The intersection of energy and justice: Modeling the spatial, racial/ethnic and socioeconomic patterns of urban residential heating consumption and efficiency in Detroit, Michigan

Dominic J. Bednar*, Tony Gerard Reames, Gregory A. Keoleian

Center for Sustainable Systems, School of Natural Resources and Environment, University of Michigan, 440 Church St., Ann Arbor, MI 48109, United States

1. Introduction

Residential utility costs place a disproportionate burden on low-income households. Following the Great Recession, nearly 14 million American households had utility bills in arrears and 2.2 million households experienced utility shutoffs [1]. Residential energy burdens, or the percentage of annual income spent on energy costs, are a major source of utility hardship. While the average American household spends 7.2% of their annual income on residential energy costs, the average low-income household has an energy burden nearly double, spending 13.8% [2]. Energy burden disparities are often expressed through the concept of fuel poverty, also referred to as energy insecurity [3,4]. Fuel poverty reflects an inability of a household to meet basic energy needs or to adequately heat or cool their home [3]. Fuel poverty results from the interplay between low household incomes, rising energy costs and energy inefficient homes [3].

Among solutions to alleviate fuel poverty, energy conservation and efficiency retrofit programs have proven successful [5–8]. However, the inability to identify and distinguish between households with high energy consumption compared to those that are highly energy inefficient has halted interventions from utilizing systematic approaches to appropriately and effectively target energy conservation and efficiency programs. The need for more effective targeting is supported by previous studies exploring the spatial dynamics of energy consumption that find distinguishable spatial disparities in both consumption and energy use intensity (EUI). For instance, Heiple and Sailor [9] using national data, building energy simulation and geospatial modeling...
techniques found variations in peak energy profiles for electricity and natural gas across building types in Houston, Texas. Howard et al. [10] built models from citywide data to estimate building sector EUI finding major differences in the magnitude of consumption and spatial variation across New York City. Santamouris et al. [11] conducted interviews on household and housing unit characteristics finding higher costs per person and unit area for low-income residence in Athens. These studies provide rich information on the relationship between place and energy consumption; however, their focus on both commercial and residential energy consumption makes it difficult to identify residential energy disparities for program targeting. Moreover, few studies investigate correlations between residential energy consumption, efficiency, race/ethnicity and socioeconomic status for a more holistic understanding of urban residential energy dynamics. Reames [12] developed a model estimating urban residential heating EUI and found positive relationships with areas with higher percentages of racial minorities and lower socioeconomics. Albeit some exploration, little remains known about the spatial, racial and socioeconomic differences between residential energy consumption and efficiency.

To this end, this paper develops models for residential heating consumption and efficiency at the census block group level and explores the spatial patterns alongside racial and socioeconomic relationships in Detroit (Wayne County), Michigan. The remainder of this paper is structured as follows. Section 2 presents background information on modeling energy consumption, efficiency and disparities. Section 3 describes the study area, data and methodological framework for first developing two regression models to estimate residential heating energy consumption and heating EUI, then secondly using small area estimation techniques to predict consumption and EUI in the study area. Section 4 presents results of the regression models, spatial distributions of results mapped using geographic information systems (GIS) and bivariate analysis of the relationship between predicted energy consumption and efficiency with selected racial and socioeconomic block group characteristics. Section 5 discusses key results, policy implications and study limitations. Lastly, concluding remarks and areas of future research are presented in Section 6.

2. Background

To understand the factors that impact energy consumption, scholars apply two general frameworks: the physical-technical-economic model (PTEM) and the lifestyle and social-behavioral tradition (LSB) [13–23]. In 1993, Lutzenhiser proposed the PTEm tradition arguing that the physical characteristics of buildings, investment in technical energy efficiency, energy prices and environmental factors are integral to understanding and managing energy consumption. On the other hand, the LSB tradition contends that these factors alone can only offer minimal explanation of energy consumption in the built environment and draws attention to the importance of human occupants of the building, such as, social (noneconomic), behavioral, cultural and lifestyle factors [13, 14, 17–20, 24, 25]. The models developed for this study include variables merging the PTEm and LSB modeling traditions for a more holistic understanding of residential energy consumption and efficiency.

