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ORIGINAL ARTICLE

Spatial and temporal analysis of energy use data in Los Angeles public schools

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Abstract School buildings are significant energy consumers. They are important targets for energy efficiency improvements, which can reduce energy spending and meet energy policy goals for state and federal governments. In the US, few studies have quantified electricity and natural gas consumption patterns in schools. Such information vitally supports energy planning and benchmarking. We present an analysis of high-detail electricity and natural gas consumption for schools in Los Angeles County over an extended period of time. Using a robust database of monthly account-level consumption, we examine electricity and natural gas consumption trends for hundreds of schools in relation to key structural and categorical characteristics, including size, geography, and school type. Results show that school energy use varies greatly across socio-demographic, structural, and climate factors. Correlations between electricity and natural gas consumption are time dependent and seasonally distinct. The analysis provides a useful case study with benchmarks for US public schools and demonstrates challenges with devising large-scale studies of school energy use. We conclude with a discussion of policy implications.

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Introduction

Public schools are important targets for improving energy conservation and efficiency. School districts spend significant sums on energy costs. For instance, US schools nationwide have spent up to $5 billion dollars annually on electricity and natural gas (Sharp 1998). As public buildings, reducing energy bills in schools can reduce operational budgets, potentially freeing up taxpayer funds for other educational needs. Additionally, rising energy costs, mandated reductions in greenhouse gas (GHG) emissions, and public sector funding shortfalls all motivate local governments to reduce energy spending in schools. Other benefits, for example indoor air quality that boosts student performance, are additional motivations for making energy system upgrades (Wachenfeldt et al. 2007; Clements-Croome et al. 2008; Bakó-Biró et al. 2012). Some technologies, such as lighting improvements, are more appropriate for meeting goals to both reduce consumption and improve learning environments (Roslizar et al. 2014; Plympton et al. 2000).

Globally, energy efficiency measures have generated energy savings (Geller et al. 2006). Regional and national governments support energy efficiency improvements in buildings, both public and private, through direct payments or rebate programs. But many factors can reduce program effectiveness in some building sectors, including rebound effects and difficulty engaging lower-income and minority demographics (Palmer et al. 2013; Greening et al. 2000; Morrissey and Horne 2011; Sadineni et al. 2011; Brown 2012). In the US, one key shortfall of many current programs is the lack of broadly available data for benchmarking and evaluation (Porse et al. 2016). Policymakers responsible for designing energy efficiency retrofit programs often have limited access to data for evaluating the effectiveness of measures that support public investments in energy conservation (ACEEE 2014; Kolter and Johnson 2011). In California, for instance, ratepayers and taxpayers contribute more than $1 billion annually to energy efficiency improvements, with only small studies and no comprehensive baseline data to evaluate performance (CPUC 2016).

The lack of publicly available consumption data in the US is particularly acute for public school buildings. Data remains dispersed among local school districts and often unavailable for research or benchmarking. Public initiatives to conserve energy in public schools can exacerbate the impact of data shortfalls. For instance, voters in California approved a ballot measure (Proposition 39) in 2012 that devoted nearly $1 billion to energy efficiency and renewable energy for public schools from 2013 to 2016. The methods specified by policymakers to estimate savings are based on a mix of data and modeling assumptions, and specific upgrade measures derived from existing programs (CCC 2016; CEC 2016). But reported performance data for funded projects is limited and funds will likely expire before comprehensive performance evaluations are available (CEC 2017). In addition, school buildings may be lumped with other non-residential sectors in energy efficiency programs, even though their habitation characteristics are unique. Consumption data for a small set of schools (n = 449), extracted from the Commercial Buildings Energy Consumption Survey from the US Energy Information Administration, was used to report normalized energy consumption trends across the US at a broad geographic scale (EIA 2012).

Outside of the US, existing studies of school energy consumption report benchmarks for school buildings in Europe, East Asia, and the Middle East. They typically focus on quantifying consumption and efficiency in sample sets of 150 buildings or fewer (Dascalaki and Sermpetzoglou 2011; Corgnati et al. 2008; Kim et al. 2012; Desideri and Proietti 2002; Airaksinen 2011; Katafygiotou and Serghides 2014; Beusker et al. 2012; Thewes et al. 2014). But extrapolating results to regions such as North America is subject to data limitations. The climate, building stock, and behavioral characteristics of school buildings in the reported studies can differ significantly across counties and climates. As with many building types, studies reveal performance gaps between predicted consumption via modeling and actual performance (Demanuele et al. 2010; Menezes et al. 2012). Standardized and normalized measurements allow for better comparisons and advanced benchmarking, but current reporting does not always support comprehensive evaluation (Dias Pereira et al. 2014).

