ESTIMATING HOUSEHOLD TRAVEL ENERGY CONSUMPTION IN CONJUNCTION WITH A TRAVEL DEMAND FORECASTING MODEL

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ABSTRACT

This paper presents a methodology for the calculation of household travel energy consumption at the level of the traffic analysis zone (TAZ) in conjunction with information that is readily available from a standard four-step travel demand model system. The methodology presented in this paper embeds two algorithms. The first algorithm provides a means of allocating non-home-based trips to residential zones that are the source of such trips, while the second algorithm provides a mechanism for incorporating the effects of household vehicle fleet composition on fuel consumption. The methodology is applied to the Greater Atlanta metropolitan region in the United States. The methodology is found to offer a robust mechanism for calculating household travel energy footprint at the level of the individual TAZ, which makes it possible to study variations in energy footprint across space. It is found that the travel energy footprint is strongly correlated to density of the built environment, although it is likely that socio-economic differences across TAZs also contribute to differences in travel energy footprints. The TAZ-level household travel energy footprint calculator can be used to analyze alternative futures and relate differences in the energy footprint to differences in a number of contributing factors, thus enabling the design of urban form, formulation of policy interventions, and implementation of awareness campaigns that may bring about more sustainable energy consumption patterns.

Keywords: integrated modeling of travel demand and travel energy consumption, travel energy consumption estimation, household travel energy demand, built environment and transport energy demand

1. INTRODUCTION

Despite great strides over the past decade in improving the energy efficiency of the transportation system, the energy footprint of the transport sector continues to be of staggering size. Worldwide crude oil consumption is once again on the rise after a brief and small dip during the depth of the recession in 2008-2009, and stood at more than 90 billion barrels per day in 2013 (*1*). The United States accounts for 20.7 percent of the world's oil consumption and 13.7 percent of its production or supply (*2*). Transportation accounts for 28 percent all energy (*3*), and nearly 70 percent of all petroleum consumed in the United States (*2*). Travel by light duty vehicles, including cars, light trucks, and motorcycles, accounted for a bulk of this footprint at 58.6 percent of transportation-related petroleum consumption (*2*). Vehicle miles of travel (VMT) is on the rise again (*4*) in the United States, and transportation energy consumption is expected to continue rising in rapidly developing economies around the world with rapid motorization and increase in trade and commerce (*5*).

The emission of greenhouse gases is intricately tied to the energy footprint of a society. Considering the health and global climate change implications of a society's carbon footprint, and concerns about energy sustainability in an increasingly energy-hungry world, it is important to understand, measure, estimate, and accurately forecast the energy footprint of the transportation sector to explore ways in which the contribution of transportation to the total energy footprint can be reduced. Although the importance of quantifying the transport energy footprint is well-recognized (*6*, *7*), rigorous modeling frameworks to forecast transport energy demand under different socio-economic, demographic, built environment, and vehicle fleet scenarios continue to prove elusive. Estimates of transport-related energy consumption are often calculated based on aggregate statistics of transport activity and average fuel efficiency measures that may be used to convert measures of transport demand into measures of energy consumption (*8*, *9*).

There are undoubtedly many contributors to transport energy consumption. This paper focuses on transport energy consumption that is attributable to personal or household travel demand, given its large contribution to the total transport energy footprint. Household travel energy consumption is naturally tied to household travel demand and the VMT that households generate using different vehicles that they own and operate. Most metropolitan areas in the United States (and around the world) have a travel demand forecasting model system that is capable of estimating origin-destination travel flows (OD trip matrices) as a function of a number of socio-economic, demographic, built environment, and network accessibility variables. These matrices provide measures of trip exchanges between traffic analysis zones (TAZs) and offer a basis to estimate the household travel energy footprint of a region at the level of the individual TAZ. However, these models largely ignore the household vehicle fleet composition characteristics that are vital to accurately estimating the household travel energy footprint.

Moreover, typical OD trip matrices generated by traditional zone-based travel demand models include a number of non-home-based trip exchanges that are not attributed to the residential zone that is responsible for these trips. Thus, there is a need for an integrated modeling methodology that can effectively utilize the outputs of a travel demand model system to compute the household travel energy footprint for each TAZ. This paper is aimed at presenting, illustrating, and applying a methodology that would allow the calculation of the household travel energy footprint while explicitly accounting for the residential source of non-home-based trips and the mix of vehicle types in the household vehicle fleet. The methodology is illustrated and applied to a 20-county Greater Atlanta metropolitan region to demonstrate its ability to return estimates of the zonal household travel energy footprint using outputs of a typical travel demand forecasting model and information in a typical household travel survey data set such as the National Household Travel Survey (NHTS) in the US.

The remainder of this paper is organized as follows. The next section provides a discussion of alternative methods and various considerations in the modeling of household energy footprint. The third section presents the modeling methodology in detail. The fourth section describes the case study area and the fifth section presents results of the energy footprint estimation using the methodology developed for this study. Concluding thoughts and directions for future research are offered in the sixth and final section.