Individual housing unit energy data is often not readily available for exploring residential energy dynamics at various spatial scales. Thus, the absence of detailed information on residential energy use presents an impediment to spatially identifying fuel poor households and developing strategic conservation and efficiency program targeting. As a result, scholars have employed small area estimation statistical techniques to spatially explore residential energy patterns. This approach requires finding the best predictors to model energy consumption and efficiency, for instance, energy characteristics of housing structure and a selection of household characteristics; then, connect to matching spatial data (i.e. census data).

A growing body of literature investigating geographical approaches to target fuel poverty in Europe have used this approach [26–29]. Fahmy [26] developed regression models to predict the incidence of fuel poverty in England using sample survey data and applied resultant weights to Census spatial data sets. Similarly, Walker and Day [30] developed a small area fuel poverty risk index using environmental and socioeconomic variables via geographical methods finding significant clusters of high and low-risk areas. “The underlying idea is that there are higher probabilities of fuel poverty in particular areas and/or housing types” [31].

In the U.S., Min et al. [32] applied this approach for spatially modeling national residential energy consumption end uses. Combining regression models based on national data from the U.S. Energy Information Administration’s (EIA) Residential Energy Consumption Survey (RECS) with U.S. Census data, they mapped energy consumption estimates for space heating, cooling, water heating and all other electrical uses at the zip code level. Reames [12] used both the RECS and Census data to explore racial and socioeconomic disparities in the spatial distribution of urban heating EUI. Both studies found that significant predictors of energy consumption and EUI included age of housing unit, type of housing unit, number of rooms, type of heating fuel and household income.

3. Data and methodology

3.1. Description of study area

Detroit (Wayne County) is the largest urban area in the State of Michigan and represents nearly 20% of the state population. According to the 2010 decennial census, the county had a total population of 1,820,584 residents in 821,693 housing units. Michigan homes are typically older than homes in other states. Nearly three-quarters of housing stock in Detroit (Wayne County) was built before 1970. Fig. 1 illustrates the distribution of housing stock age, displaying the median year built for block group housing structures.

Socioeconomic characteristics vary in the study area. Detroit exhibits a high and increasing level of residential segregation by income. The Pew Research on Social and Demographic Trends found that the Detroit metropolitan area’s RSI score increased from 43 in 1980–54 in 2010 [33]. Fig. 2 displays the spatial distribution of block group median household incomes, ranging from $6833 to $183,462 per year. Households in the Detroit metropolitan were hit particularly hard during the economic recession and recovery. A survey of Detroit metropolitan area households found that 1 in 2 respondents reported experiencing some type of material hardship [34]. While roughly 14% of high-income households fell behind on utility payments, nearly 40% of low-income households reported being behind and were seven times more likely to have a utility shutoff [34].

Detroit has long been the most segregated metropolitan area in the nation, having a majority African American and Hispanic city population and a majority White suburban population [35]. This segregation is evident in Fig. 3, a dot density map illustrating

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2 The Pew Research Center developed a single Residential Income Segregation Index (RISI) score for the nation’s top 30 metropolitan areas. The score is calculated by summing the share of lower-income households living in a majority lower-income tract and the share of upper-income households living in a majority upper-income tract. The maximum possible RISI score is 200, indicating that 100% of lower-income and 100% of upper-income households would be situated in a census tract where most households were in their same income bracket.
the spatial distribution of residents by race/ethnicity. The household racial/ethnic composition included 52.3% White, 40.5% African American and 5.2% Hispanic households. Historically marginalized communities of color in Detroit experience higher rates of arrears and shutoffs. For instance, African Americans were almost twice as likely as non-African Americans to report being behind on utilities payments and more than three times more likely to experience a utility service shutoff than non-blacks [34].

Michigan households experience harsher winters increasing the average household demand for space heating to 55% of total energy consumption compared to 41% nationally [2]. Consequently, Michigan households also consume 38% more energy and spend six percent more than the average U.S. household [2]. Thus, space heating is the ideal energy end use for investigating patterns and disparities in consumption and efficiency.