The relatively small size of many existing studies, in particular, poses challenges for program managers looking to implement energy conservation programs in small sectors of buildings that span broad geographic areas with diverse climates. Large-scale analysis of energy consumption using “big data” sets increasingly helps support benchmarking and identify consumption patterns across building, socio-demographic, geographic, and other characteristics (Porse et al. 2016; Hamilton et al. 2013; Steadman et al. 2014; Widén et al. 2009). Consumption data with hourly or sub-hourly resolution across many school buildings has been used to detect changes in consumption patterns (Stuart et al. 2007). For instance, data from the UK’s Display Energy Certificate (DEC) database, which was developed to support GHG emissions inventories, was used in a particularly extensive analyses of 8350 DECs to show how electricity consumption varies by school type, location, and student enrollment profiles, where older students may use more electronics or secondary schools are used more hours of a day. The density of student occupants affects GHG emissions more than building size (Godoy-Shimizu et al. 2011). But in the US, very few large sources of account-level energy consumption are available for planning (Pincetl et al. 2015).

When large-scale data sets are not available, statistical techniques such as k-means clustering have been used to categorize schools by energy use patterns, allowing for the application of principal component analysis (PCA) to determine which linear combinations of variables best describe consumption in a group of schools (Gaitani et al. 2010; Santamouris et al. 2007). Advanced analytical techniques such as classification using artificial neural networks can also expand applications of large-scale databases, illustrating how building characteristics and layout can affect consumption and benchmarking, while consumption changes over time complicate the benchmarking process (Hong et al. 2014).

This paper addresses a gap in literature regarding energy consumption data for US public school buildings. Drawing on recent advances in data availability, the paper presents a spatial and temporal statistical analysis of monthly electricity and natural gas consumption patterns in schools of varying characteristics across several years (2006–2010). Specifically, we analyze aggregated consumption trends across Los Angeles County (LA County) public schools to: 1) provide better benchmarks of consumption for devising more effective retrofit programs, and (2) describe the technical and institutional challenges associated with calculating public school energy consumption benchmarks for many schools in a single region. The study reports consumption patterns across school types (elementary, middle, and high), sizes, locations (hotter and cooler climate zones), ages, and seasons. We also investigate relationships between electricity and natural gas use in a given school. The analysis supports regional benchmarking and planning for energy efficiency and GHG emissions reductions. We conclude with a discussion of challenges associated with assembling and analyzing energy data in the US and directions for future research.

Methods

The analysis used data from the *LA Energy Atlas*, which catalogs, aggregates, and displays geospatially linked account-level billing data for electricity and natural gas use in LA County (Pincetl 2015). The *LA Energy Atlas* 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. Utility billing data includes consumption for each energy source across all uses (heating, cooling, appliances, etc). Previous research extensively describes the methodology used to create the platform, which reports social, geographic, and building characteristics associated with energy use, as well as estimates of greenhouse gas emissions (Porse et al. 2016; Pincetl et al. 2015). The platform is one of the largest and most advanced repositories of energy data in North America.

The *LA Energy Atlas* includes a spatially explicit, object-relational database depicting service addresses, energy consumption, and demographic characteristics for over 2.3 million parcels throughout the County over a 5-year period (2006–2010). It contains parcel-level consumption data obtained from utilities and building characteristics derived from the 2008 Los Angeles County Assessor's property dataset, including schools to the extent they are delineated (LA County Office of the Assessor 2008). The software reports aggregated energy use with high geographic specificity and protects privacy of account-holders by aggregating consumption according to mandated procedures (CPUC 2014). Data for electricity and natural gas consumption was obtained from regional municipally owned utilities (MOUs) and the California Public Utilities Commission (CPUC). The data for 2006–2010 was acquired through a long regulatory process in California that provides university researchers special exception to view and use disaggregated energy consumption data for purposes of research (CPUC 2014). As such, the labor-intensive process of acquiring the data restricts shapes the time frames for data availability.

Identifying schools

School parcels in LA county, which are linked to utility billing accounts by address, were identified and classified through an iterative procedure. School parcels have specific land use categorizations in the tax assessor database, but identifying schools based solely on the assessor data yielded an incomplete inventory. School parcels are often misclassified since they are not sources of local tax revenue. We first identified and corroborated schools in the Assessor's database that were directly classified as school buildings. Consumption records for these accounts were then extracted from the *LA Energy Atlas* database, where schools fall into the "meta-category" of institutional buildings.

However, joining known school parcels (based on assessor data classification) with the full database of parcels revealed that many schools fell into multiple building categories, sometimes inappropriately. We used external data to confirm or correct geographic locations and parcels for school buildings. Next, publicly available address data for schools was used to manually classify the list of schools by elementary, middle, and high categorizations. Finally,

Table 1 Attributes used for classifying schools

Attribute	Levels	Source
School type	Elementary, middle, high	LA County Office of the Assessor (2008)
School size	Small, small-medium, medium, medium-large, large	Building Volume Data derived from LA County Tax Assessor data and LARIAC Data (LA County Office of the Assessor 2008; LARIAC 2012)
Climate zone	Zone 6, zone 8, zone 9, zone 14	California Energy Commission climate planning zones

electricity and natural gas accounts were matched to parcels associated with schools based on the identifiers. Some schools in the database had multiple electricity and natural gas accounts. In these instances, the accounts were combined after matching addresses with all the associated parcels.

