Connecting Household Socioeconomics and Travel Carbon Footprint: Empirical Results from High-Resolution GPS Household Travel Survey

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ABSTRACT

Household travel related carbon emissions have been identified as one of the major contributors of greenhouse gases. There is a strong theory support for the fact that household travels and its associated carbon footprints are greatly related with land use type and socioeconomics of the household. However, the current method for quantifying the carbon footprint related with household travel was estimated using aggregated vehicle activity data (i.e. average speed) from sources such as the National Household Travel Survey, American Community Survey, etc. As it gains more popularity, the GPS-based household travel survey stranded out because it provides high-resolution travel trajectory data which maximizes the capability of emission models and produces more accurate results. This research connects the household travel carbon footprint with the land use and socioeconomics of the household by utilizing the greater Cincinnati GPS household travel survey data. The household travels are accurately mapped and traced with their socioeconomics and demographic characteristics. Specifically, the carbon emissions were calculated by the MOVES model and compared across household number of workers, income, life cycle and area type.

This research establishes a timely reference connecting household socioeconomic and demographic characteristics with its travel related carbon emissions using the best available high-resolution data. It provides solid grounds for analyzing, modeling and evaluating sustainable development strategies, adaptive planning policies etc. and contributes to regional carbon emission management strategies.

INTRODUCTION

Carbon footprint is traditionally defined as “the total sets of greenhouse gas (GHG) emissions caused by an organization, event, product or person [1].” However, since it is almost impossible to calculate the total carbon footprint since it requires large amount of data and carbon dioxide can be generated from natural build. A more practical definition of carbon footprint, as cited from a publication of the Carbon Management journal, is stated as follows: “A measure of the total amount of carbon dioxide (CO$_2$) and methane (CH$_4$) emissions of a defined population, system or activity, considering all relevant sources, sinks and storage within the spatial and temporal boundary of the population, system or activity of interest. Calculated as carbon dioxide equivalent (CO$_2$e) using the relevant 100-year global warming potential (GWP100). [2]”

Carbon footprint, sometimes also refers to greenhouse gases are emitted through transportation, electricity generation, industry, agriculture and commercial and residential related activities [3]. The transportation end-use sector is one of the largest contributors to U.S. GHG emissions. According to the Inventory of U.S. Greenhouse Gas Emissions and Sinks 1990-2010 [3,4], the national inventory that the U.S. prepares annually under the United Nations Framework Convention on Climate Change (UNFCCC), transportation represented 27% of total U.S. GHG emissions in 2010. Cars, trucks, commercial aircraft, and railroads, among other sources, all contribute to transportation end-use sector emissions. Within the sector, light-duty vehicles (including passenger cars and light-duty trucks) were by far the largest category, with 62% of GHG emissions, while medium- and heavy-duty trucks made up the second largest category, with 22% of emissions. Between 1990 and 2010, GHG emissions in the transportation end-use
sector increased more in absolute terms than any other end-use sector (industrial, agriculture, residential, commercial) [5]. Greenhouse gas emissions from transportation have increased by about 19% since 1990. This historical increase is largely due to increased demand for travel and the stagnation of fuel efficiency across the U.S. vehicle fleet. Among many travel related carbon emission reduction recommendations, the United States Environmental Protection Agency (U.S. EPA) advocates its Smart Growth Program by employing integrated land use, transportation and emission for the purpose of reduce the vehicle miles traveled (VMT), and therefore, reduce the carbon emissions [6].

U.S. EPA developed MOtor Vehicle Emission Simulator (MOVES) to estimate emissions from mobile sources covering a broad range of pollutants and allows multiple scale analysis such as emission budgeting of State Implementation Plan (SIP) and transportation conformity purposes (1,2). Traffic operation activity inputs to MOVES model are crucial in maximizing its capability to accurately reflect the greenhouse gases emission associated. Previous research has proved that on-road traffic related emission varies with traffic operating conditions (i.e., speed, acceleration or deceleration) [7,8,9,10,11]. Recent studies indicate potential deficiencies in converting travel demand outputs into the emission model inputs. Emission models often rely on traditional travel demand models for vehicle activity input, but traditional travel demand models are mostly calibrated and validated by using aggregated total vehicle data [12]. Therefore, the hourly emissions estimates may not be accurate because hourly VMT and speed variations are under presented as well as for the reason that aggregated input data are used in the emission models [12,13].