3.2. Data

In the absence of detailed individual energy data for every household in the study area, the EIA’s RECS provides household-level data for a representative sample of occupied, primary residences at the state-level. First conducted in 1978, RECS collected data on energy consumption, annual expenditure, energy-related behavior, household demographics and housing unit characteristics. Using a multi-stage, area probability design, carefully controlled at specific levels of precision, the 2009 RECS microdata set (released in 2013) has a sample size of 12,083 housing units representing the U.S. Census Bureau’s statistical estimate of 113.6 million occupied primary residences [36]. The RECS allows for state-level analysis with the collection of representative samples in 12 states, including Michigan. A sample of 274 Michigan households were surveyed to represent the state’s 4.5 million occupied housing units. Since the scope of this study focuses on annual space heating, six of the total 274 observations were removed from the sample because of missing heating data, resulting in 268 total observations for this study. 1

Spatial data for modeling and mapping the study area were obtained from U.S. Census Bureau 2006–2010 American Community Survey (ACS) [37,38] 5-year estimates. This survey is issued each year to provide current information about social and economic needs of the community. Households are sampled randomly in each state, including Puerto Rico to provide a representative sample. The census block group was used as the unit of analysis, as the most appropriate spatial resolution for household and housing unit characteristics data [12]. A GIS data layer of Wayne County census block groups was created by clipping the U.S. Census Bureau TIGER/Line Shapefile with demographic and economic data from the 2006–2010 ACS [37,38] 5-year estimates. Block groups were only retained if both population and number of occupied housing units were greater than zero. Subsequently, 1808 of 1822 block groups were included in this analysis.

The RECS microdata set can be used to develop a bottom up statistical model. These models have been used to explore relationships between household energy consumption and various exogenous variables [39,40,32,12,41]. Statistical models also allow for capturing consumption variations due to demographic and

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1 For a 95 percent confidence interval, a sample size of 246 RECS observations are needed to prove statistical significance. For geographic domain estimation purposes, base sampling w(γ"\text{base}) or (γ"\text{census}) eights were applied to each housing unit. Each sampling weight value was used as a weighting factor in the weighted regression model.
socioeconomic characteristics. Similar variables found in both the RECS and ACS allow relationships derived from statistical models using RECS, known as direct estimates, to be applied to block group level ACS spatial data as indirect estimators for constructing small-area estimates with the assumption that the small area exhibits the same characteristics as the large area [42]. The next section clarifies this methodological framework.

3.3. Methodological framework for estimating block group heating consumption and efficiency

The goal of this study is to explore residential heating consumption and efficiency at a geographic domain smaller than the RECS microdata set, which is collected with adequate precision at a state-level scale. Fig. 4 displays a schematic of the methodological framework for estimating heating energy consumption and EUI at the block group level.

The first step uses household and housing unit variables $x_{RECS}$ from the RECS microdata set, specifying two robust regression models—one to predict residential heating energy consumption and the other to predict heating EUI (Blue ovals). The second step uses census data for small area estimations at the block group level (purple rectangles). Resultant weights, $\beta_i$, derived from the aforementioned robust regression models are multiplied to matching household and housing unit spatial variables (e.g. housing unit type, housing units built in each decade, housing unit heating fuel type, median household income), $x_{CENSUS}$, from the U.S. Census 2006–2010 ACS 5-year estimates.

The objective of the first step is to develop two robust statistical regression models that explain the relationship between the two response variables, heating energy consumption and EUI, with the predictor variables, housing unit characteristics (age of home, type of heating fuel, type of home and size of home) and controlling for household characteristics (household ownership, number of household members and household income). Dependent variables were natural log values of per-household final consumption and EUI for heating. The models are formulated as:

$$\ln(Y_{\text{Heat}}) = \beta_0 + (\beta_{\text{Housing unit}} * x_{RECS}) + (\beta_{\text{Household}} * x_{RECS}), \quad (1)$$

$$\ln(Y_{\text{EUI}}) = \beta_0 + (\beta_{\text{Housing unit}} * x_{RECS}) + (\beta_{\text{Household}} * x_{RECS}) \quad (2)$$

where:

$Y_{\text{Heat}}$ is energy consumption in MJ,

$Y_{\text{EUI}}$ is EUI in MJ/m²,

$\beta_0$ is the regression intercept,

$\beta_{\text{Housing Unit}}$ is the resultant weight for housing unit characteristics,

$\beta_{\text{Household}}$ is the resultant weight for household characteristics,

$x_{RECS}$ is household and housing unit RECS data.

