Development of an Integrated Model System of Transport and Residential Energy Consumption

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ABSTRACT

The energy footprint of households is inextricably tied to the amount of travel undertaken by households. The transportation energy consumption is dependent on the mix of vehicles that a household owns and uses, and the extent to which different vehicles in a household are driven. Integrated models of activity-travel demand and transport energy consumption often do not consider the mix of vehicle types owned and used by households, thus making it difficult to assess the energy implications of shifting vehicle/fuel type choices – particularly in a rapidly evolving marketplace. More importantly, integrated models of activity-travel demand and transport energy consumption do not consider the residential energy consumption implications of travel. If people travel more (and spend more time outside home), they may consume more travel energy, but consume less in-home residential energy. Thus, an integrated model system that tightly connects activity-travel demand, travel energy consumption (sensitive to vehicle fleet/fuel type), and residential energy consumption (sensitive to activity-travel choices) is needed to obtain a holistic picture of household energy footprints. This paper describes the integrated model system that connects these three entities. The model is developed by fusing information between two survey data sets, namely, the National Household Travel Survey (NHTS) data set and the Residential Energy Consumption Survey (RECS) data set. The integrated model system is applied to a synthetic population for the Greater Phoenix area in Arizona to illustrate the efficacy of the model system.

Keywords: Integrated models, Transport energy, Residential energy, Household energy footprint, Data fusion and imputation

1. INTRODUCTION

The US Environmental Protection Agency (EPA) estimates that the nation's transportation, commercial, and residential sectors contributed 29, 19, and 21 percent respectively, of the total greenhouse gas (GHG) emissions in 2016 (EIA, 2017), indicating that human activity plays a significant role in shaping the carbon footprint in communities and cities. It is therefore of considerable importance to quantify the consumption of energy that is attributable to each of these sectors, as the energy consumption patterns directly translate into GHG emissions that contribute to global climate extremes. In an effort to address this need, this paper presents an integrated model system that can be used to compute the household energy footprint.

Within the scope of this paper, household energy footprint is assumed to comprise of two main components. The first component is the *transport energy consumption* and the second component is the *residential energy consumption* that stems from electricity, natural gas, and other utility expenditures. The transport energy consumption is dependent on the mix of vehicles that a household owns and uses, and the extent to which each of the different vehicles in a household is driven. The residential energy footprint primarily stems from the consumption of electricity and natural gas, although other fuel sources may also contribute to a household's utility expenditure pattern. The scope of analysis of residential energy footprint can be very broad depending on the extent of the supply chain that is considered and the extent to which embedded energy is included in the accounting system. For purposes of quantifying and characterizing the residential energy footprint in this paper, only the actual operational energy consumption (utility expenditures) is considered. The total household (operational) energy footprint may then be viewed as a sum of the transport energy consumption and residential energy consumption, with both components accounting only for the operational energy consumption within the respective domains.

There is a relationship, however, between residential and transport energy consumption. The residential energy consumption may be posited as being influenced by activity-travel characteristics of household members. If household members travel extensively outside the home, then the residential energy consumption may decrease if the households take necessary energy saving precautions when they are not at home. Such households may have large transportation energy footprints and smaller residential energy footprints. Conversely, households that spend a lot of time at home may have smaller transport energy footprints, but larger residential energy footprints. The estimation of the total energy footprint of a household should take into account the potential relationship that may exist between transport and residential energy footprint.

Despite considerable work in this area, an integrated model of household energy footprint that accounts for the relationship between transport and residential energy consumption remains elusive. This paper aims to fill this critical gap by presenting a comprehensive integrated model system and energy analysis tool that can be used to quantify the total household energy footprint, including the separate transport and residential energy consumption components. The model system is developed through a multi-step process that involves fusing information contained in the 2017 National Household Travel Survey (NHTS) data set (which includes detailed vehicle and travel information) and the 2015 Residential Energy Consumption Survey (RECS) data set (which includes detailed residential energy-related information). The model system involves computing the transport energy footprint based on household vehicle mix and miles of travel, and then computing both electricity and natural gas consumption while explicitly accounting for the influence that activity-travel behavior may have on the residential energy consumption patterns.

The remainder of this paper is organized as follows. The next section offers a brief overview of the work in this topic area. The third section presents a brief overview of the two data sets used and fused in this study. The fourth section offers a detailed description of the integrated modeling framework and methodology. The fifth section presents an illustrative application of the model system to a synthetic population for the Greater Phoenix area in Arizona. The sixth and final section offers concluding remarks.

2. UNDERSTANDING AND QUANTIFYING THE HOUSEHOLD ENERGY FOOTPRINT

There is a vast body of literature devoted to analyzing and quantifying energy consumption patterns of various entities. However, modeling tools developed thus far do not explicitly account for inter-dependencies among constituent energy consumption components that are vital to forecasting the energy footprint in response to changes in population characteristics and built environment conditions, technology, transportation network attributes, and public policies.

Many studies have focused on analyzing residential energy consumption patterns. It has been reported that spatial configuration and land use patterns are important determinants of residential energy consumption (e.g., Wang et al, 2016). Yang et al (2019) studied the impact of urbanization on China's residential energy consumption and found that increased urbanization leads to an increase in both urban and rural residential electricity consumption. However, another study using data from Thailand found that urban residents consume less energy than rural counterparts (Meangbua et al, 2019). Other studies (e.g., Belaid, 2019) have explored the influence of dwelling unit characteristics and size, household characteristics, and household behaviors on residential energy consumption. Variation in temperatures, especially due to global climate change, significantly influences residential energy consumption. Maengbua et al (2019) concluded that a 1° Celsius rise in temperature results in 200 percent increase in energy consumption. More recently, Zhang et al (2018) applied a microsimulation-based approach to estimate residential energy consumption. The study involved the fusion and synthesis of data across energy and census data sets to estimate a model of residential energy consumption of the individual household. The work in this paper is intended to extend that model in very significant ways by integrating transportation energy consumption and activity-travel behaviors to obtain a holistic household energy footprint estimation model system.