2. MODELING THE HOUSEHOLD TRAVEL ENERGY FOOTPRINT

The US Environmental Protection Agency (*10*) reports that the nation's transportation sector accounted for 17 percent of total emissions in 2013. Total greenhouse gas (GHG) emissions in the United States were six percent higher in 2013 compared to 1990, but emissions from the transportation sector rose 16.4 percent during that same time period (*10*). There is considerable literature dedicated to analyzing and modeling the energy and emissions footprints of transport activity in recognition of the importance of their impacts on quality of life, human health, and climate phenomena. In an early study, Newman and Kenworthy (*11*) quantified and compared the gasoline consumption across 32 cities in North America and identified the transportation and land use factors that contribute to higher gasoline consumption. Based on aggregate travel and energy consumption statistics, Breheny (*12*) conducted an analysis to assess the change in energy consumption patterns due to decentralization patterns observed in UK cities. Hunt (*6*) used a travel demand model to investigate the potential of different policy options to reduce transport emissions at the link level.

The "Vulcan" system (*13*) is capable of depicting emissions (due to both residential and transportation energy consumption) at spatial scales of 100 km^2 and temporal scales as small as a few hours. While this inventory is effective in mapping existing conditions, it is aggregate in its spatial scale and does not offer a behaviorally robust platform to perform policy analysis and scenario-based forecasting. In an aggregate level analysis of the metabolism of four representative neighborhoods in Toronto, Codoban and Kennedy (*8*) computed transportation energy use by multiplying mode-specific energy efficiency factors by the number of trips and median trip length. Kockelman et al (*7*) quantify the travel related carbon footprint for the US population and identify areas where reductions in the footprint may be achieved. Porter (*9*) presents findings from an aggregate sketch-level analysis of VMT, and corresponding GHG emissions for states and subareas of states using census data.

While the studies presented above are largely aggregate in nature, other efforts focused on computing transportation energy use at a more disaggregate level. Harrington et al (*14*) developed LUSTRE, a behaviorally complex as well as a spatially detailed simulation model of transportation, land use, and economic activity to analyze the impacts of travel demand management policies on transportation-related emissions in the Washington D.C. area. Behan et al (*15*) use IMULATE, an integrated urban transportation and land use model, to analyze the changes in emissions, traffic congestion, and energy consumption in response to policy scenarios. Hensher (*16*) employed TRESIS, an integrated transport, land use, and environmental strategy impact simulation program, to evaluate the impact of several policy interventions on transportation related emissions. Derrible et al (*17*) developed a macroscopic model of greenhouse gas emissions for municipalities, called Municipal Transportation and Greenhouse Gas (MUNTAG).

Tirumalachetty et al (*18*) present a microsimulation model that is capable of estimating travel, commercial, and household energy consumption related emissions. Chester et al (*19*) developed a comprehensive inventory for lifecycle energy and emissions of passenger transportation for San Francisco, Chicago, and New York City. Despite the comprehensive methodology, this study is limited by the fact that travel survey data was used as the sole basis for modal and passenger travel data. Guhathakurta and Williams (*20*) use a parametric lifecycle assessment analysis to quantify the energy demands for infrastructure as well as transport in two subareas of the Phoenix metropolitan region. As these studies do not leverage the information furnished by a travel demand forecasting model, they are not able to serve as platforms for analyzing the energy impacts of alternative future transport scenarios.

Many metropolitan planning organizations (MPOs) in the United States and elsewhere couple their travel model system with an energy and emissions model to compute energy and emissions outcomes. For example, in the United States, the US Environmental Protection Agency has developed an emissions model system called MOVES that takes the outputs of travel demand models and provides detailed estimates of energy and emissions footprints for a region. However, MOVES generally provides region-wide estimates of fuel consumption and emissions, as well as link-level emissions inventories based on the traffic volume and speed profile for each link. Hence, it is difficult to attribute link-level energy consumption and emissions to the zones that generated the travel in the first place.

There are two key issues that this paper intends to address. First, the paper is aimed at developing a methodology that permits the computation of the energy (and eventually, emissions) footprint at the level of the TAZ. A comparison of footprint estimates across TAZs would allow the identification of the role of built environment attributes, multimodal accessibility measures, and socio-economic and demographic characteristics in shaping the travel energy footprint. This means that the non-home based travel demand that is output in the form of an origin-destination (OD) trip matrix needs to be (re-)allocated to the residential TAZs that generated the travel in the first place. A methodology to accomplish such a (re-)allocation has proven elusive and this paper offers a robust, yet practical, methodology to accomplish this.

Second, the vehicle fleet composition in most existing energy and emissions models is input at a regional level; this single distribution is then used to compute energy and emissions inventories at the link, corridor, and zonal levels. While this approach is simple and allows scenario analysis (by exogenously varying the vehicle fleet mix and determining the energy and emissions impacts of a fleet change), it does not adequately account for the fact that the vehicle fleet mix distribution is likely to vary spatially (*21*). This paper proposes a methodology that recognizes the spatial variation in vehicle fleet composition across a region and facilitates obtaining TAZ level estimates of the energy (and emissions) footprint while explicitly accounting for such variations in vehicle fleet mix. At this time, the proposed methodology focuses on estimating energy consumption attributable to automobile travel. The methodology can be easily extended to incorporate the footprint due to transit and other motorized modes of travel.

3. STUDY METHODOLOGY

This section presents the study methodology in detail. It should be recognized that there are (at least) three methods for computing the residential travel energy footprint in a region at the level of the TAZ. They may be described as follows:

1. *Where a Four-Step Travel Demand Model Exists*: Many planning agencies have a four-step travel demand model capable of providing OD trip matrices that quantify the number of trips that are exchanged (in each direction) between any pair of TAZs. The challenge is that the OD matrix provides estimates of trip exchanges between zones without any consideration of the linkages between trips. The question then is: how can the non-home-based trips be apportioned (re-allocated) to residential TAZs that generated them, in order to obtain an accurate household travel energy footprint by TAZ? This is the challenge addressed in the methodology developed in this paper. In addition, virtually all four-step travel demand models do not incorporate vehicle fleet mix considerations in forecasting travel demand. The methodology developed in this paper is also intended to address this limitation, thus providing a strong connection between vehicle fleet mix distribution and energy consumption.