The RECS notation is used to differentiate for model creation in this step, and estimation in the subsequent step using Census data. Step one uses resultant weights, $\beta_i$, from the RECS, 2009 data to model energy consumption and EUI. Using the observed data from the state of Michigan, a statewide ordinary least squares (OLS) regression model is developed for each response variable, measured in mega joules (MJ) and MJ per square meter per annum. The goal of the OLS is to model the relationship between the response and predictor variables; simply, how housing units and household characteristics influence total heating fuel consumption and EUI. Total heating consumption is the total annual heating energy consumed from all fuel types (i.e. natural gas, electric, fuel oil, liquid petroleum gas, and kerosene). The EUI is measured as the ratio of total heating consumption to total square meters of heated space. A
Fig. 3. Block group racial/ethnic segregation dot density map.

Fig. 4. Methodological framework for modeling and mapping.
larger EUI value indicates relatively less efficiency when compared to another housing unit.

Step two applies resultant weights from the regression models, \( \beta \), as weighting factors to corresponding variables in the ACS to estimate, then map the median annual heating energy consumption and EUI at the block group level in Wayne County. The corresponding variables are standardized as the ratio of the number of housing units in a block group with a certain characteristic to the total number of housing units in the block group.\(^4\) This is done for each corresponding variable (age of home, type of heating fuel, type of home, size of home, household ownership, number of household members and household income). These values then become comparable with binary variables in the RECS data set. Values are then mapped via GIS to estimate\(^5\) heating consumption and EUI:

\[
\ln(\hat{Y}_{\text{Heat}}) = \hat{\beta}_0 + (\hat{\beta}_{\text{Housing unit}} \times X_{\text{Census}}) + (\hat{\beta}_{\text{Household}} \times X_{\text{Census}}),
\]

\( (3) \)

\[
\ln(\hat{Y}_{\text{EUI}}) = \hat{\beta}_0 + (\hat{\beta}_{\text{Housing unit}} \times X_{\text{Census}}) + (\hat{\beta}_{\text{Household}} \times X_{\text{Census}}),
\]

\( (4) \)

where:

- \( \hat{Y}_{\text{heat}} \) is estimated energy consumption, in MJ
- \( \hat{Y}_{\text{EUI}} \) is estimated EUI, in MJ/m²
- \( \hat{\beta}_0 \) is the estimated regression intercept,
- \( \hat{\beta}_{\text{Housing unit}} \) is the estimated sampling weight for housing unit characteristics,
- \( \hat{\beta}_{\text{Household}} \) is the estimated sampling weight for household characteristics,
- \( X_{\text{Census}} \) is household and housing unit Census data.

4. Results

The final regression models for estimating annual heating consumption and EUI are summarized in Table 1, expressed as natural logs. Model 1, heating consumption, consists of five statistically significant variables representing housing unit type, primary heating fuel and number of household members. Model 2, heating EUI, consists of six statistically significant variables representing housing unit type, primary heating fuel, number of household members and housing unit size. Both models explained a considerable proportion of the variability in heating consumption and EUI \( (R^2 = 0.52, F(18,249) = 15.18, \text{p}<0.001 \text{ and } R^2 = 0.52, F(18,249) = 11.09, \text{p}<0.001, \text{ respectively}) \). Based on the F-values, the final models’ sample sizes are large enough to make them significant.

Figs. 5 and 6 display the spatial distribution in quintiles of the estimated mean annual block group heating energy consumption and heating EUI, respectively. Red shading represents higher estimates, while green shading represents lower estimates. The 14 uninhabited block groups were left uncolored. It is important to note that estimates represent the block group mean rather than any specific house [32,43].

Among the 1808 block groups, there was a significant range in estimated heating consumption (Fig. 5) values, from a minimum 18,658 MJ to a maximum 123,120 MJ. The study area mean heating consumption, 85,107 MJ (SD=16,342 MJ), was lower than the state mean heating consumption, 131,883 MJ. The 104,451 MJ variation in heating consumption estimates demonstrates that within the study area some homes consume a disproportionate amount of energy when compared to others. Block groups exhibiting the highest quintiles of heating consumption primarily surround Detroit in the east, north and west sides of city.