Assessing trends and relationships

Electricity and natural gas consumption was calculated and compared across school categorizations for three primary attributes: type, size, and climate zone (Table 1).

The analysis used a multi-step procedure to correlate building, consumption, and geographic data. We calculated monthly electricity and natural gas consumption data for each school with available data, summing accounts in each month for all parcels associated with a school. In the LA County Assessor's database, schools can be situated on multiple distinct land parcels. We also aggregated the consumption values to larger geographic regions, neighborhoods, and cities, to meet privacy guidelines (LA Times 2015; LACDPW 2012). We calculated median total consumption of electricity and natural gas, reported separately, in each month for each category of schools. The minimum number of schools needed to report median total consumption (six schools in a category) resulted in masking some data from the analysis. The median values were graphed over time (2006–2010) across type, size, and climate zone classifications. The sample sizes (n) for each procedure, based on available data and masking requirements, are included in Tables 9, 10, and 11 in the Appendix.

Table 2 Building sizes

Size	description
Small	Bottom 20% of total building volume for all schools
Small-medium	20th percentile to 40th percentile of total building volume for all schools
Medium	40th percentile to 60th percentile of total building volume for all schools
Medium-large	60th percentile to 80th percentile of total building volume for all schools
Large	Top 20% of total building volume for all schools

To determine school size, we estimated the total buiding volume for each school as the product of: 1) the area of first-story building footprints from the parcel shape file (equivalent to gross floor area) obtained from the LA County Assessor's Database (LA County Office of the Assessor 2008) and (2) the building height derived from the imagery dataset (LARIAC 2012). To compensate for potential uncertainties in this volume calculation, we binned the total building volume variable into quintiles to compare relative, but not absolute, sizes. Bins included small, small-medium, medium, medium-large, and large based on percentile ranking (Table 2).

The categories correspond with the quintiles (intervals of 20%) of building size. We devised this estimate of size due to deficiencies in public records. The tax assessor database does not have gross floor area that would include multiple stories for most schools in the county. When data is available, its accuracy is suspect because public schools are not subject to taxation, which drives localities to collect accurate data on building square footage including multiple floors. The imagery data provided an alternative source for this calculation.

LA County spans five climate zones as classified by the California Energy Commission, ranging from cooler coastal areas to hotter inland areas to the east and north. Based on requirements that limit reportable data, we calculated school electricty use for four of the five major climate zones in LA County (zones 6, 8, 9, and 14), and natural gas use on three of the five major climate zones in Los Angeles County (zones 6, 8, and 9).

Table 3 Median electricity and natural gas use by school type

School type	Sector	Units	Mean (monthly)	Median (monthly)
Public elementary schools	Electricity	kWh	32,330	27,470
Public elementary schools	Natural gas	Therms	376.7	190.8
Public middle schools	Electricity	kWh	65,630	61,830
Public middle schools	Natural gas	Therms	1,066	570.3
Public high schools	Electricity	kWh	144,000	141,300
Public high schools	Natural gas	Therms	2,707	1,245

School age can influence consumption, as newer buildings would be more efficient and as such have lower energy unit intensity. But building vintage data for schools in the tax assessor database is poor. Instead, we estimated the median age of a school by assuming a correlation between the age of a school and the age of all other surrounding buildings in a neighborhood. Other building sectors, including residential and commercial, have much better data regarding vintage. For each neighborhood, we calculated the median age of buildings, ranked the neighborhoods by vintage, and plotted the corresponding seasonal median electricity and natural gas consumption.

Finally, we calculated the correlation coefficient between electricity and natural gas consumption in a school over the time period of analysis. This procedure not only assessed whether a school's electricity use is correlated with its natural gas use, but also tested if the correlation is time-dependent. To quantify the correlation between electricity and natural gas use, we calculated the Pearson correlation coefficient between the natural log of electricity consumption and the natural log of gas consumption, based on the verified assumption of a linear relationship between the two variables.

Results

Results are reported below based on data for the years 2006–2010. The reported results include (1) consumption by school type; (2) consumption by school size (volume); (3) consumption across climate zones (coastal to arid) and building age in LA County; and (4) seasonal correlations in electricity and natural gas consumption.

Energy consumption by school type

Electricity and natural gas consumption differ across school types (Tables 3 and 4). Total consumption for each is highest in high schools, followed by middle schools and elementary schools (Table 3). Comparing across categories, electricity use in elementary and middle schools is 19 and 44% of the median value in high schools, respectively. For energy use intensity (per unit volume), results are mixed (Table 4). Electricity consumption per cubic meter is similar between elementary and high schools, but lower across middle schools (Fig. 1). The difference in median and mean values is right-skewed in the distributions of all three types, but for high schools