2. *Where an Activity-Based Travel Microsimulation Model Exists*: In activity-based microsimulation models, the entire trip chain of each agent in the population is preserved in the output; the model returns a full activity-travel pattern (consisting of a series of inter-linked activities and trips) for each individual. This detailed set of outputs may be used to calculate the travel energy footprint of every person in every household of the region. If the activity-based microsimulation model incorporates a household-level vehicle fleet composition model that facilitates tracking of vehicle usage, then it would be possible to estimate the travel energy footprint while explicitly accounting for the specific attributes of the vehicle (age, body type, fuel type) used to accomplish each trip. Given that a vast majority of agencies have not yet implemented activity-based travel models and those that have been implemented rarely (if ever) incorporate a vehicle fleet composition and vehicle tracking model, it was considered prudent to first develop an energy calculator that can be effectively interfaced with traditional four-step travel models.

3. *Where No Travel Demand Model Exists*: Most regions would generally fall within the two categories noted above. However, in the few instances where a travel demand model is non-existent, estimates of travel demand need to be obtained before the travel energy footprint can be calculated. To do this, an agency that does not have a travel demand model would still need to assemble TAZ-level socio-economic data files as well as travel time, cost, and distance matrices. Then, a region (with a travel demand model) that is as similar in characteristics as possible should be identified. Using the OD trip matrices, TAZ socio-economic data files, and travel time-cost-distance matrices of this similar region, direct demand equations that model OD trip exchanges as a function of various attributes (i.e., socio-economic characteristics of the origin and destination TAZs, and measures of separation or impedance between them) should be estimated. These direct demand equations may then be spatially transferred to the region in question that does not have a travel demand model. In addition, national level household travel survey data sets may be used to obtain information about vehicle fleet composition (similar to the first method), thus facilitating estimation of residential (TAZ-level) travel energy footprint while accounting for vehicle fleet mix distribution.

This paper focuses on the first method because that is likely to be the most common situation (i.e., an agency has a four-step travel demand model to work with); the development and application of the latter two methods remains a future research task. The remainder of this section describes the first method.

3.1. Spatial Reallocation of Travel Demand in Origin-Destination (OD) Matrices

TAZs are of different types with some heavily residential, others heavily non-residential (commercial), and yet others multi-use (good mix of residential and commercial activity) in nature. An OD matrix output by a four-step travel demand model will provide trip exchanges between these zones; a region with 2,000 zones would have four million such entries (although many of them may be zero or small numbers). In addition, four-step travel models have travel time, cost, and distance matrices that furnish measures of separation or impedance between every pair of zones. Trips that emanate from a purely residential zone may be attributed to the households in that zone; the energy footprint of those trips belongs to that particular zone. However, for non-home-based trips that are exchanged between non-residential and/or multi-use zones, it is necessary to re-allocate or properly attribute the non-home-based trips to the residential TAZs (households) that are responsible for these trips. When an individual residing in zone X makes a trip between zones Y and Z, the trip between zones Y and Z (and the associated energy footprint) needs to be re-allocated and attributed to zone X where that individual lives. This is the re-allocation question that this methodology addresses.

The methodology to appropriately (re-)allocate non-home-based travel and energy footprint to the source (residential) TAZs is best illustrated with an example as shown in Figure 1. Because the travel energy footprint is dependent on both number of trips and distance (miles) traveled, the first step involves a multiplication of the OD trip matrix with the OD distance matrix to obtain a trip-mile matrix. This computation is shown in Step A of the figure. Consider five zones (Z1 through Z5) and let Z5 be a purely non-residential zone. All other zones are multi-use zones including a mix of residential and non-residential land uses. At the end of Step A, the trip-mile matrix provides estimates of the amount of travel (in trip-miles) exchanged by each pair of zones. In addition, for each zone, the total trip-miles produced (column labeled "P") and attracted (row labeled "A") can be computed as a sum of the corresponding row (column) entries.

The re-allocation process commences in Step B, which shows the home-based trip-mile matrix for the illustrative example. First, consider the multi-use zone, Z1. This zone generates a total of 120 home-based trip-miles, leaving a residual amount of 20 non-home-based trip-miles (140-120 trip-miles) that need to reallocated to their residential source zones. In Step B, the non-home-based trip-miles generated by Z1 are re-distributed to the various multiuse zones (including zone Z1) based on the *home-based trip-mile* attraction proportion of each zone. The logic here is that the home-based trip-mile attraction proportion is a good measure of the extent to which households in a zone contribute to the trips that are generated by a multiuse zone. The attraction proportion for the first zone, Z1, is 17/61 = 0.278689. Similar fractions are calculated for the other zones. Note that zone Z5, which is a purely non-residential zone obtains no allocation of non-home-based trip-miles produced by Z1. Based on this home-based trip-mile attraction-proportion based re-allocation, the 20 non-home-based trip-miles of zone Z1 are re-allocated to various multiuse zones. This re-allocation is shown in column $Z1_{NHBTM}(R)$ of the latter table of Step B. Note that the home-based trip-miles of a zone need not be reallocated as these trip-miles are presumably generated by individuals residing in that zone.

