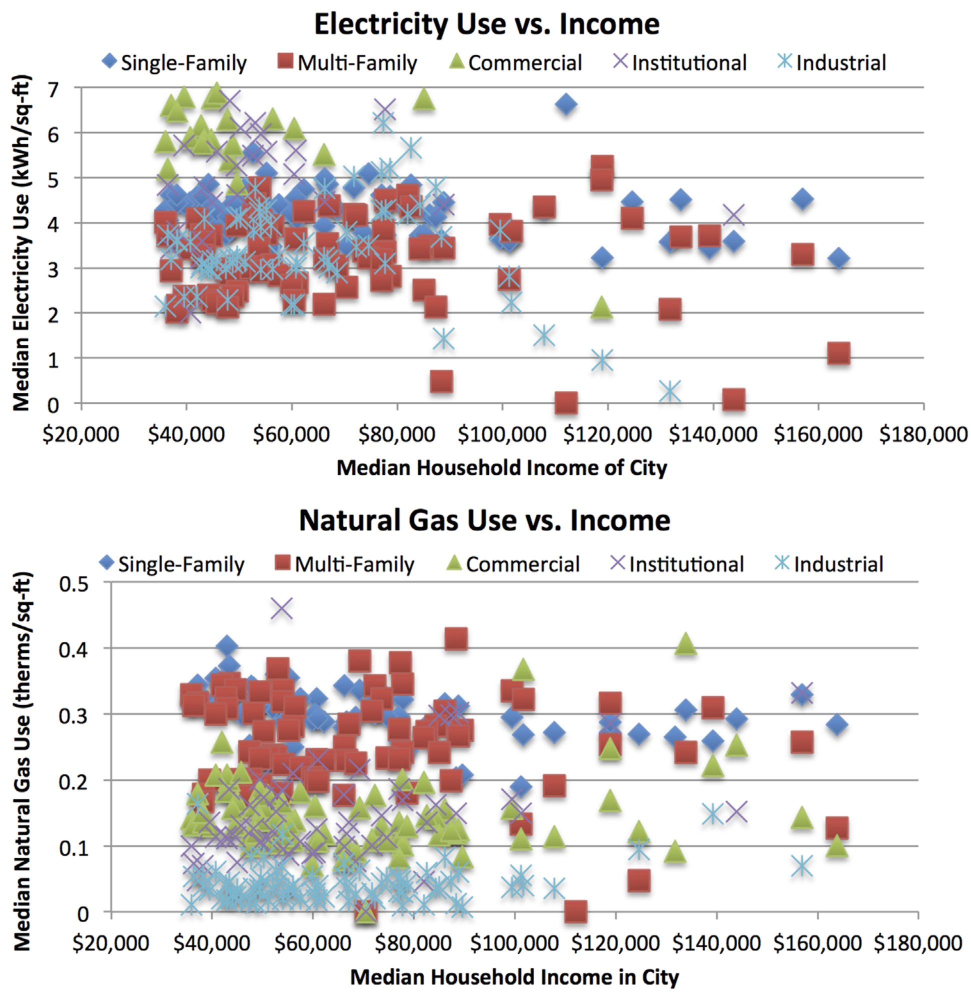

Fig. 4. 2010 Energy consumption (per square-foot) in cities by building type and median household income, for (a) electricity (top) and (b) natural gas (bottom).

Table 3.
Cities with highest 2010 median parcel energy use (BTUs/sq-ft) for single-family, multi-family, commercial, industrial, and institutional buildings. Bold highlighting notes cities that rank highly for both lower-income and all cities.

	Single-Family Buildings		**Multi-Family Buildings**	
Rank	***Lower-Income***	***All***	***Lower-Income***	***All***
1	**Compton**	Westlake Village	**Glendale**	Glendale
2	**West Hollywood**	Compton	Hawaiian Gardens	Culver City
3	**San Fernando**	West Hollywood	Palmdale	Lakewood
4	Inglewood	Hidden Hills	Santa Fe Springs	Rancho Palos Verdes
5	South El Monte	San Fernando	Inglewood	Carson