Likewise, there is a vast body of work dedicated to measuring and quantifying transport energy consumption. Recently, Brand et al (2019) assessed the impacts of lifestyle changes and transition to electric vehicles (EV) on transportation energy consumption. Disruptive transportation technologies offer a promising mobility future, but an uncertain energy consumption future. Wadud et al (2016) assessed the impact of autonomous vehicles on energy consumption and found that automation could double energy use or cut it to one-half of current levels under different scenarios. Similarly, Chen et al (2017) concluded that fuel consumption in an autonomous vehicle future would reduce by 45 percent under optimistic scenarios and increase by 30 percent under pessimistic scenarios. Another study assessed the energy implications of ride-hailing services in Austin and found that the energy use may increase by 41-90 percent compared to baseline, pre-ride hailing, personal travel conditions (Wenzel et al, 2019). Ding et al (2017) explored the impacts of the built environment on vehicle miles of travel (VMT) and energy consumption and found that vehicle energy consumption is inversely related to employment density and street connectivity. Other efforts aimed at quantifying transport energy consumption include those by Tirumalachetty et al (2013) and Das and Parikh (2004). More recently, Garikapati et al (2017) developed a framework to estimate household energy footprint at the traffic analysis zone (TAZ) level through an interface with a standard metropolitan travel demand model. They noted that any travel energy footprint calculation that does not account for variation in vehicle fleet mix distribution across space is likely to not only be erroneous, but also fail to provide the policy sensitivity that may be desired for analyzing alternative fuel vehicle scenarios (owing to evolution of technology, changes in the marketplace, or incentives and disincentives instituted through public policy interventions).

In summary, there is much interest in analyzing and computing household energy consumption patterns. In fact, a few studies have attempted a more holistic and integrated approach to energy analysis; for example, Shekar et al (2018) studied the impact of changes in activity time use on energy consumption. The authors find that lifestyle changes caused by technology contribute to shifts in energy use across sectors. Despite these and many other advances (e.g., Sheppard et al, 2017; Auld et al, 2018) in the development of energy modeling tools, an integrated model system that considers the inter-relationship between transport and residential energy consumption in computing a household energy footprint remains elusive; this effort is intended to fill this gap.

3. THE TRAVEL AND ENERGY SURVEY DATA SETS

An integrated transport and residential energy analysis tool requires information from two major survey data sets as explained previously. Transportation, activity participation, and vehicle fleet related information need to come from a travel survey data set while residential energy consumption information needs to come from an energy survey data set. For the development of the integrated model, the two data sets used in this study are the 2017 National Household Travel Survey (NHTS) data set and the 2015 Residential Energy Consumption Survey (RECS) data set. To control for geographic variations, the model development and application efforts utilized samples exclusively from the western region of the country in this study. The model system can be estimated, calibrated, and applied in any context using appropriate geographically local data.

The National Household Travel Survey (NHTS) data set is derived from a large scale travel survey conducted about every 8-10 years by the US Department of Transportation to understand and quantify travel undertaken by people on a daily basis. Respondent households are asked to furnish detailed information about household and person level socio-demographic characteristics, vehicles owned or leased by the household, and trips undertaken by each member of the household on a specific travel day. Thus, the NHTS is a rich source of information about vehicle ownership and fleet composition for households, which is precisely the information needed to compute the transport energy consumption of households.

The integrated model system includes a household vehicle fleet composition and utilization (VFCU) model so that energy estimates are sensitive to vehicle fleet mix. In this study, four vehicle types were considered: car, van, SUV, and truck. These four vehicle types were further subdivided according to age based on whether the vehicle is less than or equal to eight years old. Thus, there are a total of eight vehicle type categories; in addition, the motorcycle is added as a ninth vehicle category. A multiple discrete continuous extreme value (MDCEV) model of VFCU is developed in this effort to determine the mix of vehicle types that a household may own, together with the amount of mileage that each vehicle will be driven by the household on an annual basis (Bhat, 2008). Information about vehicle type and mileage is available in the NHTS, thus making it possible to estimate such a model. In addition, the NHTS provides detailed activity-travel information for each member of the household for a specific travel survey day. The activity-travel information is used to derive the total time that an individual spends outside home at various activity locations, time spent traveling, and time spent in home (although in-home activities are not explicitly recorded). By aggregating information about travel and activities across individuals within a household, it is possible to derive the total time spent outside home, inside home, and traveling for a household.

The Residential Energy Consumption Survey (RECS) data set is derived from a large scale energy consumption survey that is conducted about every six years. The most recent edition of the RECS data set is of 2015 vintage and used in this study. Although the sample size is reasonably large (by survey design standards), the sample is rather small when compared with the sample size for the NHTS. The sample size utilized in this study comprises 1,555 households (with complete information) distributed across the western region of the country. Similar to the NHTS, the RECS data set includes information about the respondent household, together with detailed information about residential energy consumption – that can be used to estimate residential electricity and natural gas consumption models.

To account for potential inter-relationships between transport and residential energy consumption, the proposed integrated modeling framework involves imputing vehicle fleet composition and utilization (VFCU) information and activity-travel behavior information derived from the NHTS to the household records in RECS. The enhanced RECS data set can then be used to estimate residential energy consumption models that are sensitive to activity-time allocation patterns, VFCU, and transport energy consumption, as well as household characteristics, location attributes, climatic conditions, and housing unit characteristics.