A similar re-allocation process is performed for the next zone (Z2). This zone generates 150 total trip-miles and 125 home-based trip miles. The 25 non-home-based trip-miles (150 – 125) are re-allocated to all multiuse zones based on the home-based trip-mile attraction proportion that is attributable to each TAZ (Step C). The 25 non-home-based trip-miles are re-allocated according to the attraction proportions (AP) and the final column of the table in Step C ($Z2_{NHBTM}(R)$) shows the non-home-based trip-mile footprint re-allocated to various zones. This procedure is repeated for all zones, Z1 through Z5. Finally, in Step D, the re-allocated non-home-based trip-miles are accumulated for each zone to calculate the total non-home-based trip-miles generated by and attributable to each multiuse TAZ. The home-based trip-mile footprint is then added to the non-home-based portion to get the total trip-mile footprint for each zone. Note that, at the end of the process, the total trip-miles (footprint) attributed to the non-residential TAZs (e.g., Z5) is zero. While businesses in such zones generate travel and have an associated footprint, the focus of this study is purely on the computation of household travel energy footprint. All household travel energy footprint must be attributed to TAZs that have households in them, and hence purely non-residential TAZs will have a zero household travel footprint at the end of the process in Figure 1. The total trip-mile footprint of zone Z1 increases from 140 trip-miles in Step A to 175 trip-miles at the end of the re-allocation process. This is because some of the non-home-based trip-miles generated by other multiuse zones and some of the 130 trip-miles produced by the non-residential zone (Z5) are actually attributable to (made by) households that reside in zone Z1.

3.2. Incorporation of Sensitivity to Vehicle Fleet Composition

Virtually all four-step travel demand models incorporate vehicle ownership as a key determinant of travel demand. However, vehicle ownership is often solely represented by the number of vehicles owned by households and no information about household vehicle fleet composition is considered in travel demand forecasts. Planning agencies largely rely on default vehicle fleet mix distributions available in MOVES to obtain estimates of energy and emission inventories. While such procedures are able to provide energy and emissions estimates for the region as a whole and by network link, they are not able to provide these estimates at the traffic analysis zone (TAZ) level. Therefore, a procedure that can account for vehicle fleet mix distribution at the zonal level is needed to accurately estimate energy footprint. Two residential zones may generate the same number of trip-miles, but have a vastly different energy footprint if the trip-miles are made by a very different mix of vehicles.

Figure 2 presents the methodology to account for household vehicle fleet composition in the calculation of the household energy footprint. A travel survey data set may be used to obtain the number of households by two key dimensions that are strongly correlated with vehicle fleet composition, namely, income and vehicle ownership (*22*). These two dimensions are used in this methodology because TAZ-level socio-economic data is often available in travel demand model systems for these variables. For illustrative purposes, consider a cross-classification matrix of three levels of income by five levels of vehicle ownership. The vehicle file in a travel survey data set can be used to generate the cross-classification matrix showing distribution of vehicles by income and vehicle ownership. The vehicle file in a travel survey data set will also identify the vehicle type, fuel type, and vintage of each vehicle owned by households in the survey sample. Using a combination of these attributes, consider vehicle type A (say, gasoline cars 0-5 years old). The survey data set can be used to generate the distribution of vehicles of type A by income and vehicle ownership. In the illustrative example depicted in Figure 2, the survey data shows that 78 percent of all vehicles owned by one-vehicle households in the first income category are of vehicle type A.

The right hand side of Figure 2 shows the socio-economic data that is often associated with a travel demand model. If an agency only has univariate distributions (of households by income and vehicle ownership), then a standard iterative proportional fitting procedure may be applied to derive the joint distribution for *each TAZ*. By multiplying the number of households by the number of vehicles in each category, the total vehicles owned by households in each cell of the cross-classification matrix may be derived for *each TAZ*. An average value is used to compute vehicles owned by households in the last (highest) vehicle category. In this particular numerical example, it is found that the households in the TAZ own a total of 164.2 vehicles (the decimal value is due to the average vehicle ownership rate used in the last category). The percent distribution of vehicles by type is then applied to the socio-economic data to obtain the number of vehicles of each type in each cell of the cross-classification matrix for *each TAZ*. In the example, there are a total of 30 vehicles owned by households of income category 3 and vehicle ownership 3. Of these, 56 percent are of vehicle type A according to the survey data. Then, 56 percent of 30 yields 16.8 vehicles of type A for this cross-classification cell in the specific TAZ under consideration. In total, it is found that 96.2 vehicles in the TAZ are of type A, thus implying that 58.6 percent of all vehicles in the TAZ are of type A. Similar percent values are calculated for other vehicle types. Note that the same survey data distribution matrix is used for all TAZs, although the survey data may be further stratified by additional dimensions of interest. Finally, assuming that zonal trip-miles are distributed in the same proportion as the vehicle type distribution for each TAZ, the proportion of trip-miles by each vehicle type may be calculated. The trip-miles associated with each vehicle type are divided by a vehicle type-specific fuel efficiency value (miles/gallon) to obtain the fuel consumption attributable to travel undertaken by that vehicle type. A summation of fuel consumption over all vehicle types yields the total travel energy footprint for a zone.

