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Targeting energy justice: Exploring spatial, racial/ethnic and socioeconomic disparities in urban residential heating energy efficiency

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ABSTRACT

Fuel poverty, the inability of households to afford adequate energy services, such as heating, is a major energy justice concern. Increasing residential energy efficiency is a strategic fuel poverty intervention. However, the absence of easily accessible household energy data impedes effective targeting of energy efficiency programs. This paper uses publically available data, bottom-up modeling and small-area estimation techniques to predict the mean census block group residential heating energy use intensity (EUI), an energy efficiency proxy, in Kansas City, Missouri. Results mapped using geographic information systems (GIS) and statistical analysis, show disparities in the relationship between heating EUI and spatial, racial/ethnic, and socioeconomic block group characteristics. Block groups with lower median incomes, a greater percentage of households below poverty, a greater percentage of racial/ethnic minority headed-households, and a larger percentage of adults with less than a high school education were, on average, less energy efficient (higher EUIs). Results also imply that racial segregation, which continues to influence urban housing choices, exposes Black and Hispanic households to increased fuel poverty vulnerability. Lastly, the spatial concentration and demographics of vulnerable block groups suggest proactive, area- and community-based targeting of energy efficiency assistance programs may be more effective than existing self-referral approaches.

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1. Introduction

Climate change concerns highlight a number of serious social and environmental inequalities that can be traced to energy consumption. These concerns form the foundation of a growing field of scholarship, and activism, on energy justice. For instance, Hernández (2015) issued "*A Call for Energy Justice*," which acknowledged four basic human rights to energy: the right to a healthy, sustainable energy production; the right to best available energy infrastructure; the right to affordable energy; and the right to uninterrupted energy service. For the many US households suffering in fuel poverty, nearly 14 million with unpaid utility bills and 2.2 million with disconnected utilities, these rights are unfulfilled promises (Seibens, 2013). Fuel poverty (also known as energy poverty or energy insecurity) is the inability of households to afford energy services for adequate heating and cooling resulting in uncomfortable indoor temperatures, material deprivation, and accumulated utility debt (Li et al., 2014, Hernández 2013, Buzar, 2007; Boardman, 2012). More than a matter of mere comfort, indoor temperatures that are too cold in winter or too hot in summer have detrimental mental and physical health impacts, including death, for vulnerable populations like children, the elderly, and minorities (Anderson et al., 2012; Liddell and Morris, 2010, Howden-Chapman et al., 2009, Howden-Chapman et al., 2007, Klinenberg, 2002; Taylor et al., 2001). A key measurement of fuel poverty is the proportion of gross income spent on home energy costs, or the energy burden. Low-income US households have an average heating energy burden of 4.7% that is more than double the 2.3% national average and more than four times the 1.1% average burden for high-income households (US Department of Health and Human Services [HHS] 2011). Analysts consider a heating energy burden greater than 2% unaffordable (Fisher et al., 2014).

However, fuel poverty is more than a straightforward relationship between household income and energy costs. The concept became prominent in the 1980s and has been well-studied in the UK (see special issue Volume 49 of this journal) and even codified in law with the passage of the Warm Homes and Energy Conservation Act of 2000. Investigations of fuel poverty, including those beyond the UK, demonstrate that a pure financial assessment of its prevalence does not account for the variety of factors and relationships that produce and sustain it. Buzar (2007) advocated a "relational approach" to studying fuel poverty, one that combines understanding energy policy, housing infrastructures, and the lived experience of the fuel poor. Hernandez and Bird (2010) found the incidence of high inner-city energy burdens was due in part to a lack of energy assistance funding, a lack of housing and energy policy coordination, and a lack of understanding the social and economic benefits of energy conservation and efficiency. Harrison and Popke (2011) suggested fuel poverty be understood "as a geographical assemblage of networked materialities and socioeconomic relations" determined by household socioeconomic characteristics, material conditions of the home, and the structure that defines the provision of energy.

The conceptualization of fuel poverty as an energy justice concern speaks to the energy-related distribution, procedure, and recognition of "what constitutes the basic rights and entitlements of sufficient and

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healthy everyday life" (Walker and Day, 2012). Consequently, fuel poverty violates the basic principle of distributive justice. Distributive justice is the idea that all members of society have the right to equal treatment, and that outcomes should be fairly distributed, and provides moral guidance for the political processes and structures that affect the distribution of economic benefits and burden across and within society (Rawls, 1971; Sen, 1999 Schlosberg, 2013). As a distributive injustice, fuel poverty results from three interconnected inequalities: income inequality, inequality in energy prices, and inequalities in housing and energy efficiency (Walker and Day, 2012). Although fundamentally, fuel poverty is a problem of distributional injustice, its production and persistence are also the result of an injustice in recognition of the specific energy-related needs of vulnerable populations, and procedural injustice related to access to information, meaningful participation in decision-making, and access to legal processes for achieving redress or challenging decision-making processes (Walker and Day, 2012).

Addressing the distributive injustice of fuel poverty requires first determining what should be fairly distributed. Since inequalities in income and energy prices require larger social and economic solutions, residential energy efficiency retrofits have become a key fuel poverty intervention strategy (Howden-Chapman et al., 2007, Howden-Chapman et al., 2009, Bird and Hernández 2012, Gibson et al., 2011, Harrison and Popke, 2011). However, the absence of easily accessible data on individual household energy consumption and efficiency, and an incomplete understanding of the spatial distribution of vulnerability presents an impediment to effectively targeting those most in need (Walker et al., 2013; Sefton, 2002,). Recently, scholars have conducted small-scale, area-based studies using readily available public data and geographic information systems (GIS) to offer visualizations of spatial disparities in the distribution of fuel poverty vulnerability and energy consumption to facilitate policymaking and intervention targeting (Pereira and de Assis, 2013; Walker et al., 2013; Fahmy et al., 2011; Morrison and Shortt, 2008;).