Over the past two decades, a growing body of research has aimed at improving the understanding of the influence of land use changes and its corresponding changes in transportation pattern and its related emissions. Such analyses usually investigate the interaction between specific attributes of land use, household travel demand and associated vehicle emissions, while accounting for demographic factors cited as significant in the literature including income, household size, and vehicle ownership using the available household travel survey data [14,15,16]. Some recent studies have focused on land use-based residential location choice and its potential impacts on travel behavior. Since households’ social economic characteristics such as income, auto ownership and employment etc. outline their residential choices, it is argued that taking land use characteristics as exogenous variables may lead to errors in travel behavior models [17,18]. Common unknown factors that affected households’ choices on residential location, vehicle type, and usage are also reported. Therefore, limited by the modeling assumptions and insufficient data support, it is difficult to make theoretical contributions connecting land use and household travel associated carbon emissions.

SUMMARY OF EXISTING STUDIES

Household travel surveys are designed to assist transportation planners and policy makers who need comprehensive data on travel and transportation patterns at national level or statewide. Basic information it gathers includes: purpose of the trip (work, shopping, social, etc.), means of transportation (car, walk, bus, subway, etc.), travel time of trip, time of day/day of week, etc. The surveys are designed to fulfill the purpose of quantifying travel behavior, analyzing changes in travel characteristics, relating demographics to the travel behavior, etc [19].
Lots of studies also used the Household Travel Survey data and attempted to connect land use, household demographics, and travel behaviors [20,21,22,23]. A most common approach is to statistically link household demographics and socio-economic characteristics with the number of trips associated with. Using the 2001 NHTS (National Household Travel Survey) data, Liu et al [24] investigated how urban land use characteristics influence on the household travel and the energy consumption associated with that. Their results demonstrate that accessibility explains more than the use of 3D (Density, Design, and Diversity measures) approach [25]. They also reported that there is a strong correlation between household characteristics, vehicle ownership, Vehicle Miles Traveled (VMT) and energy consumption. Lindsey et al [26] investigated the relationship between household location on household patterns of vehicle miles traveled, and by extension, energy consumption and GHG emissions. They reported that VMT, energy use and GHG emissions increase with residential distance from city center. Various scenario show that with increases in privately vehicle fuel efficiency, the overall reduction in fuel use creates a more uniform spatial profile of energy/greenhouse gas emissions across the region.

The U.S. EPA’s MOVES model use the Vehicle Specific Power (VSP) approach to connect vehicle instantaneous engine power with the measured emissions and then use adjustment factors and statistical methods to estimate the emissions. Sensitivity analysis [27,28] of MOVES model GHG emissions shows that the second-by-second vehicle speed, acceleration, and roadway grades all have significant impact to the VSP and therefore, its corresponding GHG emissions. GPS data is a very common approach for VSP calculations and emission estimation. Although there are alternative method such as use video to develop operating mode distribution inputs [29] and loop detector data [30,31] for MOVES model available.

METHODOLOGY

The goal of this research is to quantify the household travel carbon footprint using GPS survey data to fulfill the identified research gap. To achieve the goal, two objectives are designated to fulfill: (1) to calculate carbon emissions for each household travel trips using the best available operating mode distribution, vehicle age inputs of the MOVES model; and (2) to bridge the carbon emissions to the household socioeconomics and demographic characteristics. The proposed research addresses the challenges and identified research gap through the development and testing of the proposed BINS with a case study. The advantage of the proposed BINS system is that it is a ground truth video data-based, non-intrusive classification method. The ground-truth based method is reliable since it bypasses the modeling and malfunctioning errors which conventional sensors might have.