Table 4 Median electricity and natural gas use intensity by school type

School type	Sector	Units	Mean (annual)	Mean (monthly)	Median (monthly)	% of largest (median)
Public elementary schools	Electricity	kWh/(m^3)	11.9268	0.9939	0.8259	100%
Public elementary schools	Natural gas	Therms/(m^3)	0.13188	0.01099	0.005389	72%
Public middle schools	Electricity	kWh/(m^3)	8.898	0.7415	0.659	79%
Public middle schools	Natural gas	Therms/(m^3)	0.107772	0.008981	0.005566	74%
Public high schools	Electricity	kWh/(m^3)	18.972	1.581	0.8291	100%
Public high schools	Natural gas	Therms/(m^3)	1.2096	0.1008	0.007498	100%

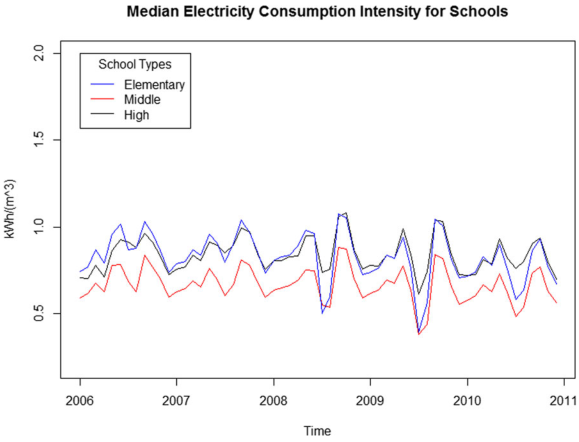

Fig. 1 Median electricity use intensity by school types in LA County

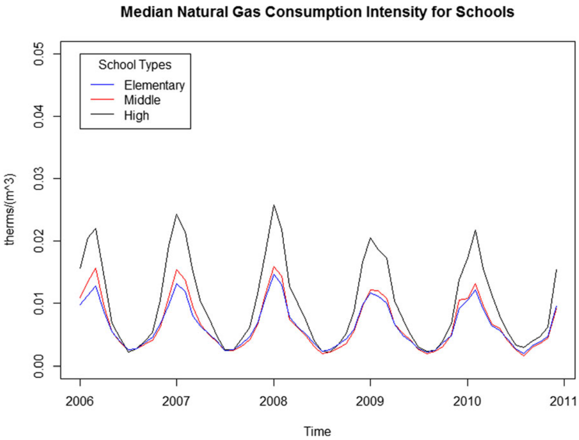

Fig. 2 Median natural gas use intensity by school types in LA County

in particular, a few larger buildings account for a significant percentage of consumption.

Natural gas consumption is highly seasonal, with consumption peaking in winter months and lowest in summer months (Fig. 2). High schools are the most energy intensive. The seasonality likely correlates with the typical use of natural gas for winter heating, while summertime cooling is done using electric air conditioners. In addition, high school natural gas use is more variable relative to middle and elementary schools, with elementary school natural gas consumption being least variable.

Energy consumption and school size

Energy consumption correlates with school size (Tables 5 and 6) and is highly seasonal. Distributions tend to be right-skewed. Larger schools predictably consume more total energy. Comparing energy use intensity across school size categories, however, reveals different trends in consumption (Table 6). Smaller schools use 30–40% more electricity than larger schools per unit volume (Fig. 3). For natural gas, trends are less consistent. Taking the median across the entire periods, smaller schools tend to be larger consumers based on natural gas per unit volume, being 20–30% larger than other categories (Table 6).

But natural gas consumption across other categories is similar. Moreover, smaller schools are not always the most energy intensive during a given year (Fig. 4). This could result from gaps in data availability. The distribution of school size varies by type of school (Fig. 9). Elementary schools tend to be smaller. But we were not able to report

Table 5 Median electricity and natural gas use by school size

Size	Sector	Units	Mean (monthly)	Median (monthly)
Small	Electricity	kWh	24,170	21,240
	Natural gas	Therms	441.8	138.3
Small-medium	Electricity	kWh	27,710	26,240
	Natural gas	Therms	274.9	169
Medium	Electricity	kWh	32,060	30,810
	Natural gas	Therms	394.9	218.4
Medium-large	Electricity	kWh	52,330	44,900
	Natural gas	Therms	766.1	346.6
Large	Electricity	kWh	128,700	118,600
	Natural gas	Therms	2,257	1,050

Table 6 Median electricity and natural gas use intensity by school size

Size	Sector	Units	Mean (annual)	Mean (monthly)	Median (monthly)	% of largest (median)
Small	Electricity	kWh/(m^3)	25.896	2.158	1.031	100%
	Natural gas	Therms/(m^3)	0.996	0.083	0.007	100%
Small-medium	Electricity	kWh/(m^3)	10.572	0.881	0.837	81%
	Natural gas	Therms/(m^3)	0.096	0.008	0.005	71%
Medium	Electricity	kWh/(m^3)	9.384	0.782	0.765	74%
	Natural gas	Therms/(m^3)	0.1164	0.0097	0.0054	77%
Medium-large	Electricity	kWh/(m^3)	8.904	0.742	0.699	68%
	Natural gas	Therms/(m^3)	0.108	0.009	0.005	71%
Large	Electricity	kWh/(m^3)	7.968	0.664	0.668	65%
	Natural gas	Therms/(m^3)	0.132	0.011	0.0059	84%

statistics or perform regression of consumption based on multiple school attributes (i.e., consumption in small elementary schools) due to required data masking that occurs from too few schools contributing to results (CPUC 2014).