Estimated heating EUI (Fig. 6) values ranged from a minimum 285 MJ/m² to a maximum 1108 MJ/m². The study area mean heating EUI, 613 MJ/m² (SD = 9.8), was lower than the state mean heating EUI, 727 MJ/m². The 818 MJ/m² variation in heating EUI estimates demonstrates that within the study area some homes are far less energy efficient than others. Block groups exhibiting the lowest quintile EUI (shown in green) are located along the west, southwest and east sides of the county, representing homes with higher levels of energy efficiency. Moderate estimated EUIs, (shown in yellow) are located in the north central portion of the county, while a majority of the higher EUIs, (shown in red) are located in the central region of Detroit, indicating lower levels of energy efficiency. This matches areas where houses are older (Fig. 3) and may suggest that older homes are less energy efficient than newer homes a few miles outward.

To understand the relationship between heating consumption and EUI with measures of race/ethnicity and socioeconomic status, bivariate analysis using pairwise correlation was conducted. Pearson correlations, shown in Table 2, reveal statistically significant relationships between socioeconomics, education, and housing tenure with estimated heating consumption \( (p<0.001) \). Heating consumption is positively correlated with block groups with median household income (0.28) and percent of homeowners (0.56). Furthermore, heating consumption is negatively correlated with number of households in poverty \( (−0.25) \) and the percentage of adults without a diploma \( (−0.07) \). There are no significant correlations between heating consumption or EUI with householders above the age of 65. Table 2 also shows statistically significant relationships between socioeconomics, education, race/ethnicity, housing tenure and estimated heating consumption and EUI \( (p<0.001) \). Contrary to heating consumption, heating EUI is positively correlated with block groups with a higher number of adults without a high school diploma (0.32), higher number of households in poverty (0.32), percentage of African American (0.24) and Hispanic householders (0.16). Heating EUI is negatively correlated with median household income \( (−0.28) \), percent of White householders \( (−0.28) \) and percent of homeowners \( (−0.38) \). Thus, census block groups with lower socioeconomics, lower median household incomes, and higher percentages of African American or Hispanic households are more likely to have higher heating EUIs. Simply put, low-income, African American and Hispanic households reside in housing areas where homes consume more and are less energy efficient.

5. Discussion

Results mapped using GIS illustrate inverse spatial disparities in heating consumption and EUI, with higher estimated consumption in block groups surrounding the central city, while block groups with higher estimated EUIs are concentrated within the city of Detroit. The findings also demonstrated that inverse relationships exist between the racial and socioeconomic correlations with block group predicted consumption and EUI. While areas with greater percentages of minority households and lower socioeconomic statuses exhibited lower predicted heating consumption, those same areas exhibited higher EUI, signaling that although low-income,
Fig. 5. Estimated residential heating consumption in MJ.

Fig. 6. Estimated residential energy use intensity (Efficiency) in MJ/m².
Table 1
OLS regression models for small-scale heating consumption and EUI estimation.

<table>
<thead>
<tr>
<th>Categories</th>
<th>Model 1: Heating Consumption (MJ)</th>
<th>Model 2: Energy Use Intensity (MJ/m²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type of Housing</td>
<td>β</td>
<td>Robust S.E.</td>
</tr>
<tr>
<td>Apt 2-4</td>
<td>0.1431</td>
<td>0.1317</td>
</tr>
<tr>
<td>Apt 5+</td>
<td>−0.2989</td>
<td>0.1401</td>
</tr>
<tr>
<td>Mobile Home</td>
<td>0.5173</td>
<td>0.2361</td>
</tr>
<tr>
<td>Single Family Detached</td>
<td>Reference</td>
<td>0.1402</td>
</tr>
<tr>
<td>Single Family Attached</td>
<td>0.01531</td>
<td>0.0048</td>
</tr>
<tr>
<td>Decade Constructed</td>
<td>Before 1950s</td>
<td>0.3317</td>
</tr>
<tr>
<td></td>
<td>1950s</td>
<td>0.3223</td>
</tr>
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<td></td>
<td>1960s</td>
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</tr>
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<td></td>
<td>1970s</td>
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</tr>
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<td></td>
<td>1980s</td>
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</tr>
<tr>
<td></td>
<td>1990s</td>
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</tr>
<tr>
<td></td>
<td>2000s</td>
<td>Reference</td>
</tr>
<tr>
<td>Primary Heat (MJ)</td>
<td>Natural Gas</td>
<td>Reference</td>
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<td>Propane</td>
<td>0.0138</td>
<td>0.0855</td>
</tr>
<tr>
<td>Electricity</td>
<td>−1.627**</td>
<td>0.1404</td>
</tr>
<tr>
<td>Wood</td>
<td>−1.170</td>
<td>0.0978</td>
</tr>
<tr>
<td>Fuel Oil Heat</td>
<td>−0.6926</td>
<td>0.270</td>
</tr>
<tr>
<td>Control Variables</td>
<td>Household Income ($)</td>
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</tr>
<tr>
<td>No. Household Members</td>
<td>−0.0506*</td>
<td>0.0256</td>
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<tr>
<td>Home Ownership (own + 1)</td>
<td>0.0806</td>
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<tr>
<td>Total No. of rooms</td>
<td>0.0203</td>
<td>0.0279</td>
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<tr>
<td>Model Statistics</td>
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</tr>
<tr>
<td></td>
<td>N</td>
<td>268</td>
</tr>
<tr>
<td></td>
<td>F (18,249)</td>
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</tr>
<tr>
<td></td>
<td>Adjusted R²</td>
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<tr>
<td></td>
<td>RMSE</td>
<td>0.514</td>
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</table>