To fulfill the research gap identified, an integrated approach is proposed by using the Greater Cincinnati Household Travel Survey Data. The purpose of the methodology is to build up a linkage from household travel related carbon emissions with land use, socioeconomic, demographic, and spatial and temporal factors. And to rapidly quantify the carbon emissions through simulation of scenario-based land use and socioeconomic changes.
Figure 1 Heuristic Framework of Spatial Regression Model-based Household Travel Carbon Footprint Modeling

Figure 1 illustrates the heuristic framework of this research. The household travel data processing module extracts household travel characteristics based on the survey database. The purposes are twofold. First, to calculate the carbon emissions from the location specific household by using traditionally unavailable vehicle specific power (VSP) approach and the EPA approved MOVES model. Second, the extracted trip features based on household socioeconomic data will be used to update the trip rates table for the customized travel demand model. Module two, the contributing variables, is to produce contributing variables for spatial cross-sectional modeling including TAZ level, trip level attributes and spatial weights. The spatial cross-sectional model will then be estimated. Thirdly, the policy and planning scenarios module will provide justified land use patterns and associated household spatial distribution based on the adaptive planning from module four: carbon footprint assessment. The last part of this research will be using the scenario data generated in the previous step to forecast the carbon emissions of the scenario.

GPS Household Travel Data

Giaimo et al [32] introduced the preliminary findings of the first largest GPS-based household travel survey – Greater Cincinnati Household Travel Survey (HTS). It is a proof of concept study for replacing travel diaries with a large-scale multiday Global Positioning System (GPS) survey. They conclude that a representative sample of households can be recruited for a GPS-based survey, based on a comparison of pilot sample household characteristics with available Public Use Microdata Samples data, and response rates for difficult-to-reach households such as cell phone-only, lower income, and zero-vehicle households can be improved with a cash incentive ($25). The preliminary results have proven that using the GPS-base travel survey is a viable approach.
approach for household travel survey which is much reliable and informative comparing to traditional survey methods such as a computer-assisted telephone interview (CATI). As the project report indicates, the survey identified 2,059 GPS complete and 549 GPS incomplete household travel surveys. The database includes 3,853 drivers, 60,900 trips with a daily motor vehicle trip rate of 7.60. The report also conclude that it is feasible to undertake a GPS-only household travel survey, achieving a high standard of representativeness of the population, while imputing trip mode and purpose at a sufficiently accurate level. The high level of accuracy attained in this survey for imputing mode and purpose with 96 percent on mode and around 90 percent on activity is far superior to other forms of surveys such as the self-report survey. The richness of the “ground-truth” of time, location (latitude and longitude), distance, speed, and routes data collected from this survey provided state-of-the-practice data to support research and studies such as development of activity-based travel demand model and even emission analysis.

Figure 2 shows the locations household travel survey samples over the Hamilton County land use map. There are 2,697 sampled households within the county. Each household’s land use information will also be included in the household stratification.

**Legend**

**Household Survey Sample Locations**

- Hamilton County Boundary
- Hamilton County Land Use
  - Agriculture
  - Vacant
  - Single Family
  - Two Family
  - Mobile Homes
  - Congregate Housing
  - Multi Family
  - Mixed Use
  - Office
  - Public/Semi Public
  - Commercial
  - Light Industrial
  - Heavy Industrial
  - Educational
  - Institutional
  - N/A
  - Public Utilities
  - Parks & Recreation

**Figure 2 Household Travel Survey Sample Locations with Land Use Map**
The household travel carbon footprint is extracted by using the key concept of the MOVES emission model – Vehicle Specific Power. The mathematical expression of VSP was first developed by J. L. Jiménez [33] at the Massachusetts Institute of Technology. It is a mathematical representation of engine load against aerodynamic drag, acceleration, rolling resistance, plus the kinetic and potential energies of the vehicle, all divided by the mass of the vehicle. In practice, a generic set of coefficients values estimating VSP for a typical light duty fleet is applied as a useful basis for characterization [34]. The VSP values are calculated by the following equation:

\[
VSP = v \times [1.1a + 9.81 \times grade(\%) + 0.132] + 0.000302 \times v^3
\]  

(1)

where:

- \( v \) = vehicle speed (m/s)
- \( a \) = vehicle acceleration/deceleration rate (m/s\(^2\))
- \( grade \) = vehicle vertical rise divided by the horizontal run (%)

As described above, one of the key facts that made this study different from the previous studies is the availability of second-by-second GPS speed data. Table 1 shows a sample of the GPS household travel records.