	Commercial Buildings		**Industrial Buildings**		**Institutional Buildings**	
Rank	***Lower-Income***	***All cities***	***Lower-Income***	***All cities***	***Lower-Income***	***All cities***
1	West Hollywood	Malibu	**West Hollywood**	Manhattan Beach	**Hawthorne**	Hawthorne
2	Palmdale	Lakewood	Maywood	Beverly Hills	**Bell**	La Canada Flintridge
3	Baldwin Park	Hermosa Beach	Palmdale	Calabasas	Downey	Bell
4	Hawaiian Gardens	Diamond Bar	Lancaster	West Hollywood	San Gabriel	West Covina
5	South El Monte	Rolling Hills Estates	La Puente	South Pasadena	Montebello	Walnut

(Fig. 4(a)). For natural gas (therms per square-foot), single- and multi-family homes are most intensely consuming, in many cases twice as much as industrial and institutional buildings (Fig. 4(b)).

Analysis at the smaller geographic level of neighborhoods reveals similar trends in variance and dispersion of consumption. Ranking median parcel energy consumption (BTUs/sq-ft) for neighborhoods and comparing the top five in lower-income vs. all neighborhoods again shows that some areas rank highly for both. In particular, lower-income L.A. neighborhoods such as Compton, Willowbrook, and Broadway-Manchester lead the overall rankings, as shown in Table 4. No lower-income neighborhoods rank highly overall for commercial and industrial, but several do rank highly of all neighborhoods for consumption in institutional buildings.

Over time, while energy consumption has generally increased in California, consumption per capita has remained stable through