In the US, while fuel poverty is neither recognized colloquially or politically, a few studies have modeled the spatial distribution of residential energy consumption, including socioeconomic and demographic control variables in their models (Howard et al., 2012; Min et al., 2010; Heiple and Sailor, 2008). Others have explored the socioeconomic and demographic relationships of national residential energy consumption patterns (Health and Human Services [HHS] 2011; Steemers and Yun, 2009; Ewing and Rong, 2008; Adua and Sharp, 2011; Newman and Day, 1975). Generally, these studies concluded that, all else being equal, low-income households consume less energy. This broad assessment of consumption rather than efficiency, tends to mask fuel poverty vulnerability. Instead, when analyzing energy use intensity (EUI), or energy consumption normalized by building square area, as a proxy for energy efficiency, national data from the US Energy Information Administration (EIA) show that low-income household, on average, are less efficient, with an EUI 27% greater than high-income households. The spatial distribution of energy efficiency is further complicated by a persistent system of racial and income residential segregation that defines housing development and consumption patterns in many US metropolitan areas. A substantial amount of research is aimed at understanding the causes and consequences of residential segregation, primarily from the fields of sociology and public health (Sampson, 2012; Sharkey, 2011; Anthopolos et al., 2011; Sampson and Wilson, 1995; Wilson, 1987). But very little of this research is connected to energy-related research in meaningful ways that illustrates the critical importance of place to the presence of energy efficiency disparities and fuel poverty vulnerability.

This paper uses publically available data to model residential heating energy efficiency, as a function of various housing and household characteristics for a tri-county metropolitan area. The study extends previous energy consumption and social justice oriented research by predicting small-area estimation of end use energy efficiency, and then examining racial/ethnic and socioeconomic relationships. This analysis not only furthers our understanding of the dynamics and distribution of energy efficiency disparities, it has practical applications that may assist policymakers and practitioners with developing and implementing more equitable, efficient, and effective targeting of energy assistance programs and weather-related vulnerability prevention activities. This study seeks to answer two research questions. First, does residential heating energy efficiency vary within a metropolitan area? And if so, what are the spatial characteristics of that variation? Second, what are the patterns of association between residential heating energy efficiency and racial/ethnic, and socioeconomic characteristics? The remainder of the paper summarizes the modeling and mapping of residential heating energy efficiency and analysis of the spatial, racial/ethnic, and socioeconomic patterns. Section 2 describes the study area, and methods for developing a model for heating energy efficiency and small-area predictions. Section 3 presents the results of the geographic and statistical analyses. Section 4 concludes with policy implications.

2. Methodology

2.1. Description of study area

Kansas City is the largest city in the State of Missouri and lies mostly in Jackson, Clay, and Platte counties (see Fig. 1). This tri-county region also represents the service area for United Services, one of nation's roughly 1000 Community Action Agencies (CAAs). CAAs are mostly nonprofit, anti-poverty social service organizations covering nearly 96% of US counties. CAAs are responsible for administering federal low-income energy assistance programs, such as, the Department of Health and Human Services Low-income Home Energy Assistance Program which provides utility bill assistance and the Department of Energy Weatherization Assistance Program which provides no-cost energy efficiency retrofits. According to Building America, which determines building practices based on climate zones to achieve the most energy savings in a home, the counties are located in Climate Zone 4, which has a range of 4000–5499 heating degree days (HDDs) annually, and where the average monthly outdoor temperature drops below 47 °F (7 °C) during the winter (U.S. Department of Energy, 2015).[1] Hence, homes in the area exhibit relatively high usage of heating equipment. In fact, space heating accounts for 41% of total household energy consumption in Missouri. The main heating fuel sources are natural gas (52%) and electricity (35%). Overall, the average Missouri household total energy consumption is roughly100 million BTUs per year, approximately 12% more than the national average (EIA, 2013a).

According to the 2010 decennial census, the counties had a total population of 985,419 in 398,124 households. The area covers urban,

[1] Climate zones range from 1 (warmest) to 7 (coldest). Heating degree days (HDDs), commonly used in calculations relating to the energy consumption required to heat buildings, is a measurement of the difference in temperature between the mean outdoor temperature, over a 24-h period, and a given base temperature for if a building's indoor temperature fell below would require heating, typically 65 °F (18 °C) in the US. For example, if the mean outdoor temperature for a day is 35 °F, the HDDs measurement for that day is 65−35=30. Essentially, areas with a larger number of HDDs have colder outdoor temperatures and require more energy for heating.

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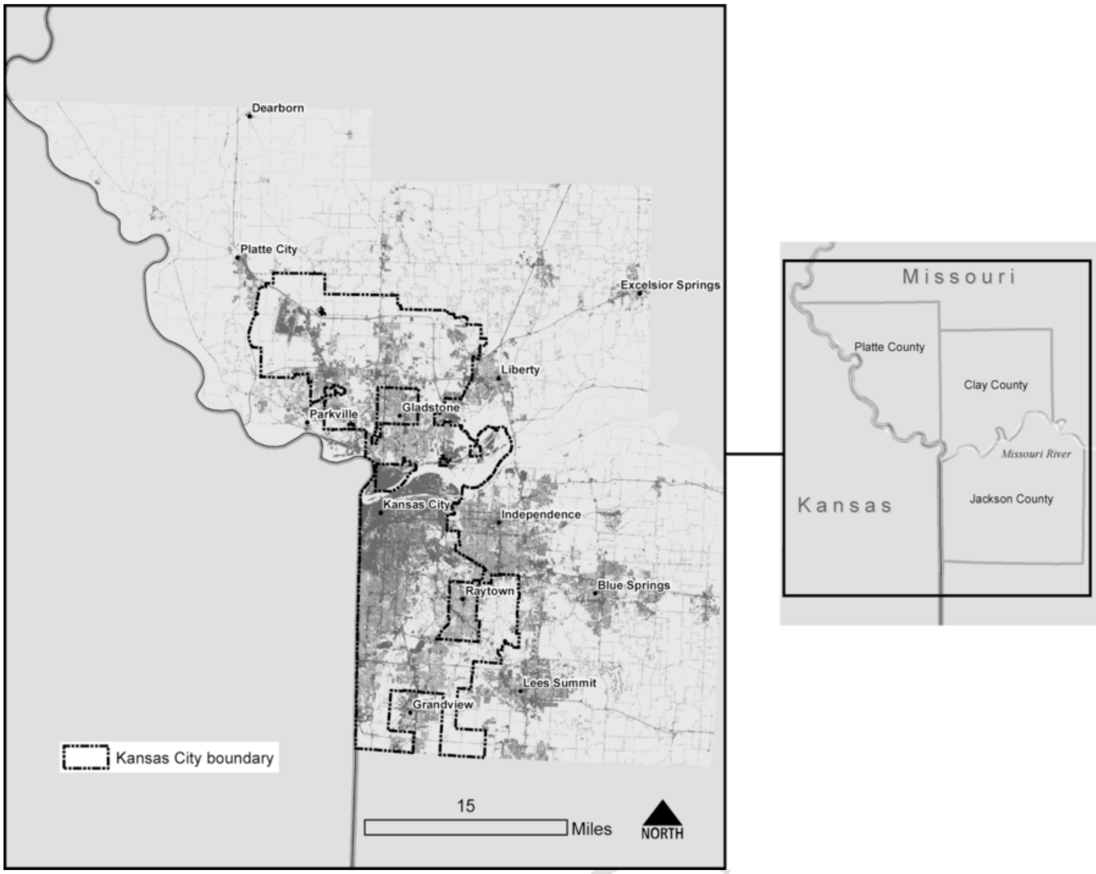