Table 1 Sample GPS Household Travel Records

<table>
<thead>
<tr>
<th>Longitude</th>
<th>Latitude</th>
<th>Speed (km)</th>
<th>Course (degrees)</th>
<th>Number Of Satellites</th>
<th>HDOP</th>
<th>Altitude (meters)</th>
<th>DD/MM/YY</th>
<th>HH:MM:SS</th>
<th>Distance (meters)</th>
</tr>
</thead>
<tbody>
<tr>
<td>-84.4966</td>
<td>39.17164</td>
<td>85</td>
<td>266</td>
<td>9</td>
<td>0.93</td>
<td>167</td>
<td>31/8/2009</td>
<td>11:37:04</td>
<td>23</td>
</tr>
<tr>
<td>-84.4969</td>
<td>39.17164</td>
<td>85</td>
<td>266</td>
<td>9</td>
<td>0.93</td>
<td>167</td>
<td>31/8/2009</td>
<td>11:37:05</td>
<td>24</td>
</tr>
<tr>
<td>-84.4971</td>
<td>39.17162</td>
<td>85</td>
<td>266</td>
<td>8</td>
<td>1.2</td>
<td>168</td>
<td>31/8/2009</td>
<td>11:37:06</td>
<td>23</td>
</tr>
<tr>
<td>-84.4974</td>
<td>39.17161</td>
<td>83</td>
<td>264</td>
<td>8</td>
<td>1.2</td>
<td>168</td>
<td>31/8/2009</td>
<td>11:37:07</td>
<td>23</td>
</tr>
<tr>
<td>-84.4977</td>
<td>39.17159</td>
<td>83</td>
<td>262</td>
<td>9</td>
<td>0.93</td>
<td>169</td>
<td>31/8/2009</td>
<td>11:37:08</td>
<td>23</td>
</tr>
<tr>
<td>-84.4977</td>
<td>39.17159</td>
<td>81</td>
<td>260</td>
<td>9</td>
<td>0.93</td>
<td>170</td>
<td>31/8/2009</td>
<td>11:37:09</td>
<td>0</td>
</tr>
<tr>
<td>-84.4982</td>
<td>39.17153</td>
<td>81</td>
<td>258</td>
<td>8</td>
<td>1.1</td>
<td>170</td>
<td>31/8/2009</td>
<td>11:37:10</td>
<td>45</td>
</tr>
<tr>
<td>-84.4985</td>
<td>39.17149</td>
<td>80</td>
<td>256</td>
<td>8</td>
<td>1.2</td>
<td>170</td>
<td>31/8/2009</td>
<td>11:37:11</td>
<td>22</td>
</tr>
<tr>
<td>-84.4987</td>
<td>39.17144</td>
<td>80</td>
<td>254</td>
<td>8</td>
<td>1.2</td>
<td>170</td>
<td>31/8/2009</td>
<td>11:37:12</td>
<td>22</td>
</tr>
<tr>
<td>-84.499</td>
<td>39.17139</td>
<td>78</td>
<td>252</td>
<td>9</td>
<td>0.93</td>
<td>169</td>
<td>31/8/2009</td>
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<td>22</td>
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<tr>
<td>-84.4992</td>
<td>39.17134</td>
<td>78</td>
<td>252</td>
<td>8</td>
<td>1.1</td>
<td>169</td>
<td>31/8/2009</td>
<td>11:37:14</td>
<td>21</td>
</tr>
<tr>
<td>-84.4994</td>
<td>39.17127</td>
<td>78</td>
<td>250</td>
<td>8</td>
<td>1.1</td>
<td>169</td>
<td>31/8/2009</td>
<td>11:37:15</td>
<td>21</td>
</tr>
<tr>
<td>-84.4997</td>
<td>39.1712</td>
<td>80</td>
<td>248</td>
<td>8</td>
<td>0.95</td>
<td>169</td>
<td>31/8/2009</td>
<td>11:37:16</td>
<td>21</td>
</tr>
<tr>
<td>-84.4999</td>
<td>39.17113</td>
<td>78</td>
<td>248</td>
<td>8</td>
<td>0.95</td>
<td>169</td>
<td>31/8/2009</td>
<td>11:37:17</td>
<td>22</td>
</tr>
</tbody>
</table>

Note: HDOP = Horizontal Dilution of Precision.