Table 1 presents a summary of the two household samples. A slightly larger percent of households in the RECS data rent their home compared to the sample in the NHTS data. The household income categories do not line up exactly between the two surveys; in the NHTS, nearly 30 percent of households make less than \$35,000, while in the RECS, nearly 40 percent of households make less than \$40,000. Over 85 percent of households in both data sets reside in urban areas. The distribution of the sample from a geographic perspective suggests there is significant differences in the spatial distribution of the samples across the western region, but the differences do not adversely affect the model development efforts described in this paper. Similarly, the two samples exhibit noticeable differences in distributions of household size, number of adults and children, and dwelling unit type. While these differences are noteworthy and merit some additional investigation, they do not adversely affect data fusion/imputation processes here because models are specified to account for such differences. In terms of other characteristics, nearly 50 percent of the households reside in hot-dry/mixed-dry conditions and about 36 percent of the households have three bedrooms. The table also furnishes descriptive statistics for square feet of residences.

4. MODEL DEVELOPMENT AND ESTIMATION RESULTS

This section of the paper provides a summary of the model development and estimation process. The effort undertaken in this study can be broken down into two distinct phases. First, there is the model development phase in which information is fused between two data sets and models are estimated so that they can be applied to any region's population to quantify the household energy footprint. Thus, there is the data fusion and model estimation phase (Figure 1, Steps 1-4). Second, there is the model application phase (Figure 1, Step 5). In this phase, the efficacy of the model is demonstrated by applying the model system developed in the first phase to a real-world case study.

TABLE 1 Description of Household Characteristics (Western Region)

2017 National Household Travel Survey (NHTS) Household Characteristics (N = 26,743 households)		2015 Residential Energy Consumption Survey (RECS) Household Characteristics (N = 1,555 households)	
Variable	Value (%)	Variable	Value (%)
Home ownership		*Home ownership*	
Own	72.4	Own	66.2
Rent	27.6	Rent	33.8
Annual Household income		*Annual Household income*	
Low (less than $35,000)	26.4	Low (less than $40,000)	35.9
Medium ($35,000 to $99,999)	41.9	Medium ($40,000 to $99,999)	37.0
High ($100,000 or more)	31.7	High ($100,000 or more)	27.1
Household in urban/rural area		*Household in urban/rural area*	
Urban	86.6	Urban	86.9
Rural	13.3	Rural	13.1
Region		*Region*	
Mountain West States	15.7	Mountain West States	30.2
Pacific States	84.3	Pacific West States	69.8
Household Size		*Household Size*	
One	31.8	One	20.1
Two	42.6	Two	37.2
Three or more	25.6	Three or more	42.7
Number of Adult household members (Age ≥ 18 years)		*Number of Adult household members (Age ≥ 18 years)*	
One	34.4	One	24.1
Two	54.6	Two	55.7
Three or more	11.0	Three or more	20.2
Number of Young household member (Age ≤ 17 years)		*Number of Young household member (Age ≤ 17 years)*	
Zero	84.4	Zero	65.6
One	8.2	One	14.2
Two or more	7.4	Two or more	20.2
*Housing unit type**		*Housing unit type*	
Detached	70.5	Detached	68.7
Attached	26.2	Attached	9.1
Apartment	3.3	Apartment	22.2
		Climatic Condition	
		Very Cold/Cold	22.8
		Hot-Dry/Mixed-Dry	48.2
		Hot-Humid	1.7
		Mixed-Humid	27.3
		Number of Bedrooms	
		≤ One	12.0
		Two	25.9
		Three	36.0
		Four or more	26.0
		Total Square Feet of Home	Min: 228; Max: 7986; Mean: 1862.6

**Housing unit type information is not available in 2017 NHTS and was imputed based on 2009 NHTS data.*

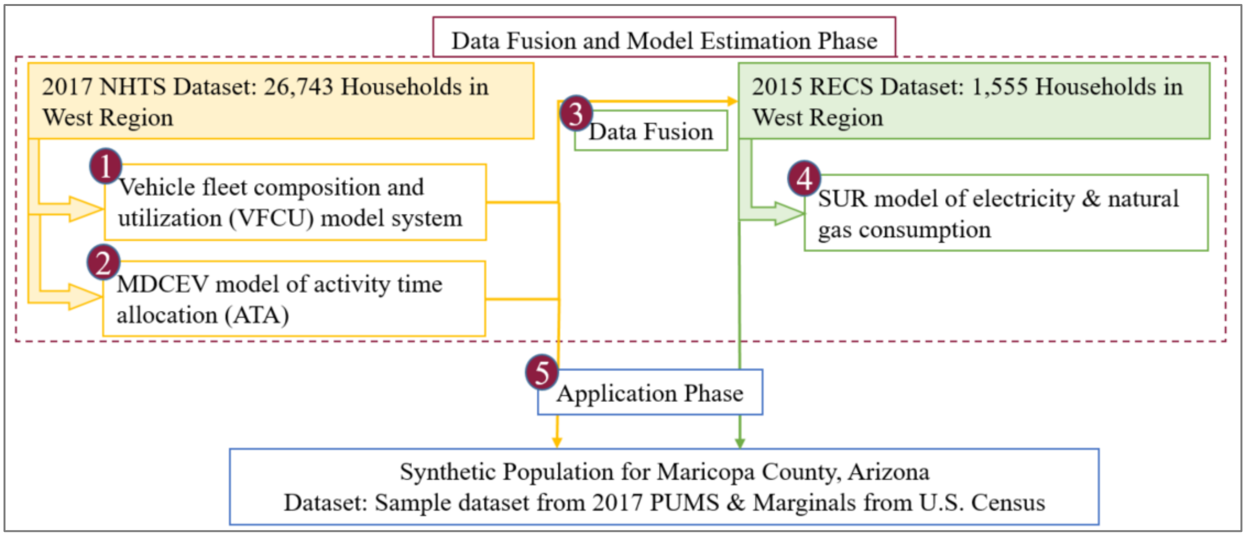

Figure 1 Model Development and Application Framework

An integrated model of transport and residential energy consumption should include components capable of estimating and quantifying:

