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Spatial Analysis of Travel Demand and Accessibility in Vermont: Where will EVs work?

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Disclaimer

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Substantial portions of this report are published as "*Travel Demand and Charging Capacity for Electric Vehicles in Rural States: Vermont Case Study*" in the Transportation Research Record (in press).

1. Abstract

The suitability and charging requirements of electric vehicles (EVs) may differ in rural areas, where the electrical grid may be less robust and daily VMT higher. Although other studies have examined issues of regional power requirements of EVs, none have done so in conjunction with the spatial considerations of travel demand and accessibility. We use three datasets to forecast the future spatial distribution of EVs, as well as to assess these vehicles' ability to meet current daily travel demand: the National Household Travel Survey (NHTS), geocoded Vermont vehicle fleet data, and an E911 geocoded dataset of every building statewide. We consider spatial patterns in existing daily travel and home-based tours to consider EV charging locations, as well as area-types that are unsuited for widespread electric vehicle adoption. We also consider how built environment attributes, including residential and commercial density and retail accessibility, affect travel demand and thus future EV energy requirements. We found that existing hybrid vehicles were more likely to be located near other hybrids than conventional vehicles were. This clustering of current hybrid vehicles, in both urban and rural areas, suggests that the distribution of future EVs may also be clustered. Our analysis suggests that between 69 and 84% of the state's vehicles could be replaced by a 40-mile range EV, and 96-99% could be replaced by a 100-mile EV, depending on the availability of workplace charging. We did not find a strong relationship between land-use and travel demand, perhaps due to our low number of urban data points, the highly variable nature of rural travel, and the limitations of using a one-day travel log dataset. Our results suggest EVs are a viable option to serve existing travel demand by rural residents but may require special consideration for power supply and vehicle charging infrastructure.

2. Introduction

As electric (EV), hybrid electric (HEV), and plug-in hybrid electric (PHEV) vehicle technologies advance, these vehicles are increasingly seen as a means of reducing greenhouse emissions and dependence on foreign energy. Previous research has shown that depending on the mix of electricity used for charging, there may be substantial environmental benefits associated with EV use. A 2007 study by EPRI [1] examined PHEVs with all-electric ranges of 10, 20 and 40 miles and found gasoline displacement ranging from 42% to 78% relative to conventional vehicles and from 12% to 66% relative to HEVs. Other studies that quantified gasoline displacement found reduction values within these ranges [2-5].

Most research on the feasibility of EVs has either been focused on the overall power requirements, the electric system's ability to meet that demand or the vehicle technology required to provide a given driving range. Except for a few studies, data are regionally based and there is an assumption that EVs may be an urban, not rural, transportation energy solution [6, 7]. These studies generally do not consider the spatial distribution of travel demand in assessing EV and PHEV market penetration. PHEVs offer the ability to travel on gasoline when trip distances exceed the electric range, an important factor for rural areas.

Overall, there is a need to consider where we want EVs to be deployed and travel and how this spatial distribution impacts not just overall efficiency of energy and emissions, but also mobility. The distribution of away-from-home charging stations, the robustness of electrical infrastructure, and pricing schemes will impact where EVs are adopted and where they travel. For rural areas, the policies and infrastructure needed to make efficient use of EVs, or PHEVS in electric mode, may be different from urban areas. Choosing an EV over an HEV and PHEV will be a decision for individual households that is based not only on their total travel demand, but also on the availability of non-home charging stations over their activity space. There has been a general acceptance that rural trips are longer and will require more range. However, transportation demand modelers have focused less on non-urban travel and there is not solid established data on how, and to what extent, rural travel is different from urban travel. These differences may have implications for designing sustainable transportation systems including the fleet conversion to EVs.

Very little consideration has been given to the spatial overlap between travel demand and EV power demand in either urban or rural settings. In this report, we use three spatial datasets to consider this problem. The first is the National Household Transportation Survey (NHTS) and the associated add-on survey collected in the rural state of Vermont in 2009. The second dataset consists of home address and vehicle type of every vehicle registered in the state from the Vermont Department of Motor Vehicles (DMV). The third dataset, referred to as the Vermont E911 data, is a Geographic Information System (GIS) point layer of all residences and commercial buildings in the state of Vermont. This paper aims to assess potential spatial clustering patterns in EV ownership, whether the travel demand served by existing household vehicles can be met with EVs, and possible locations for EV charging. Using the household location as a focal point, particular emphasis is placed on considering how a rural versus urban landscape results in different travel patterns and charging opportunities.

One original goal of this research was to identify areas of the state that were less well suited to widespread EV adoption due to high daily travel demand or limitations in the available grid infrastructure. This spatial suitability framework is based on the assumption that the spatial distribution of destinations or activities relative to your home is a factor that affects travel in terms of number of trips, number of tours, stops per tour and total distance traveled. Despite the intuitive nature of the assumption that the spatial distribution of destinations affects travel patterns, these relationships have been hard to document in prior research. Travel patterns are more often associated with socioeconomic characteristics. Our spatial analysis included examination of clusters of travel demand (areas with a high density of high-mile vehicles), as well as an examination of land use characteristics that may be associated with such clustering. We expected that people living in close proximity to work, shopping, schools, and/or recreation would require less total daily travel. Those areas with relatively low retail (and employment) accessibility may be home to large numbers of high-mile vehicles that will ultimately require more electric power. An important aspect of this research thus includes development of an accessibility metric to relate land use to patterns in travel demand and possible electric power demand.

2.1 Framework for Problem Definition

Based on the evidence of environmental and sociopolitical benefits from EVs, there is a public interest in promoting the use of EVs but it is unclear whether this equates with maximizing the use of EVs in all contexts. Depending on trip and travel patterns and existing electricity transmission and distribution infrastructure, there may be some households for which the private and public cost of EV ownership and operation is greater than the total costs of alternative modes of travel. This is most likely to be the case where average trips lengths exceed EV range, where distribution infrastructure is at or near capacity and where charging stations would not have a sufficiently high utilization rate to be economical viable. Longer trip lengths require greater investments in away-from-home charging infrastructure which increases the cost of EV adoption. Areas where the grid is at capacity could require substantial investments to support charging for a significant number of EVs, raising important question about whether EV sales are likely to be clustered rather than evenly spatially distributed. Since trip and tour lengths are on, average, longer and the electric grid frequently less robust in rural areas, optimal EV ownership patterns are likely to differ between urban and rural areas.

Daily trip tours or chains are of primary interest when evaluating the viability and impact of EV adoption. Although trip length will be an important determinant of whether or not EVs can meet people's travel demand, the total distance driven between potential charging events may be more relevant to our analysis. Previous research has often anchored tours at home, thus a home-based tour will include all trips that occur between a vehicle's departure and return home [13, 14]. Alternative definitions could also include work-based tours and school-based tours and divide trips into primary activities (trips to and from home, and trips to work and school) and secondary activities (all other trips) [15]. We assume that the bulk of vehicle charging will occur at home, thus we use home-based tours as our primary unit of analysis in this paper. Because the proximity of one's home and work to retail locations may in large part determine the amount that individuals are required (or choose) to drive each day [9, 10] and the length of the vehicle tours, these factors are also likely to be determinates of EV viability, travel and charging patterns.

Figure 1 illustrates how EV travel and charging patterns are inherently spatial systems that differ for rural and urban areas. In this figure, the elements that are typically part of transportation demand planning modeling are shown in boxes. Since destination accessibility is a key component of this system, a portion of this research is devoted to developing accessibility metrics for Vermont. Accessibility can be used to describe a variety of phenomena, but generally refers to the ease with which people are able to reach services and amenities. Distance measures estimate accessibility by calculating the distance from a location to different destinations, while cumulative opportunity measurements sum the total number of opportunities within a given distance or travel time [11]. In this report, we estimate accessibility using a gravity model, a commonly used accessibility metric (reviewed in [12]). A gravity model sums the number of retail locations within a given radius, accounting for distance in an exponential function, giving less weight to destinations that are farther away.