Fig. 1. Study site: Kansas City, Missouri (Jackson, Clay and Platte counties).

suburban, and rural landscapes. In addition to the urbanization gradient, socioeconomic characteristics in the area vary greatly. Median block group income ranged from $14,250 to $154,250. The household racial composition included 77.1% White households, 17.3% Black households, 5.2% Hispanic households, as identified by the head of household. Kansas City is consistently identified as one of the nation's twenty-five most racially segregated metropolitan areas due to its high placement on a range of housing segregation indices, most recently ranking 23rd based on black-white segregation (Logan and Stults, 2011; Denton, 1994; Massey and Denton, 1993). Kansas City also exhibits a high, and increasing, level of residential segregation by income. According to Pew Research on Social and Demographic Trends, Kansas City's Residential Income Segregation Index score increased from 38 in 1980 to 47 in 2010 (Fry and Taylor, 2012).

2.2. Data

In the absence of detailed individual household energy data, the EIA's Residential Energy Consumption Survey (RECS) provides household-level energy consumption data for a representative sample of occupied, primary residences in the US. The RECS employs a multi-stage area probability design to ensure the selection of a representative sample of housing units, carefully controlled at specified levels of precision, to allow analysis of housing using characteristics and energy consumption and expenditures at the following geographic levels: national, census region, census division, groups of states within a census division, and individual states (EIA, 2013b). The RECS, first conducted in 1978, collects data on energy consumption, expenditure and behavior along with a number of household demographics and housing unit characteristics. In the past, the RECS sample size has not been particularly useful for analyzing energy patterns at spatial scales lower than the census region, except for the most populous US states; California, Texas, New York, and Florida. The 13th iteration of the survey, conducted in 2009 and released in 2013, nearly tripled in sample size to 12,083 housing units (up from 4382 in 2005) representing the US Census Bureau's statistical estimate of 113.6 million occupied primary residences. Subsequently, the 2009 RECS allows for additional state-level analysis with the collection of representative samples in 12 additional states, including Missouri. A sample of 686 households were surveyed to represent the 2.35 million occupied housing units in Missouri. For geographic domain estimation purposes, base sampling weights were applied to each housing unit, which was the reciprocal of the probability of selection into the sample and is the number of households in the population each observation represents (EIA, 2013b). Each sampling weight value was used as a weighting factor in the weighted regression model.

Data for spatial modeling and mapping of the study area were obtained from the U.S. Census Bureau 2006–2010 American Community Survey (ACS) 5-year estimates. The census block group was used as the unit of analysis for this research. Census block groups are a contiguous cluster of blocks within a census tract and generally consist of between 600–3000 people. The census block group is the smallest spatial resolution for which household and housing unit characteristics similar to RECS variables are publically available from the U.S. Census Bureau. In addition, it is assumed that physical and social homogeneity are more likely at the smaller block group level than larger spatial levels, such as, census tracts or zip codes. A GIS data layer of census block groups for the study area was created by clipping data from the U.S. Census Bureau TIGER/Line Shapefiles with demographic and economic data from the 2006–2010 ACS 5-year estimates. Block groups were retained for analysis only if data values for both population and number of occupied housing units were greater than zero. Subsequently, 757 of 763 block groups in the three-county study area were included in this analysis.

The RECS microdata set can be used to develop a bottom up statistical model. Bottom up statistical models use input data at a granular level, such as a sample of individual households, for extrapolation to a geographic area of interest. These statistical models have been used to establish relationships between various characteristics of household energy consumption (i.e. specific end use consumption, total consumption, energy use intensity) while controlling for exogenous variables such as housing unit characteristics, household characteristics, urban form and climatic conditions (Min et al., 2010; Ewing and Rong, 2008; Tso and Yau, 2007). Min et al. (2010) developed a statistical framework for modeling residential space heating (and other end use) consumption at a zip code- level resolution using the 2005 RECS microdata. Their results were validated against residential energy sales data. This study extends their framework to estimate residential heating efficiency by creating a state-level regression model using the Missouri sample of housing units in the 2009 RECS microdata set and exploring small-area spatial, racial/ethnic, and socioeconomic patterns. Since many of the variables identified in the RECS can also be found in the Census ACS, relationships derived from the statistical model, known as direct estimators, can be applied to the block group level dataset as indirect estimators for constructing small-area estimates, under the assumption that the small areas have the same characteristics as the large areas (Rao and Molina, 2015). The next two sections detail this process.