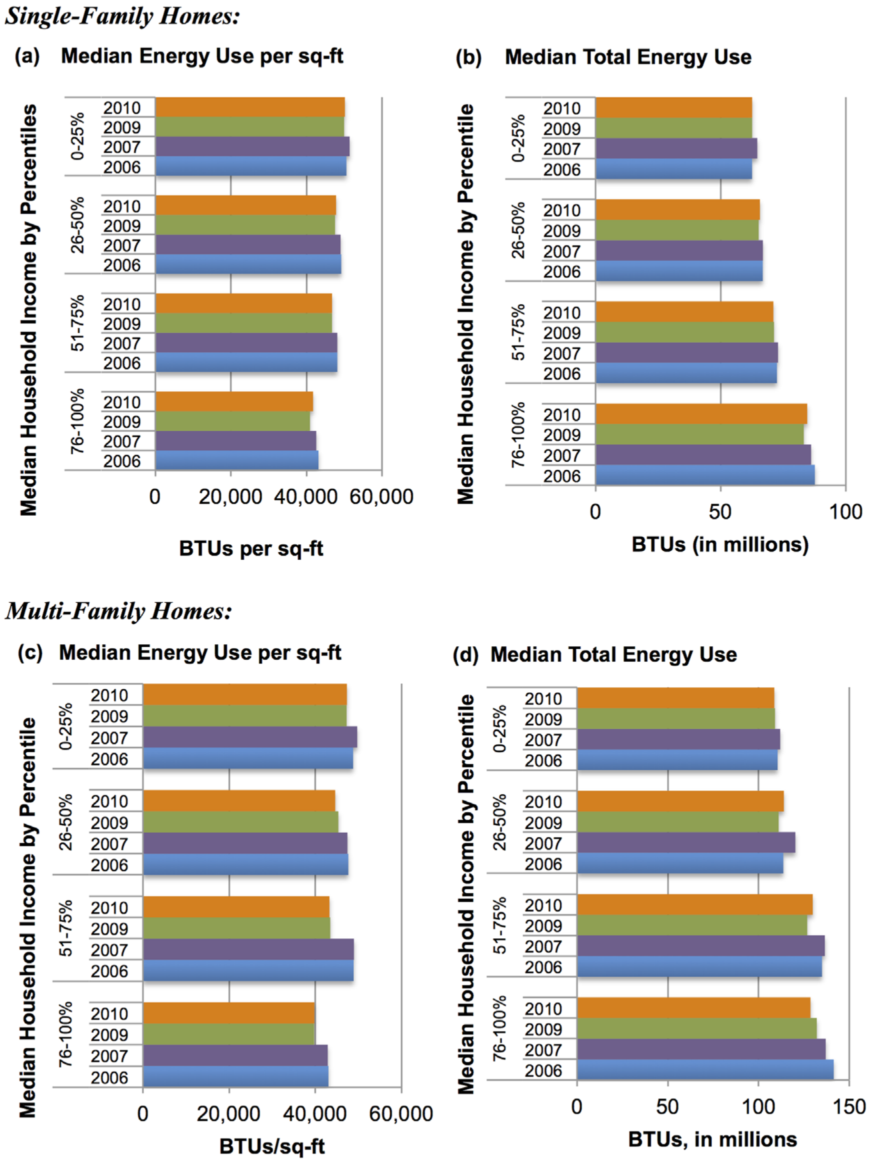

Fig. 5. Median Energy Use in households by percentiles of median household income. The top row shows Use per Square-Foot and Total Energy Use for *single-family homes* (a and b), while the bottom row shows Energy Use per Square-Foot and Total Energy Use for *multi-family homes* (c and d).

energy efficiency improvements (CEC, 2015; Ettenson, 2014; Geller et al., 2006; US EIA, 2015c). With this in mind, we examined energy use trends during the time frame of available data in the *LA Energy Atlas* database (2006–2010, excluding 2008 where data was not provided for certain building types). Median total consumption in single-family homes generally increases across income quartiles (Fig. 5(b)), with a slight trend of increasing consumption between 2006 and 2010 across all quartiles. Alternatively, median consumption per square-foot decreases as median household income increases (Fig. 5(b)). In multi-family homes, energy consumption per square-foot is also higher in the neighborhoods with median household income in the lowest quartile (Fig. 5(c)). Across multi-family buildings in neighborhoods, median total consumption increases with median household income in a neighborhood (Fig. 5(d)).

3.4. Energy consumption and building age

The *LA Energy Atlas* database contains four categories of building vintages: pre-1950, 1950–1978, 1978–1990, and post 1990. We chose 1978 specifically to correspond with the year that the California Energy Commission first implemented Title 24 energy efficiency standards for residential and commercial buildings in California.

There is a distinct decreasing trend in the distribution of energy consumption in newer buildings (Fig. 6). However, energy consumption of all buildings most closely resembles use in the two oldest vintage categorizations (pre-1950 and 1950–78), likely because most buildings in L.A. County are fall into the two oldest vintage categories (roughly 80%). Lower-income neighborhoods tend to have many more buildings constructed before 1950, while higher-income neighborhoods have many more constructed between 1950 and 1978. Pre-1950 buildings typically have the highest energy consumption intensity, relative to the other vintages. Thus, building age may be a significant contributing factor to increased intensity of energy use in certain lower-income areas. Notably, while the L.A. County Assessor's database captures original construction dates, it does not often account for subsequent improvements or remodeling.

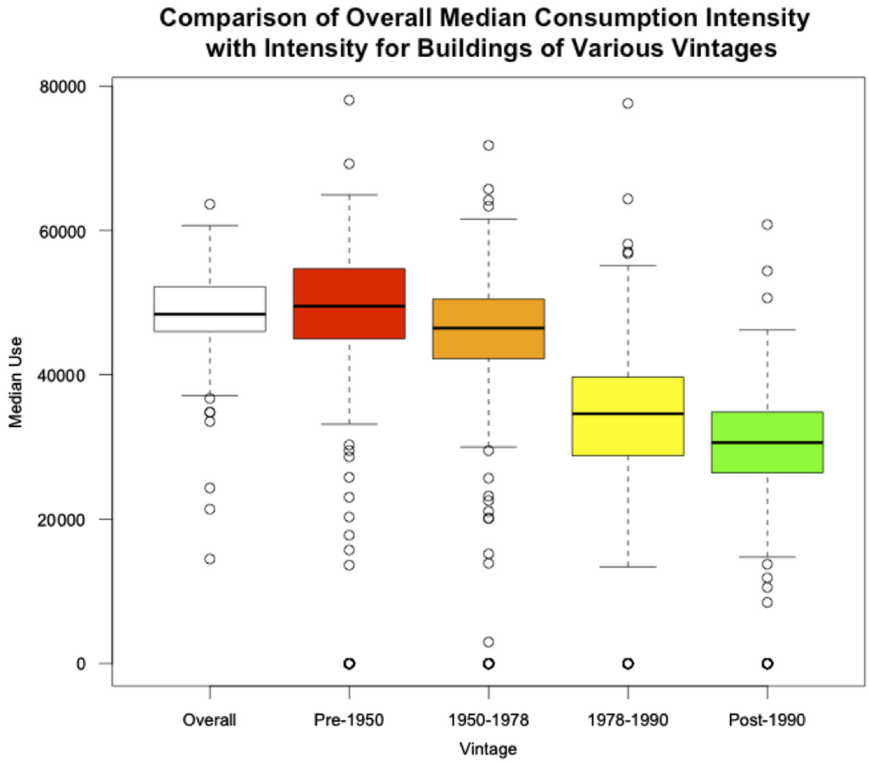

Fig. 6. Single-family energy consumption per square-foot (2010) by building age.