* Significance p < 0.05.
** Significance p < 0.01.
*** Significance p < 0.001.

Table 2
Pairwise Correlation of Estimated Heating Energy Consumption and Energy Use Intensity.

<table>
<thead>
<tr>
<th>Category</th>
<th>Description</th>
<th>Pearson’s Correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Heating Consumption</td>
</tr>
<tr>
<td>Socioeconomic Status</td>
<td>Median Household income</td>
<td>0.28***</td>
</tr>
<tr>
<td></td>
<td>Percent households below poverty level</td>
<td>−0.25***</td>
</tr>
<tr>
<td>Education</td>
<td>Percent Population with Less Than High School Diploma</td>
<td>−0.07***</td>
</tr>
<tr>
<td>Age</td>
<td>Percent Households with Householder aged 65+</td>
<td>0.01</td>
</tr>
<tr>
<td>Race/Ethnicity</td>
<td>Percent White Householders</td>
<td>0.23</td>
</tr>
<tr>
<td></td>
<td>Percent African American Householders</td>
<td>−0.01</td>
</tr>
<tr>
<td></td>
<td>Percent Hispanic Householders</td>
<td>0.02</td>
</tr>
<tr>
<td>Housing Tenure</td>
<td>Percent Owners</td>
<td>0.56</td>
</tr>
</tbody>
</table>

* Significance p < 0.01.
** Significance p < 0.001.

minority households on average consume less energy, they are more likely to live in less efficient housing.

Studying cities like Detroit is important because they often have older housing stock central to the city with much newer, suburban developments outside the city. As shown, householders occupying much older housing stock are at a greater risk for increased demand and a greater need for energy assistance programs. Although this study is focused in the south-east region of Michigan within the United States, this study could be replicated in other urban areas, as well as other countries using a similar household energy consumption survey (i.e. Zheng [44]; ODYSSEE MURE Project) and that country’s census data. The significance of the results presented calls for an integrated approach that tackles fuel poverty from both a physical and policy standpoint – evaluating building energy efficiency and energy assistance programs.

5.1. Policy implications

Energy assistance programs provide eligible householders with monetary or housing unit efficiency upgrade support. The federally funded Low Income Heating Energy Affordability Program (LIHEAP) provides energy assistance to residents who are unable to afford their high utility bills. Identifying concentrated areas of high EUI and energy burden is still a concern given the aforementioned support from government. LIHEAP eligibility primarily depends on income; however, many qualified householders do not receive energy assistance. While attenuating exorbitant utility bills provides temporary relief for some householders, it perpetuates fuel poverty by not combatting a root cause, energy inefficiency.