2.3. Specifying a robust regression model for heating energy efficiency

The ordinary least square (OLS) method was used to analyze how housing unit and household characteristics influence residential heating energy efficiency. Heating energy efficiency is operationalized as annual heating energy use intensity (EUI). Generally, a lower EUI signifies relatively efficient performance. The EUI is defined as the quantity of energy used in producing a given level of service, expressed as energy consumed per unit of output. The heating EUI (kBtu/m^2) was calculated for each RECS observation by dividing the total annual heating consumption (kBtu) by the housing unit square area (m^2). Trained interviewers use a standardized method for measuring and collecting the dimensions of the housing unit. Total annual heating consumption is the aggregation of a household's space heating consumption from all fuel types (i.e. natural gas, electricity, liquefied petroleum gas (LPG), fuel oil, and/or kerosene). The RECS captures consumption data from actual utility bills. Of the Missouri RECS sample, 676 observations had total annual heating consumption greater than zero kBtu. Another observation was dropped as it was the only housing unit in the sample reporting fuel oil/kerosene as the primary heating source. Fuel oil/kerosene are not major sources of heat in the tri-county area; only 0.09% of homes use fuel oil/kerosene as their primary heating source (US Census 2016). Upon testing for outliers, an additional observation was dropped that exhibited an extremely high EUI for a relatively small footprint. The final data set consisted of a sample of 674 Missouri housing units.[2]

The OLS model can be formulated as,

$$\ln E = \beta_0 + \sum_{i}^{n} \beta_i * \chi_{i,RECS} + \varepsilon$$

where E is the annual heating EUI, and $\chi_{i,RECS}$ is the predictor variable χ_i from the RECS dataset (Min et al., 2010). The dependent variable was natural logged to better fit the nonlinear relationship between heating EUI and the independent variables (Min et al., 2010; Ewing and Rong, 2008).

Since many of the predictors of heating EUI are themselves correlated, it is important to consider their simultaneous effects using multivariate analysis techniques. This approach therefore requires determining the best subset of predictors of heating EUI. Initial selection of independent variables was guided by previous studies using OLS to understand residential energy consumption. The two major themes on factors that contribute to residential energy consumption are categorized as the physical-technical-economic model (PTEM) and the lifestyle and social-behavior tradition (LSB) (Adua and Sharp, 2011). Many models include variables from the PTEM perspective which explains energy consumption as a result of housing unit characteristics, or the building's physical structure and equipment characteristics, and economic and environmental factors. These variables include: type of home, year home built, home size, household income, price of energy, geographic location, and climate variables (Ewing and Rong, 2008; Min et al., 2010; Adua and Sharp, 2011, Valenzuela et al., 2014). The LSB tradition draws on the importance of human occupants to energy consumption, or household characteristics. LSB-related variables often include: race/ethnicity, household size, age of householder, and sex of householder (Ewing and Rong, 2008; Min et al., 2010; Adua and Sharp, 2011, Valenzuela et al., 2014). For this model, variables representing housing unit characteristic included three dummy-coded variables for housing type (mobile home, single family detached, and single family attached, with multifamily as the reference category), six dummy-coded variables for decade constructed (1950s through 2000s, with homes built before 1950 as the reference category), and three dummy-coded variables for primary heating fuel (liquid petroleum gas (LPG), electricity, and wood, with natural gas as the reference category). Household characteristic variables included one interval variables for number of rooms, one categorical variable for household income (divided into eight categories), and one dummy-coded variable for home ownership coded as "1″, otherwise "0″. Final model selection of independent variables was based upon backward stepwise selection.

2.4. Utilizing census data for small area heating EUI estimation

Since the goal of this study is to explore heating energy efficiency at a geographical domain smaller than the RECS microdata (collected with adequate precision at the state-level), the second step involves using the model above to estimate and map heating EUI for Kansas City. This technique, known as small-area estimation, combines individual level data (i.e. household surveys) and spatial characteristic estimates (i.e. Census data). There have been significant theoretical ad-

[2] A sample size of 674 can predict with accuracy at a 95% confidence interval and ±4 confidence level, for 2,339,684 housing units (population size). Based on the assigned sampling weights, the final sample represents 2,286,868 housing units.

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vances in small-area estimation methodologies for modeling and mapping (Fay and Herriot, 1979; Fahmy et al., 2011; Rao and Molina, 2015). To accomplish this, resultant weights derived from the regression model are applied to spatial data (e.g., housing units by type, housing units built in each decade, housing units using each fuel type for heating, median household income), from the US Census 2006–2010 ACS 5-year estimates. The derived regression weights are therefore intended to reflect the observed pattern of influence at the household level, which is essential to the small area estimation. Regression coefficients β_i are applied to block group level data, $\chi_{i,CENSUS}$, for each of the 757 block groups in the study area (Min et al., 2010), using ARCMap (v.10.3.1) software (ESRI, Inc) to predict block group level heating EUI estimates $\widehat{E}$:

$$\widehat{\ln} E = \widehat{\beta}_0 + \sum_i \widehat{\beta}_i * \chi_{i,CENSUS}.$$

Since this modeling approach involves matching two different datasets (RECS and ACS), these sources must first be harmonized with respect to their measurement and weighting. Each census variable was weighted by the percentage (or ratio) of its presence in the Census block group. For example, if the number of housing units heated by electricity in census block group 1 is 100 and the block group has 200 housing units, the variable is standardized as 100/200=0.5, which is comparable to the binary variable for whether or not an observation in the RECS data set uses electricity as its primary heating source. The ratio for each block group is then multiplied by the coefficient for electricity from the regression model.

Lastly, to simply exponentiate the log-linear model, $\widehat{\ln} E$, will systematically underestimate the expected value of EUI, thus the scaling value $\exp\left(\frac{RMSE^2}{2}\right)$ is needed (Wooldridge, 2009: 211). RMSE is the root mean square error of the model. From the estimated log values $\widehat{\ln} E$, the actual estimated EUI is obtained by the equation

$$\widehat{E} = \exp\left(\frac{RMSE^2}{2}\right) * \exp(\widehat{\ln} E).$$

2.5. Statistical analysis

The relationships between the predicted mean block group heating EUI and measures of race/ethnicity, and socioeconomic status are examined using bivariate and multivariate analyses. First, correlation analysis was conducted between heating EUI and each demographic and social variables. Next multivariate regression was used to explore the relationship between predicted heating EUI and block group racial/ethnic and socioeconomic characteristics. Lastly, logistic regression was used to model how the proportion of racial/ethnic minority headed households, and other block group demographic characteristics affect the probability of block group vulnerability, thus prime for energy efficiency intervention targeting.