4. CASE STUDY APPLICATION OF ENERGY FOOTPRINT ESTIMATION

The methodology described in the previous section was applied to estimate the household travel energy footprint for a 20-county region comprising the Greater Atlanta metropolitan area in the State of Georgia in the United States. The Atlanta Regional Commission (ARC) is the planning agency for the region, and maintains a state-of-the-art four-step travel demand model system in addition to a newer activity-based travel microsimulation model system. Data from the four-step model was used for this exercise. The socio-economic data corresponds to a model base year of 2010. In that version of the four-step travel demand model, there are 2,024 internal traffic analysis zones (TAZs) that together account for a total population of 5,231,307 residing in 1,835,786 households. The household travel energy footprint in the Atlanta metropolitan region is substantial, and there is considerable interest in developing policies and promoting land use development patterns that would reduce this footprint (*23*).

For each TAZ, socio-economic data is compiled in the form of cross-classification matrices as depicted in Figure 2. These cross-classification matrices are constructed using readily available data in the travel demand model system. To obtain cross-classification matrices of the distribution of vehicles by type, National Household Travel Survey (NHTS) data (limited to samples from the Sun Belt of the United States) is used because it provides adequate sample sizes in all cells of the cross-classification matrix. A full run of the four-step travel demand model yields OD matrices of vehicle trip exchanges between zones. These matrices are obtained after the mode choice modeling step of the four-step travel demand model. In addition, the model provides travel time, travel cost, and travel distance matrices (often referred to as skim matrices).

The methodology described in the previous section was then applied to each TAZ in the region. Ideally, it would be nice to consider a very disaggregate representation of vehicle types in the computation of travel energy footprint. However, for this initial effort, a somewhat aggregate classification of vehicle types was used. This classification is based on the availability of fuel efficiency data by vehicle type, which remains somewhat coarse in its representation (*24*). Moreover, the travel survey data does not yet provide adequate sample sizes to consider the fuel-type dimension in classifying vehicles by type. So, this study adopted a cross classification of two body types (cars and light duty trucks) by three age categories (0-5 years, 6-11 years, 12 years and over) for a total of six vehicle types. For each TAZ, all vehicles were assumed to fall into one of these six categories, and fuel efficiency values provided by the US Department of Transportation (*24*) were used to calculate energy consumption. In the future, as additional vehicle ownership survey data becomes available, market penetration of alternative fuel vehicles increases, and more disaggregate fuel efficiency information (by vehicle type) is acquired, the methodology can easily accommodate such data and fuel efficiency factors without the need for any modification of the algorithm.

After the computations were completed, thematic maps were generated to depict fuel consumption (travel energy footprint) by TAZ. Figure 3 shows a thematic map of the household-level travel energy footprint (obtained by dividing the total TAZ fuel consumption by the number of households in the TAZ) juxtaposed against the TAZ density map, where density is calculated as the sum of population and employment divided by zonal area. The city center (Downtown Atlanta) is indicated with a '★' for ease of interpretation. The thematic maps reveal how households residing in suburban and rural TAZs have a higher fuel consumption footprint than households residing in higher-density neighborhoods closer to the city center. The pattern in the figure shows that households residing in the denser TAZs around the city center had substantially less travel energy consumption compared to those living in the suburbs. The results are further summarized in Figure 4, which shows average fuel consumption values and vehicle trip miles for different TAZ density classes. Based on density values, TAZs were identified as falling within various quartiles. Energy footprint per household, energy footprint per vehicle, and energy footprint per capita are all smaller in higher-density TAZs. The analysis shows that households in the lowest density TAZ bin travel more than 75 vehicle miles per day (on average), which translates to about 25 vehicle miles per capita. The corresponding values for households in the highest density category of TAZs, namely, 30 and 11 miles respectively, are a little less than one-half of the values for households in the lowest density TAZ category. Differences in gallons of fuel consumed follow similar trends.

Given that zones near the city center generally have a greater density of opportunities, access to destinations, and multimodal accessibility (transit service is better in higher density areas), it appears that these built environment attributes contribute to differences in the energy footprint associated with household travel. It is, however, very important to recognize that socio-economic characteristics of households residing in different locations (TAZ types) are likely to be different, and such differences can also contribute substantially to differences in the travel energy footprint. However, findings reported in the literature indicate that there is a net effect of density and multimodal accessibility that contributes to a reduced carbon footprint of personal travel even after controlling for socio-economic, demographic, and self-selection effects (*25*). In addition, the energy footprint calculated in this case study is sensitive to vehicle fleet composition of each TAZ. The differences seen between the suburban (red) and urban (green) TAZs may be partly due to the different vehicle fleet composition patterns depicted by these TAZs. Households in lower density suburban neighborhoods own a higher proportion of larger vehicle types in comparison to households in higher density neighborhoods. These types of differences are adequately reflected in the methodology.

It is possible to correlate and examine the travel energy footprint of each TAZ relative to the housing stock present in the TAZ, the TAZ density and accessibility, and the socio-economic and demographic characteristics of the TAZ. Future research can explore the contributions of different causal factors to the differences in the travel energy footprint, i.e., to what extent do socio-economic differences, built environment differences, multimodal accessibility differences, vehicle fleet composition differences, and lifestyle preference differences contribute to the variation in travel energy footprint across space? Armed with such insights, it would be possible to address specific factors and identify strategies that can enhance sustainable energy consumption patterns without adversely affecting quality of life and activity participation of residents.