3.5. *Energy use and population density*

Household income and population density in neighborhoods are correlated ($R^2 = .34$), with median income decreasing as population density increases (Fig. 2(b)). It follows that total consumption in buildings tends to decrease with population density, while consumption per square-foot increases (Fig. 7). In single-family homes, this trend is most clear (Fig. 7(a),(b)). For multi-family parcels, however, the trend shows more variability (Fig. 7(c),(d)). In particular, median total energy use of multi-family parcels decreases significantly as population density increases (Fig. 7(c)). This could be because areas of lower population density actually have multi-family parcels with fewer residents (i.e. smaller apartment buildings). Median consumption per square-foot of multi-family parcels tends to increase with population density (Fig. 7(d)).

3.6. *Energy Consumption and Home Ownership*

We compared energy consumption, both total and per square-foot, by neighborhoods based on the percentage of owners and renters in single-family and multi-family homes (Fig. 8). Consumption per square-foot in single-family homes is nearly equivalent between majority-owner and majority-renter neighborhoods, with a slight decrease between 2006 and 2010 (Fig. 8(a)). In contrast, total median energy consumption of single-family homes is higher in majority-owner neighborhoods (Fig. 8(b)). The trend continued for multi-family homes; however, the differences in median total energy consumption between renter- and owner-dominated neighborhoods was greater in 2006 than in 2010, when they were nearly equal (Fig. 8(c),(d)).

4. Discussion

Deciphering factors that drive urban energy consumption patterns is challenging. In a large, diverse metropolitan region such as Los Angeles, many variables including income, home ownership rates, energy prices, and building age likely relate to geography in multi-faceted ways. Long-established cities in the coastal plain often have older buildings, since urban infrastructure lasts for decades. Newer areas in the hotter San Gabriel and San Fernando valleys are more mixed between old and new buildings. Throughout the region, lower-income households are less likely to have capital for structural building improvements or appliance upgrades, which all significantly influence energy consumption. Through this analysis, we present relationships in energy consumption, geography, and socio-demographic factors without declaring the definitive drivers of consumption. Cities are complex systems and deciphering precise causes of energy use in a given parcel is limited by these factors along with limitations in predicting human behavior.

Climate, too, likely plays a significant role in energy consumption across an arid coastal city with many climate zones like L.A. Average temperatures of inland areas can be 10 or more degrees higher than coastal zones. This affects occupant choices when, for example, they must use energy-intensive indoor air conditioning during a greater portion of the day. The analysis did not control for changes in climate, which is a noted limitation to interpreting consumption trends, both seasonally and during the course of a day. Yet, many buildings in lower-income neighborhoods, which lie closer to the coast where temperatures are cooler, do not necessarily even have sufficient heating or cooling but still rank highly for energy consumption measured per square-foot. Thus, local climate conditions do shape decisions of urban residents, but within the context of available technologies, building stock, and economic resources. Analysis of energy consumption in metropolitan areas must further investigate how broader climates trends, local climate variations influenced by human landscape decisions, socio-demographic factors, and income all affect energy use.

While the *LA Energy Atlas* reports greenhouse gas emissions, these values are not included here. Even with these noted