3. Results

The final regression model for estimating annual heating EUI, expressed as natural log, is presented in Table 1. The final model consisted of 11 statistically significant variables representing housing unit type, decade housing unit was constructed, primary heating fuel, and control variables for household income, home ownership, and housing unit size. The model explained a considerable proportion of variability in heating EUI (R^2=0.62, F(11, 662)=85.9, p<0.001). Based on the F value of the model, the final sample size of 674 is large enough to make the model significant. Cross-sectional studies are at greater risk of exhibiting heteroskedasticity. Weighted regression is one method to correct residuals and the model's residual versus fit plot exhibits a constant variance and shows no evidence of heteroskdasticity. Additionally, robust standard errors were used and are report in Table 1 (Wooldridge, 2009). Multicollinearity can also be a major problem for statistical models of residential energy use, and can result in poor predictions of certain end uses (Swan and Ugursal, 2009). Multicollinearity commonly arises with variables that tend to be correlated, such as household income and housing unit size. However, correlations between any two variables in the final model did not exceed 0.45, and the variance inflation factor is 1.32. Thus, the model did not indicate a noticeable presence of multicollinearity.

Table 1
OLS regression model for small-scale heating EUI estimation.

DV = ln (EUI_{heat})	Coeff.	Robust Std. Err.
Type of Housing		
Multi-Family	Reference	
Mobile Home	0.68^{***}	0.09
Single Family Dettached	–	
Single Family Attached	–	
Decade Constructed		
Before 1950	Reference	
1950s	–	
1960s	-0.24^{***}	0.07
1970s	-0.18^{**}	0.07
1980s	-0.34^{***}	0.08
1990s	-0.26^{***}	0.07
2000s	-0.29^{***}	0.07
Primary Heat		
Natural Gas	Reference	
Electricity	-1.10^{***}	0.05
Wood	-2.07^{***}	0.23
Liquid Petroleum Gas	–	
Control Variables		
Household Income	-0.03^{*}	0.01
Home ownership	-0.15^{**}	0.05
No. of rooms	-0.09^{***}	0.01
Model Statistics		
Intercept	6.57^{***}	0.08
N	674	
F (11, 662)	85.9^{***}	
Adjusted R^2	0.62	
RMSE	0.523	

-dropped from stepwise regression

* Significance p <0.05.

** Significance p <0.01.

*** Significance p <0.001.

Fig. 2 illustrates the spatial distribution, in quintiles, of the predicted mean annual heating EUI for each block group, darker shading represents higher predicted heating EUI. The six uninhabited block groups were left uncolored. It is important to note that predicted values reflect the mean heating EUI of all housing units in the block group rather than any specific house (Min et al., 2010). Among the 757 block groups there was significant difference in values of heating EUI, ranging from 88 to 481 kBtus/m^2. The metropolitan mean heating EUI, 269.6 kBtu/m^2 (SD=66.7 k/Btus/m^2), was higher than the state mean heating EUI, 218.9 kBtus/m^2. The heating EUI variation, nearly 400 kBtus/m^2, is quite large. This means that within the same metropolitan region, homes in some areas were far less efficient than others. While block groups with higher heating EUIs are scattered throughout the three counties, the majority of block groups with the

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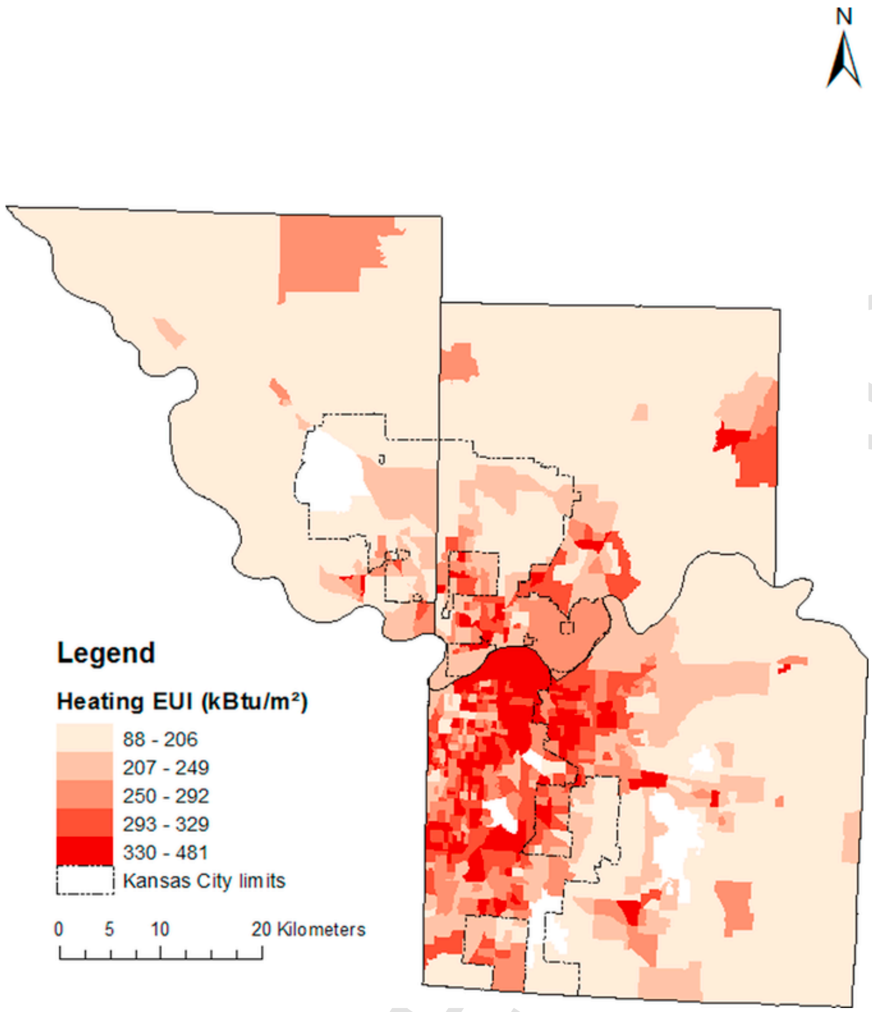

Fig. 2. Predicted block group mean annual heating EUI (kBtus/m^2).

highest EUIs were concentrated within the Kansas City limits and its urban core. Of the 151 block groups with the highest (fifth quintile) predicted heating EUI, 119 (78.8%) were located within the city limits.