5. CONCLUSIONS

This paper is concerned with the development of a practical methodology to derive the household travel energy footprint for different geographic entities in a metropolitan region. Most regions have travel demand model systems that provide estimates of the number of trips between traffic analysis zones (TAZs) and measures of separation (e.g., travel time) between zones. However, the outputs of travel models have not been effectively used in the past to obtain household travel energy consumption estimates at the level of the individual TAZ. The difficulty arises from the need to allocate non-home-based trips appropriately to residential TAZs that constitute the source of the non-home-based trips. In addition, any travel energy footprint calculator should recognize the sensitivity of the energy footprint to variations in vehicle fleet composition across space. However, virtually none of the four-step travel demand models account for vehicle fleet mix distribution in estimating travel demand. 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).

This paper presents a very detailed methodology to calculate household travel energy footprint (consumption) at the level of the traffic analysis zone. The methodology has two major algorithms that facilitate this calculation. The first algorithm apportions non-home-based travel to zones that contain households, thus ensuring that the energy consumption due to such trips is fully attributed to households (residential zones) that constitute the source of such trip making. The second algorithm embedded in the methodology provides a mechanism to account for the variation in vehicle fleet mix distribution across TAZs, even though the travel demand model itself does not consider vehicle type in its estimation of travel demand. This feature of the methodology enables an assessment of the impacts of emerging transportation technologies (e.g., electric and hybrid vehicles) on household travel energy consumption under alternative future scenarios. The methodology presented in this paper is practical and can be applied easily in conjunction with any standard four-step travel demand model maintained by a metropolitan planning organization.

The methodology is applied to the Greater Atlanta metropolitan region using the outputs of a travel model with 2,024 zones. The travel energy footprint is mapped across the region and a very clear pattern emerges, with zones in the outskirts of the region showing substantially larger travel energy footprints than zones within the heart of the region and closer to the city center. Although this result is not unexpected, the methodology offers a mechanism by which the energy consumption can be actually quantified, numerically compared across TAZ categories (defined in any way), and estimated under a wide variety of socio-economic, demographic, built environment, modal level of service, and vehicle fleet composition scenarios. An analyst can vary any of these variables and compare scenarios to identify those that would lead to more sustainable energy outcomes and reduced vulnerability to energy shocks.

Future research efforts could focus on extending the proposed methodology to account for transit and other motorized mode energy consumption, developing an energy footprint calculator that can be used in the absence of a travel demand model, and developing a full-fledged microsimulation model of person- and household-level travel energy consumption based on newer activity-based travel demand models. Another area for future exploration lies in the representation and visualization of the energy footprint in the form of flows. The current work provides energy footprint for the zone, but does not adequately capture energy flows; i.e., how does the travel energy footprint of a zone flow to various places in the region? Through the representation of energy flows using network graphs, it may be possible to visualize changes in travel energy flows in response to changes in land development patterns.

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List of Figures

Aggregate OD Matrix: HBW + HBO + NHB Trips

	Z1	Z2	Z3	Z4	Z5
Z1	40	10	20	20	10
Z2	20	20	20	20	30
Z3	10	20	100	12	10
Z4	8	10	16	20	30
Z5	20	25	40	5	20

$\otimes$

Distance Matrix

	Z1	Z2	Z3	Z4	Z5
Z1	0.5	1	2	3	1
Z2	1	0.5	2.5	0.5	2
Z3	2	2.5	0.5	5	1
Z4	2.5	2	5	0.5	2
Z5	1	2	1	2	0.5

$=$

Aggregate Trip Mile Matrix

	Z1	Z2	Z3	Z4	Z5	P
Z1	20	10	40	60	10	140
Z2	20	10	50	10	60	150
Z3	20	50	50	60	10	190
Z4	20	20	80	10	60	190
Z5	20	50	40	10	10	130
A	100	140	260	150	150	800

A. Trip Mile Computation

Home-Based Trip Mile (HBTM) Matrix: HBW + HBO

	Z1	Z2	Z3	Z4	Z5	HBTM
Z1	17	9	34	51	9	**120**
Z2	17	8	42	8	50	**125**
Z3	10	25	25	30	5	**95**
Z4	17	17	67	8	51	**160**
Z5	0	0	0	0	0	**0**
A	**61**	**59**	**168**	**97**	**115**	**500**

$Z1_{NHBTM} = 140 - 120$

$\text{AP}_{Z1} = 17/61$

$Z1_{NHBTM}$	Z1(AP)	$Z1_{NHBTM}$(R)
20	0.2787	5.5738
0	0.2787	5.5738
0	0.1639	3.2787
0	0.2787	5.5738
0	0.0000	0.0000

B. Reallocation of Trip Miles – Zone 1

	Z1	Z2	Z3	Z4	Z5	HBTM
Z1	17	9	34	51	9	**120**
Z2	17	8	42	8	50	**125**
Z3	10	25	25	30	5	**95**
Z4	17	17	67	8	51	**160**
Z5	0	0	0	0	0	**0**
A	**61**	**59**	**168**	**97**	**115**	**500**

$Z2_{NHBTM} = 150 - 125$

$\text{AP}_{Z2} = 9/59$

$Z2_{NHBTM}$	Z2(AP)	$Z2_{NHBTM}$(R)
0	0.1525	3.8136
25	0.1356	3.3898
0	0.4237	10.5932
0	0.2881	7.2034
0	0.0000	0.0000

C. Reallocation of Trip Miles – Zone 2

$Z1_{NHBTM}$(R) + $Z2_{NHBTM}$(R) + $Z3_{NHBTM}$(R) + $Z4_{NHBTM}$(R) + $Z5_{NHBTM}$(R) + HBTM = FTM

$Z1_{NHBTM}$(R)	$Z2_{NHBTM}$(R)	$Z3_{NHBTM}$(R)	$Z4_{NHBTM}$(R)	$Z5_{NHBTM}$(R)	HBTM	FTM
5.5738	3.8136	19.2262	15.7732	10.1739	120	174.5606
5.5738	3.3898	23.7500	2.4742	56.5217	125	216.7096
3.2787	10.5932	14.1369	9.2784	5.6522	95	137.9393
5.5738	7.2034	37.8869	2.4742	57.6522	160	270.7905
0.0000	0.0000	0.0000	0.0000	0.0000	0	0.0000

$$\sum_i FTM_i = 800$$

D. Reallocated Trip Miles

FIGURE 1 Illustration of zonal trip-mile reallocation algorithm.