By the combinations of speed and VSP representing real-world vehicle operating mode, MOVES adopted the 23 operating mode bins, plus additional operating modes for starts and evaporative emissions. Table 1 is the summary of the VSP bins which MOVES model implies. The VSP values are then binned into the below table and the operating mode distribution has therefore generated.
Table 2 Operating Mode Bins for MOVES Running Emissions

<table>
<thead>
<tr>
<th>Instantaneous Speed (mi/h)</th>
<th>0</th>
<th>0-25</th>
<th>25-50</th>
<th>&gt;50</th>
</tr>
</thead>
<tbody>
<tr>
<td>&gt;&gt;30</td>
<td>Bin 16</td>
<td>Bin 30</td>
<td>Bin 40</td>
<td></td>
</tr>
<tr>
<td>30</td>
<td>Bin 29</td>
<td>Bin 39</td>
<td></td>
<td></td>
</tr>
<tr>
<td>27</td>
<td>Bin 28</td>
<td>Bin 38</td>
<td></td>
<td></td>
</tr>
<tr>
<td>24</td>
<td>Bin 27</td>
<td>Bin 37</td>
<td></td>
<td></td>
</tr>
<tr>
<td>21</td>
<td>Bin 15</td>
<td>Bin 25</td>
<td></td>
<td></td>
</tr>
<tr>
<td>18</td>
<td>Bin 14</td>
<td>Bin 24</td>
<td></td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>Bin 13</td>
<td>Bin 23</td>
<td></td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>Bin 22</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>Bin 21</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>Bin 12</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Bin 11</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>Bin 0 (Braking)</td>
<td>Bin 11</td>
<td></td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>Bin 21</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 3 Sample Operating Mode Distribution for Household Travel Trips

Household Cross-Classification

Table 3 shows the categories of the household cross-classification. The first category is the area type, area type 1 is the combination of CBD and Urban area since the data in CBD along is very small. Area type 2 and 3 are for suburban and rural respectively. Number of workers in household is the second category ranging from 0 to 4 or above. The life cycle category describes the status of the household as adult, adult student, retiree, and household with children. The last category is the income group divided by less than $25,000, $25,000 to $49,999, $50,000 to $74,999 and $75,000 or above.

Table 3 Household Cross-Classification Categories

<table>
<thead>
<tr>
<th>Area Type</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>CBD &amp; Urban</td>
</tr>
</tbody>
</table>
RESULTS AND ANALYSIS

Household Distribution Cross-Classification

Figure 4 shows the household distributions by the cross-classification categories. In the household distribution by area type chart, the area type suburban has the most sample comparing to the other three area types. 0, 1, and 2 workers household are dominating in the household distribution by number of workers. Among the household by lifecycle, the adult household and household with children are most dominating type. Income level for under $75,000 are similar distributed but households with higher income are more in the dataset.
Household Travel Carbon Emission Reasonableness Check

It is crucial to check the emission results from the survey data falls in the correct range by conforming to existing literature. A commonly recognized carbon emissions from a gallon of gasoline is 8,887 grams [35] and the average fuel efficiency of U.S. light duty vehicles is 23.5 mpg [36]. Therefore, the average carbon emission per mile is calculated using equation 2.

\[
\text{CO}_2 \text{ emissions per mile} = \frac{\text{CO}_2 \text{ per gallon}}{\text{MPG}} = \frac{8,887}{23.5} = 378.17 \text{ grams}
\]  

(2)

Table 4 shows the empirical household travel carbon emission results from the survey data. The grams per mile emissions matches the EPA published carbon emission rates and the emission results from this calculation are valid.

Table 4 Household Travel Carbon Emissions Reasonableness Check

<table>
<thead>
<tr>
<th>Workers</th>
<th>Carbon Emissions (lbs)</th>
<th>Trip Distance (miles)</th>
<th>Pounds per mile</th>
<th>Grams per mile</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>4.95</td>
<td>5.51</td>
<td>0.90</td>
<td>407.51</td>
</tr>
<tr>
<td>2</td>
<td>5.00</td>
<td>5.68</td>
<td>0.88</td>
<td>399.70</td>
</tr>
<tr>
<td>3</td>
<td>6.60</td>
<td>7.80</td>
<td>0.85</td>
<td>383.85</td>
</tr>
<tr>
<td>4</td>
<td>7.67</td>
<td>9.52</td>
<td>0.81</td>
<td>365.76</td>
</tr>
<tr>
<td>5</td>
<td>6.83</td>
<td>8.25</td>
<td>0.83</td>
<td>375.30</td>
</tr>
</tbody>
</table>