- Transport energy consumption due to vehicle fleet mix and vehicle miles of travel
- Electricity consumption due to household operations
- Natural gas consumption due to household operations

The *first* step of the system development process involved estimating a vehicle fleet composition and utilization (VFCU) model system on the NHTS data set. The VFCU model system estimated and implemented here is similar to that developed previously (You et al, 2014). The model system includes a number of components:

a) A household mileage budget prediction model: The MDCEV model allocates a continuous household mileage to different vehicle alternatives, thus creating a vehicle fleet composition and mileage profile for each household. To accomplish this, a budget prediction model is needed. The mileage reported in the NHTS data is used to estimate a log-linear regression model of total household mileage.
b) A MDCEV model of vehicle fleet composition: The MDCEV model explicitly recognizes that households may choose to own and consume multiple vehicles of different types. A total of nine vehicle-type alternatives are considered in this study and the MDCEV model is estimated for this choice set. The model is capable of accounting for diminishing marginal utility (satiation effects) and zero consumption (corner solutions) wherein some vehicle alternatives may not be chosen by a household at all.
c) Ordered Probit models of vehicle counts by type: The MDCEV model is able to predict the types of vehicles that a household owns (consumes), but it does not explicitly provide the number of vehicles within each type that a household may own. For example, a household may own two cars that are less than eight years old. While the MDCEV model is able to predict that the household owns cars less than eight years old, it does not explicitly provide a count of the number of cars within that vehicle class. The ordered probit models of vehicle counts by type help establish the number of vehicles that are owned within each class of vehicles that the MDCEV predicts that a household owns.

This entire VFCU model stream was estimated on the NHTS sample for this study and the model was subjected to extensive testing and validation. A few additional steps explained in You et al (2014) were implemented to ensure that the model predictions matched real world vehicle fleet composition and utilization distributions.

The *second* step of the process involved *estimating* a MDCEV model of activity time allocation (ATA). The activity time allocation model allocates a budget of 1440 minutes to various activity categories including out-of-home mandatory activity time (e.g., work, school), out-of-home non-mandatory activity time (e.g., social, shopping), in-home time, and travel time. Further, separate MDCEV time allocation models were estimated for weekdays and weekend days to account for the fact that individuals perform different activities by day of week with consequent implications for residential energy consumption patterns. The activity-travel diary information in the NHTS is used to compute these time durations for each household in the sample. The household time budget is assumed to equal 1440 × number of adults in the household × number of weekdays/weekend-days in a year. This budget is then allocated through a multiple discrete continuous choice process to the four broad activity categories. Because the budget is predetermined in the activity time allocation (ATA) context, there is no need for a model component dedicated to estimating the budget. The MDCEV-*predicted* time allocation patterns are compared against the *actual* patterns in a 20 percent holdout sample to calibrate and validate the model. The model was found to perform very well in replicating observed distributions of activity time allocation and was hence deemed appropriate for imputing activity time allocation patterns to households in the RECS data.

The *third* step involved the application of the MDCEV model of vehicle fleet composition and utilization (estimated in Step 1) to the RECS data set to predict, impute, and append vehicle ownership and mileage information to the household records in the RECS data set. Similarly, the MDCEV model of activity time allocation was applied to the household records in the RECS data set to estimate and append the amount of time that each household devoted to various activity categories. It should be noted that all records in the RECS data set are household level records; hence the time allocation pattern predicted and appended corresponds to activity durations at the household level (for example, the time spent traveling corresponds to the total time spent traveling accumulated over all adult household members).

At the end of the *third* step, each RECS household record has vehicle fleet composition information and corresponding annual mileage values. These vehicle mileage values were converted into transportation energy consumption estimates using the fuel economy data published by the US Environmental Protection Agency (2018). Using energy conversion factors, the total BTU of transport energy consumption was computed for each household and appended to the records in the RECS data set. It should be noted that vehicle body type and age are explicitly considered in the computation of the transportation energy footprint.

The fully enhanced RECS data set now contains information about household characteristics, climatic conditions, and the housing unit (original variables contained in RECS), together with vehicle fleet composition and utilization information, transport energy consumption information, and household activity time allocation information. In the *fourth and final step*, this enhanced data set was used to estimate a seemingly unrelated regression (SUR) equations model of residential electricity and natural gas consumption (these variables are native to the RECS data set). The SUR model recognizes the presence of error correlation between the two linear regression equations embedded in the model system and incorporates transport energy consumption and activity time allocation variables as explanatory factors, thus capturing the potential interdependency between residential energy consumption and household time allocation to activities and travel. Estimation results for the SUR model are presented in Table 2.

TABLE 2 Seemingly Unrelated Regression (SUR) Equations Model Estimation Results

Electricity Regression Equation		*Natural Gas Regression Equation*	
Explanatory Variable	**Coef (t-stat)**	**Explanatory Variable**	**Coef (t-stat)**
Constant	36423 (19.12)	Constant	10637.6 (4.60)
Home Ownership = Owned	2750.3 (2.20)	Low Income Hhld (< $40,000)	-3895.8 (-2.53)
High Income Hhld (≥ $100,000)	1809.7 (1.67)	High Income Hhld (≥ $100,000)	5099.1 (3.02)
Number of Adults ≥ 3 (age ≥ 18)	2958.8 (2.45)	Number of Adults ≥ 3 (age ≥ 18)	2639.3 (1.52)
Housing unit type = Apartment	-10470.0 (-6.86)	Housing unit type = Apartment	-15036.5(-7.97)
Location = Urban	-10649.6 (-7.31)	Location = Urban	15878.4 (7.95)
Region = Mountain	5580.1 (4.39)	Region = Mountain	14138.1 (8.86)
Climate = Mix-Humid	4581.1 (3.88)	Climate = Mix-Humid	-4925.1 (-3.00)
Number of Bedrooms = 1	-2203.6 (-1.18)	Number of Bedrooms = 1	-3690.1 (-1.46)
Total Square Feet ≤ 600 sq ft	-4290.6 (-2.00)	Number of Bedrooms ≥ 4	15277.8 (9.39)
Annual Out-of-Home Non-Mandatory Activity × HHSize = 1	-0.054 (-2.78)	Annual Out-of-Home Non-Mandatory Activity × HHSize ≥ 3	0.010 (2.29)
Annual Out-of-Home Non-Mandatory Activity × HHSize ≥ 3	0.0093 (3.02)	Travel Time × HHSize ≥ 3	0.011 (1.93)
Travel Time × HH Size =1	-0.067 (-2.95)		
Number of Observations: 1,555 households R-squared: 0.199		Number of Observations: 1,555 households R-squared: 0.269	