Pearson correlations, shown in Table 2, revealed statistically significant relationships between socioeconomics, race/ethnicity and predicted heating EUI (p<0.001). Heating EUI is positively correlated with block groups with a higher number of adults without a diploma (0.51), higher number of households in poverty (0.47), more renters (0.40), more Black householders (0.32), more Hispanic householders (0.31), and more senior householders (0.12). Furthermore, heating EUI was negatively correlated with median household income (−0.62) and proportion of White householders (−0.37). Thus, census block groups with lower socioeconomics, lower median household incomes, and higher proportions of Black or Hispanic households are more likely to have higher heating EUIs. Additionally, Kruskal-Wallis tests were conducted to determine if heating EUI was different among block groups divided into quintiles by the socioeconomic and race/ethnicity variables of interest. Individual Kruskal-Wallis tests showed there were statistically significant differences in heating EUI between the quintiles of median household income (χ^2=330.9), percent poverty (χ^2=171.1), percent less high school education (χ^2=195.2), percent senior headed households (χ^2=20.2), percent renters (χ^2=168.2), percent White householders (χ^2=78.1), percent Black householders(χ^2=97.2), and percent Hispanic householders (χ^2=94.7), (DF=4, p<0.001).

Regression models examining how race/ethnicity are related to heating EUI are shown in Table 3. Model 1 in Table 3 shows this relationship when socioeconomic characteristics of the block group are not taken into account. This model reveals a strong relationship between race/ethnicity and heating EUI. The model shows that as the percentage of Black households and Hispanic households in a block

Table 2
Pearson's correlation between race/ethnicity, socioeconomics and predicted heating energy use intensity (EUI).

Category	Description	Pearson's correlation
Economic status	Median household income	-0.62
	Percent households below poverty level	0.47
Education	Percent population with less than high school diploma	0.51
Age	Percent households with householder aged 65+	0.12
Race/Ethnicity	Percent white householders	-0.37
	Percent black householders	0.32
	Percent Hispanic householders	0.31
Tenure	Percent renters	0.40

All coefficients significant at p<0.001

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Table 3
Relationship between estimated heating EUI and block group race/ethnicity, segregration and socioeconomic characteristics.

	Model 1		Model 2		Model 3		Model 4	
	b	S.E.	b	S.E.	b	S.E.	b	S.E.
Percent black householders	0.75^{***}	0.07	0.19^{*}	0.09				
Percent Hispanic householders	2.58^{***}	0.29	0.71^{*}	0.32				
Percent households below poverty level			1.24^{***}	0.20				
Percent population with less than high school diploma			1.47^{***}	0.28				
Percent households with householder aged 65+			0.75^{***}	0.17				
Black residential segregation					90.93^{***}	7.19	37.09^{***}	9.19
Hispanic residential segregation					238.68^{***}	22.03	94.27^{**}	29.92
Proportion households below poverty level							98.37^{***}	22.87
Proportion population with less than high school diploma							146.14^{***}	29.97
Proportion households with householder aged 65+							64.32^{***}	16.89
Intercept	240.13^{***}	3.29	210.56^{***}	4.75	232.34^{***}	3.39	210.09^{***}	4.82
N	757		757		757			757
R^2	0.21		0.33		0.23			0.33

* Significance $p<0.05$.

** Significance $p<0.01$.

*** Significance $p<0.001$.

group increase, heating EUI increases by 0.75 and 2.58 kBtu/m^2, respectively.

The second model in Table 3 (Model 2) shows how race/ethnicity are related to heating EUI when the effects of socioeconomic characteristics of the block group (percent poverty, percent less than high school diploma and percent senior householders) are held constant. In this model, while the positive relationship between race/ethnicity and heating EUI remain, as in Model 1, the effects are moderated by the socioeconomic characteristics of the block group with percent of households below poverty, percent of population with less than a high school diploma, and percent senior headed households having a larger effect on heating EUI, 1.24 (t=6.3), 1.47 (t=5.4), and 0.75 (t=4.5) kBtu/m^2, respectively. After controlling for socioeconomics, the effect of a percent increase in Black or Hispanic households increasing a block group's heating EUI drops to 0.19 (t=2.2) and 0.71 (t=2.2) kBtu/m^2, respectively.

The final two models reported in Table 3 (Models 3 and 4) exchange the percentage of Black and Hispanic households in the block group with a measure of the block group's level of Black and Hispanic racial residential segregation (RRS). The RRS, a measure of the geographic isolation of race/ethnicity from other racial groups (Massey and Denton, 1993, Reardon and O'Sullivan, 2004, Anthopolos et al., 2011). RRS has received increased attention as a major social determinant in poor outcomes (i.e. health effects) and may be a proxy for concentrated neighborhood disadvantage, including exposure to socio-physical environmental stressors in the built environment (Anthopolos et al., 2011). Model 3 shows that RRS has a strong positive relationship with heating EUI. Each unit increase in Black isolation increases heating EUI by roughly 91 kBtu/m^2. Hispanic isolation has an even greater effect on heating EUI. Every unit increase in Hispanic isolation increases heating EUI 239 kBtu/m^2. In Model 4 the relationship between segregation and heating EUI remains strong even after controlling for the socioeconomic characteristics of the block group. Given that the isolation index is a value between 0 and 1, the socioeconomic block group characteristics in Model 4 are in proportions rather than percentages. The Black and Hispanic isolation indexes maintain a strong positive relationship with heating EUI but are slightly moderated by block group socioeconomic characteristics. Once socioeconomic characteristics- poverty (t=4.3), less high school (t=4.9), senior households (t=3.8)- are taken into account, the effect that a unit increase in Black and Hispanic isolation increases heating EUI drops to 37 (t=4.0) and 94 (t=3.2) kBtu/m^2, respectively.