Survey Data

Income by Vehicle Ownership

Income Category	Vehicle Ownership 0	1	2	3	4 or more
1	0	13084	15472	6444	3689
2	0	7018	24584	14244	9631
3	0	2276	28010	20832	17224

Income by Vehicle Ownership (Vehicle Type A)

Income Category	Vehicle Ownership 0	1	2	3	4 or more
1	0	10207	9093	3545	1987
2	0	5142	14081	7531	5246
3	0	1590	15994	11618	9737

Percent of Vehicles that are Type A in Each Cell

Income Category	Vehicle Ownership 0	1	2	3	4 or more
1	0	78%	59%	55%	54%
2	0	73%	57%	53%	54%
3	0	70%	57%	56%	57%

$$P_{11} = \frac{10207}{13084} = 78\%$$

Socio-Demographic Data (Zone Level)

$Zone_x$: Number of Households

Income Category	Vehicle Ownership 0	1	2	3	4 or more
1	5	7	9	3	1
2	10	6	4	6	2
3	7	11	16	10	3

$Zone_x$: Number of Vehicles

Income Category	Vehicle Ownership 0	1	2	3	4 or more
1	5*0	7*1	9*2	3*3	1*4.2
2	10*0	6*1	4*2	6*3	2*4.2
3	7*0	11*1	16*2	10*3	3*4.2

$Zone_x$: Number of Vehicles

Income Category	Vehicle Ownership 0	1	2	3	4 or more
1	0	7	18	9	4.2
2	0	6	8	18	8.4
3	0	11	32	30	12.6

$$\sum_{ij} V_{ij} = 164.2$$

$Zone_x$: Number of Vehicles that are Type A in Each Cell

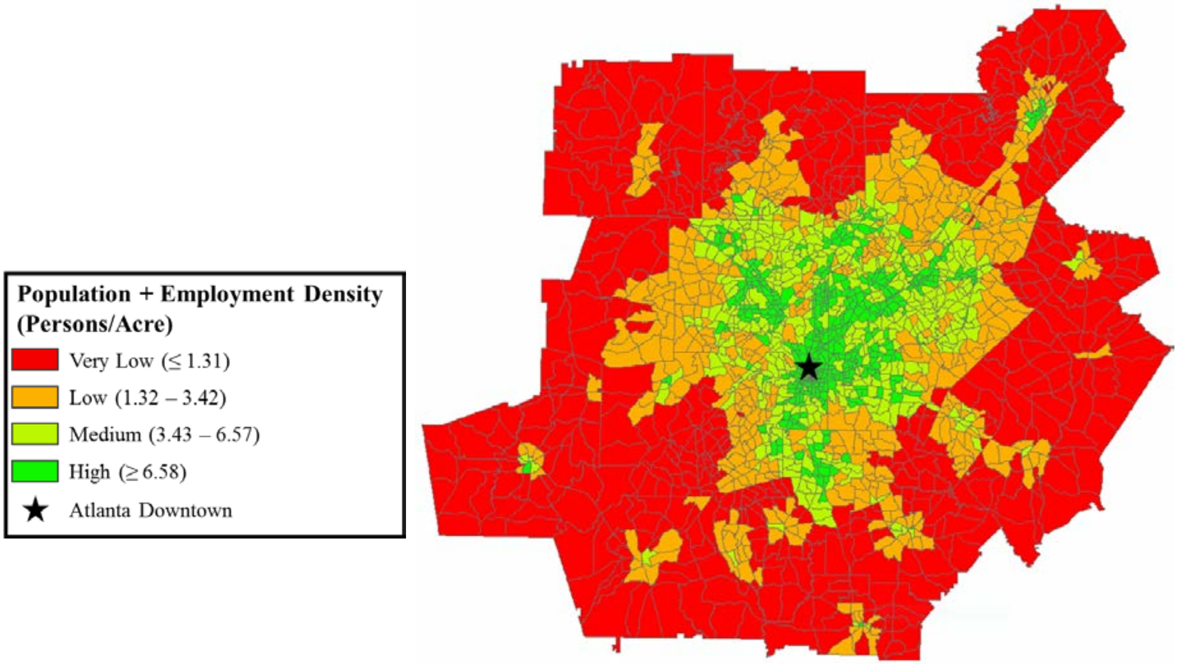
Income Category	Vehicle Ownership 0	1	2	3	4 or more
1	0.0	5.5	10.6	5.0	2.3
2	0.0	4.4	4.6	9.5	4.5
3	0.0	7.7	18.2	16.8	7.2