Model estimation results are behaviorally intuitive and consistent with expectations, potentially suggesting that the data imputed to RECS is consistent with patterns of energy consumption and household activity time allocation that are seen in the real world. In the electricity consumption regression equation, it is found that out-of-home non-mandatory activity time (e.g., time spent outside home shopping or socializing) negatively affects electricity consumption for one-person households, but positively for three or more person households. When the individual in a single-person household spends time outside home, there is presumably nobody at home – thus reducing energy consumption. In a large household with three or more persons, it is possible that some individuals are at home (consuming energy) even when others in the household are pursuing activities outside home. Thus, multi-person households are likely to exhibit higher levels of activity both inside and outside home, thus contributing to a larger energy consumption footprint. Similar findings emerge for out-of-home travel time for single person households. High-income households consume more electricity than other households, presumably because they can afford greater levels of consumption of goods and services (e.g., ability to own large homes with larger number of rooms) (Maengbua et al, 2019). Larger households consume more electricity, as expected. Homes in urban areas consume less electricity as do households in apartments. These tend to be smaller homes in urban locations and hence consume less energy (Maengbua et al, 2019). Similarly, houses with one bedroom and square footage less than 600 feet consume less electricity, a finding similar to that reported by Belaid et al. (2019). Houses in mix-humid conditions and mountain regions tend to consume more electricity, presumably due to the need to run the air conditioning.

The equation for natural gas consumption also offers behaviorally intuitive interpretation. Out-of-home time allocation for non-mandatory activities has a positive impact on natural gas consumption for larger households, similar to the finding for electricity consumption. The same pattern is seen for travel time as well. As household income increases, so does natural gas consumption, presumably due to higher levels of consumption of goods and services in high-income households (Davis and Muehlegger, 2010). Natural gas consumption also increases with number of adults in the household. Interestingly, it is found that homes in urban areas consume more natural gas as do homes in mountain regions. This may be reflective of the energy mix in homes located in these spatial contexts. As the number of bedrooms increases, energy consumption increases. Households in mix-humid condition tend to consume less natural gas, presumably because natural gas is often used for heating; and in mix-humid conditions, households may need more cooling that uses electricity rather than natural gas.

At the end of the four steps in the model development and estimation phase, an integrated model of transport and residential energy consumption that can be applied to a population of agents (households) is obtained (Figure 1, Step 5). The suite of models that comprise the integrated transport and residential energy analysis tool constitute the following:

a) MDCEV model of household vehicle fleet composition and utilization (mileage)
b) MDCEV model of household daily activity time allocation
c) Transport energy computation model utilizing energy intensity tables that provide conversion factors (EPA, 2018) to translate miles of household travel by various vehicle types to equivalent energy consumption
d) Residential energy consumption model (SUR model) of electricity and natural gas consumption

It should be noted that both NHTS and RECS are national data sets, and hence caution should be exercised when applying models estimated on large regional samples to individual jurisdictions (e.g., cities or counties). Unfortunately, the RECS data set is not quite large enough to support very localized model estimation efforts. Hence, in this study, the entire sample from the western region was used for model development purposes. Given this geographic scope of the model estimation data set, it may be reasonable to apply the model to jurisdictions that fall squarely within the region. For illustrative purposes, the model was applied to the Greater Phoenix area in Arizona; this case study is described next.

5. ILLUSTRATIVE CASE STUDY

The case study involved applying the model system to a synthetic population generated for Maricopa County (Greater Phoenix area) in Arizona, and computing and mapping the energy footprint per household across the census tracts in the region. Synthetic population generation and energy computations may be done at any geographic resolution; the census tract is used here for illustrative purposes and convenience.

The case study region of Maricopa County, AZ, includes 916 census tracts and encompasses a population of 4,155,501 persons residing in 1,489,533 households in 2017. A synthetic population was generated for the region using a software package called PopGen (Konduri et al, 2016). PopGen creates a synthetic population for a region by weighting and expanding a sample data set such that the weighted sample is representative of the true population with respect to marginal distributions on a number of control variables of interest such as household size, household income, number of workers, number of children, person age, person gender, and person employment status. The marginal control distributions representing true population characteristics are typically obtained from the census or regional agency databases. The American Community Survey (ACS) Public Use Microdata Sample (PUMS) data serves as the seed sample which will be weighted and expanded to a full synthetic population that matches the marginal control distributions. For each census tract, the sample is weighted to match marginal control distributions on variables of interest, and then households are drawn according to weight-based probabilities to create a synthetic population that matches true population numbers. More details about PopGen algorithms can be found in Konduri et al (2016). Synthetic populations for all census tracts are combined to form the county-wide synthetic population of households and persons. As the sample records drawn into the synthetic population are derived from PUMS, the records are rich with information necessary to apply a model of the nature described in this paper.