Fig. 3 illustrates the spatial distribution of high-risk block groups, which would be prime candidates for energy efficiency interventions. High-risk block groups are defined as those where predicted heating EUI was greater than study area mean (269.6 kBtu/m^2), median year home built was less than the study area mean (1966.5), and median household income was less than the study area mean ($51411.50). There were 263 block groups meeting these criteria (34.7% of block groups). More than a quarter of the area's population (26.6%) resided in high-risk block groups. The racial composition included 49.7% of the Black population, 46.9% of the Hispanic population, and 18.7% of the White population. Black and Hispanic households within the high-risk block groups are highly overrepresented compared to their representation within the entire study area (29.6% Black, and 8.6% Hispanic), while White households are underrepresented (62.4%). If there were no disparities in heating EUI this would not be the case.

To understand the odds that the racial/ethnic and socioeconomic characteristics of a block group contribute to that block group's likelihood of being high-risk, logistic regression results are presented in Table 4. Table 4 suggests that a 10% difference in percent households in poverty increased the odds by 2.7% ($p<0.01$) that the block group is high-risk. Racial/ethnic characteristics (percentages of Black and Hispanic households) are significant predictors of high-risk block groups ($p<0.001$). For instance, a 10% increase in Hispanic households increased the high-risk odds by a factor of 10.8. Logistic regression results showed that high-risk block groups are poorer, have less educational attainment, have more households headed by seniors, and have greater percentages of Black and Hispanic households.

4. Conclusion and policy implications

This study estimated the mean heating EUI for 757 census block groups in the Kansas City, Missouri (Jackson, Clay, and Platte counties). The findings demonstrate that disparities exist in the relationships between the spatial, racial/ethnic, and socioeconomic characteristics of census block groups and the estimated mean block group heating EUI (kBtu/m^2), a proxy for energy efficiency where a higher EUI signals relatively less efficiency when compared to similar sized homes. Predictions reveal that block groups with lower median incomes, a greater percentage of households below poverty, a greater

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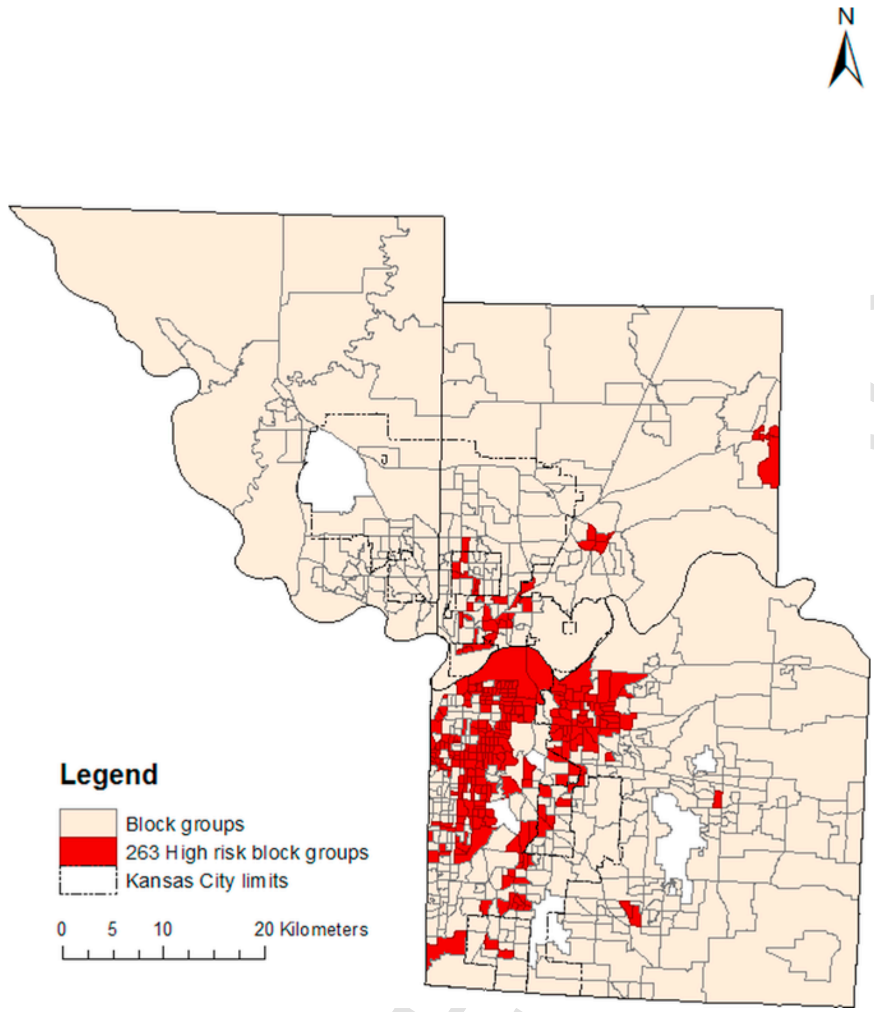

Fig. 3. High-risk block groups. High-risk block groups are defined as those where heating EUI, median age of home, and median household income were worse than the study area average. There are 263 high-risk block groups identified.

Table 4
Logistic regression – high-risk block groups.