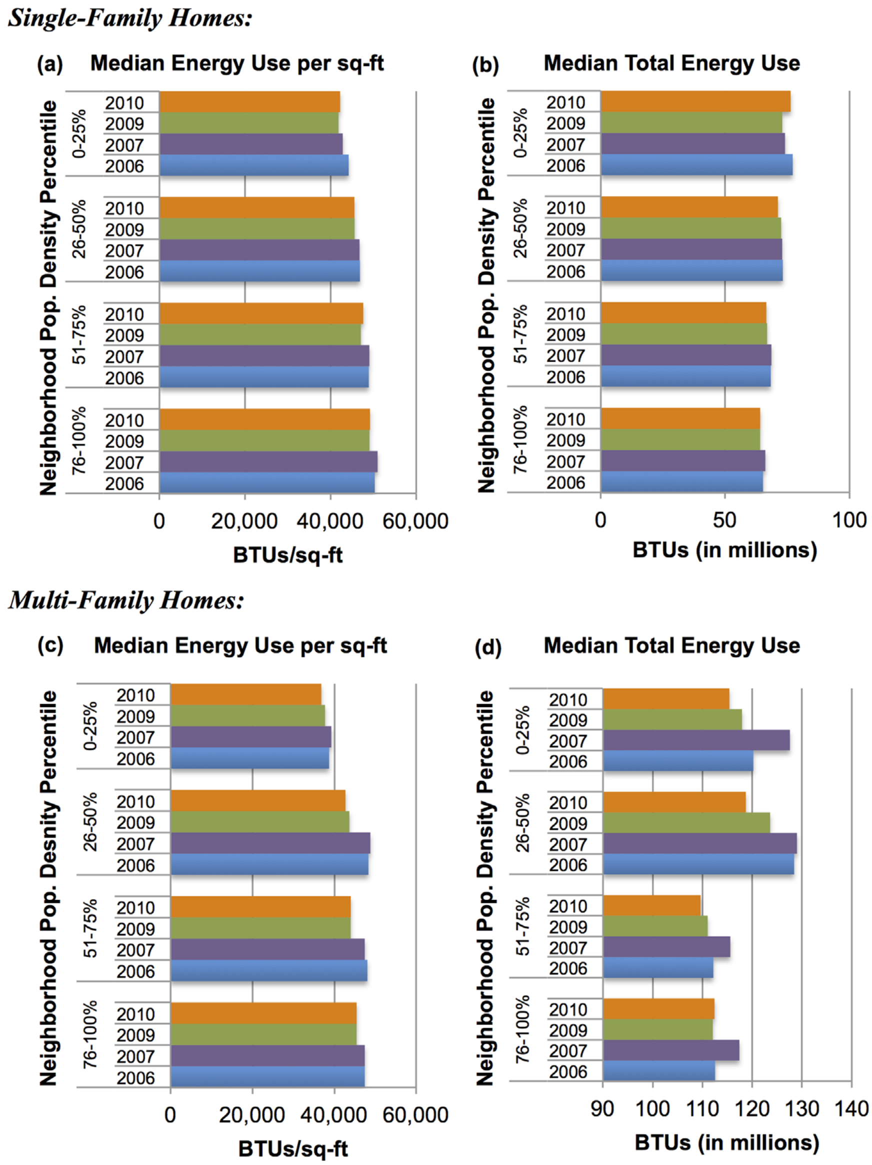

Fig. 7. Median Energy Use in households by percentiles of population density. The top row shows Use per Square-Foot and Total Energy Use for *single-family homes* (a and b), while the bottom row shows Energy Use per Square-Foot and Total Energy Use for *multi-family homes* (c and d).

limitations, the presented analysis of aggregated account-level data across time and space is novel and provides important insights to understand energy use in cities. It identified fundamental relationships between income and total energy consumption in a building as well as energy consumption per square-foot. It also revealed how building age could significantly influence this trend, demonstrating the importance of incorporating building characteristics and socio-demographic factors into such an analysis.

Through this methodology, institutional buildings pose particular difficulties for accurately assessing some energy use metrics. Building characteristics such as square-footage are undercounted because municipalities do not generate property tax assessment revenues from such buildings. For instance, while the L.A. County Assessor's property database has a land use designation for schools, it only represents a fraction of the schools identified through L.A. County's land use shape file. Detailed energy use can be particularly important for schools in California, where voters approved Proposition 39 to provide public funds for improving energy efficiency in schools. Thus, policy-relevant analysis of high-resolution energy consumption and demand data can still be constrained by other deficiencies in data.