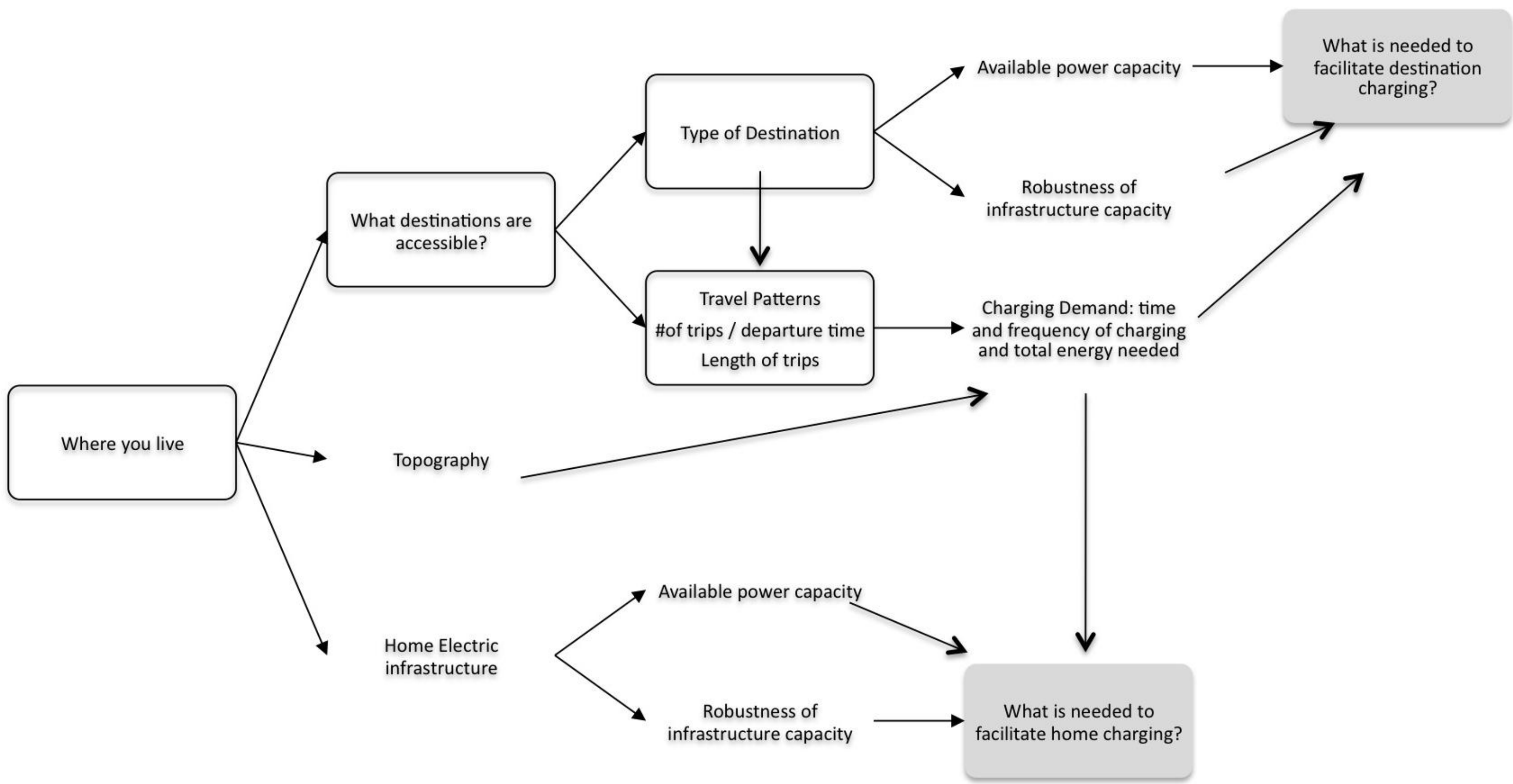


Figure 1. Potential Spatial Impacts of Home Location in Travel and Electric Vehicle Charging Needs.

As shown in Figure 1, trip lengths and topography, along with factors such as climate and driving style, determine the timing, frequency and energy demand for EV charging. If trips are long and one-way distance exceeds half the vehicles' range, away-from-home charging will be required. Socially desirable and/or economically viable away-from-home charging stations will have a number of common characteristics. Charging stations should be located at destinations where trip lengths are relatively long so that the battery state-of-charge of arriving vehicles is low enough to make charging desirable. This could include workplaces with long commutes, tourist destinations or entertainment centers. The economic viability of these station will depend both on installation costs and utilization rates. To limit the upfront costs of installing charging infrastructure, stations are more likely to be established in places that have existing electricity infrastructure, such as lighted parking lots. High utilization rates are most likely to be achieved where dwell times are long enough to make charging worthwhile but short enough that vehicles do not continue to occupy the charging station long after their batteries have been full charged. Destinations with short dwell times (e.g., a bank) do not provide adequate time for vehicle re-charge. Conversely, charging stations should not be located where vehicles are parked for too long (e.g., an intercity rail station where vehicles may park for multiple days) or charging infrastructure will be used only for a small fraction of the time that a vehicle is at the location. Finally, charging stations need to be located where the electric grid is robust and capable of supporting the added demand from vehicle charging, which is less likely to be the case in rural areas. We hypothesize that in rural states, the limited land uses, smaller scale activities, and lower land use density increase travel distances and reduce the opportunities for cost effective away-from-home EV charging because activity centers are smaller and lower volume.

Studying these problems in a rural area is limited by methodological and data issues. Even to this day, the transportation planning agencies which build and maintain our transportation infrastructure use a binary measure of geographic context: rural and urban. Road standards, safety records and miles of travel are reported in these two categories. But increasingly, engineers, planners and health care professionals are recognizing that spatial context and landscape, including our options for travel and mobility, affect our activity level and our health. The character and characteristics of our context as they impact healthy living cannot be captured by a binary measure.

Researchers in many fields have developed more disaggregate measures of geographic context. The most common geographic zones are political such as town or county boundaries. These historic boundaries are convenient in that data are often recorded and available in these units. Unfortunately these spatial units are problematic because their area is large and boundaries do not correspond to the spatial context as perceived by the humans who travel within them. The average population density of a town or the presence of a particular destination at a given location does not equally impact all residents dispersed throughout the town.

In urban areas, Census block groups are small enough that they can often be reasonably used to describe the neighborhood or surroundings of a household. In this unit of spatial measure, population density and availability of destinations can be meaningful in predicting travel patterns. In the last decade, advances in both Geographic Information Systems (GIS) and the widespread availability of geographic spatial datasets (especially in larger cities) have made calculation of contextual variables feasible in Census block groups and useful in predicting behavior. Given this context, our team used disaggregate data for this study. First, when we know the reasonable point location of a household and the surrounding buildings as an address or a latitude and longitude, we can measure more than simply the characteristics of the rigidly bounded census block within which the house exists. Rather, we can calculate the other features, characteristics and opportunities within given distances of the household. Second, we believe the accessibility variables developed and tested to date are appropriate for urban locations but not rural or maybe even suburban ones. This is more than a matter of scale. Certainly, census blocks that are defined for a set population are larger and less useful in rural areas and therefore less reasonable for any given household. But we also know that rural and suburban residents have different activity and travel patterns that ultimately affect their time budget and opportunities they have for travel.

This study considered the spatial patterns of potential EV market penetration in the rural state of Vermont by considering travel demand data from the NHTS as well as geocoded vehicle fleet data from the Vermont DMV. Rather than considering overall power demand at the network or regional level, we are interested in examining limitations to widespread market penetration of EVs in rural areas by assessing the following four research questions:

> Question 1: Does the expected pattern of vehicle adoption show uniform dispersion or a more clustered pattern? It is conceivable that social networks and socioeconomics will result in PHEV or EV adoption that is clustered at the street/block or neighborhood level. If this is the case, high density demand for electric vehicle charging in areas with aging or weak electricity distribution infrastructure could create the need for significant localized infrastructure investments.
>
> Question 2: What percentage of Vermont vehicles, given existing daily travel demand, could be replaced by a 40-mile range EV with different levels of workplace charging? Based on dwell time within vehicle-based tours by stop purpose in the NHTS, we propose that vehicle charging will be mainly at home or work. By re-tabulating the NHTS data, we consider daily vehicle tour length away from home and whether a tour includes work.
>
> Question 3: Are there rural areas where vehicles in need of non-home non-work charging converge? For rural travel, when one-way trip distances exceed half the EV range and home or work charging is not possible, other charging options will be required if the travel demand is to be met by an EV. If these types of tours have stops or clusters of stops in similar areas, this could be a target for charging station provision that would support the adoption of EVs in rural areas.
>
> Question 4: Are there spatial patterns or clusters of travel demand that suggest areas where EV adoption should not be encouraged?

3. Data and Study Area

Vermont encompasses approximately 9,250 square miles and has a population of 626,000. Vermont's town centers are small; the state is predominantly rural and mountainous as are the proximate areas in neighboring states. As of the 2010 census, 66% of the state's population is estimated to live in rural areas. For the analysis in this paper, we used the 2000 census categories of urban area, urban cluster, and not urban (rural) which are contained in the NHTS. There are a total of 19 urban clusters in Vermont (four with populations between 10,000 and 20,000) and one urbanized area (centered around Burlington with population 42,400) (Table 1). According to the U.S. Census, areas with a density of at least 1,000 people per square mile and a population between 2,500 and 50,000 people are defined as urban clusters. Areas with a density of at least 1,000 people per square mile and a population of at least 50,000 are defined as urbanized areas. Vermont's urbanized areas and clusters, shown as red stars on Figure 2, are dispersed throughout the state with most counties containing at least one urban cluster.