	Odds ratio	S.E.
Percent black householders	1.014***	0.004
Percent Hispanic householders	1.079***	0.023
Percent households below poverty level	1.027**	0.010
Percent population with less than high school diploma	1.050***	0.013
Percent households with householder aged 65+	1.021**	0.008
Intercept	0.060***	
Pseudo R^2	0.24	
N	757	

*Significance $p<0.05$

** Significance $p<0.01$.

*** Significance $p<0.001$.

percentage of racial/ethnic minority headed households, and a larger percentage of the population with less than a high school education experienced higher mean heating EUIs. Essentially, homes in block groups exhibiting these demographic and socioeconomic characteristics are more likely to be less energy efficient when compared to other block groups in the region.

This analysis also reveals an association between the enduring effects of residential racial and income segregation and the distribution of residential energy disparities. The figures above illustrate that past institutionalized residential segregation continues to influence urban housing consumption and translates directly to energy-related disparities. Urban sociologists often associate residential segregation with concentrated social and economic disadvantage (Sharkey, 2013; Sampson, 2012; Klinenberg, 2002). The results of this study follow decade-old reports by two major African American organizations about the relationship between Blacks, energy and climate change. Both the Congressional Black Congress Foundation and the American Association of Blacks in Energy released reports in 2004 assessing the disproportionate effects of energy inequities on Blacks. Since these reports, there has been little research conducted on this issue and virtually no policy advances. Recognizing that the uneven development patterns and high levels of residential segregation evident in Kansas City occur in other US urban areas, such as St. Louis and Detroit, this study should be replicated to explore if similar energy disparity patterns exist and determine the need for a national urban energy justice policy.

Space heating remains the largest, single end use, accounting for 41% of residential energy consumption (EIA, 2013c). Modeling the efficiency of residential space heating (and cooling) is important because of its responsiveness to weather. Prioritizing heating energy efficiency and targeting building envelope retrofits, before appliance and lighting efficiency, may have greater potential as the lifespan of a housing unit most likely outlasts the current occupant and appliances.

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Additionally, in dominant discussions on climate change, global warming specifically, winter weather and cold conditions receive far less attention. Nevertheless, recent studies have found that the effects of global warming (i.e. the loss of Arctic sea ice) can be linked to extreme and prolonged cold weather patterns in mid-latitudes, such as the cold spells experienced by northeastern and Midwestern states during the polar vortex of winter 2014 (Peings and Magnusdottir, 2014, Tang, 2013, Francis and Vavrus, 2012). Subsequently, as climate change adaptation discourse becomes more prevalent, it is necessary to understand the material experience of changing environmental conditions, the effect on everyday life, and the potential ways in which communities are threatened (Schlosberg, 2013).

Furthermore, energy related disparities increase the sensitivity of low-income and other vulnerable households to extreme temperature exposure resulting in detrimental health implications (Noe, Jin and Wolkin, 2012; Centers for Disease Control [CDC], 2006; Taylor et al., 2001). The Centers for Disease Control (CDC) found that between 2006 and 2010, 63% of weather-related deaths were attributed to extreme cold exposure, compared to 31% attributed to heat-related causes (Berko et al., 2014). Weather-related death rates varied by age, race/ethnicity, sex, location, and income (Berko et al., 2014). For vulnerable populations like the elderly, extremely cold temperatures can be deadly, even indoors. Elderly patients admitted to the intensive care unit for hypothermia are more severely affected and die more frequently when found indoors compared to those found outside with equivalent body temperatures (Mégarbane et al., 2000). In another study, almost half of hypothermia-related deaths occurred indoors, with death rates particularly high among Blacks aged 80 years or older (Taylor et al., 2001). Despite these findings, there is a lack of recognition of the magnitude of problems associated with dangerous indoor temperatures when homes are not adequately heated. Instead, public health agencies often issue broad cold-weather injury risk reduction precautions primarily focused on outdoor protection, like layering clothes and keeping emergency kits and blankets in the car (CDC, 2006). Mapping heating energy efficiency can be combined with hypothermia health data for additional analysis on the connection between efficiency and winter-related injuries and death.

To the disadvantage of the millions of Americas who struggle to access and maintain affordable heating energy services, the consequence of not identifying distinct forms of social inequality in residential energy efficiency means more broad-based energy policies that fail to serve those with the greatest need. For instance, the passage of the 2009 economic stimulus bill created various residential energy efficiency programs across the country. Most programs, however, were market-based interventions in the form of low-interest loans and tax rebates which limited participation by low-income households who often lack adequate credit worthiness to qualify for loans and rarely earn enough annual income to file for tax rebates. Although \$5 billon was committed to the Department of Energy's Weatherization Assistance Program, the rollout was slow and inconsistent (Grunwald, 2012). In part, the lack of comprehensive accounting of local energy consumption and efficiency disparities, forced weatherization agencies to rely on prevailing practices of first-come, first-served self-referral operating procedures (Fuller et al., 2010; Madrid and James, 2012). A growing body of research demonstrates that the spatial concentration of fuel poverty risk factors, justifies taking proactive, targeted, area- or community-based approaches for implementing energy assistance programs to overcome participation barriers, including those that are social and cultural, and to more efficiently and effectively deliver services in vulnerable communities (Reames, 2016; Walker et al., 2013; Hallinan et al., 2012).

Moreover, modeling energy use intensity rather than total energy consumption provides more meaningful information for analyzing disparities and targeting the most appropriate intervention to the appropriate location. The residential sector has made energy efficiency progress, continuing a three-decade decline in average consumption per home even as the number and average size of housing units increase. This trend is primarily a result of efficiency improvements for newer homes. While aggregate residential sector statistics and analyses are useful for policy and program development, they often mask the heterogeneity of energy users, resulting in a lack of equity considerations. The use of bottom-up statistical models and mapping, extrapolated to smaller-scale spatial areas allows a more nuanced analysis of energy consumption. While several energy-mapping projects are in various stages of development and implementation across the nation (e.g., Twin Cities Energy Mapping Tool in Minnesota), a barrier to more of these projects remains the proprietary nature of individual energy data, as utilities express concerns about customer privacy, or have little incentive to participate in projects that have the potential reduce revenue. In the meantime, using readily available public data and the methodological procedures presented in this study, offer an alternative for community energy mapping when local utility energy data are unavailable.

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