The U.S. Department of Energy Weatherization Assistance Program’s (WAP) purpose, as established by law, “provides low-to no-cost energy efficiency improvements of dwellings owned or
occupied by low-income persons, reduces their total residential expenditures, and improves their health and safety, especially low-income persons who are particularly vulnerable such as the elderly, person with disabilities, families with children, high residential energy users, and households with high energy burden" [45]. WAP is monitored by the Department of Energy’s Oak Ridge National Laboratory (ORNL). ORNL provides technical support to the program and conducts the evaluations. Led by ORNL, the Department of Energy sponsored two major national evaluations: The Retrospective Evaluation (covering Program Year 2008, which is reflective of a typical year in WAP operations) and the Recovery Act Evaluation (covering Program Year 2010, providing insight to the national effort of job creation and economic recovery as a part of the American Recovery and Reinvestment Act of 2009 [Recovery Act]) were multiyear, peer-reviewed and statistically robust efforts. The former was performed to provide a cost-benefit analysis of WAP services for varying housing unit types and locations across the country. Additionally, to assess program administration and to provide a comprehensive overview of the program, including information on its clients, housing stock and service providers ORNL, 2014. Effective and optimal funding of the system is verified through “whole-house” weatherization approaches via energy audits and the three-pronged WAP funding allocation formula: percent of low-income population, climatic conditions and approximate residential energy burden. Challenges of WAP presented revolve around maintaining and improving work quality, handling health and safety issues discovered in homes and meeting a growing demand for program services. Further, the Recovery Act did not address renewable energy measures average costs per home.

Though LIHEAP and WAP help mitigate energy burdens, these programs do not permit the use of sustainable energy, such as renewable energy for heating and cooling. Renewable energy systems have proven beneficial for energy generation with respect to retrofits [46–48]. There is an opportunity for growth that introduces renewables as a conduit for greater efficiency; however, a community based approach would be more fruitful for effective targeting.

Community-based energy programs have shown success for overcoming various barriers and increasing participation in the adoption of energy technologies [43]. A community-based approach to energy efficiency that targets low-income and minority communities recognizes the unique characteristics and needs of the community and can better foster equity and justice over typical self-referral, broad-based program development and implementation which relies on a homogeneous view of energy users [49,43,30].

5.2. Limitations

As with all research, this study is limited in its scope to fully understand individual households in fuel poverty. Information obtained from this data is often not precise enough to identify individual households; rather, only census block groups at risk of suffering from fuel poverty. Although, some homes that are not considered fuel poor may become integrated spatially with surrounding ones that are, this study provides a model of mean block group estimates to inform policy and program targeting while exploring relationships with race/ethnicity and class. Specific information about individual household utility bills is not accessible. Further, the influence of behavior on disparities in energy consumption or efficiency are not observed in these models.

6. Conclusion

This study used publically available data from the U.S. Energy Information Administration’s Residential Energy Consumption Survey (RECS) and the U.S. Census Bureau’s American Community Survey (ACS), bottom-up modeling, and small-area estimation techniques to predict mean annual heating consumption and energy use intensity (EU), an energy efficiency proxy, for census block groups in Detroit (Wayne County), Michigan. This study’s relevance provides a best estimate of areas where households may experience the greatest threat of fuel poverty. The key findings of the study illustrate inverse spatial disparities in heating consumption and EUI throughout Detroit (Wayne County), Michigan. Inverse relationships were also found between the racial and socioeconomic correlations with block group predicted consumption and EUI.

Modeling both heating consumption and efficiency provides a useful tool that may assist policymakers, energy conservation and efficiency program administrators and retrofit installers develop more effective targeting strategies. Combining consumption and efficiency information with an understanding of the racial and socioeconomic context of neighborhoods may also improve program implementation effectiveness.

Using spatial proximity as a guide to identifying fuel poor households eliminates onerous applications to determine eligibility and provides a quicker and more robust response to households in need. Furthermore, there is a need to understand the cultural/racial differences within identified neighborhoods. Simply creating energy assistance programs without effective marketing, maintains the energy divide, leaving many in fuel poverty. To overcome cultural and social barriers, community-based approaches would enable more access to help that is readily available. Future research should pursue a more granular level of understanding, such as incorporating individual parcel data. Additionally, spatially modelling of energy burdens would provide a more holistic view of residential energy assistance demands. With this information in hand, program administrators could target local churches, community centers and neighborhood groups to more effectively and efficiently assist those with the greatest need.

Addressing fuel poverty and energy consumption more broadly, requires an integrated approach to identify the specific energy needs of communities. The modeling framework presented in this study is one approach to understand those needs both visually and statistically. Moreover, this research unpacks disparities in consumption and efficiency concluding that one-size-fits-all approaches to conservation and efficiency are not appropriate for all energy users in an urban area.

References