Table 1. Urban clusters and urbanized areas either located in Vermont or serving Vermont residents.

City	Population	Census Classification
Barre-Montpelier	16,907	Urban Cluster
Bellows Falls	3,148	Urban Cluster
Bennington	9,074	Urban Cluster
Brattleboro	7,414	Urban Cluster
Burlington	42,417	Urbanized Area
Fairhaven	2,269	Urban Cluster
Lebanon, NH	13,151	Urban Cluster
Lyndonville	1,207	Urban Cluster
Middlebury	6,588	Urban Cluster
Newport	4,589	Urban Cluster
North Adams, MA	13,708	Urban Cluster
Northfield	2,101	Urban Cluster
Rutland	16,495	Urban Cluster
St. Johnsbury	6,193	Urban Cluster
Springfield	3,979	Urban Cluster
Swanton	2,386	Urban Cluster
Waterbury	1,763	Urban Cluster
Windsor	2,066	Urban Cluster
Vergennes	2,588	Urban Cluster

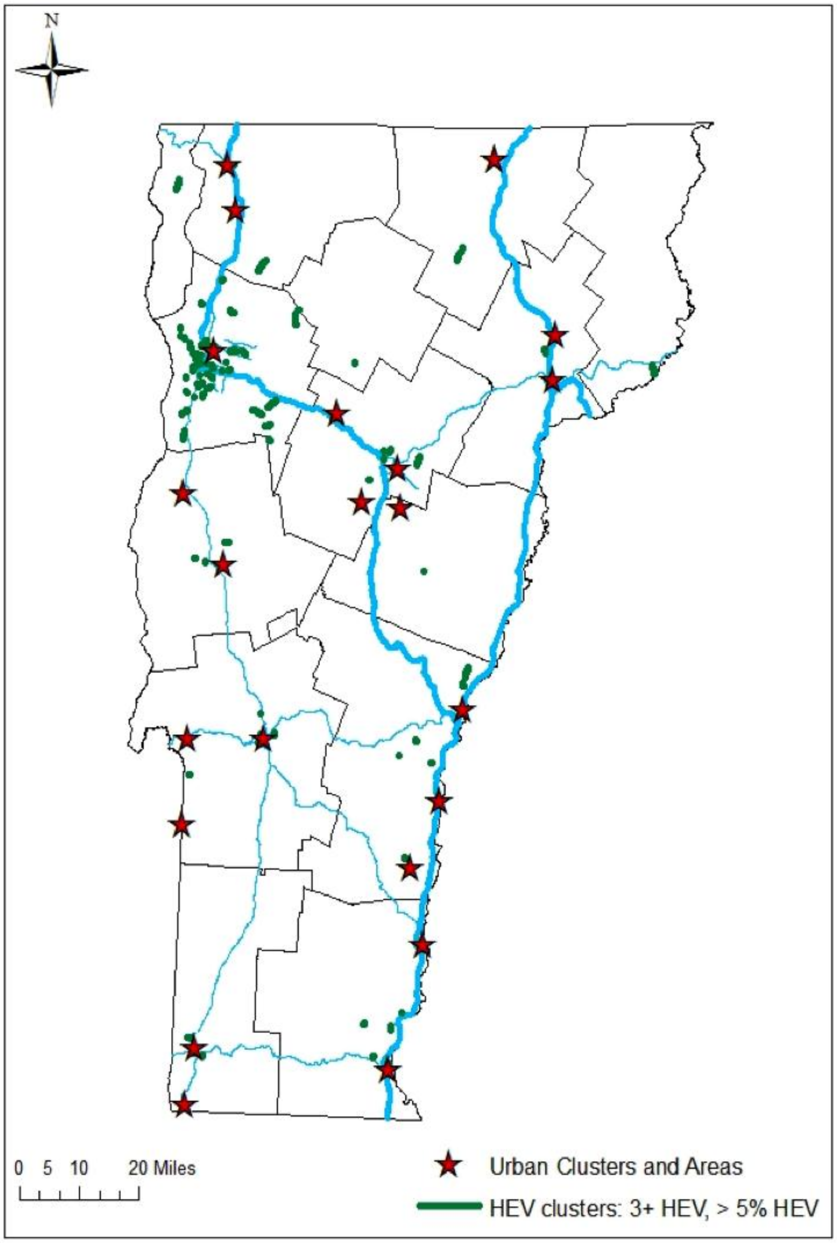


Figure 2. Clusters of hybrid electric vehicles (HEVs) by road link.
Here vehicle clusters are defined as those road links with 3+ hybrid vehicles and > 5% hybrids total. Red stars signify census-designated Urban Clusters and Urban Areas. Blue lines represent arterial roads and bold blue lines represent interstate highways.

We used the spatial distribution of current hybrid vehicles, to consider the spatial pattern of future EV and PHEV adoptions. To do this, we used vehicle registration data from the Vermont DMV to calculate the total number of hybrids currently registered in the state (Table 2). This data set contains all personal vehicles registered in the state, totaling 558,464 vehicles, 324,182 of which are geocoded by home address, and includes vehicle fuel type (e.g., gasoline, hybrid, diesel). For each of the 76,529 road links in the state-wide GIS dataset of roads (Source: Vermont Agency of Transportation), we calculated the number of total vehicles, the number of hybrids, the percent of vehicles that were hybrids, and the number of hybrids per mile by associating each vehicle location with the closest road link (Table 3). The average road link length was 0.26 miles (SD = 0.27). The number of road links with registered vehicles was 38,345. The number of road links with registered HEVs was 4,261.

Table 2. Fuel Type of Registered Vehicles in Vermont, October, 2010

	Total vehicles	Total geocoded vehicles
All vehicles	558,464	324,182
Hybrid vehicles	5,237	5,237

Table 3. Vermont Road Links

Number of Road Links	76,529
Average Link Length (miles)	0.26 (SD = 0.27)
Number of road links with registered vehicles	38,345
Number of road links with registered HEVs	4,261

Travel data from the Vermont NHTS add-on and was used to characterize existing travel patterns in the state. The data set includes information on a total of 3,550 people and 3,531 vehicles across 1,650 households. For this study, we re-aggregated the Vermont NHTS person-trip file by vehicle and then used this vehicle-based trip file to develop home-based tours for each vehicle. A home-based tour includes any series of trips that occur between departing from and returning to home. Home-based tours thus have a minimum of two legs (e.g. home to work, work to home) but potentially many more (home to work, work to shopping, shopping to home). Calculating home tour lengths allowed us to estimate the miles that Vermonters would drive between potential home charging of EVs. In our analysis, we use the longest tour length in a day (henceforth 'tour length') calculated for each vehicle. We also totaled each vehicle's miles traveled on the given travel day across all tours (daily VMT).

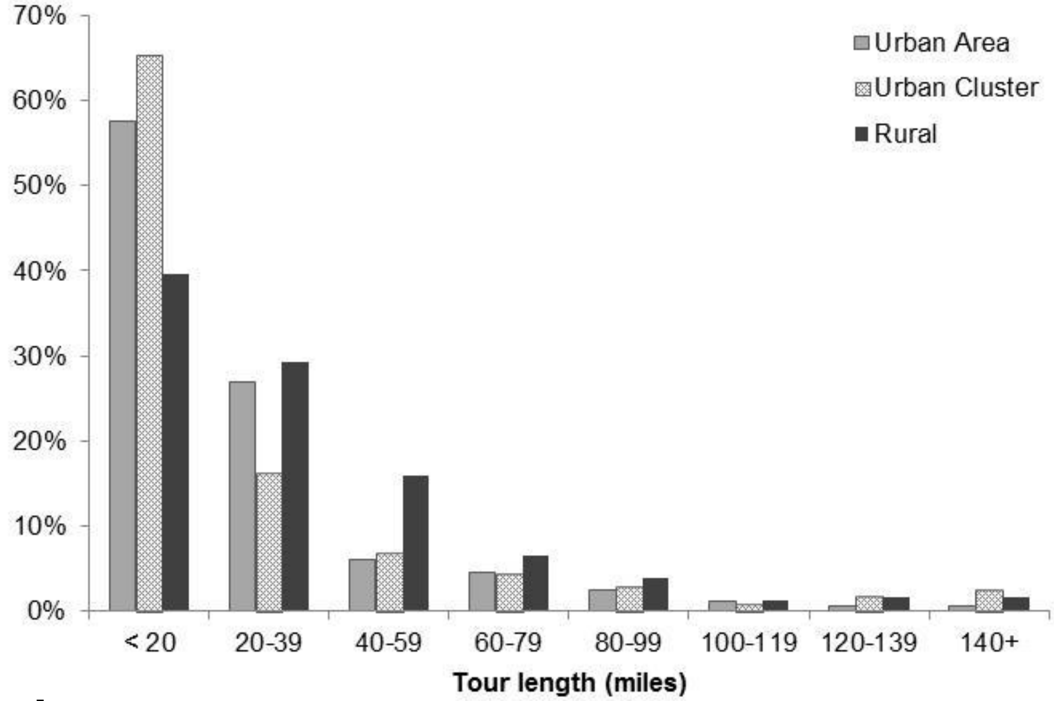
A total of 1,359 households and 1,926 vehicles were included in our analysis. Of the longest tour made by each vehicle in a day, the mean tour length was 32.3 miles (SD = 38.7). The mean number of tours completed by a vehicle in the survey day was 1.4 tours (SD = 0.7). The mean total daily VMT was 37.3 miles (SD = 41.6). On average, the longest tours were taken by rural residents (Table 4). The distribution of tour length by census area type (urban, urban cluster and rural) is shown in Figure 3. Homes were geocoded by the NHTS to exact address for 84% of our sample. For destinations, 63% were geocoded to exact address and 25% were geocoded to the nearest intersection.