5. Conclusions and policy implications

Detailed urban energy consumption data is highly valuable for devising informed strategies to reduce customer energy bills, plan utility infrastructure, and craft effective energy efficiency programs. Moreover, energy consumption data supports better estimates of greenhouse gas emissions. Customers, utilities, and policy-makers can all benefit from such data. To date, however, researchers and local governments have limited access to detailed data. In this paper, we describe a detailed methodology for collecting, aggregating, and analyzing account-level urban energy consumption data in Los Angeles County. Across L.A. County, consumption noticeably varies not only by geography, but also by income, land use, building age, and home ownership rates. In particular, while higher-income areas consume more total energy per parcel, many lower-income areas are top consumers of energy when measured as use per square-foot. This correlates with the older building ages found in many lower-income neighborhoods. High-resolution spatial and historical billing data helps uncover such complex relationships, which can lead to a better understanding of urban development and resource use.

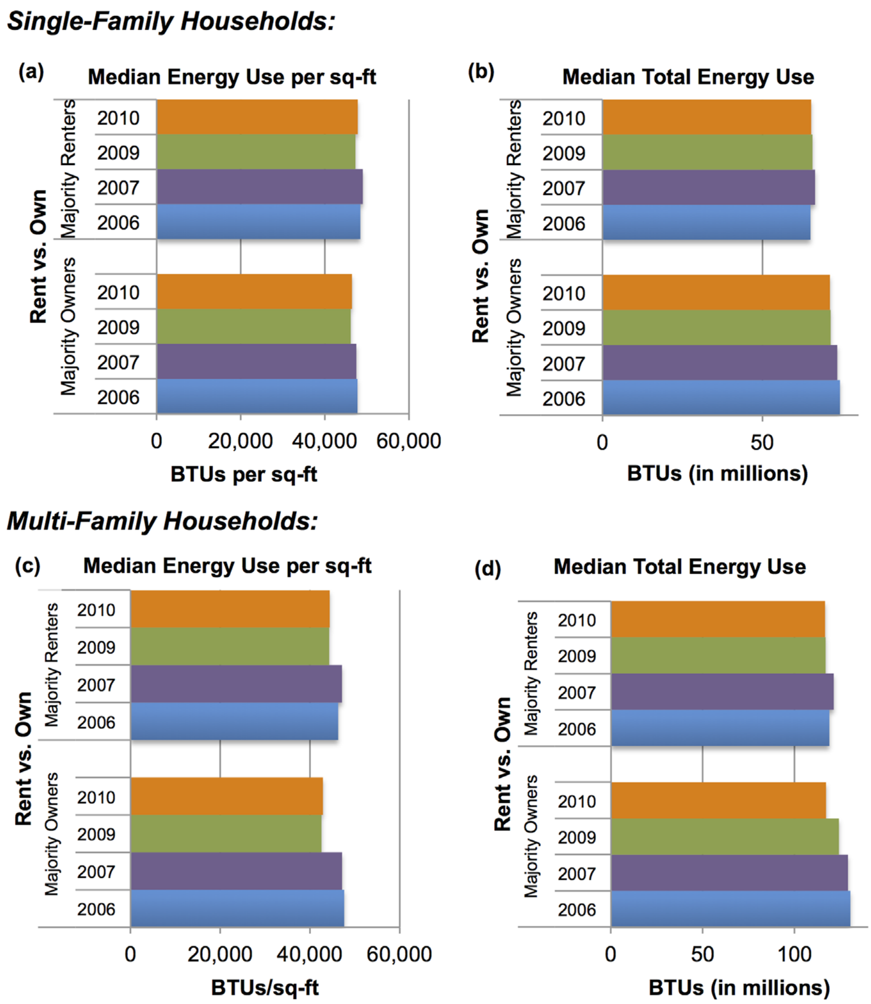

Fig. 8. Median Energy Use of *Single-Family Homes* and *Multi-family Homes* in Majority-Renter vs. Majority-Owner Neighborhoods: Energy Use per Square-Foot (a and c) and Total Energy Use (b and d).

Table 4.
Neighborhoods with highest 2010 median parcel energy use (BTUs/sq-ft) for single-family, multi-family, commercial, industrial, and institutional buildings. Bold highlighting notes cities that rank highly for both lower-income and all cities.