Energy use by climate zone and age

Across climate zones, distinct differences exist in monthly consumption. Schools in climate zone 14 (a hotter, arid region) show highest total electricity use, while schools in climate zone 6 (a cooler coastal region of the county) consume the least (Tables 7 and 8). These trends are also consistent over time (Fig. 5). Median total electricity use increases moving inland. But the intensity of electricity use in the hotter inland climate zone (0.686 kWh/m^3) is within the range of other cooler zones (0.573–0.870 kWh/ m^3) and actually less than two of the zones. This may result because inland areas generally have newer buildings that are more efficient, though further investigation would be needed to more precisely identify contributing factors. For natural gas, while total median consumption tends to decrease with distance from cooler coastal areas, the median energy use intensity is consistent (Tables 7 and 8). Seasonal trends are again consistent over time (Fig. 6). Examining seasonal differences in consumption by school age, using neighborhood age as a proxy for building age, showed variations but inconsistent trends (Fig. 7). Results of linear regression with consumption as the response variable and age and climate zone as explanatory variables were not reportable. Categorizing school buildings by age resulted in a small number n of school buildings, which violated data disclosure regulations established to protect privacy of account holders.

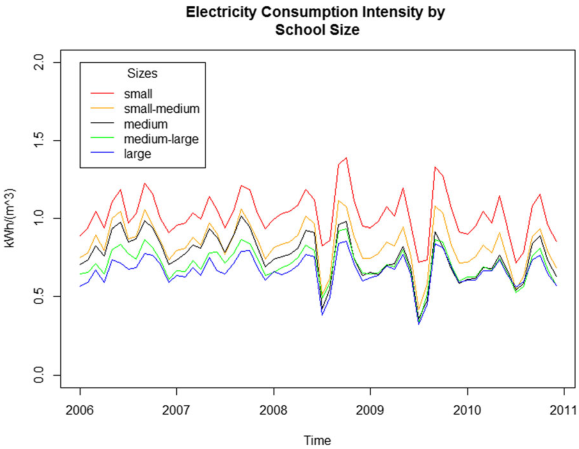

Fig. 3 Median electricity use intensity by school size in LA County

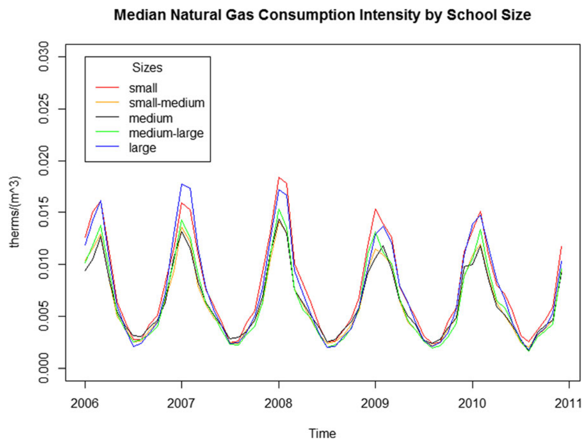

Fig. 4 Median natural gas use intensity by school size in LA County

Table 7 Median electricity and natural gas use by climate zone

Climate zone	Sector	Units	Mean (monthly)	Median (monthly)
Zone 6	Electricity	*kWh*	42,030	25,410
	Natural Gas	*Therms*	877.1	263.1
Zone 8	Electricity	*kWh*	51,540	32,860
	Natural gas	*Therms*	682.3	267.2
Zone 9	Electricity	*kWh*	56,720	33,110
	Natural gas	*Therms*	881.5	244
Zone 14	Electricity	*kWh*	59,440	43,400

Table 8 Median electricity and natural gas use intensity by climate zone

Climate zone	Sector	Units	Mean (annual)	Mean (monthly)	Median (monthly)	% of largest (median)
Zone 6	Electricity	*kWh/(m*^{3}*)*	7.248	0.604	0.573	66%
	Natural gas	*Therms/(m*^{3}*)*	0.108	0.009	0.006	100%
Zone 8	Electricity	*kWh/(m*^{3}*)*	11.016	0.918	0.777	89%
	Natural gas	*Therms/(m*^{3}*)*	0.108	0.009	0.005	83%
Zone 9	Electricity	*kWh/(m*^{3}*)*	14.7	1.225	0.87	100%
	Natural gas	*Therms/(m*^{3}*)*	0.396	0.033	0.006	100%
Zone 14	Electricity	*kWh/(m*^{3}*)*	13.524	1.127	0.686	79%

Seasonal correlations in electricity and natural gas consumption

Finally, the seasonality of natural gas and electricity consumption relationships in a school was confirmed. Comparing the natural logarithm of values of each shows a linear relationship with moderate fit (Pearson correlation coefficient over time typically near 0.6). Analysis across months showed that the relationship between electricity and natural gas use in a school is more strongly correlated during cooler months, likely corresponding to many schools using natural gas for heating schools during fall and winter seasons (Fig. 8). Moreover, in cooler climates, such as climate zone 6 in California, the correlation is more consistent over the year. Across climate zones, the corre-