Table 4. Vermont Mean Tour Length by Census Category			
Census Category	n	Mean± SD (miles)	Range (miles)
Urban Area	330	24.1±26.3	0.5-201
Urban Cluster	254	27.6±48.9	0.2-459
Rural	1,342	35.2±38.7	0.2-589

To consider the context for the state of Vermont and consider the effect that a larger metropolitan area may have on travel demand, we ran similar descriptive statistics for the Boston metropolitan area using the national NHTS dataset (Table 5). We did not have access to the same E911 data used to develop the land use and retail accessibility metrics described in the section above (and modeled for Vermont in Section 4.4 of this report), but we were able to examine patterns in census category and tour length. The tour lengths in Table 4 and 5 are similar. Mean tour length was 22.7 (SD=27.9) with non-urban residents generally taking longer tours (in Vermont there are no 'areas surrounded by urban areas'). This suggests that our comparison of urban and rural areas in Vermont is potentially generalizable and also reinforces the findings of prior research that travel patterns at least in terms of travel distance, are not explained by household location.

Table 5. Boston MSA Mean Tour Length by Census Category			
Census Category	n	Mean± SD (miles)	Range (miles)
Urban Area	480	21.5±28.0	0.2-210
Urban Cluster	4	29.2±19.8	19-59
Area surrounded by urban areas	6	31.5±17.2	11-56
Rural	73	29.2±28.0	0.2-158

a.



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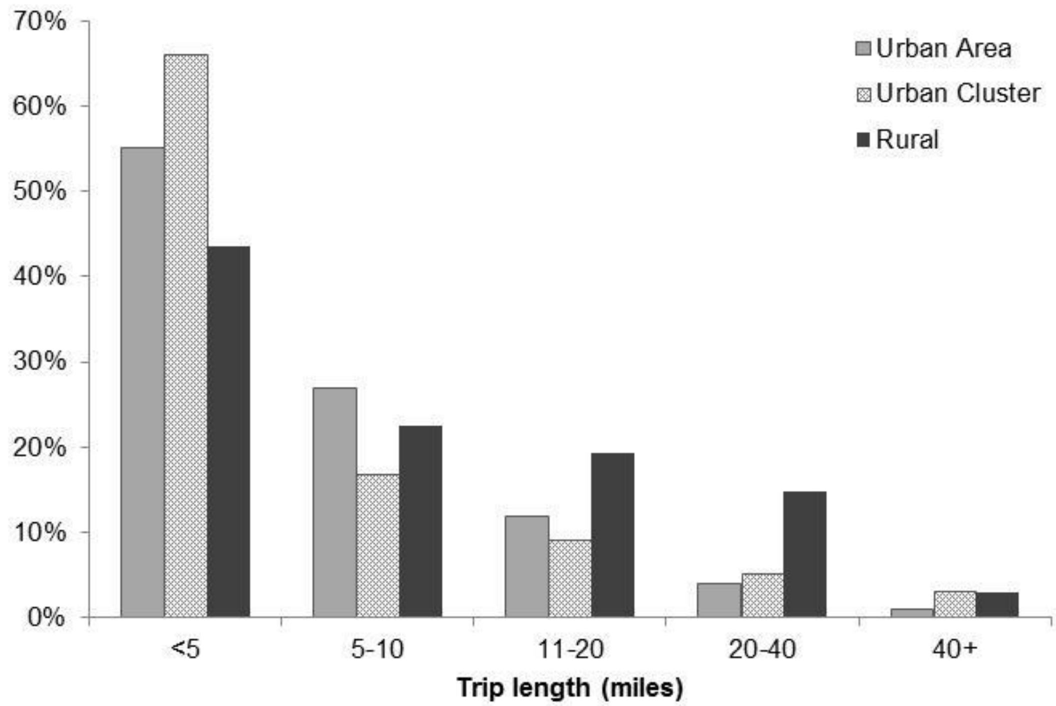

Figure 3. Distribution of vehicle (a.) tour and (b.) trip length in miles by census area type in Vermont. Area types include: urbanized area (n=330 vehicles), urban cluster (n=254 vehicles), rural (n=1,342 vehicles).

4. Analysis and Results

4.1 Clustering Patterns of Vehicle Adoption

We propose using the existing hybrid electric vehicles (HEV) as a proxy for how EVs might cluster in space. To assess the spatial clustering of existing HEVs, we considered the percent HEVs per road link, the percent per unit length, and the percent HEVs in neighborhoods surrounding existing hybrid vehicles. Figure 4 illustrates the percent hybrids as a function of total number of vehicles per road link. Naturally, the number of vehicles varies not only by land use but also because road links vary in length. The distinct curves on the graph are a function of the discrete count of HEVs on the various road links (e.g., 1 HEV/road link, 2 HEVs/road link, etc.) on the graph.

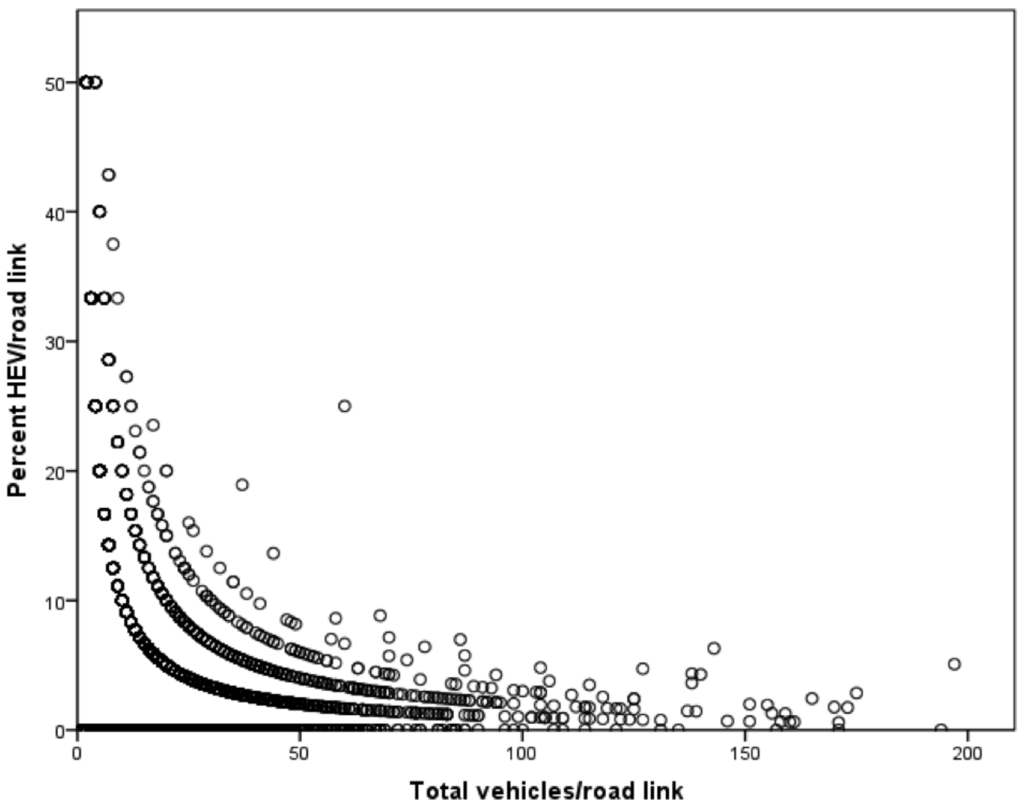

Figure 4. Percent hybrid electric vehicles /road link vs. total vehicles/road link in Vermont.