	Single-Family Buildings		Multi-Family Buildings	
Rank	*Lower-Income*	*All*	*Lower-Income*	*All*
1	**East Compton**	East Compton	**Westmont**	North El Monte
2	**Lennox**	Lennox	Harvard Park	Westmont
3	**Willowbrook**	Willowbrook	Florence-Firestone	Manchester Square
4	**Westmont**	Westmont	Hyde Park	Sunland
5	**Broadway-Manchester**	Broadway-Manchester	Willowbrook	Tujunga

	Commercial Buildings		Industrial Buildings		Institutional Buildings	
Rank	*Lower-Income*	*All*	*Lower-Income*	*All*	*Lower-Income*	*All*
1	Willowbrook	Lake View Terrace	Westmont	Pacific Palisades	**Chesterfield Square**	East San Gabriel
2	Valley Glen	Vincent	Hollywood	Tujunga Canyons	**Maywood**	Hawaiian Gardens
3	Lake Los Angeles	Castaic	Koreatown	Westlake Village	Harbor Gateway	La Puente
4	Panorama City	Hollywood Hills West		Beverlywood	Highland Park	Chesterfield Square
5	University Park	Green Valley		Hollywood Hills	North Hollywood	Maywood

Results of the analysis directly inform energy efficiency policies (Table 5). First, as noted, California expenditures on energy efficiency programs exceed $1 billion annually, but programs aimed at some sectors such as residential buildings have minimal verification of predicted energy savings. The *LA Energy Atlas* represents a scalable approach for efficiently organizing billing data from before and after improvements to support measurement and verification procedures. Second, existing reporting and evaluation procedures often fail to tie energy efficiency and billing data with other data sets such as real estate assessments and U.S. Census surveys. The presented procedure illustrates necessary steps for doing so. Third, we present shortfalls in available datasets at the local level, such as the inconsistency of tax assessor data for schools and other institutional buildings. This inhibits accurate

Table 5.
Key findings of direct relevant for improving data-driven energy efficiency programs.

Key Policy Issue	Policy Actions
Measuring energy consumption	Expand metrics for collecting and analyzing energy consumption data, including energy use per area (sq-ft) Correlate energy use with building characteristics and socio-demographic trends Promote better local property records data for public and non-profit buildings, including schools Identify climate influences of building energy use in context of social and economic factors
Assessing and using detailed energy consumption data in planning	Promote greater access to energy use data that protects privacy Implement monitoring before and after energy efficiency upgrades in buildings Promote access to more detailed energy use data for non-profit groups
Linking consumption with other key datasets	Prioritize building funding by sector, geographic location, and vintage Improve datasets for county tax assessors and building stock across all types of buildings
Supporting data-driven policies for energy efficiency programs	Incentivize energy efficiency rebates by returns on investment Incorporate energy consumption data into pre-upgrade assessments and post-upgrade monitoring as regular procedure Incorporate consumption data into Title 24 regulations and SB350 implementation for building energy efficiency Address equity by increasing participation of disadvantaged households in energy efficiency programs

assessments of energy consumption (per square-foot) in many public buildings and state and federal assistance should support better local data. Fourth, combining energy consumption data with building and socio-demographic characteristics can inform smarter energy conservation investments. Energy efficiency is a critical component of more sustainable future cities, but incentive programs should spend public funds in equitable and cost-effective ways. Despite the lack of rigorous program evaluations based on billing data, new policies supporting energy efficiency continue. For instance, in California, Senate Bill 350, enacted in 2015, establishes a goal of a 50% increase in building energy efficiency by 2030, but still does not incorporate any mandates for verification through billing data. Finally, aggregated energy consumption information for neighborhoods and cities supports local governments in developing *Climate Action Plans* to meet GHG reduction targets as part of AB 32.

The results are subject to several limitations. First, geographic differences in climate are not integrated in the *LA Energy Atlas* and the presented analysis does not control for climate variation throughout L.A. Second, the property records database from the L. A. County Office of the Assessor, used to correlate building characteristics with account-level energy consumption, has noted issues of accuracy, especially for building types such as schools and government buildings. Third, while geocoding results were very accurate in the context of typical procedures, it was not 100% accurate. Fourth, while the *L.A. Energy Atlas* includes estimates of GHG emissions, they were not part of this analysis.

Geographic changes in energy consumption are only verifiable by aggregating and analyzing actual account-level data. Yet, such procedures also require caution to prevent published results from revealing personally identifiable information of utility customers. When published responsibly, such data can inform energy policy. Energy efficiency rebate programs, for instance, could implement monitoring and evaluation to estimate actual returns from public investments over time. This research can be extended by: reporting results with greater temporal resolution; integrating consumption records with grid management decisions, distributed generation, and combined heat-and-power operations; and refining the analysis of particular building categorizations such as institutional buildings. Given the current push for smarter, data-driven cities, high detail energy use data is a critical component to creating future, more sustainable, urban systems.