The entire suite of models (Figure 1, Step 1-4) described in the previous section is applied to the synthetic population. First, the MDCEV model of vehicle fleet composition and utilization is applied; this provides the vehicle fleet mix and mileage for each household. Second, the MDCEV model of activity time allocation is applied; this provides the time spent by each household (as a whole) in various activity categories including in-home, out-of-home mandatory activities, out-of-home non-mandatory activities, and travel time. Note that the application of the MDCEV models requires that they be exercised in forecasting mode; the procedures described in Pinjari and Bhat (2011) are used to accomplish this. By the end of this step, each synthetic population household is appended with vehicle fleet composition and utilization as well as activity-time allocation information. Then, the energy intensity conversion factors are used to compute the transport energy consumption for each household. Finally, the SUR model of residential energy consumption is applied to compute residential electricity and natural gas consumption as a function of various factors, while accounting for the relationship between residential energy consumption and activity time allocation.

After the residential and transport energy footprints are computed for each household in the synthetic population, summaries are derived and aggregate measures of energy consumption are calculated at the census tract level. Figure 2 shows the spatial distribution of energy consumption per household for census tracts in the Maricopa County, AZ, region. The first picture depicts transport energy consumption, the second graphic depicts residential energy consumption (sum of electricity and natural gas consumption), and the third graphic displays total energy footprint obtained by adding up the residential and transport energy consumptions. The thematic maps reveal that total energy consumption is higher in more affluent, lower density outlying cities and towns. In general, a clear pattern can be seen across all three figures. Census tracts in the middle (urban core areas) are greener, while census tracts in outlying suburban areas and towns are more red (signifying a higher level of energy consumption per household). This pattern may emerge because of a number of reasons; households in outlying suburban areas are likely to be more affluent and residing in larger homes, have larger households, have higher vehicle ownership, and need to drive to reach destinations. Census tracts can be categorized into one of four groups, depending on where they fall – on average – compared to the overall region wide average energy footprint per household:

- HH: Both residential and transportation energy consumption per household are above the regional averages
- HL: Higher residential energy consumption and Lower transport energy consumption
- LH: Lower residential energy consumption and Higher transport energy consumption
- LL: Lower residential energy consumption and Lower transport energy consumption

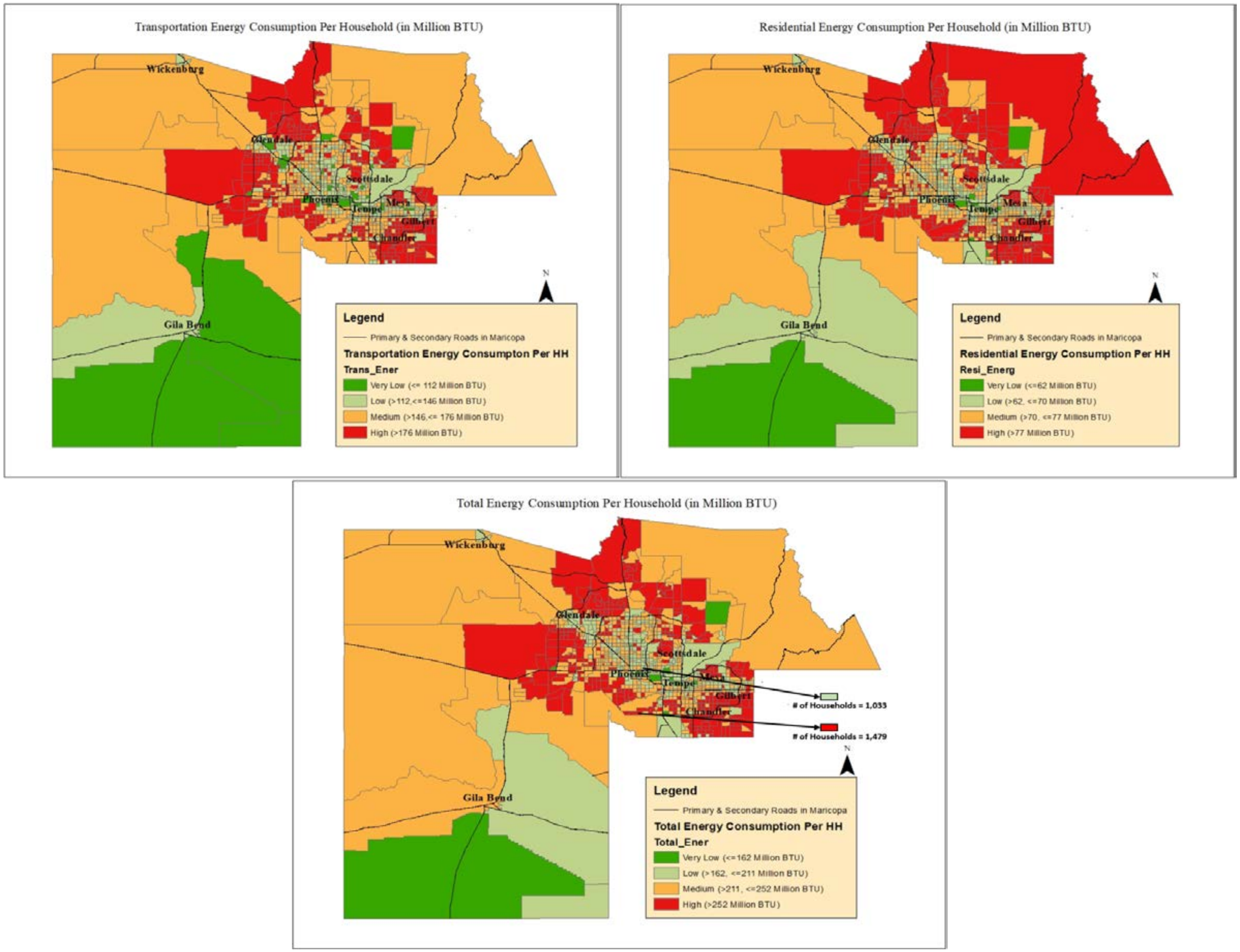

Figure 2. Visualization of Energy Consumption Distribution for Maricopa County, Arizona

The average annual energy footprints were computed to be 59,405,158 BTU of residential energy consumption and 119,604,797 BTU of transport energy consumption (per household). These numbers are generally consistent with expectations and match real-world energy consumption estimates (EIA, 2017).