We used two methods to identify HEV clusters[1]. In the first, we defined a HEV cluster as any road link in the state with three or more hybrids and greater than 5% total hybrids. In the second method, we defined a cluster as any road link with at least 10 hybrids/mile and greater than 5% hybrids total. Using method 1, we identified 106 cluster road links throughout the state (Figure 2). In urbanized areas, urban clusters and rural areas, there were 41, 32, and 33 clusters respectively. These clusters are concentrated primarily in the

[1] Note that cluster is used here to denote a road segment or area with a larger number of HEVs above a pre-defined threshold. Cluster is not meant to denote the results of either a spatial analysis or a statistical cluster analysis.

greater Burlington area, the state's largest city and only urbanized area. The remaining HEV clusters are spread fairly evenly among the remaining two census area types: urban cluster, and rural. Using method 2, we identified considerably more HEV clusters: 900 road links (Figure 5). By method 2, there were 300, 313, and 297 clusters in urbanized areas, urban clusters and rural areas respectively. These road links are similarly distributed throughout the state, with a high concentration in the Burlington area, and the rest spread among smaller urban clusters and rural areas. Approximately a third of HEV cluster road links are in rural areas, suggesting EV adoption could be clustered in rural residential areas, creating challenges for electric infrastructure.

Finally, we investigated whether these clustering patterns were due to variability in vehicle density, or if the patterns resulted from certain locations having an increased preference for hybrid vehicles. To do so we counted the number of hybrid vehicles within a 1-mile radius of each vehicle in the state (Figure 6). Areas that encompassed fewer than 50 total vehicles within the 1-mile radius were excluded from this analysis. These vehicle counts were compared for hybrids and non-hybrids. For non-hybrids, surrounding vehicles within the 1-mile radius were comprised of 1.6% hybrids. The proportion of hybrids surrounding hybrid vehicles was 1.8%. While this difference is not large, a Kolmogorov-Smirnov test revealed that the two distributions differ significantly ($p<0.0001$). This result provides additional evidence that hybrid adoption has been clustered in rural Vermont and that electric vehicle adoption may also be clustered.

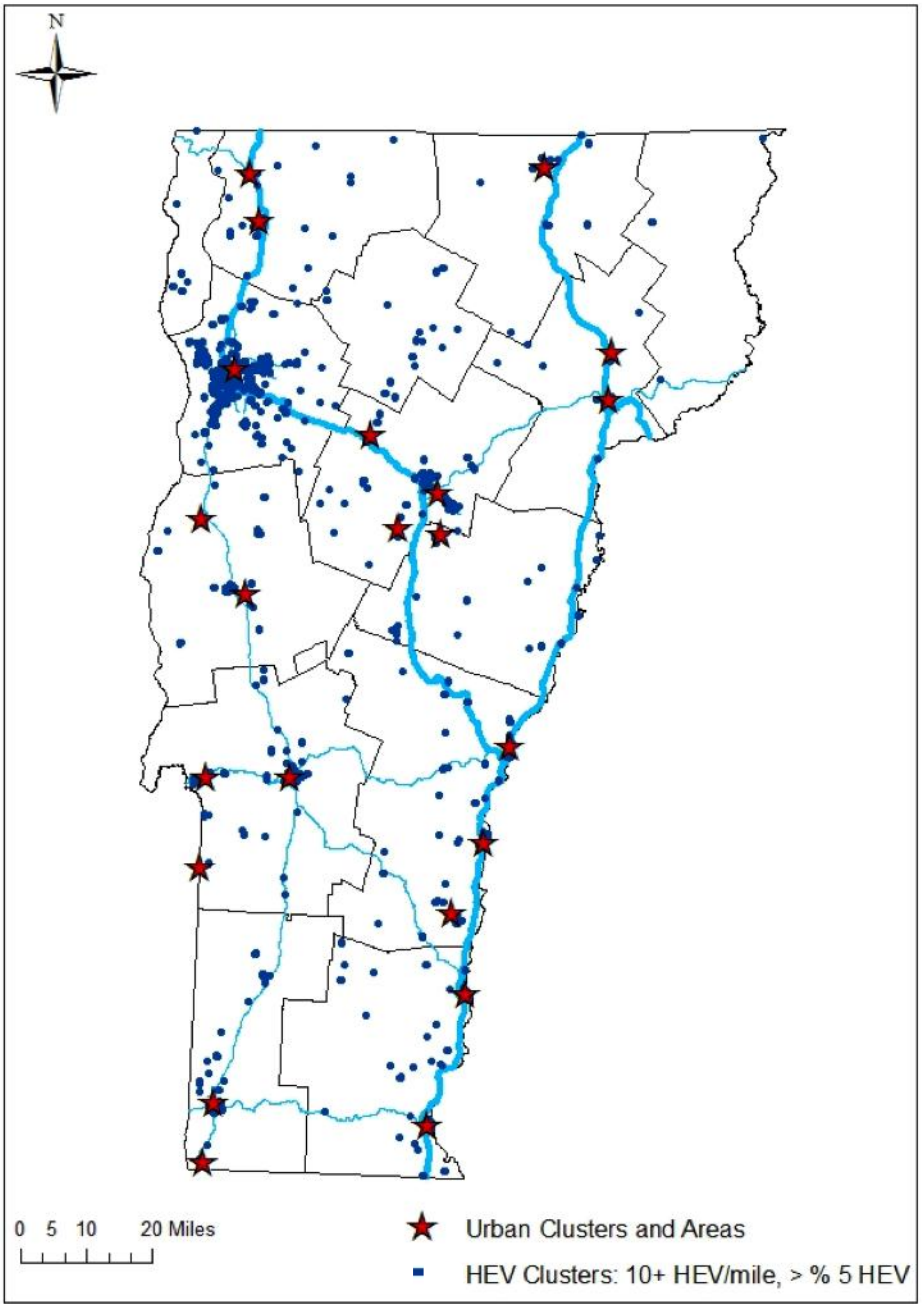

Figure 5. Clusters of hybrid electric vehicles (HEVs) by road link, b.
Here clusters are defined as those road links with 10+ hybrid vehicles/ road link mile and > 5% hybrids total. Red stars signify census-designated Urban Clusters and Urban Areas.

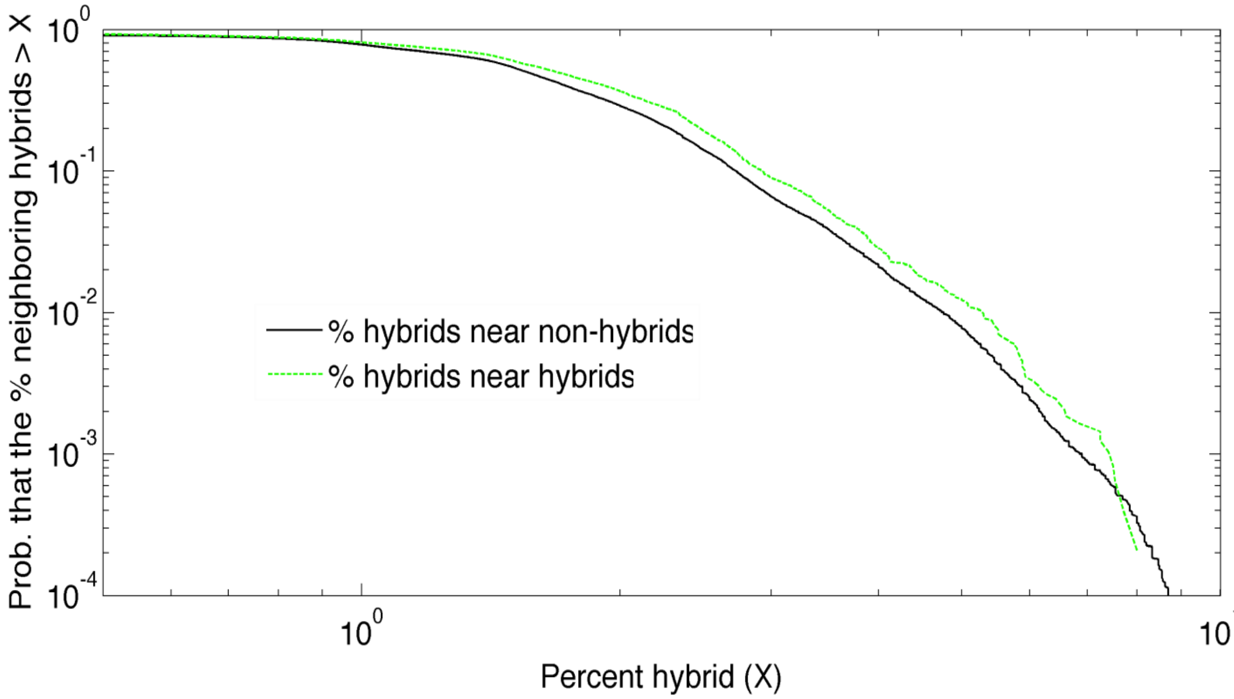

Figure 6. Hybrid adoption density near hybrids and non-hybrids.
The complementary cumulative probability distribution of hybrid densities for vehicles within 1 mile of a hybrid vehicle for all vehicles in Vermont in which there are at least 50 neighboring vehicles. This figure shows that a slightly higher percentage of vehicles neighboring hybrid vehicles are also hybrid vehicles.