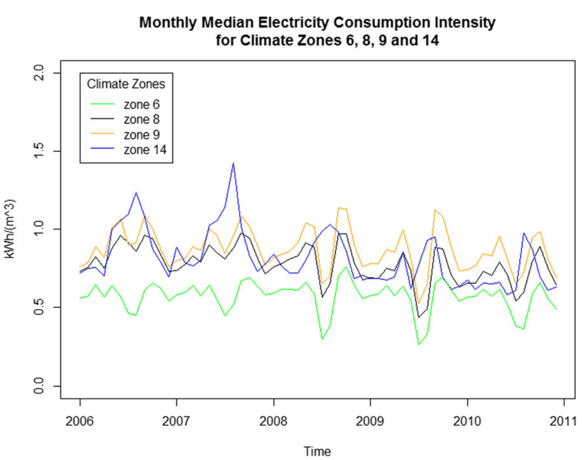

Fig. 5 Median electricity use intensity across climate zones in LA County

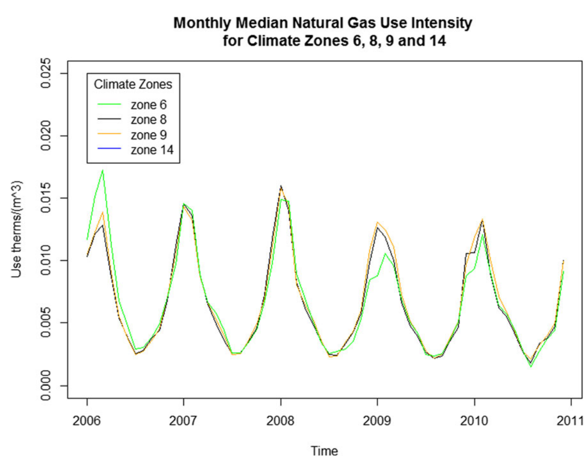

Fig. 6 Median natural gas use intensity across climate zones in LA County

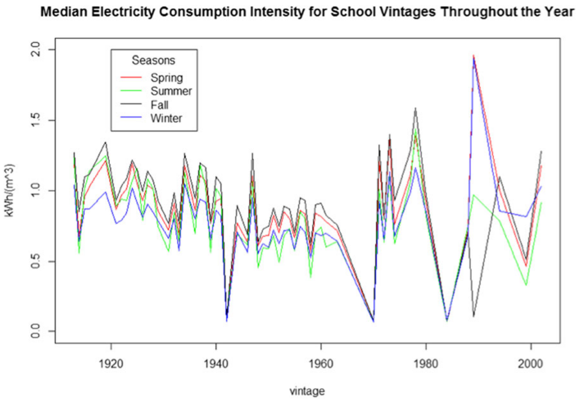

Fig. 7 Seasonal and temporal variations in electricity use intensity of LA County schools, by estimated school vintage based on age of surrounding neighborhoods

lation drops in hotter summer months, but the cause of this likely varies. In hotter climate zones (climate zones 8 and 9), electric air conditioners are predominant cooling devices. The correlation coefficient in these areas is more dispersed during summer months as use of these devices peaks in relation to baseline natural gas loads, which primarily include indoor water heating. In cooler climates (zone 6), air conditioning demand is less, or even nonexistent in some buildings. Figure 8 displays these trends by climate zone over the course of the year.

Discussion

Energy consumption benchmarks are important in devising regulatory mandates and retrofit strategies for energy efficiency. In California, the voter-approved Proposition 39 (noted earlier) supports energy efficiency improvements in schools and promotion of green jobs. To access funds, school districts develop and submit energy efficiency upgrade plans, which are approved by state regulators. Program recipients must report estimated savings and later report actual savings as part of the funding, but the program has a limited length. Consumption benchmarks were generally unavailable at the outset of the program. This work originated to fill a noted gap in publicly available consumption data for public schools in Southern California and the US, which can inform Proposition 39 and future energy efficiency investments for public schools.

In that regard, the analysis demonstrated the methods necessary to generate benchmarking data across a large geographic region for the unique building sub-sector of US public schools. Emerging methods of building-scale energy analysis that employ "big data" techniques encounter unique issues in merging data sets. Building size, vintage, and location data may be unavailable, or masked by regulations. Yet, energy efficiency programs