Household Travel Carbon Emissions by Area Type

Figure 5 shows the carbon emission results from the survey data grouped by life cycle of the household located in CBD and urban area. Regression curves are superimposed and showing R-squares ranging from 0.59 to 0.92. Adult households daily carbon emissions are within the 4~7 pounds. Adult student household has less carbon emissions and usually below 4 pounds per day. Retiree households generates 4~6 pounds of carbon emissions per day. The households with children contributing more carbon emissions as the number of household works increase. The
range is approximately 2 pounds per day for households with 1 worker and up to 14 pounds per day.

Life Cycle 1: Adult Household

Life Cycle 2: Adult Student Household

Life Cycle 3: Retiree
Figure 5 Household Travel Carbon Emission per Day for CBD and Urban

Figure 6 shows the carbon emission results from the survey data grouped by life cycle of the household located in suburban area. Regression curves are superimposed and showing R-squares ranging from 0.40 to 0.99. Adult households daily carbon emissions are within the 4-7 pounds. Adult student household has bigger variations in carbon emissions and ranges from 0 to 12 pounds per day. Retiree households generates 4-6 pounds of carbon emissions per day. The households with children contributing more carbon emissions as the number of household works increase. The range is approximately 3 pounds per day for households with 1 worker and up to 8 pounds per day.
Figure 6: Household Travel Carbon Emission per Day for Suburban Area

Figure 7 shows the carbon emission results from the survey data grouped by life cycle of the household located in suburban area. Regression curves are superimposed and showing R-squares ranging from 0.67 to 0.99. Adult households daily carbon emissions are within the 4~6 pounds. Adult student household has bigger variations in carbon emissions and ranges from 4 to 16 pounds per day. Retiree households generates 5~7 pounds of carbon emissions per day. The households with children contributing more carbon emissions as the number of household works.
increase. The range is approximately 4 pounds per day for households with 1 worker and up to 11 pounds per day.

Life Cycle 1: Adult Household

Life Cycle 2: Adult Student Household

Life Cycle 3: Retiree
Figure 8 shows the carbon emission results from the survey data grouped by life cycle for all the samples. Regression curves are superimposed and showing R-squares ranging from 0.77 to 0.89. Adult households daily carbon emissions are within the 4~7 pounds. Adult student household has bigger variations in carbon emissions and ranges from 2 to 12 pounds per day. Retiree households generates 4~6 pounds of carbon emissions per day. The households with children contributing more carbon emissions as the number of household works increase. The range is approximately 3 pounds per day for households with 2 worker and up to 12 pounds per day.
The carbon emissions from the survey results when grouped by life cycles are very interesting. Adult household tends to contribute steady carbon emissions per day even when number of workers increases. Generally, as the number of workers in an adult household increase, their carbon emissions goes down. Retiree households tends to emit a range of 4-6 pounds of
carbon emissions per day with variations on income. And lastly for household with children, the increasing carbon emissions is very obvious as the number of workers increases.

CONCLUSION

This research set out an empirical results from the best available traffic activity survey data and connected the household socioeconomics with their carbon emissions. Although the results maybe pertaining to the specific dataset but it helps transportation decision makers to better connects the land use development and its related household socioeconomics with their carbon emission characteristics. Particular, the household travel carbon emission footprint quantification results made its contribution to current body of knowledge on the following: (1) provides accurate carbon emission results by using the best available traffic activity data inputs (VSP distributions) for emission modeling; (2) provides connections between household socioeconomics and their travel carbon footprint. The results showed using the cross-classification method is likely to use as carbon emission generation rates for the purpose of rapidly estimate household travel carbon footprint. Furthermore, the results from inter-life cycle differences further characterized the carbon footprints of the adult, adult student, retiree and households with children. The research suggest important potential to provide solid grounds for analyzing, modeling of sustainable community strategies, adaptive planning policies etc.

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