4.2 EV Range and Vehicle Substitution

To estimate EV substitution rates for existing Vermont travel, we created a re-tabulation of the NHTS data from a trip-based format to a tour-based format. As described in Section 4.1 of this report, tour length is the sum of all miles driven between the time a vehicle leave and returns to the home. The total number of stops on each tour were also summed. Tours that included a stop at work were flagged as work tours, while those that did not were flagged as non-work tours. Each time a vehicle departed from home and returned home counted as a one tour, thus it was possible for vehicles to make multiple tours on their travel day. Travel that was not part of a complete tour (one that both started and ended at home) was not included in this analysis.

Table 6. Vermont Trip and Tour Descriptive Statistics

	Mean number per Day	Mean Length	Mean number legs
Trips	4.1±2.4	9.1±15.0	
Tours	1.4±0.7	36.5±40.7	2.8±1.4

We queried the re-tabulation of NHTS vehicle tour data using the decision tree in Figure 7. Preliminary analysis of the NHTS data confirmed what is widely speculated among transportation and planning professionals: work is the most common trip destination-type with a consistently adequate dwell time to allow charging. In light of this finding, we conducted further analysis, flagging those tours that included a stop at work. This allows us to examine the effect that workplace charging may have on facilitation and prevalence of EV use. We had a total of 978 geocoded work locations in our data set, a plurality of which were located in rural areas (Table 7).

Table 7. Geocoded work destinations by census category

Census category	# Work destinations
Urban area	286
Urban cluster	267
Rural	425

Of the 1,926 vehicles in the sample, 63% of the vehicles have total daily VMT under 40-miles. Of the 37% of vehicles that have daily travel longer than 40-miles, 6% of the total number of vehicles have tours less than 40 miles and are home for greater than one hour between tours to re-charge at home. For vehicles with tours longer than 40 miles that include a work stop, availability of work charging affects the number of vehicles whose daily travel demand could have been served by an EV. Overall we estimate that between 69-84% of the Vermont fleet could be substituted while still meeting existing travel demand (69% if 0% of workplaces have charging and 84% if 100% of workplaces have charging).

In addition, because there are a variety of EVs either already on the market or soon to be, we also examined the extent to which 100-mile electric range vehicles could meet daily travel demand in Vermont. These analysis revealed that 92% of vehicles had a daily VMT under 100 miles, 96% took tours less than 100 miles and spent time at home to allow charging between tours, and an additional 3.6% took tours greater than 100 miles that included work. Based on this analysis, between 96 and 99.4% of vehicles could be substituted with a 100-mile range EV.

Note that these estimates assume the NHTS survey day data represents travel throughout the year. It is reasonable to assume on other days shorter and longer tours are made by many vehicles compared to the survey day. If many tours are longer than those reflected in the NHTS data, our estimates for EV deployment potential will be somewhat high. However, households that generally drive fewer than 40 miles but sometimes drive longer distances (as is the case with most American households), could opt for PHEVs, which can use gasoline to extend their range.

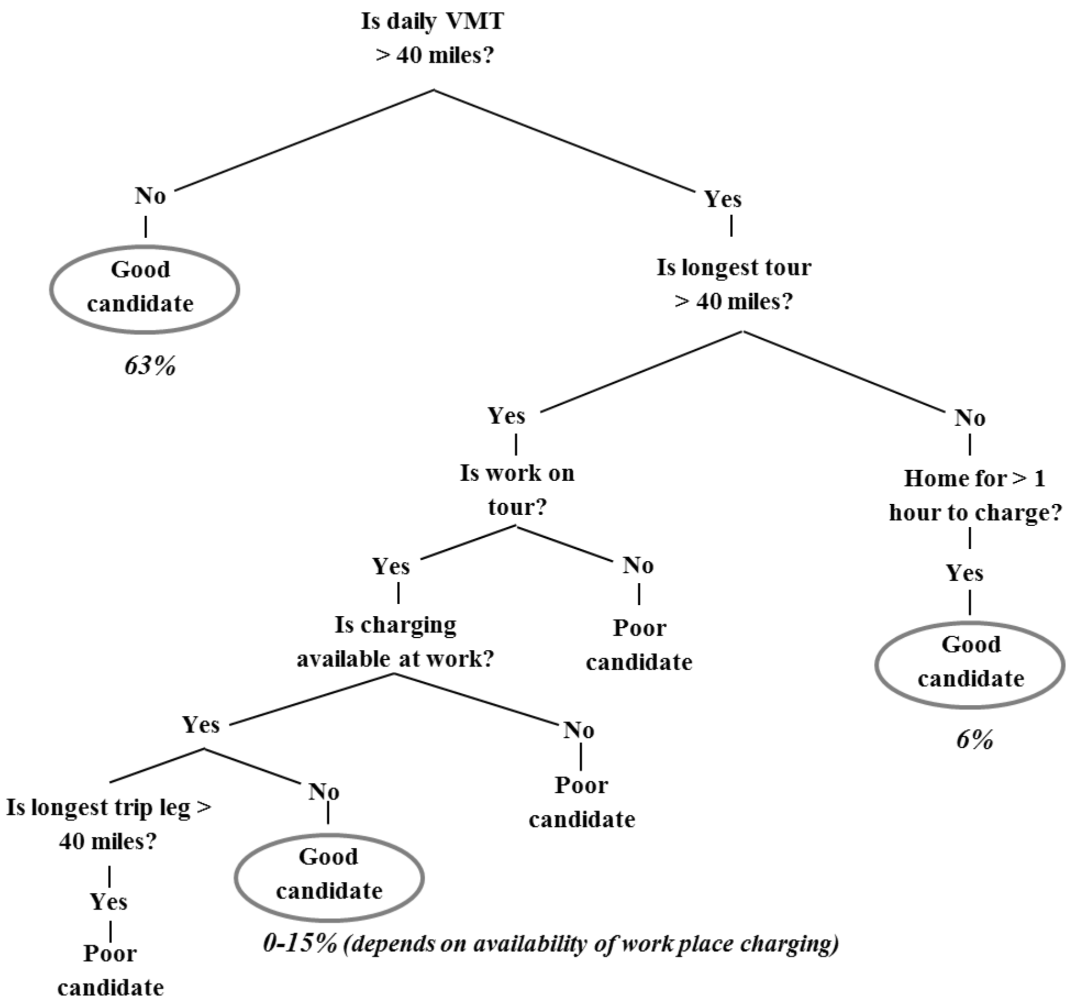

Figure 7. Electric vehicle (EV) substitution decision tree under a scenario of home and work charging. Ovals indicate those vehicles that are viable candidates for substitution, accompanied by estimated proportion of the Vermont fleet that could be substituted by 40 mile range EVs while still meeting daily travel demand.

4.3 Spatial Patterns of Non-home Non-work Charging

Given that the Vermont data do not show distinct rural versus urban patterns in HEV clusters or vehicle tour length, this section models vehicle miles traveled (VMT), which is a strong predictor of the additional electric energy required for vehicle charging, to identify spatial patterns of home location with higher demand that might be discouraged from EV adoption. We identified 150 vehicles (or 7.8%) in the Vermont NHTS that made home-based tours greater than 40 miles that did not include a stop at work. Of these 474 tour stops or destinations (not including trips returning home), 104 were stops of at least one hour (our minimum designated required charging time). Figure 7 illustrates that these destinations are not clustered and are not consistently in urban or suburban locations. Most are in rural locations that suffer from the barriers for charging station provision discussed previously (Table 8). Among these trip legs, the most common purposes were those for recreation (39%), shopping (22%), and meals out (15%). These results suggest provision of rural charging at non-home and non-work locations will be challenging.