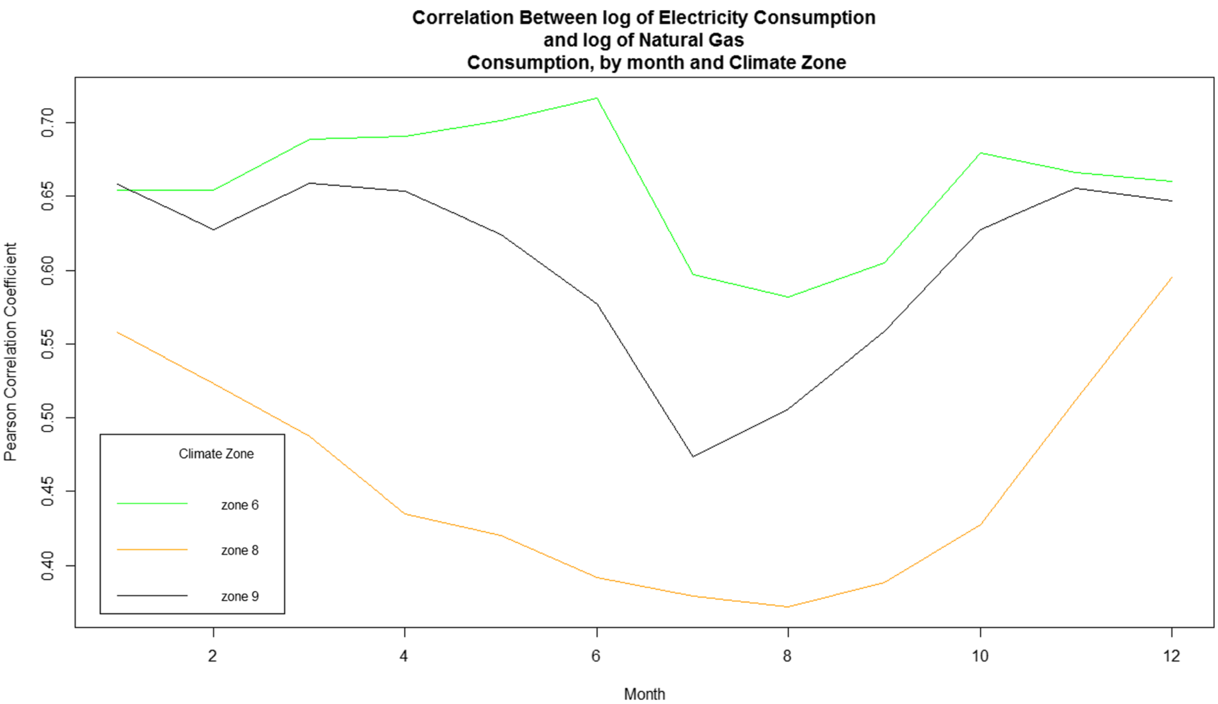

Fig. 8 Seasonal correlations of median electricity and natural gas consumption (2006–2010) in LA County schools

need data to structure policies and allocate funds based on detailed analysis that promotes not just efficiency, but actual conservation to reduce energy consumption. Prioritizing program funds by age, type, geographic situation, and size are all useful methods for maximizing investment returns. Readily available data for pre- and post-retrofit consumption supports the community of researchers and practitioners that devise best practices for effective retrofit programs. The methods and results of this analysis support that goal.

Comparing consumption in different climate zones revealed correlations in school electricity consumption and environmental factors. Schools in regions with more extreme changes in temperature, namely, higher daily maximum temperatures, use more electricity than those in more temperate regions. This correlates with prior research at the national scale, which showed that hotter areas had higher energy use intensities (Sharp 1998). But the lack of building vintage data reduces the strength of this relationship. In Los Angeles, inland hotter areas were typically urbanized more recently, and as such, they tend to have more energy efficient buildings (Porse et al. 2016). The indirect method of determining school ages, an assumed correlation with neighborhood ages based on other building types, needs further investigation. If this finding would be validated through further analysis, as population growth in California's hotter inland areas, statewide energy reduction goals may grow increasingly difficult to achieve.

The analysis is subject to several limitations. First, the schools included in calculations were opportunistic, but not randomly sampled. We calculated consumption for as many schools as we could identify and correlate consumption accounts. But, not being randomly sampled, we did not conduct tests to identify the statistical significance of differences in consumption across categorizations. Second, we did not have accurate building area or vintage information for schools through direct sources. The analysis instead included gross floor area and volume estimated using imagery data. Third, energy consumption records for several schools in the database were incomplete. Some schools did not have records for the entire time period considered (2006–2010), perhaps due to meter failures or general inconsistencies in the utility billing database. Other schools did not have recorded usage for all of the parcels belonging to a school, likely resulting from inconsistencies in data sets managed by separate parties (utilities, local school districts, and the region tax assessor).

Fourth, our investigations identified that billing data for a school located on a parcel can be centralized in the main offices of a school district, which aggregates consumption across all the schools and skews metrics. Fifth, electricity data was more complete than natural gas data, an issue apparent when analyzing natural gas use by climate zone. While the overall analysis showed no apparent differences in natural gas use across climate zones, the absence of school data for climate zone 14, the most variable, could be a causal factor of this result. Finally, data masking issues, driving by California data disclosure restrictions for account-level consumption, limited our ability to conduct statistical tests such as regression for multiple categories of schools. Doing so would have elucidated trends in consumption with greater resolution.