$$\sum_{ij} V(Type\ A)_{ij} = 96.2$$

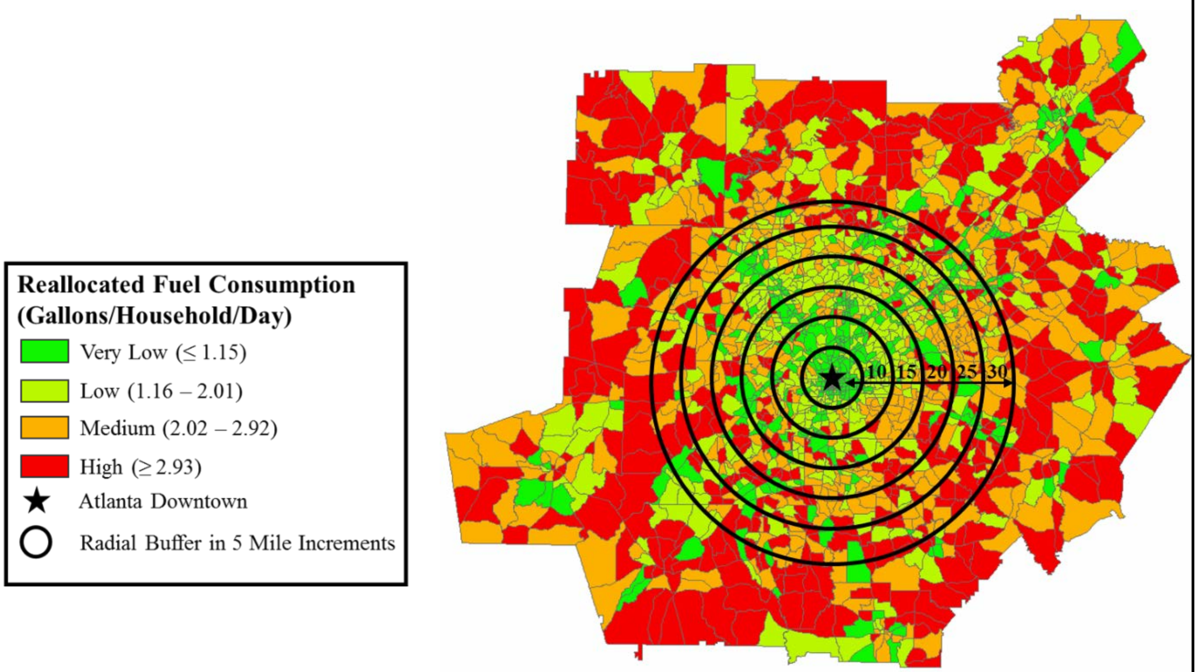
$$\%\ V\ (Type\ A) = \frac{96.2}{164.2} = 58.61\%$$

Zone	Trip Miles	% Vehicle Type A	% Trip Miles by Vehicle Type A	Fuel Efficiency of Vehicle Type A	Fuel Consumption by Vehicle Type A
Z1	174.56	58.61	102.31	27	3.80
Z2	.	.	.	.	.
Z3	.	.	.	.	.
Z4	.	.	.	.	.
Z5	.	.	.	.	.

FIGURE 2 Illustration of algorithm to account for vehicle fleet mix distribution in the calculation of household travel energy consumption.



a) Density of Traffic Analysis Zones ([pop+emp]/area)



b) TAZ Map Showing Daily Travel Energy Footprint per Household (Gallons)

FIGURE 3 Comparison of TAZ density and daily household travel energy footprint for the Greater Atlanta metropolitan region.

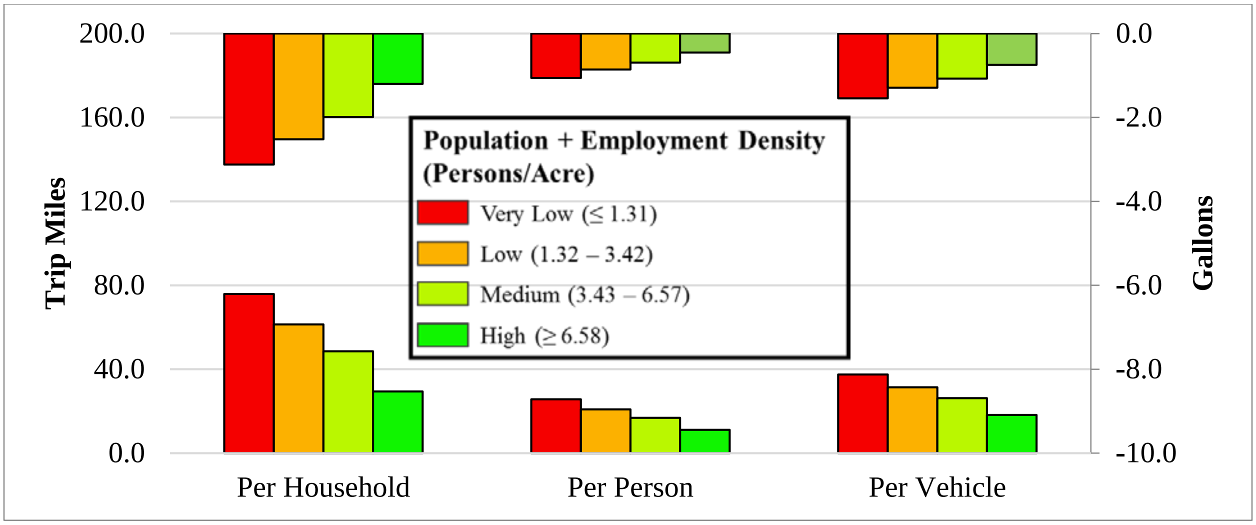


FIGURE 4 Daily average household travel energy footprint by TAZ density quartile.