Figure 3 shows a comparison between the HH and LL household segments. It can be seen that there are very clear differences between households that are high consumers of residential and transport energy and households that are low consumers of energy. Because the distributions of energy consumption are skewed, the size of each segment varies. While 17 percent of households fall into the HH segment, 40 percent of households fall into the LL segment. This is consistent with expectations as the average is likely to be impacted by outliers in the energy consumption spectrum. The comparison between the HH and LL segments shows a number of patterns that are very consistent with expectations, suggesting that the integrated model developed in this effort offers intuitively reasonable estimates of household energy footprint.

Households that are energy guzzlers have substantially higher incomes levels than households in the LL category. In fact, of the households in the HH category, nearly one-half belong to the high-income group. While 88 percent of households in the HH category own their homes, only 46 percent of households in the LL category do so. Among households in the HH category, 95 percent reside in detached housing units; the corresponding percent for households in the LL category is just 45 percent. Households in the LL category show substantially smaller household sizes, with about 40 percent of the households in this segment having only one person. Overall, it can be seen that household structure, composition, and income significantly impact household energy consumption patterns.

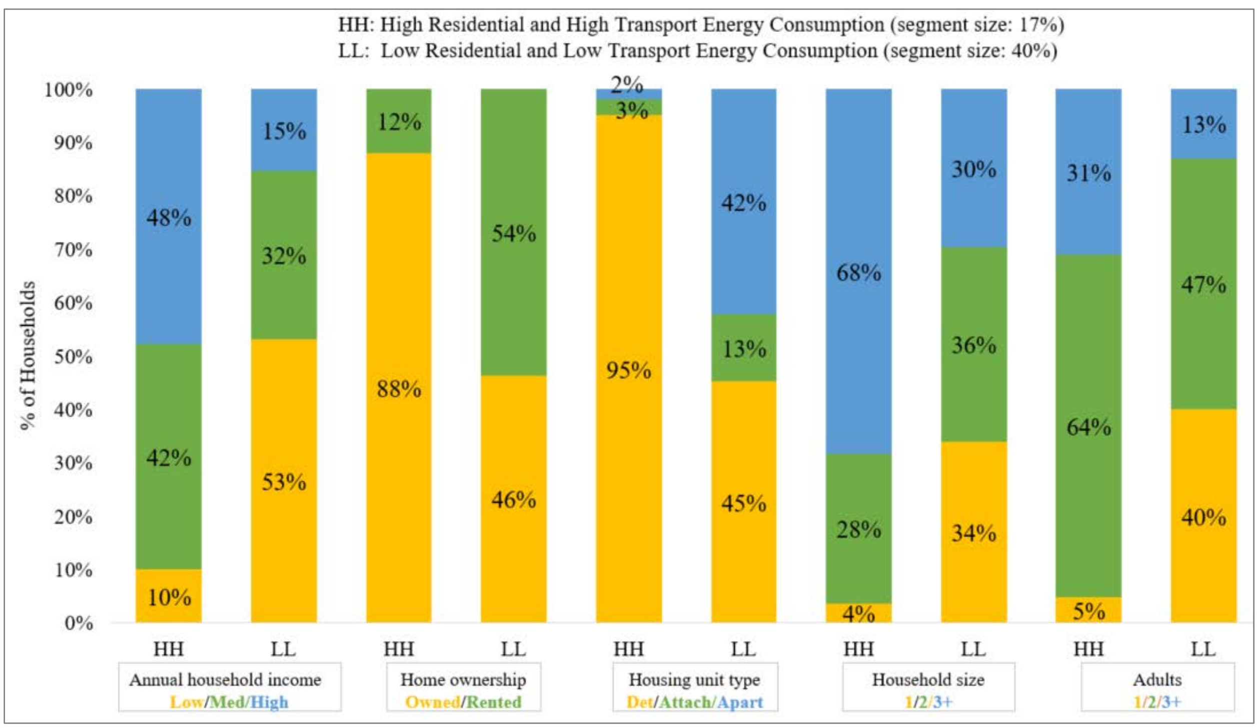

Figure 3. Comparison of Household Profiles Based on their Energy Consumption Bin

In the interest of brevity, the graph comparing HL and LH households is not shown in this paper. However, some interesting differences are seen between these two groups of households. The HL segment (high residential and low transport energy consumption) comprises 26 percent of the population, while the LH segment comprises 17 percent of the households in the region. In general, households that have higher transport energy consumption tend to be larger and more affluent, which is to be expected given their higher activity levels.

To further illustrate the efficacy of the modeling tool presented in this paper, two census tracts that have different energy consumption profiles were compared. The two census tracts that were compared are highlighted in the third panel of Figure 2. One census tract has a low per-household energy consumption (L) while the other has a large per-household energy consumption (H). What makes households in one census tract to be higher energy consuming entities than households in another census tract? Households in the respective census tract were compared with respect to their attributes and the results are shown in Figure 4. Both census tracts have about an equal number of households. The census tract with high-energy consumption (H) has 1,476 households while the census tract with low total energy consumption (L) has 1,033 households. In other words, the number of households in the census tracts is not necessarily affecting the energy consumption per household. Rather, it is the attributes of the households that contribute to the differences.