The research can be extended in several ways. First, developing actionable policies to reduce school energy consumption should include both efficiency and on-site generation capacity for schools. This requires more detailed analysis of overlapping trends in consumption and generation across climate zones. The *LA Energy Atlas* has electricity consumption records for several schools in LA County with solar arrays, and these could serve as a case study for how the installation of solar arrays affects monthly grid-based electricity consumption. Second, the cost-effectiveness of energy efficiency incentive programs should be evaluated based on actual, not estimated, savings. This analysis serves as a baseline for such work. Third, surveying building footprint measurements more accurately for a subset of schools in LA County would facilitate comparisons of energy intensity (consumption per cubic meter) with other types of buildings sectors such as residential and commercial. This could provide support for additional funding and incentives promoting improved energy practices in K-12 school buildings.

Conclusions

The analysis demonstrated a methodology for analyzing spatial and temporal consumption (electricity and natural gas) trends in public schools within LA County. It addresses a gap in literature regarding energy consumption in US public schools by analyzing aggregated consumption trends for a large geographic and metropolitan area over an extended time period. Using account-level data, linked to specific school parcels and aggregated to meet privacy guidelines, the analysis showed detailed metrics of school electricity and natural gas consumption that provide an empirical benchmarking capacity for future policies and programs. Schools, like other buildings sectors, will see increasingly stringent requirements for energy efficiency and conservation. In California, the push towards zero-net energy buildings will likely continue. As affordable alternative energy sources become available, school districts will make decisions regarding investments in energy efficiency and on-site generation. For school districts with larger schools or more schools, this technology could substantially lessen the burden of energy costs while maintaining the environmental requirements for a positive learning environment.

Results show that larger schools consistently consume more electricity and natural gas than smaller schools, but trends are more mixed when considering an alternative metric of consumption per cubic meter. Large schools do show greater volatility in consumption. Consumption varies significantly across school type (elementary, middle, and high schools), which may be correlated instead to school size. Thus, when considering energy efficiency implementations across a school district, the composition of school types within the school district is the important factor. Finally, the location of a school influences natural gas and electricity consumption patterns in alternative ways.

Electricity and natural gas consumption in schools is dynamic, influenced by characteristics of the school itself such as size, along with external factors such as climate. As energy demand reductions continue as a policy priority, large energy consumers such as schools must be increasingly included in conversations. Promoting efficiency and healthy environments in these public buildings can support lower energy bills, better student performance, and long-term climate goals.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Appendix

Sample sizes for each calculation of electricity and natural gas consumption are reported in Tables 9, 10, and 11

Table 9 Sample sizes for electricity and natural gas calculations by school type

Type	Gas (number of schools)	Electricity (number of schools)
Elementary schools	496	562
Middle schools	91	111
High schools	92	111

Table 10 Sample sizes for electricity and natural gas calculations by climate zones

Climate zone	Gas (number of schools)	Electricity (number of schools)
Zone 6	87	120
Zone 8	168	207
Zone 9	410	443
Zone 14	0	12

Table 11 Sample sizes for electricity and natural gas calculations by school size

Size	Gas (number of schools)	Electricity (number of schools)
Small	127	135
Small-medium	147	159
Medium	126	156
Med-large	109	149
Large	161	186

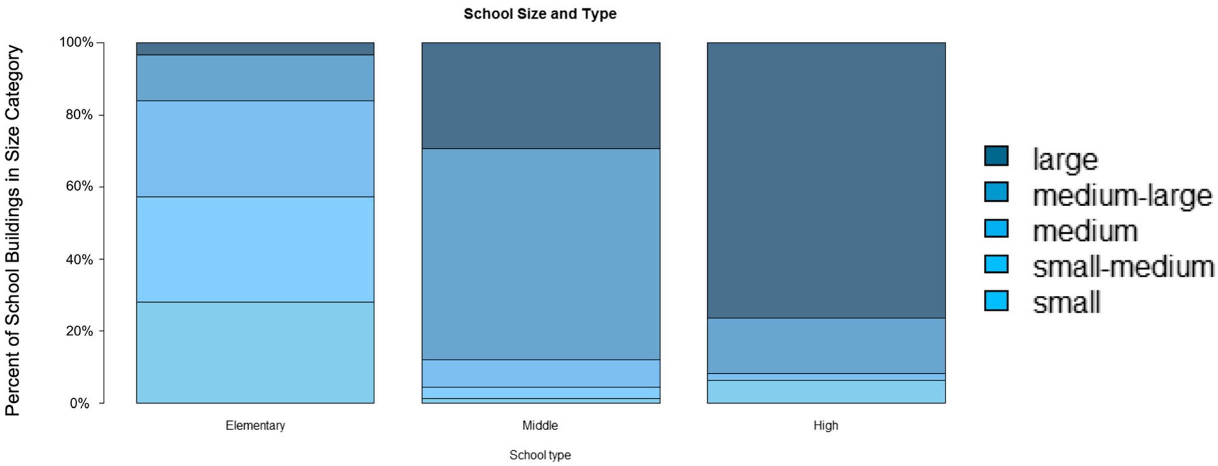

Fig. 9 Comparing school size and type

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