Table 8. Geocoded destinations on non-work tours > 40 miles, by Census category

	Urban Area	Urban Cluster	Rural
# non-work tour destinations	34	15	55

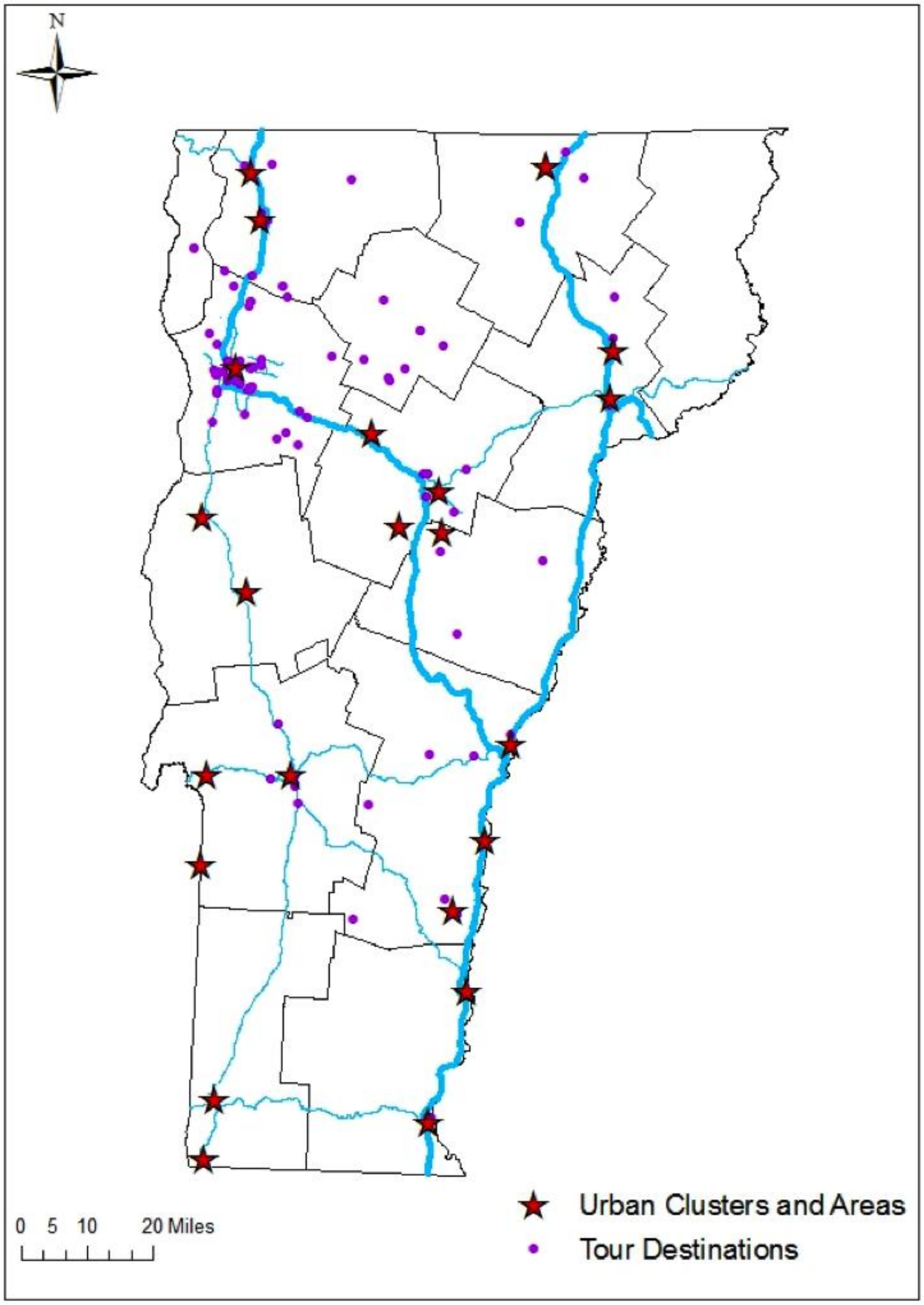

Figure 8. Tour destinations of home-based vehicle tours > 40 miles, with no work leg and dwell time > 60 minutes (n=104 destinations).

Destinations outside of Vermont are not included. Red stars signify census-designated Urban Clusters and Urban Areas.

4.4 Spatial Patterns of Travel Demand

We used general linear mixed models (in SAS v9.2) to evaluate those environmental factors and attributes of the built environment that may affect vehicle tour length and total travel for each vehicle. We constructed two separate models: one for total travel and one for longest tour driven in each vehicle. In both models, miles traveled served as the dependent variable. Independent variables included: urban/rural 2000 census designation, residential and commercial density of the home address at multiple scales, distance to closest urban center, access to retail locations and season.

Because travel patterns may be in large part determined by the built environment around someone's residence [16-18], we generated a number of spatial variables to relate where NHTS respondents live to the number of miles their vehicles drove on their assigned travel day. These spatial variables were created in the ArcGIS and include:

1. Distance to closest urban area or urban cluster (Figure 1)
2. Commercial density at scales ranging from 0.5 km radii to 30 km radii from each individual household using the Vermont E911 database.
3. Residential density from Vermont E911 database (as an alternative, we also used a categorical measure of residential density, based on 2000 U.S. Census definitions)
4. Retail access using a gravity function and the E911 data:
   Retail Access = $\sum 1/d^{1.7}$ where d is the distance to each retail locations within 50 km of each surveyed household [10].

Travel patterns can be heavily influenced by household structure [19- 21 for example], so we also included the NHTS variable household 'life cycle' in our models. There are 10 life cycles included in the NHTS and these are categorized by the number of adults in the household, the number and age of children present, and the number of retirees (Table 9) [22].

Table 9. Vermont NHTS Life Cycle Categories and Sample Size

Life Cycle	Household characteristics	n
1	1 adult, no children	137
2	2+ adults, no children	585
3	1 adult, 1 child < 5 years	5
4	2+ adults, youngest child < 5years	142
5	1 adults, youngest child 6-15 years	27
6	2+ adults, youngest child 6-15 years	314
7	1 adult, youngest child 16-21 years	18
8	2+ adults, youngest child 16-21 years	140
9	One adult, retired, no children	121
10	2+ adults, retired, no children	437

A total of 1,359 households and 1,926 vehicles were included in our analysis and all life cycle groups were represented. Both tour length and daily miles traveled exhibited highly positive-skewed distributions. Transformations did not improve model fit.

Table 10. Vermont Tour length and total daily travel mean, median, and range (miles)

	Mean ± SD	Median	Range
Tour length	32.3±38.7	21.3	0.2-589
Total daily travel	36.5±40.7	24.8	0.2-589

Because of the large number of models tested and relatively low explanatory power of most of them, we only report on the top model for each dependent variable (total miles traveled and miles traveled on the vehicle's longest tour). Our models (Table 11) were able to explain only a small portion of the variability seen in daily vehicle miles traveled (~3%). Models for total miles traveled and miles traveled on longest tour had similar results, and included census designation, life cycle and commercial density as significant factors. The following five observed patterns are particularly notable:

1. Distance to city center: Distance to urban cluster was not a significant model effect, nor was the interaction effect between this distance and urban cluster population.

2. Commercial density: Commercial density at 5 and 10 km had similar model effects and were both marginally significant factors in the model of tour length, although our gravity function of retail access was not. Although miles driven generally decreased with commercial density, the relationship is weak due to high variability, especially at lower levels of commercial density.

3. Retail access: A similar pattern is seen between total miles traveled versus retail access although this was not a significant factor in either model. Most vehicles included in our sample were in rural areas with limited retail access.

4. Residential density: The urban/rural census designation (a categorical variable with 3 levels) was a better predictor of travel than residential density, a continuous variable included in models at a variety of scales.

5. Life cycle: Life cycle was a significant model factor. Retirees for example tended to have shorter than average tour lengths (~25-28 miles) while those households with two adults and children tended to have higher daily VMT.

Table 11. Model variables and results (n=1,926)

Dependent variable	Independent variable	Parameter estimate	F	p	R^2
Model 1: Total miles traveled	Census designation		4.16	0.02	
	Life cycle		2.46	0.01	
	Commercial density at 10 km	-0.4	2.17	0.14	
Model results			4.22	<0.01	0.03
Model 2: Tour length (miles)	Census designation		7.19	<0.01	
	Life cycle		2.75	<0.01	
	Commercial density at 10 km	-0.4	7.70	0.06	
Model results			4.17	<0.01	0.03