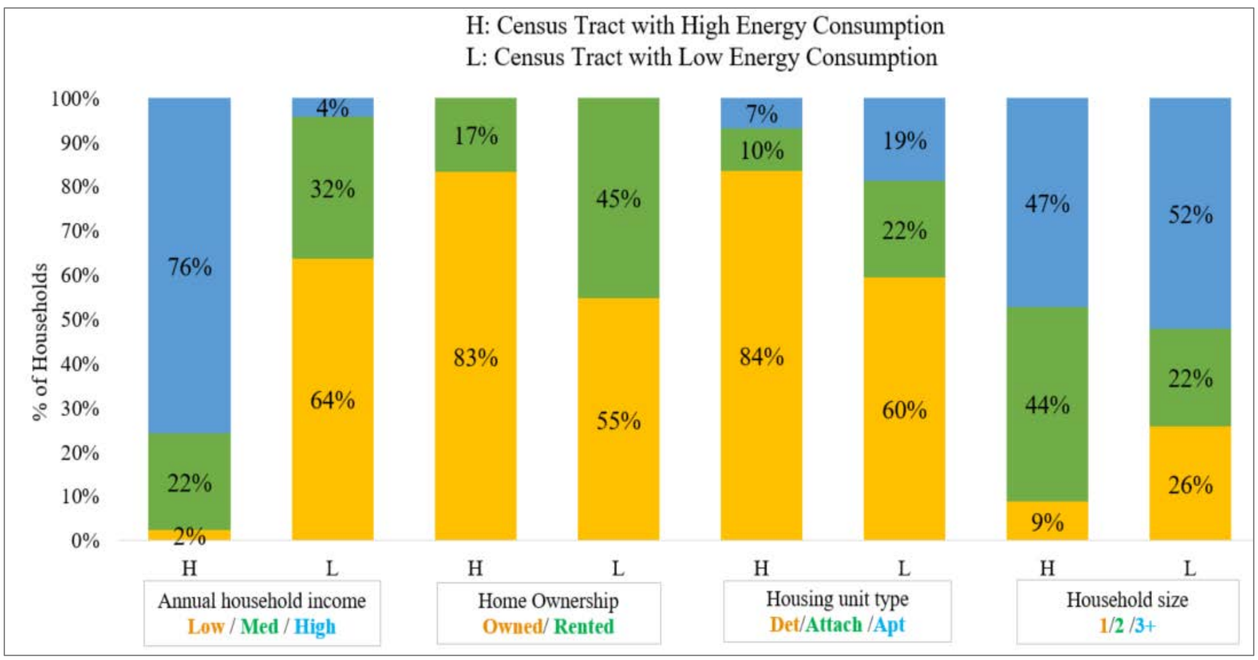

Figure 4. Comparison of Two Zones with Different Energy Consumption Profiles

As expected, a larger proportion of households in the high-energy consumption zone are owned (than in the lower energy consumption zone). The disparity in income distribution is extremely telling. While 64 percent of households in the low-energy consumption zone are low income, only 2 percent of households in the high-energy consumption zone fall into this income category. Similarly, high-energy consumption zone has a higher percent of detached single-family dwelling units than the low-energy consumption zone. The low-energy consumption zone has 26 percent single-person households while the high-energy consumption zone has only nine percent in this household size category.

It is clear that socio-economic and demographic characteristics as well as housing unit attributes significantly impact energy consumption patterns of households. In addition, built environment attributes, mix and density of land uses, and availability of multiple modes of transportation are likely to impact energy consumption footprints. The spatial patterns seen in Figure 2 suggest that density and access may be playing an important role in shaping energy consumption footprints as well. It would be valuable to determine the relative contributions of socio-economic/demographic factors on the one hand and built environment and multimodal access factors on the other hand, to the household energy footprint. By doing so, it would be possible to devise land use, housing, and transportation policy interventions that reduce the energy footprint and advance sustainable development patterns.

6. CONCLUSIONS

This paper presents an integrated transport and residential energy analysis tool that is capable of quantifying the transport energy consumption and residential energy consumption of an individual household. The motivation to build such a tool stems from the possible inter-relationships that may exist between these two energy consumption footprints. A household that travels more and spends more time outside the home is likely to have a high transport energy footprint but may have a lower residential energy footprint and vice versa. Only operational energy consumption is considered within the scope of the tool presented in this paper; energy consumed during travel is transport energy consumption and electricity and natural gas consumed at home constitute the residential energy consumption footprint.

In order to facilitate an integrated approach to residential and transport energy consumption analysis, detailed activity-travel and vehicle fleet composition and utilization information is modeled using the National Household Travel Survey (NHTS) data set and then applied to the Residential Energy Consumption Survey (RECS) data set to impute transportation related variables in the RECS data set. The enhanced RECS data set is then used to estimate regression equations of electricity and natural gas consumption that incorporate transport and activity time allocation related variables as explanatory factors. In general, it is found that household activity-time allocation patterns affect residential energy consumption, albeit differently for households of different sizes. While single-person households depict a clear trade-off between residential and transport energy consumption, larger households depict a more complementary (mutually reinforcing) relationship – suggesting that integrated models of household and transport energy consumption need to recognize heterogeneity in the nature of the relationships between them across the population of households in a region. In general, households that travel more are likely to have active lifestyles that also contribute to higher levels of residential energy consumption.

The integrated model system is applied to a synthetic population for the Greater Phoenix area in Arizona to demonstrate the efficacy of the model. The entire model stream is applied to the synthetic population to estimate transportation and residential energy consumption footprints for all households in the region. These computations facilitated the identification and comparison of different energy consumption market segments and the findings are very intuitive with larger households, higher income households, households in detached single-family units, and households owning their home exhibiting higher levels of energy consumption. Households in outlying suburban areas depicted higher energy footprints, suggesting that the built environment may be playing some role in shaping energy consumption patterns. The tool presented in this paper can be used to analyze the energy footprint implications of alternative urban designs and modal investments.

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AUTHOR CONTRIBUTION STATEMENT
The authors confirm contribution to the paper as follows: study conception and design: S. Sharda, R. Pendyala, S. Khoeini; data collection: S. Sharda, S. Khoeini, T. Kim; analysis and interpretation of results: S. Sharda, R. Pendyala, I. Batur, T. Kim; draft manuscript preparation: S. Sharda, R. Pendyala. All authors reviewed the results and approved the final version of the manuscript.

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