Acknowledgements

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Appendix

Building type categories were developed by Arizona State University researchers (Reyna and Chester, 2015) and include building shell materials by vintage (year built) and use codes as assigned by the LA County Assessor (Table A1). The primary unit of analysis in the *L.A. Energy Atlas* is the *megaparcel*, a parcel layer dissolved on geometry that maintains reference to parcel polygons that comprise each *megaparcel* polygon.

Both median *total energy use* (Fig. A1a) and *energy use per square foot* (Fig. A1a) of single-family homes in neighborhoods are

Table A1.
Building codes, associated names, and percentages of building and megaparcels for each code in L.A. County.

Category	Building Codes	Name	% of Buildings	% of Megaparcels
Single-Family	R1	Single-Family Detached	63.99%	70.60%
Multi-Family	R2	Multi-Family Large	3.74%	11.62%
	R3	Multi-Family Small	12.51%	
Condo	R4	Condominium	11.77%	0.89%
Commercial	C1	Hotel	0.12%	3.58%
	C2	Department Store	0.12%	
	C3	Neighborhood Store	2.97%	
	C4	Low Office	0.21%	
	C5	High Office	0.70%	
	C6	Hospital	0.04%	
Industrial	I1	Warehouse	1.92%	1.82%
	I2	Heavy Industrial	0.15%	
Industrial	C7	Church	0.29%	1.49%
	C8	School	0.16%	
	G1	Government		
Mixed-Use	Any of residential (R) mixed with any of Commercial (C) or Industrial (I)		n/a	0.02%
Other	O	Other	0.24%	9.59%
	P	Parking	0.99%	
	V	Vacant	0.08%	
Unclassified	No Building Information Available			0.40%
			Total:	***100%***

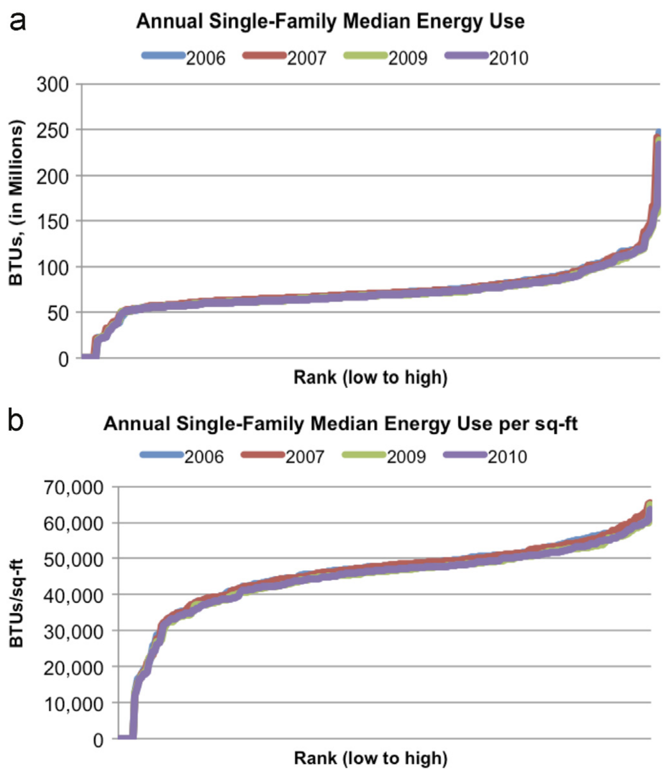

Fig. A1. Distributions of Annual Energy Use in L. A. Neighborhoods for Single-Family Homes for (a) Median Total Energy Use (left) and (b) Median Energy Use per Square-Foot (right).

relatively consistent over much of the ranked distribution function, as shown by the flatter (middle) portions of the distributions. A few high and low outliers round out the S-shaped curves. While many buildings have similar annual energy performance, near four percent of neighborhoods account for almost eight percent of total consumption. Energy use declined slightly over the 5-year period from 2006 to 2010, corresponding with reduced economic activity during the recession (also see Figs. 5, 7, and 8 in the text).

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