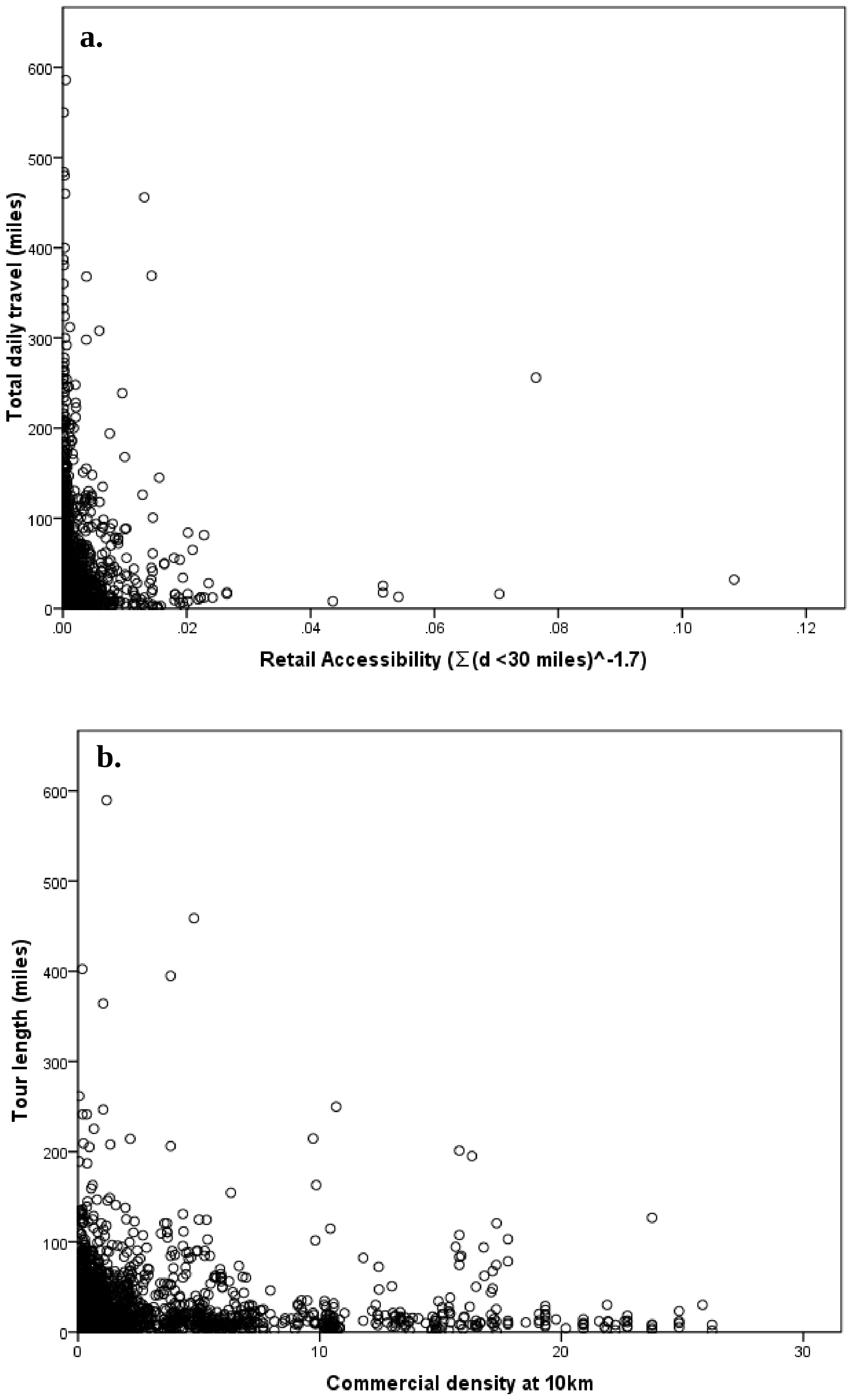

Figure 8. Total daily travel (miles) vs. retail access (a) and home-based tour length vs. commercial density at 10 km (b).

Daily VMT and home-home tour length had similar means and distributions and behaved similarly in our models regardless of the home location and home context of the vehicle. Variability was high for both of these travel variables, reducing model explanatory power. Life cycle was an important explanatory variable, affirming that travel patterns are in part a function of life style and demographics, in addition to environmental factors. While commercial density was significant at multiple scales in our models, the parameter estimates and r-square values were minimal, due most likely to the large amount of variation in the data. Miles traveled (daily total and on the longest tour) generally decreased with increased density of commercial and residential buildings, the relationship was inconsistent, though, due in large part to high variability at levels of low density. While mileage tends to be higher in these areas, low mileage vehicles occur everywhere.

Our analysis of vehicle tours revealed that urban residents generally took shorter tours, and when they did take longer tours, destinations included more suburban and rural areas. Clustering of EVs and PHEVs is expected in urban areas where residential density is higher. Electric infrastructure will probably be more robust in these areas but it may also be more variable. In contrast, while we may not see dense clustering of EVs in rural areas, miles driven is higher in these areas, meaning electricity demand will also be greater. Clustered vehicle adoption within suburban areas, where clusters of both hybrids and longer vehicle tours are likely, may trigger more significant needs for investments in electricity infrastructure. In more populous suburban areas, neighborhoods can have both relatively high residential density and long travel distances to work and amenities. High rates of vehicle adoption in these areas could expose weaknesses in the electricity infrastructure.

5. Discussion

The objective of this case study was to assess whether the spatial patterns in travel demand or vehicle adoption in rural areas suggested a particular direction for desirable market penetration of EVs. We expect that HEV and PHEVs will have substantial utility in rural areas due to the need for some longer distance trips, the frequent hilliness of some rural areas and the presumed longer distances between charging stations. Further, in colder northern climates, the electric range of these vehicles may be reduced. The travel demand data considered here indicate a large proportion of daily travel of the vehicles in Vermont could be served with a 40-mile range EV, even with only home and work charging, and nearly all travel demand could be met with a 100-mile range EV. Note that 40 miles range is relatively low for pure EVs and charging infrastructure is less critical for PHEVs. Overall, our results suggest EVs may have more utility in rural areas than expected.

We found little evidence to support our hypotheses that rural demand varies by household location in space. It appears on the surface that travel in rural areas may not be predictable as a function of location. Our models, based on a one-day travel log, of tour length and total daily VMT had very little explanatory power. We tried disaggregate focal spatial variables such as residential and commercial density as well as measures of accessibility to commercial destinations all of which had weak predictive power. The results presented here do not show a significant relationship between tour length and spatial location, area type, or accessibility to destinations. It is somewhat counter intuitive that the spatial distributions of destinations around your home location has limited impact on your travel patterns. The lack of significant relationships reported may be due to the relatively small data set, compounded by the substantial variability in individual vehicle travel patterns and the lack of multiple day data. It may be that within household variability from day-to-day in rural areas is masking the impact of accessibility.

Future work could include development of improved measures to capture the spatial patterns of rural travel over multiple days. Ultimately, the variability in rural travel patterns and the diversity of landscapes suggests a need for larger travel datasets in the rural areas where we have routinely collected little if any travel data due to lack of congestion concerns. While previous research has shown patterns in urban and suburban settings, with residential density generally inversely related to VMT, considerably less is known of vehicle travel in rural areas. Our research suggests that this relationship may not be linear. Variability was generally highest in the most rural areas, suggesting that lack of proximate accessibility to destinations may reduce rather increase VMT after a certain distance, or for some individuals.

As a largely rural state, most of the data used in this study came from people living in areas determined to have low levels of commercial density of retail accessibility. This lack of variability in our explanatory variables may have limited our ability to find patterns in travel demand and land use variables. In addition, our dependent variables (tour length and total daily travel) exhibited high variability, most notably in more rural areas. While miles driven were generally higher in these areas, the variability was even higher, making patterns in daily travel difficult to characterize. Previous research on land-use and travel behavior has often included comparisons to highly urban areas with widely available transit and a multitude of destinations within walking distance [e.g.23,24, 25]. Although Vermont does have one urbanized area (Burlington), our sample size was relatively low there and this city may not possess the density of retail, services, and employment, nor sufficient alternatives to driving, to substantially alter residents' travel.

Cervero and Duncan [26] observed that increasing access to employment reduced vehicle travel more than increased retail-residential land use mix. We did not examine employment access explicitly in this research, but in light of the high number of jobs revealed to be located in rural areas through the geocoded NHTS data, this could be an important consideration for future research exploring home and work charging needs in Vermont and other rural states. Additionally, a finer examination of tours by type (e.g., primary, discretionary as discussed in the introduction) may help to explain some of the variability observed in our travel data.

Our spatial analysis of current vehicle registrations as well as current vehicle-based demand in Vermont suggests we should expect street and block level clustering of EVs in both urban and rural areas. Therefore, rural clusters of EVs should be expected and local power infrastructure ability to support this fleet change should be investigated. None of the evidence suggests promising non-home and non-work charging locations in rural areas. Therefore, a limited amount of rural daily travel will not be served by EVs which may in turn have an impact on mobility or EV penetration rates. We recommend relatively inexpensive multi-day longitudinal vehicle-based data collections using GPS to provide a more accurate assessment of the extent to which current rural travel demands will be met with EVs and the extent to which non-home charging stations may have to be provided. Of course the penetration and utility of EVs in all areas, but especially rural areas will change as charging infrastructure is implemented.

Despite limitations, this study represents an important contribution in terms of data and methods. The use of spatially located vehicle and travel data allowed new questions to be addressed regarding where demand needs to be served that are only possible when datasets can be related in space. Our findings suggest expected EV clustering in rural areas. Current daily travel for Vermont vehicles suggests 69-84% of current vehicles could be replaced by a 40-mile range EV, and 96-99% of vehicles could be replaced with a 100-mile EV. We find that vehicle charging will occur mainly at home or work. There are very limited relationships between spatial location and vehicle-based travel demand. We find some evidence of lesser demand in urban areas and higher demand in suburban areas but recommend more robust rural travel data collection to more fully consider these questions.

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